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Dodd–Frank's impact on community-bank investment models: A Bayesian structural time series analysis

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Abstract
We use Bayesian structural time series (BSTS) methodology to test whether the Wall Street Reform and Consumer Protection Act of 2010 (DF) caused changes in community bank business models. The BSTS methodology uses the pre-DF period to create synthetic counterfactuals for community-bank dependent variables of interest. In the post-DF period, the counterfactuals become predictions of the dependent variables had DF not been enacted. Comparing post-DF predicted versus actual dependent variables allows us to estimate the causal impact of DF on these variables of interest. We find that relative to assets, community banks significantly reduce their lending activities and significantly increase investment in securities and excess reserves.

KEYWORDS
banking, Bayesian structural time series, Dodd–Frank, regulation, unintended consequences of regulatory changes

JEL CLASSIFICATION
G01, G21, G28

1 | INTRODUCTION

> Dodd–Frank's 2300 pages, with an astounding 22,000-plus pages of rules is "why so many community banks no longer exist, and those that have survived have seen their costs go up, their profits go down, and their ability to make small-business and consumer loans curtailed. It's all because of the heavy hand of government." Senator John Kennedy.
>
> (Kennedy, 2017a)

The Dodd–Frank Wall Street Reform and Consumer Protection Act (DF) was signed into law in July 2010 in the aftermath of the financial crisis of 2008. The United States had just emerged from one of its worst recessions in modern history, a recession some accused the banking industry of triggering. In this view, systemically important banks colluded with self-interested credit ratings agencies to offer complacent institutional investors mortgage-backed securities (MBS) the ratings of which were intentionally inflated. Whether this narrative is true or not, the MBS market collapsed when the US housing-market boom proved unsustainable, and subprime borrowers began walking away from their underwater mortgages.

DF was aimed primarily at a relatively small number of systemically important banks (see Acharya and Richardson, 2012). The Act's provisions, however, encompassed the activities of all banks large and small. Despite attempts to mitigate DF's effect on smaller, non-systemically important financial institutions, there is anecdotal and survey-based evidence of significant impacts of DF on community banks. To the extent that DF upended the relative profitability of previous community-bank business models, the Act could be expected to lead to changes in asset allocations as community banks respond to the new lending incentives associated with DF changes.

In allocating capital from savers to borrowers, a country's banking system is obviously a key component of its economic system. While any single community bank is not systemically important for that economy to thrive, that bank may be vital to the community it serves. This is particularly true in the US where community banks issue most small-business loans (FDIC, 2018). Well-intended federal regulations whose provisions encourage re-examinations of community-bank business models or whose costs of compliance tend to unintentionally swing the competitive balance to larger banks, may have detrimental effects on community bank viability and that of the communities they serve.

While anecdotal and survey-based studies provide important viewpoints, our more rigorous empirical study provides a more definitive answer to the question of whether and how DF impacted community-bank lending behaviour and adds to the growing body of literature on the real effects of DF. Using Federal Deposit Insurance Corporation (FDIC) quarterly call reports from the universe of US banks, and a relatively new, cutting-edge empirical methodology called Bayesian structural time series (BSTS), we explore the causal impact of DF on the post-DF asset allocations of community banks. Our results indicate that DF caused community banks to significantly decrease their lending activities. Specifically, community banks significantly cut back on their residential real estate, commercial and industrial (C&I), and agricultural lending. To balance this overall decrease in lending, community banks significantly increased relative investments in securities and excess reserves. This post-DF shift in asset allocations could signal trouble for bank customers who rely on community banks for loans, such as small businesses or agricultural borrowers in rural communities.[1]

The following section lays out the literature review that develops our hypothesis. Section 2 describes our sample, data, and methodology. Section 3 presents the results of our main analysis followed by Section 4, which presents our robustness checks. We conclude our study in Section 5.

2 | LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Well-reasoned regulation in a capitalist system is intended to step in when there is a market failure, for example, when moral hazard or negative externalities are present. In the case of

[1]The Small Business Administration reports that small businesses employed 47.1% of the private US workforce in 2017 and created 1.6 million net new jobs in 2019 (SBA, 2018).

bank regulation, moral hazard arises due to deposit insurance and designation as too big to fail, both of which could encourage some banks to take on more risk than they would without government guarantees. Negative externalities may arise, in this context, when banks cut lending to maintain capital ratios, which could create a downward spiral in lending as other banks cut lending, as well, for the same reason.

Prior to the 2008 financial crisis, the Banking Act of 1933 formed the foundation of the US financial regulatory system. This Act created the FDIC, and placed constraints on banks' risk-taking behaviours including the separation of investment from commercial banking activities (called the Glass–Steagall Act), prohibition from offering interest on demand deposits, and caps on interest rates (Mause, 2013). In order to protect the FDIC insurance fund against losses, these provisions tended to focus on preventing individual bank failures, which led to bank supervision focused primarily on maintaining individual bank capital ratios above a minimum level. Hanson et al. (2011) refer to this approach to financial regulation as microprudential and point out that banks under stress can maintain capital ratios above the specified level by either raising new capital (e.g., issuing equity), thereby increasing the capital ratio's numerator, or reducing assets (e.g., decreasing lending), thereby reducing the denominator. Since issuing new equity while in distress is economically undesirable due to depressed values, most banks in this situation would choose to cut lending instead. When a relatively small number of banks are in financial distress, the negative externality of reduced lending is inconsequential to the system as other banks pick up the slack in lending. In the presence of a system-wide shock that affects a relatively large number of banks, however, such as economy-wide recession, the aggregate reduction in lending could be large and lead to a negative feedback loop producing systemic risk that threatens the entire economy. This scenario highlights how well-intentioned regulation (e.g., minimum capital ratios) can lead to significant unintended consequences. Hanson, et al. (2011) argue that rather than focusing on individual bank solvency, a more holistic approach to bank regulation that accounts for moral hazard and negative externalities should focus more on the health of the entire financial system, referring to this as a macroprudential regulatory approach. Acharya and Richardson (2012) examine DF in the context of its ability to contain systemic risk and conclude that while it closed some loopholes and has improved financial oversight with inclusion of periodic stress testing, the Act missed an opportunity to explicitly recognise that systemic risk arises during times of stress when large numbers of banks tend to move simultaneously towards the same solutions to their individual stresses.

Community banks tend to approach commercial lending differently from larger banks. Berger et al. (2005) develop a model in which large banks focus on larger commercial loans and small banks have a comparative advantage in making smaller commercial loans. These comparative advantages stem from capital allocation differences between the two types of banks. Loan officers at community banks tend to be closer to ultimate decision makers, while loan officers at larger banks can be several steps removed from those with final loan approval authority. Because they are more certain that capital will be allocated to loans which they approve, community-bank loan officers are more willing to develop comprehensive “soft” data (e.g., borrower character data) that is required to make successful loans to small borrowers who do not have hard data (e.g., financial statements) to support a loan origination decision. Conversely, large-bank loan officers, whose proposed loans may be denied funding at a higher level of the organisation, are not incentivised to develop such comprehensive soft data and will focus instead on hard-data borrowers. Due to the incentive effects of these differing capital allocation processes, community (noncommunity) banks will focus on making commercial loans to small (large) businesses. Berger et al. (2005) report empirical findings consistent with small banks being better at using soft information to make loans to their more informationally opaque small commercial borrowers.

According to FDIC (2018), while community banks held only 17% of total US banking industry assets in 2017, they made some 53% of all small business loans that year. Moreover, community banks hold the majority of deposits in rural areas and in small communities, many of which may be unattractive markets to larger banks. FDIC (2012) reports that about one in every five US counties is only served by community banks. These facts make small community banks an integral part of the US banking system, and indispensable to the communities in which they operate and the farms and small businesses they serve.

The legislative team that wrote DF recognised that community banks did not cause the large increase in systemic risk associated with the 2007/2008 financial crisis, and that community-bank competitiveness with larger banks might be severely impacted by some of the Act's provisions. Thus, they wrote asset-size thresholds into the legislation, and for banks below these thresholds certain provisions of the Act did not apply. For example, Section 1025 exempts banks with total assets below $10 billion from direct supervision by the Bureau of Consumer Financial Protection (CFPB, see Public Law 111–203 (2010), p. 124 STAT. 1990). In testimony before the US Senate, Tarullo (2013) notes that the Federal Reserve Board recognises "the disproportionate burden that regulatory compliance can impose on smaller institutions" and that the Fed has implemented special processes intended to reduce this burden. Tarullo notes, for example, that many of the Basel III requirements, such as countercyclical capital buffers, will not apply to smaller banks.

Despite these efforts to insulate community banks from some of the more onerous DF provisions, there is anecdotal evidence that DF is differentially impacting smaller banks. Eustis Mortgage Co.'s CEO claimed that due to increased compliance costs, the cost of producing mortgage loans doubled after DF (Kennedy, 2017a). In testimony before Congress, attorney and community bank legal consultant Patrick Kennedy stated that DF:

> unleashed a plethora of new requirements and restrictions on banks and led to further significant increased costs. Many in the industry began to wonder whether they could survive these heavy costs and regulatory burden, and it became commonly discussed at banking conferences that to survive banks would have to be at least $500MM in total assets
>
> (Kennedy, 2017b).

Also testifying before Congress, the chairman of FirstCapital Bank of Midland, Texas, stated the following:

> For example, we originated 1,296 mortgage loans in 2009 with a total mortgage staff of 18. In 2012, we originated 1,080 mortgage loans with a total mortgage staff of 25. All of the additions were added to enable us to maintain compliance with all of the new requirements and ones expected.

Marsh and Norman (2013) specify the various DF titles expected to impact community bank competitiveness. For example, Marsh and Norman note that under Title 14, mortgage lenders must consider and verify borrowers using eight factors, and that failing to do so would be a violation of the Truth in Lending Act subjecting the lender to both increased borrower lawsuits as well as a clear defence for defaulted borrowers against foreclosing banks in foreclosure proceedings. Because community banks, in general, typically lack in-house expertise regarding these factors, many would be forced to hire additional compliance staff or outside consultants. An alternative response is to cut back on mortgage lending, which Gissler et al. (2016) document.

Peirce et al. (2014) surveyed small banks on the effects of DF on different aspects of their business and received responses from about 200 banks. Some 90.9% of responding banks reported increases in compliance costs, which included in-house compliance personnel as well as external consultants (38.4%), legal counsel (23.4%), and compliance personnel (22.6%). Over half the responding banks expected to engage outside consultants to comply with the various provisions of DF. Due to DF changes in residential mortgage lending rules that increase both lender costs and legal liability, Peirce et al. (2014) report that over 16% of respondents have already and 10% anticipate discontinuing offering residential mortgages. This discontinuation of an important source of balance sheet diversification will make the loan portfolios of these community banks more concentrated, and therefore, riskier (see Stiroh, 2004). Respondent banks to the Peirce et al. (2014) survey report significant changes in their fees on products and services, particularly on debit cards (due to DF's Durbin Amendment), personal checking and overdraft protection. Finally, many of these changes are due to the CFPB. Peirce et al. (2014) note that based on survey answers, the CFPB "is of great concern to small banks", even though, as mentioned above, these banks are exempt from direct CFPB supervision.

Lux and Greene (2015) use the FDIC (2014) *Statistics on depository institutions* publication to conduct a banking industry loan portfolio analysis surrounding enactment of DF. They report that community banks offer a majority of agricultural, commercial real estate and small business loans. Trends from the second quarter of 2010 (when DF was signed) through Q2 2014, indicate that community banks tend to be increasing their dominance in agricultural lending, but are losing market share to larger banks in commercial and industrial lending, in general, and especially in small business lending. Lux and Greene (2015) note that much of this decline in market share is due to industry consolidation; and argue that consolidation is being driven by regulatory economies of scale in the wake of DF.

This discussion leads us to our three main questions, which explore the causal impact of DF on community-bank lending and investing decisions:

1. Did DF cause a decline in community-bank lending activities?
2. Did DF cause an increase in community-bank securities investing?
3. Did DF cause an increase in community-bank excess reserves?

In summary, the financial crisis of 2008 illuminated the shortcomings of US banking regulation, the main foundation of which was over 75 years old. DF was enacted to modernise financial regulation, and to give government regulators the necessary tools to prevent future financial crises. Hanson et al. (2011) and Acharya and Richardson (2012) analyse DF in this context and conclude that while it succeeds at the former, it may be less successful at the latter. The authors of DF, recognising possible differential impacts on community banks exempted them from some of the Act's more compliance-heavy provisions. Anecdotal and survey evidence indicates, however, that these exemptions may not be effective in shielding community banks from being differentially impacted by the Act. We add to this growing literature by conducting a rigorous empirical analysis designed to uncover any causal effects of DF on community-bank lending and investing behaviours.

Our work is most closely related to Stiroh (2004) who reports reductions in risk-adjusted performance as community banks focus on non-interest income-generating activities, commercial and industrial lending, and securities trading. While we do not study non-interest income, our results show that DF caused community banks to cut back on C&I lending and to increase trading activities. This would suggest partial offsetting between lending and investing activities regarding bank risk-adjusted performance reported by Stiroh (2004). Beyond performance, however, this move away from C&I and agricultural lending by community banks presents potential problems for those important borrowers. Our results also complement those of Gamble et al. (2020), who report that DF caused small banks to cut back on lending to their smallest commercial borrowers. In a study of the 2008 financial crisis, Cole and Damm (2020) report that banks cut back on small-business lending, and that those banks who received more government bailout money (TARP funds) tended to cut this type of lending the most. Importantly, most of Cole and Damm's (2020) sample period is during our BSTS model's learning, or calibration period meaning that our model accounts for this pre-DF reduction in C&I lending. Our work also complements that of Hogan and Burns (2019) who report that small-bank noninterest and

TABLE 1 Sample bank average asset size by year

Date	Noncommunity banks	Community banks	All banks
31-Dec-01	$ 6,789,065	$ 149,512	$ 802,623
31-Dec-02	$ 7,807,214	$ 160,767	$ 888,117
31-Dec-03	$ 8,691,358	$ 173,386	$ 968,838
31-Dec-04	$ 9,721,097	$ 181,963	$ 1,093,393
31-Dec-05	$ 10,707,262	$ 198,438	$ 1,191,831
31-Dec-06	$ 11,707,660	$ 211,849	$ 1,346,542
31-Dec-07	$ 13,325,405	$ 222,488	$ 1,511,002
31-Dec-08	$ 15,711,388	$ 236,324	$ 1,725,879
31-Dec-09	$ 16,709,977	$ 250,934	$ 1,723,394
31-Dec-10	$ 20,879,547	$ 252,363	$ 1,841,029
31-Dec-11	$ 24,893,817	$ 266,529	$ 2,003,625
31-Dec-12	$ 26,948,766	$ 286,155	$ 2,189,681

Note: This table provides means of the total assets, as of year end, for community, noncommunity and all banks (all dollar amounts are in thousands).

compliance expenses increased post-DF. Although we do not study noninterest or compliance costs, we show that community banks made important changes to their business models that were a direct result of DF's changes in incentives.[2] Finally, our findings indicate that community banks have transformed somewhat from lending institutions to securities traders and depositors in the Federal Reserve. This transformation strikes a blow to the small businesses and agricultural borrowers and their communities, which are reliant on community banks.

3 | SAMPLE, DATA, AND METHODOLOGY

3.1 | Sample and data

Our sample consists of all commercial banks in the US with Call Report data surrounding enactment of DF. Some of the organisations that submit Call Reports are specialty financial institutions, which, following Berger and Bouwman (2013), we exclude from our sample. These include institutions with no commercial real estate or commercial and industrial loans outstanding; no deposits; and gross total assets of less than $25 million. We use the FDIC research definition to identify community banks. In addition to asset-size, the FDIC includes characteristics such as geographic location, numbers of branches, and the number of states in which the bank operates, among other characteristics, in its research definition of community banks.[3]

Our data ranges from 2001 through the third quarter of 2013, which is three years after DF was signed into law. Table 1 contains end-of-year means of total assets for community and noncommunity banks during the sample period. Note that as of the end of 2010, which was the year in which DF was signed into law, community (noncommunity) banks had about $252 million ($20,880 million) in total assets. We analyse post-DF changes in community bank asset allocations from quarterly financial data of US banks over the 12 quarters after DF was signed into law.

[2]In unreported results, our BSTS model indicates statistically significant increases in noninterest and compliance expenses resulting from enactment of DF.

[3]See FDIC (2020), Appendix Table A1. for the complete definition of a community bank.

3.2 | Methodology

The gold standard of causal analysis is the double-blind methodology in which a homogeneous sample is randomly split into two subsamples. One subsample is treated with the treatment of interest and the other is treated with a placebo. The group assigned to the placebo treatment is called the counterfactual, or control group. Since the two subgroups were randomly assigned from a single homogeneous group, the counterfactual, by design, controls for all relationships between the two subsamples other than the treatment so that any difference in outcomes between the two groups is attributed to the treatment alone. Unfortunately, it is usually impractical or impossible to use the double-blind methodology in business settings like, for example, studying the causal impact of regulatory change on bank asset allocation decisions. Instead, we employ a relatively new, cutting-edge empirical methodology designed to allow researchers to generate synthetic control groups (SCG) against which to compare the treated subsample. BSTS is a machine learning methodology that uses the pre-treatment or learning phase to establish the time-series behaviour of the dependent variable of interest as well as the dynamic time-series relationships between the dependent variable and various covariates. For example, if the learning-phase time-series data shows the dependent variable contains both a trend and seasonality, the model will learn about these dynamics. In the post-treatment or prediction phase, the learned time-series behaviour coupled with the continuing evolution of the covariates establishes a dynamically changing SCG, which is defined as the post-DF counterfactual group's estimated value of the dependent variable. In our case, the estimated community bank dependent variable value had DF not been enacted. The treatment is deemed causal when there is a statistically significant post-treatment divergence between the time-series values of the dependent variable and the values predicted by the SCG.

BSTS consists of a system of equations that define the structure of the time series where dependent variable y is defined as follows:

$$y_t = \mu_t + \tau_t + \beta^T x_t + \varepsilon_t \tag{1}$$

where μ_t defines the level of the unobserved state and is described by the following model:

$$\mu_{t+1} = \mu_t + \nu_t + \epsilon_t \tag{2}$$

where ν_t in Equation (2) represents the linear trend or basic drift of the variable:

$$\nu_{t+1} = \nu_t + \zeta_t \tag{3}$$

where τ_t in Equation (1) represents the seasonality component:

$$\tau_t = -\sum_{s=1}^{S-1} \tau_{t-s} + \omega_t \tag{4}$$

where $s = 4$ in equation 4 to denote the quarterly data with which we are working.

Finally, $\beta^T x_t$ is a regression of a set of covariates on y that adds richness to the prediction based on variables known to be related to the dependent variables. In our case, the most important community bank covariate is the analogous noncommunity bank time series for the respective dependent variable. For example, time series of noncommunity banks' agricultural lending is the primary covariate of community banks' agricultural lending because we expect both to derive from the same or similar underlying processes. Other independent covariates in the regression include the values of the ratio of core deposits to all deposits, a measure of loan concentration, the Tier 1 leverage ratio, a measure of a bank's multimarket contacts, a housing market index, and the bank's loan rate.[4]

The learning phase consists of data from the first quarter of 2001 through the second quarter of 2010. During this phase, the model learns the dependent variable's level, trend and seasonality, as well as the relationships between the dependent variable and the regression covariates. Once the treatment occurs, which in our case is enactment of DF, the learning phase is complete, and the prediction phase begins. In the first quarter of the prediction phase, the model uses what it has learned about the dependent variable's level, trend, seasonality, statistical relationships with the covariates, and the current values of the covariates, to predict what the dependent variable would be had DF not been enacted. To estimate the predicted variable, the BSTS package uses a combination of a stochastic Kalman smoother and a Markov chain Monte Carlo algorithm. In the second quarter of the prediction phase, the prediction is updated by accounting for the trend, the new season, and the new quarter's values of the regression covariates, with which the BSTS-package estimates a new prediction for the quarter's dependent variable. This prediction updating continues until the end of the prediction period – 12 quarters after DF enactment.

Dependent variables for our BSTS methodology include those designed to explore post-DF changes in community bank investment policies. Our dependent variables related to post-DF changes in community bank investment policies include community-bank total lending, total securities investments, and deposits in Federal interest-bearing accounts (required and excess reserves deposited in the central bank). Following Drechsler et al. (2021), we further break total lending into agricultural, C&I, and total real estate loans. This latter group is further sub-divided into commercial real estate, and residential real estate loans. We break down the securities investment category into those held to maturity and those that are available for sale. We normalise all these asset types by dividing by concurrent quarterly total assets.

Table 2 contains descriptive statistics related to the quarterly dependent variables and covariates over the entire sample period. The average bank had about 4.6%, 9.8%, 42.8%, and 62.7% of assets invested in agricultural, commercial and industrial, real estate, and total loans respectively. Similarly, the average bank invested about 22.6%, 19.1%, and 3% of assets in total securities, securities held for sale, and federal interest-bearing bank balances, respectively. For covariates, the average community bank had core deposits of about 79.9% of assets, a loan concentration ratio of 35.6%, a Tier 1 leverage ratio of 10.7% and a loan rate of 2%. Table 3 presents the Pearson correlation coefficients among the covariates. There are strong negative correlations between a bank's core deposits and its loan concentration (−0.285) and Tier 1 leverage (−0.345), and positive correlations between a bank's Tier 1 leverage ratio and the concentration of its loan portfolio (+0.17) and its average loan rate and its housing performance index (0.20). All other correlation coefficients are between ±0.115.

4 | FINDINGS

We report our findings on DF's causal impact on community bank asset allocation decisions in Figures 1–10. Each figure is a copy of the BSTS output, which includes two periods. The pre-DF learning phase runs from 2001 through the second quarter of 2010, while the post-DF prediction phase begins in the third quarter of 2010 and runs for 12 quarters through the

[4]Inclusion of these variables follows Berger and Bauman (2013). A more detailed description of these additional covariates is included in Appendix Table A1.

TABLE 2 Descriptive statistics

Dependent variable	Obs	Mean	Std. dev.
Loans:			
Agricultural Loans To Assets	363,999	0.046	0.077
Residential Real Estate Loans To Assets	363,999	0.163	0.106
Commercial Real Estate Loans To Assets	363,999	0.223	0.165
Commercial & Industrial Loans To Assets	363,999	0.098	0.070
Total Real Estate Loans To Assets	363,999	0.428	0.177
Total Loans To Assets	363,999	0.627	0.163
Securities:			
Total Securities To Assets	363,999	0.226	0.151
Securities Held To Maturity To Assets	363,999	0.034	0.083
Securities Available For Sale To Assets	363,999	0.191	0.145
Reserves:			
Federal Interest-Bearing Balances To Assets	363,999	0.030	0.056
Control variables:			
Core Deposits ratio	363,990	0.799	0.117
Loan concentration	362,110	0.356	0.144
Multimarket Contact	362,167	0.001	0.004
Housing Price Index	361,560	0.021	0.063
Tier 1 Leverage ratio	363,999	0.107	0.050
Average loan rate	362,104	0.020	0.010

Note: This table provides descriptive statistics for dependent variables. The data range over the entire sample period pre- and post-signing of the Dodd–Frank act. Please see Appendix Table A1 for definitions of the control variables.

TABLE 3 Correlation coefficients among independent variables

	Variable	1	2	3	4	5	6
1	Core deposits ratio	1.000					
2	Loan concentration	−0.285	1.000				
3	Multi-Market	−0.029	−0.019	1.000			
4	Housing Price Index	0.113	−0.074	0.001	1.000		
5	Tier 1 leverage ratio	−0.345	0.170	−0.042	−0.042	1.000	
6	Loan rate	0.067	−0.083	−0.012	0.198	0.115	1.000

Note: This table contains the correlation coefficients among the control variables using data over the entire sample period pre- and post-signing of the Dodd–Frank act. Please see Appendix Table A1 for definitions of the control variables.

second quarter of 2013. As time passes from 2001 to 2013, each Figure graphs the quarterly value of the respective community bank dependent variable (solid line), the quarterly value of the SCG dependent variable (dashed line), and the 95% confidence interval around the SCG value (shaded area). The x-axis represents time, and the y-axis represents the value of the respective dependent variable. The vertical dashed line just after 2010 represents the changeover from the learning to the prediction phase and represents the quarter in which DF was signed into law. The second vertical dashed line depicts the end of the sample period. During the learning phase, as mentioned earlier, the BSTS model is learning the distributional properties of the dependent variable, which it uses during the prediction phase to estimate the predicted

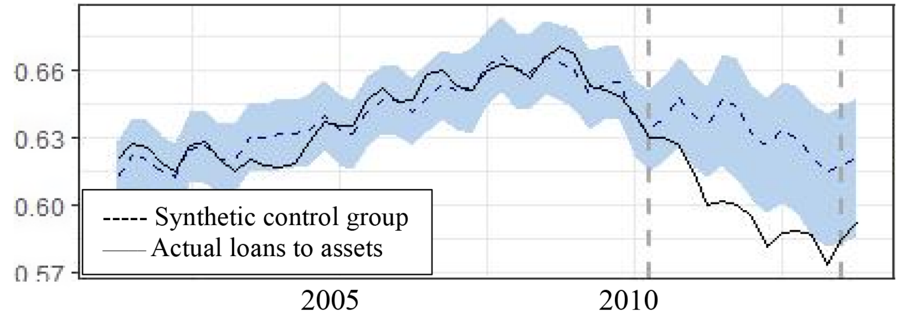

FIGURE 1 Total loans to assets time series of actual and predicted quarterly ratio of community bank loans to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

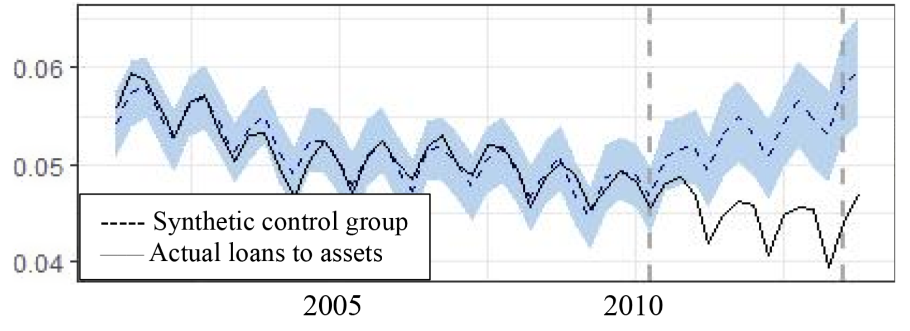

FIGURE 2 Agricultural loans to assets time series of actual and predicted quarterly ratio of community bank agricultural loans to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

value of the respective dependent variable. The association between the solid and dashed lines during the learning phase is a visual representation of the validation test of model fit, where a close juxtaposition of the two lines indicates that the BSTS model's SCG predicts well the respective dependent variable. Each dependent variable is deflated by total assets implying that each figure depicts the evolution over time of community-bank allocations to the various asset types of interest.

There are several important things to note about all the Figures. First, note the evolution of the 95% confidence interval (CI) over the sample period. During the learning period, before passage of DF, the CI is relatively tight, while in the prediction period, the CI expands as the time from DF enactment increases. This makes intuitive sense because during the learning period the BSTS model receives quarterly data updates of the actual dependent variable, implying that each subsequent prediction carries minimal risk. Once DF enactment occurs, however, the concurrent data updating terminates and the prediction becomes increasingly stale making the SCG estimate increasingly uncertain. Second, the first vertical dashed line indicates when the actual variable is "treated" by passage the DF, while the SCG remains "untreated". This implies that any divergence between the solid and dashed lines after that point indicates a DF causal effect and divergence beyond the shaded 95% CI indicates a statistically significant causal effect.

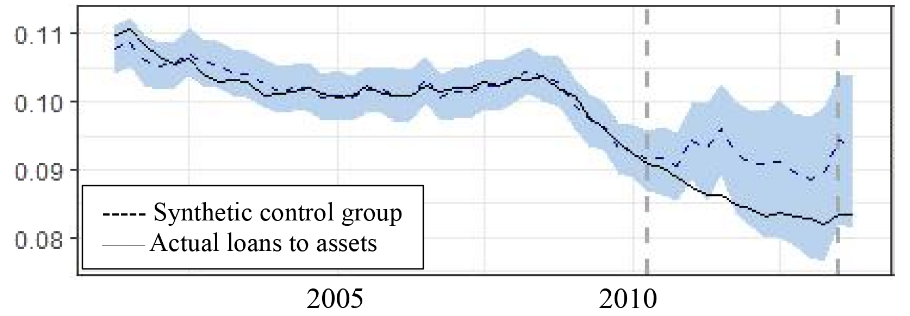

FIGURE 3 Commercial and industrial loans to assets time series of actual and predicted quarterly ratio of community bank C&I loans to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

Figure 1 sets the stage for our analysis by testing the causal impact of DF on community-bank allocation of assets to total loans (LOANS). There are many important conclusions to be drawn from Figure 1. First, it appears that the LOANS-to-assets ratio is seasonal as the solid line rises and falls periodically over the entire sample period, and the SCG mimics this seasonality quite well. Relatedly, during the learning period the solid and dashed lines are closely intertwined, especially after 2005, which indicates a well-fitted model that is accounting for the variable's seasonality. Third, there is an upward trend from 2001 through to about 2009 followed by a decline in lending leading into the passage of DF in mid-2010. This indicates increasing community-bank allocations to LOANS leading up to the 2008 financial crisis and a cutback on lending after the crisis. Fourth, the actual and SCG lines begin to diverge immediately upon enactment of DF. The model predicts a moderate post-DF downward trend in allocation to LOANS, while the actual allocation drops precipitously. Fifth, within a year of DF passage community-bank allocations to LOANS breaks below the 95% CI and stays below that level throughout the 12-quarter sample period. The numbers underlying the graph provide additional perspective. At the beginning of the sample period community banks allocated about 62% of their total assets to LOANS, which increased to about 67% by around 2009. The average post-DF LOANS-to-assets ratio was about 60%, well below the 2001 pre-DF low point, while the SCG post-DF average is 63%. The post-DF 95% CI range for average LOANS-to-assets ratio is [61%, 65%], which the actual average ratio (60%) is below (p-value = 0.002). That is, the BSTS model estimates a probability of 99.8% that passage of DF caused a reduction in community-bank lending.

Figures 2–6 break down total loans into loan types, which allows us to discover which specific loan type(s) community banks cut back after DF. From Figure 2 we note that agricultural loans (AG) are highly seasonal, and that there is a slight downward trend during the learning period. Moreover, the close intertwining of actual and SCG values during the learning period indicates a well-fitted model. Once DF is enacted, there is a noticeable divergence between the actual and SCG lines. Whereas the BSTS model predicts a post-DF recovery in community-bank allocation to agricultural lending, within the first year after enactment the actual AG-to-assets ratio drops below the 95% CI and becomes significantly lower than the SCG. Near the beginning of the sample period, AG represented about 6% of community bank assets. Leading up to passage of DF, these loans had drifted downward to about 4.5% of total assets over those ten years. Within two years of DF passage, AG represented to about 4% of bank assets. The quarterly post-DF AG-to-assets ratio averaged about 4.5% with a 95% CI range of [5%, 5.6%], while the analogous post-DF average SCG is 5.3%. The probability of obtaining a 4.5% post-DF average ratio by chance is 0.001 implying a 99.9% probability that DF had a negative causal effect on community bank agricultural lending.

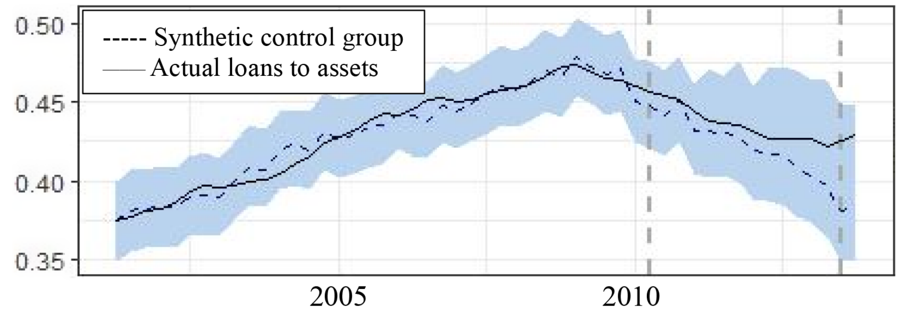

FIGURE 4 Total real estate loans to assets time series of actual and predicted quarterly ratio of community bank real estate loans to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

We present the estimated causal impact of DF on community bank C&I lending in Figure 3. The story told by this figure is much like the one told for AG loans, except the variable does not exhibit seasonality. Otherwise, the learning period shows a slight downward trend until mid-2008 when the C&I loans-to-assets ratio begins to drop concurrent with the financial crisis, consistent with Cole and Damm (2020), and the close association between actual and SCG indicates a well-fitted model. After enactment of DF, the SCG predicts the C&I ratio to level off in the fourth quarter of 2010, but the actual ratio continues to drop and falls below the lower boundary of the 95% CI within a year. Interestingly, the SCG begins to fall again around the beginning of 2012 and the 95% CI re-envelopes the actual C&I ratio through the end of the sample period. In early 2001, C&I loans represented around 11% of total assets, which declined to about 10.5% by mid-2008. In the two years prior to passage of DF, the ratio dropped a little over a full percentage point to about 9.3% when DF was enacted. The quarterly average predicted C&I loans-to-assets ratio (the SCG) for the twelve quarters post-DF is 9.2%, but the actual ratio continued to drop post-DF to a low of 8.2% in the first quarter of 2013 and averaged about 8.5% over the prediction period. The post-DF 95% CI is [84%, 98%] implying the average actual C&I ratio is near the lower boundary of the CI (p-value = 0.069). Although not below the 5% level, we argue that community-bank reductions in asset allocation to C&I borrowers is marginally significantly below where it would have been without enactment of DF.

Figure 4 presents the BSTS estimated causal impact on total real estate loans (RE). During the learning period, it appears that community banks offset the downward drift in AG and C&I lending by increasing allocations to real estate borrowers. Real estate lending climbed ten full percentage points from about 37.5% of assets in 2001 to about 47.5% of assets by early 2009. This steady climb in real estate loans is reversed in early 2009 as the financial crisis affected bank risk appetite. By the time DF was signed into law, actual RE made up about 45% of total community bank assets and began to diverge slightly upward from the SCG. While the divergence was always positive and was about five percentage points by the end of the sample period, it was always within the 95% CI, indicating the divergence was not statistically significant.

Figures 5 and 6 provide analyses after we partition real estate loans into commercial and residential real estate loans. Figure 5 presents the BSTS analysis for commercial real estate (CRE) and appears to be very similar to Figure 4. CRE-to-assets increased from about 16.5% of total assets in 2001 to about 26.5% by about 2009, then began to drop after the financial crisis to about 24% at passage of DF. The CRE ratio began to diverge upwards from the SCG upon passage of DF and remained elevated throughout the prediction period breaking through the 95% CI in the twelfth quarter. In that final quarter, the spread between the actual and SCG ratios is about five percentage points. The post-DF average CRE ratio was 22% with a 95% CI range of (19%, 23%), which

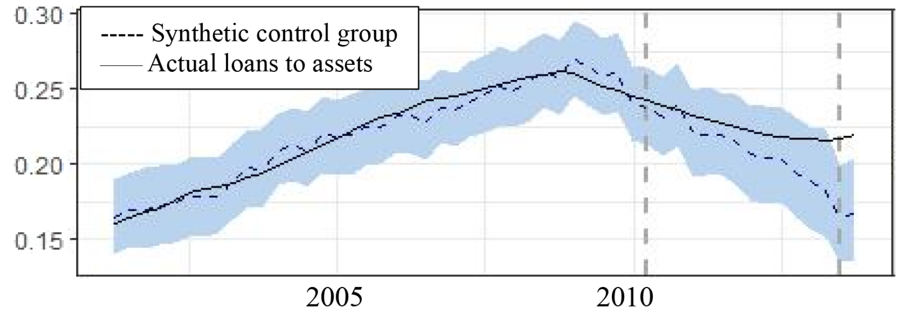

FIGURE 5 Commercial real estate loans to assets time series of actual and predicted quarterly ratio of community bank commercial real estate loans to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

presents a p-value of 0.038. Despite not breaking through the CI until the final quarter, the BSTS model estimates the probability that DF caused an increase in CRE lending to be 96.2%. Figure 6 presents the analysis for residential real estate (RRE) and contrasts sharply with Figures 4 and 5. Rather than an upward trend during the learning period, community banks were slowly cutting their allocations to RRE from about 17.5% of assets in 2001 to about 15.9% in 2007. In 2008, community bank lending to RRE borrowers climbed back up to about 16.8% where it remained through enactment of DF. Post-DF, both estimated and actual RRE ratios decline. By 2012 the SCG began to climb back to the level it began at in 2001, while the actual RRE ratio continued to decline through the end of the sample period breaking through the lower boundary of the 95% CI in early 2013. The post-DF average RRE ratio was 16% with a 95% CI of (16%, 17%). The estimated p-value is 4.7% for this below prediction RRE ratio, which provides a casual effect probability of 95.3%. This result is consistent with the anecdotal evidence outlined in the literature review above.[5]

If DF caused community banks to invest fewer assets into lending activities, to where are those assets being allocated in the post-DF period? Figure 7 presents the BSTS causal analysis for total securities (SEC). Unlike total loans (Figure 1), during the learning phase community banks tended to decrease their relative investment in securities from about 24% of assets in 2001 to about 20% when DF was enacted, at which point the SCG levels off through the end of the prediction phase. In the first quarter of 2011, however, the actual ratio of SEC-to-assets begins to climb and by the fourth quarter of 2012 breaks through the upper bound of the 95% CI for the remainder of the 12-quarter prediction phase. At the end of the sample period, the SCG predicts an SEC ratio of about 20.8% while the actual SEC ratio is 3.5 percentage points higher at about 24.3%. The post-DF average quarterly SEC-to-assets ratio is 23%, while the SCG over the same period is 21% with a 95% CI range of (17%, 22%). The estimated p-value is 0.001 implying a probability of 99.9% that DF caused an increase in community-bank allocations to total securities. Interestingly, this increase of about 3.5% in community-bank asset allocation to SEC almost exactly offsets the decrease of allocation to lending of 3.3% from an actual 58.5% of assets to a predicted 61.8%.

Figures 8 and 9 present the causal analyses when we break down total securities into those held to maturity (HELD) and those available for sale (SALE), respectively. Figure 8 shows that HELD steadily decreases from about 5% of total assets in 2001 to just under 2.5% by the start of 2010. Upon DF enactment, HELD-to-assets immediately drops below its SCG and remains

[5]Note the differences between the post-DF 95% CI in Figures 5 and 6. The CI is much wider in Figure 6, which explains the higher p-value.

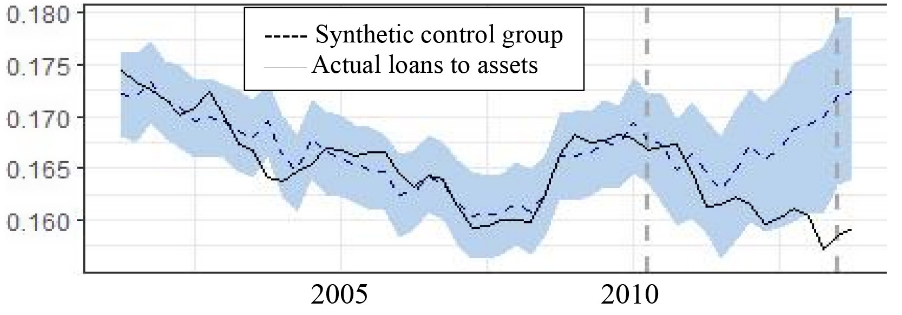

FIGURE 6 Residential real estate loans to assets time series of actual and predicted quarterly ratio of community bank residential real estate loans to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

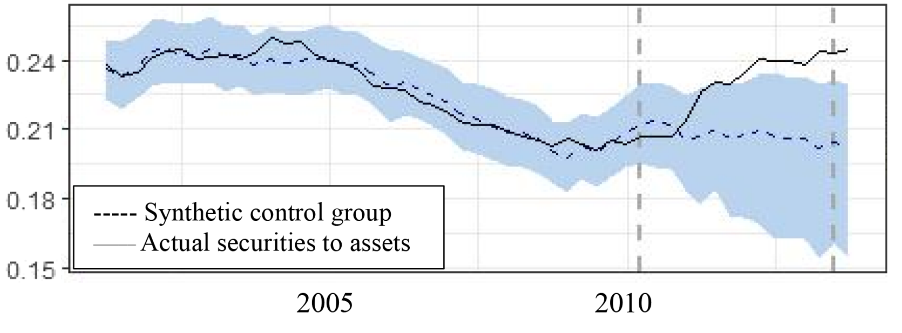

FIGURE 7 Total securities to assets time series of actual and predicted quarterly ratio of community bank securities to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

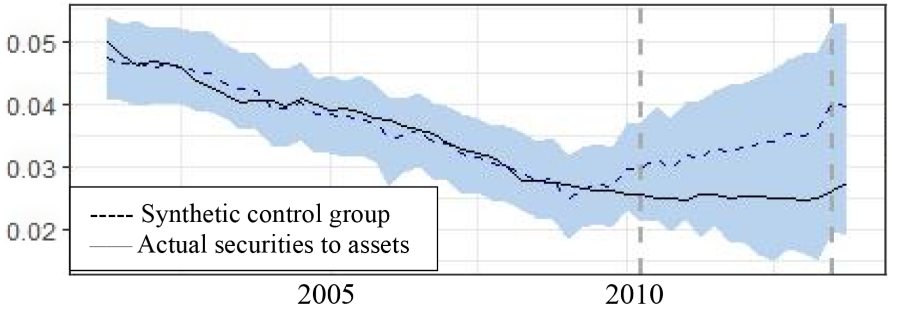

FIGURE 8 Securities held to maturity to assets time series of actual and predicted quarterly ratio of community bank securities held to maturity to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

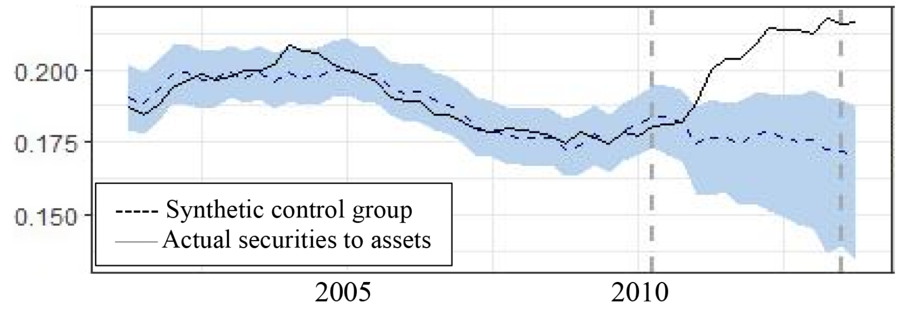

FIGURE 9 Securities available for sale to assets time series of actual and predicted quarterly ratio of community bank securities available for sale to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

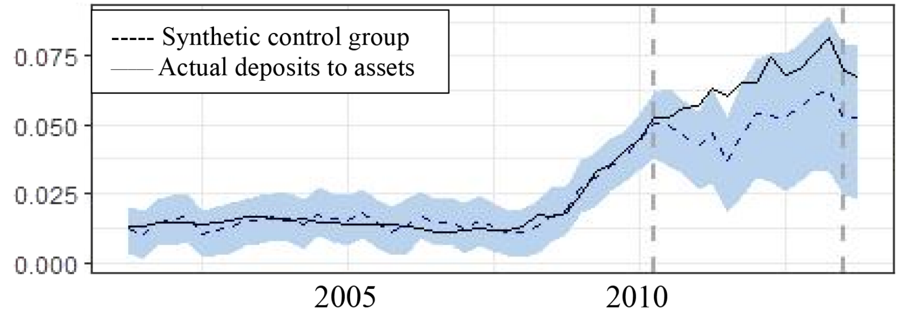

FIGURE 10 Deposits in Federal Reserve Banks Time series of actual and predicted quarterly ratio of community bank deposits in Federal Reserve banks to assets. Learning period is from 2001 through quarter 2 of 2010, the quarter before DFA was enacted. DFA enactment is shown by the first vertical dotted line after 2010. The prediction period runs between the vertical dotted lines until 12 quarters after enactment of DFA. The shaded area represents the 95% confidence interval within which the difference between actual and predicted values are insignificant.

below throughout the prediction phase. This deviation, however, never breeches the 95% CI and has a p-value of 0.11 indicating that the difference is not statistically significant. Obviously, this *reduction* in HELD cannot explain the significant *increase* in community bank investments in total securities over the prediction phase. Figure 9 solves the mystery. In the fourth quarter of 2010, relative investment in SALE begins an upward divergence breeching the 95% CI the following quarter rising from about 18% of assets at DF enactment to about 21.5% at the end of the prediction period. The average post-DF quarterly ratio of SALE-to-assets is about 20%, while the SCG is just 18%. The 95% CI ranges from 16% to 19%, which is consistent with a p-value of 0.001 and causal effect probability of 99.9%. That is, while community banks insignificantly decreased their investment in held-to-maturity securities after DF enactment, DF caused community banks to significantly increase their investment in trading securities. Figures 1–9 paint a picture story consistent with the conclusion that DF has caused banks to significantly reduce lending activities, while simultaneously significantly increasing their securities trading activities.

Finally, we analyse DF's causal impact on community-bank deposits in Federal Reserve banks (RES), which is our proxy for excess reserves. The Fed began paying interest on bank reserves in late 2008, which gave banks incentive to hold excess reserves. We can see this in Figure 10 as these deposits stayed steady at around 1% until late 2008 when they started a 5× climb to about 5% by DF enactment. The BSTS model predicted a levelling out of RES-to-assets, but the actual climb continued throughout the prediction period topping out at just over 8% in early 2013. The average quarterly post-DF community bank investment in excess reserves is 6.6%, with a 95% CI ranging from 4.7% to 6.5%, is statistically higher than the SCG's average of 5.4% (p-value = 0.022). This implies a DF causal effect probability of 97.8%.

5 | DISCUSSION AND CONCLUSION

The Dodd–Frank Act's 2200 pages spawned over 22,000 pages of rules and regulations intended to modernise banking regulation and help prevent a future financial crisis. Regulatory changes, however, do not happen in a static environment as those subject to the new rules interpret and react to them. Our BSTS analysis shows that community banks reduced their allocations to total lending and replaced these investments with allocations to tradeable securities and deposits in Federal Reserve banks. Stiroh (2004) shows increases in risk-adjusted performance and decreases in risk when community banks diversify within loan categories. Our findings, combined with those of Stiroh (2004) indicate that DF has caused community banks to significantly decrease lending activities while significantly increasing securities trading activities. Given the importance of community banks to the small business and agricultural sectors of the US economy, and to the small communities in which they dominate, these changes to their business models are troubling.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the Federal Financial Institutions Examination Council at [https://www.ffiec.gov/I]. These data were derived from the following resources available in the public domain: [https://www.ffiec.gov/].

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APPENDIX

TABLE A1 Description of covariates

Covariates:	
Non-community bank dependent variable	We test time-series changes of community-bank allocations to various asset types. The primary covariate is the respective variable for non-community banks. For example, the primary covariate for community-bank loans-to-assets is non-community-bank loans-to-assets.
Core deposits ratio	A bank's quarterly ratio of core deposits to total deposits
Loan concentration	A bank's quarterly Herfindahl–Hirschman index of these loan categories: Commercial real estate, residential real estate, construction and industrial, consumer, agriculture, and other.
Multi-Market	Deposit-weighting of a bank's quarterly multimarket contact with other banks summed across all the bank's local markets (details in Berger & Bouwman, 2013).
Housing Price Index	Quarterly housing price index for each state in which a bank operates times the ratio of a bank's deposits to the aggregate deposits in that state, all summed across all states (details in Berger & Bouwman, 2013).
Tier 1 leverage ratio	Quarterly equity to assets ratio
Loan rate	Quarterly ratio of interest income to earning assets.