MFC97 - DODD-FRANKING SMALL BANKS

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Resumo

This study investigates the Dodd-Frank effect on U.S. banks in terms of profitability and growth opportunities. Difference-in-differences models combined with Research Discontinuity sample selection tools show that smaller banks experienced a negative effect in their return on asset ratios and deposit growth after Dodd-Frank implementation. In contrast, there is evidence that the legislation provided growth to larger banks by means of a positive effect in their deposit growth rates. We show that the differences arise in banks with low market power. This study contributes to the existent literature that banking regulations should be based more on business complexity and individual risk profiles rather than merely on the size of banks.

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ABSTRACT

This study investigates the Dodd-Frank effect on U.S. banks in terms of profitability and growth opportunities. Difference-in-differences models combined with Research Discontinuity sample selection tools show that smaller banks experienced a negative effect in their return on asset ratios and deposit growth after Dodd-Frank implementation. In contrast, there is evidence that the legislation provided growth to larger banks by means of a positive effect in their deposit growth rates. We show that the differences arise in banks with low market power. This study contributes to the existent literature that banking regulations should be based more on business complexity and individual risk profiles rather than merely on the size of banks.

Keywords: Dodd-Frank Act; deposit growth; profitability; bank size; Regulatory disclosure.

1. INTRODUCTION

The Dodd-Frank Wall Street Reform and Consumer Protection Act (henceforth Dodd-Frank) was enacted in 2010 to avoid excessive bank risk-taking behavior after the 2008 financial crisis. Those in favor of the law believe that it brought transparency for investor and protection to consumers, by imposing the regulatory burden over the so-called too-big to fail. However, Dodd-Frank opponents say that it undermines the banking competition by imposing compliance costs for small lenders leading to market concentration and clogging the flow of money to the real economy. This debate albeit far from ending, has shifted as a result of the rollback signed into law in May 2018. Among other changes, the new bill lifts restrictions for smaller banks while making changes on the denomination of banks considered systematically important financial institutions (SIFI)[1].

Arguably, the most important characteristic of the law is size, since the act has escalating restrictions based on the assets of the bank: for example, in the previous version of the law, smaller and community banks (those up to $1 billion in assets) had to respond to monitoring schemes, to report activities to the Federal Reserve and, like the bigger ones, had restrictions from taking part in riskier investment opportunities. Banks exceeding $10 billion in assets were subject to increased oversight[2], and those exceeding $50 billion in assets are deemed as a systemically important financial institution (henceforth SIFIs), which made them subject to extra stress tests, such value at risk metrics, and higher standards of monitoring.

In this paper, we add to the examination of Dodd-Frank by conducting an empirical assessment of the legislation impacts on the banking industry, in terms of profitability and growth opportunities, proxied by Return on Assets (ROA) and deposit growth rates, respectively. We ask if size is a convenient criterion for tailoring one banking regulation in U.S. market, and if there was indeed an overregulation in place which supported the recent rollback of the original version of the legislation. If it is true that the main version of the Dodd-Frank Act produced distortions, we hypothesize that smaller banks experienced a different effect than their bigger counterparts in terms of return on assets, and deposit growth.

Because the legislation is an external shock affecting all U.S. banks, the lack of control groups makes it difficult to assess any effect of the legislation on financial institutions. To circumvent that, we create artificial control groups based on research discontinuity designs (henceforth, RDD) sample selectors. Our RDD sample selectors select comparable banks in terms of size (total assets) with similar potential outcomes (return on assets ratio or deposit growth), through maximum likelihood estimators. This method allows us to compare outcomes

[1] The previous version of the law considered banks to be SIFI, those banks with more than $50 billion in assets. The new bill boosts the threshold to $250 billion.

[2] Such as annual self-administered stress tests and oversight from the Consumer Financial Protection Bureau.

just above and just below size cutoffs (Calonico, Cattaneo, & Titiunik, 2014; Imbens & Kalyanaraman, 2011; Imbens & Lemieux, 2008), which are banks around $1 billion in asset and banks around $10 billion in asset.

In a sample collected between 2008 and 2012, two years before and after the Dodd-Frank implementation, our results suggest that Dodd-Frank regulation impeded small banks from growing. Specifically, the profitability for banks with less than $1B on assets after Dodd-Frank were on average 44 basis points lower than banks with more than $1B on assets. Moreover, the growth of deposits for those banks with less than $1B on assets, after Dodd-Frank were on average 1.56% lower than comparable banks with more than $1B on assets. Conversely, the evidence suggest that the legislation led to an increase in growth opportunities for larger banks: those banks with more than $10B on assets, after Dodd-Frank were on average 3.35% higher than comparable banks with less than $10B on assets. Additionally, our results show that banks with less market power were more severely affected by the legislation. We divide each group sample based on their Lerner Index, and find that small banks with lower ex-ante market power were subject to the negative Dodd-Frank effect, while small banks with higher ex-ante market power were not affected by the legislation.

There are at least three explanations for why smaller institutions' position would get worse in comparison to the bigger institutions' after Dodd took act. First, bigger banks are able to spread compliance costs over a large asset base through consolidation and scale economies, which increases their cost advantage. They have more reasonable capital access to boost loan loss reserves, absorb credit losses and smooth new legislation compliance costs, as the Dodd-Frank disclosure costs (Hughes & Mester, 2013; Kroszner, 2016; Hunter, Timme & Yang, 1990). Second, the negative effect on smaller banks' deposit growth rates may be a consequence of a "stigma effect" (Berger & Roman, 2015). Smaller banks, those who did not submitted to higher standard consumer protection regulations, may be perceived as a less safe choice from the depositors' point of view, when compared to bigger businesses.

Finally, smaller banks could assign the negative effect on their profitability and deposit growth ratios to the discontinuation of some product lines after the legislation passage, residential mortgages (Peirce, Robinson, & Stratmann, 2014). According to the Mercatus Center's Small Bank Survey, it happened due to the costly disclosure requirements imposed by Dodd-Frank related to these products. Keeping offering a diversified line of services would enhance the compliance bureaucracy.

Our results are robust to: (1) falsification tests as a placebo exam considering a fake shock implemented in 2008, in order to disentangle Dodd-Frank effects from specific 2008 financial crisis effects; (2) and to the discontinuity McCrary Test (McCrary, 2008).

This study contributes to the literature in many ways. First, we build up on recent literature works the consequences of the act in the financial industry. On this, Andriosopoulos, Chan, Panagiotis and Staikouras (2017) using a Seemingly Unrelated Regression (SUR) argue that Dodd-Frank may have redistributed value among financial institutions; Bouwman, Hu and Johnson (2018) studies the banks around the Dodd-Frank thresholds and find that those banks grow their total assets, risk-weighted assets and total loans significantly more slowly in the post-Dodd-Frank period. Second, it sheds light on how individual bank characteristics play a role in financial regulatory effects: our evidence supports the idea that banking regulation should focus on banks complexity and risk profiles rather than merely on size. Third, to our knowledge this is the first study that verify the Dodd-Frank effect on the smallest institutions based on a suitable methodology to select control groups, and analyzing the effects of Dodd-Frank in terms of profitability and growth opportunities. Finally, it emphasizes the role of regulations on corporations' survival.

The rest of the paper is organized as follows. Section 2 provides a background on Dodd-Frank and the banking regulation literature. Section 3 describes the research design and sample,

Section 4 focuses on our results and robustness checks. Section 5 concludes.

2. RELATED LITERATURE

2.1 Dodd Frank, Size and Regulations

Dodd-Frank was built under the too-big-to-fail hypothesis, the assumption that some banks are so interconnected to the rest of the economy so that their financial distress would generate a domino effect for the whole economy (Barth & Schnabel, 2013; Mattana, Petroni, & Rossi, 2015; Mishkin, 2006). Most of the Dodd-Frank affected all banks, its provisions were directed at the financial system and institutions regardless its size, granting discretionary action to the regulatory authorities in some cases. Section 171 of the law, for example, establishes minimum risk-based capital requirements for insured depository institutions of all sizes. Also, section 165 requires publicly traded bank holdings up to $10B in assets to establish a risk committee if "determined necessary" by the regulatory authorities and section 737, grants discretion to the regulators to exempt any bank or any transaction from the capital limit rules.

Nevertheless, albeit the aim of the law[3], Dodd-Frank has escalating oversight based solely on the size of the bank[4]. These distinctions signified net regulatory costs for above-threshold banks: Section 956 requires banks to disclose to federal regulators the structures of all incentive-based compensation arrangements, having a statutory exemption for banks below $1 billion in assets. Section 165 requires banks with more than $10 billion in assets to conduct annual stress tests and for the SIFIs, those bank holding companies with total consolidated assets of $50 billion or more, the stress tests must be done twice a year.

The law also addresses overall financial health of the system that consequentially have an economic impact in banks: For example, section 111 created the Financial Stability Oversight Council (FSOC), with the objective of recognizing threats to the national economic stability that could arise from relevant financial distress conditions. This council promotes costly disclosure requirements to ensure consumer transparency (Cumming et al., 2017).

In a clear effort to reduce the market power of the too-big-to-fail banks, Dodd-Frank also imposed restrictions on mergers and acquisitions that would favor monopolies. The law prohibits negotiations that would generate one singular bank with more than 10% of the aggregated liabilities of all banks in U.S. According to the legislation, bank regulators should refuse all negotiations that would concentrate banking markets beyond the pre-established limits (Wheelock & Wilson, 2012).

2.2. Banking Industry Regulation Effects

On the one hand, from papers published in the 90's until recent research, there is evidence that deregulated bigger banks may charge higher fixed fees and through it affect negatively income distribution (Greenwood & Jovanovic, 1990; Banerjee & Newman, 1993; Galor & Zeira, 1993). Deregulated consolidation and expansion of the banking industry may harm the poorest population, protect local banking monopolies, curtailing competition (Beck, Levine, & Levkov, 2010). On the other hand, an overregulated environment can be as harmful as a deregulated for the real economy as community banks, usually affected by costly regulation, play an important role in U.S. rural areas, expanding credit access to poorest country villages (Peirce et al., 2014). Additionally, Biswas et al. (2017) stands out the relevance of the small banks to the small, privately held firms since they face severe information asymmetry problems and rely on small lenders to fund their activities.

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[3] As stated, the aim of the act is "to promote the financial stability of the United States by improving accountability and transparency in the financial system, to end "too big to fail", to protect the American taxpayer by ending bailouts, to protect consumers from abusive financial services practices, and for other purposes". H.R. 4173, 2010.

[4] Bouwman et al. (2018) accounts for these size related provisions.

Berger and Roman (2015) emphasize the duality of banking regulations effects, but from the funding access point of view. Analogically, banks that are subject to regulatory requirements may be perceived as a safer choice for depositors, due to the selection criteria which targeted "healthy or viable institutions". In this case, customers trust their money to these institutions, increasing their deposit rates, since they seem to be less prone to become financially unstable under the regulation. It is a safety effect. Likewise, smaller banks subject to lower requirement standards by law and with ex-ante lower market share can be seen as riskier institutions, resulting in a stigma effect.

Moreover, the legislation may have generated overall costs and negative consequences that bigger banks could go through easily in relative terms with small banks. For example, Acharya et al. (2018) find that stress-tested banks reduced their credit supply to relatively risky borrowers, Morris-Levenson et al. (2017) finds that one of the effects of regulation is that less regulated and nonbank companies took a market share of the mortgage origination industry, hence reducing the profit opportunities for regulated bank. Peirce et al. (2014) studies the effect of Dodd-Frank in banks with less than $10 billion in asset. The analyze the Mercatus Center's Small Bank Survey, which includes responses from banks across 41 American states. They reported increased compliance costs in the wake of new regulations: hiring new compliance personnel and experts; and interrupting some product and service offerings, including residential mortgages. Their finding suggest that Dodd-Frank has deeply affected small banks.

Overall, these arguments support the idea that banking legislations tailored on size stimulates the stigmatization of small banks. Small institutions already face increasing barriers to obtaining credit and ex-ante cost disadvantages compared to larger entities (Beck et al., 2010), and overregulation schemes would increase the distance between smallest and biggest banks. Bertay et al. (2013) reinforce how controversial can be the size effect. Too-big-to-fail banks may have reduced funding costs, as mentioned before, however their systemic risk may drive it to a bank too big to be saved. In their empirical exercise, they found that the funding costs of a bank decline in absolute terms with systemic size. On this, Bouwman et al. (2018), study the banks around the Dodd-Frank size thresholds and find that those banks grew their total assets, risk-weighted assets and total loans significantly more slowly in the post-Dodd-Frank period. Additionally, Andriosopoulos et al. (2017), using seemingly unrelated equations they examine the wealth and risk effects of Dodd-Frank on U.S. financial institutions, and find that the legislation may have redistributed value among financial institutions, while not necessarily reducing the industry's riskiness. They also find evidence that large investment banks and life insurers experience higher excess returns than their smaller peers.

Furthermore, Allen et al. (2018) using an event study on the process of eliminating the too-big-to-fail condition, find that while there was a limited stock reaction among the largest banks and SIFIs, there is some evidence that the smaller banks had negative returns reaction to the legislation.

3. RESEARCH METHODOLOGY AND DATA SET

3.1. Differences-In-Differences Design

We test the effects of Dodd-Frank Act on banks' deposit growth and profitability ratios using a combined methodology of research discontinuity design (RDD) and difference-in-difference (DID) models. We explain each method below, and then present the advantages of the combined approach.

Because of the lack of control groups, it is difficult to evaluate the effect of Dodd-Frank. Research Discontinuity Design (RDD) is useful in this context because it provides comparable subjects around known bank size cutoffs, when there is absence of data on counterfactual outcomes. RDD is a quasi-experimental technique where the assignment of the treatment and control is not random, or at least locally randomized (Imbens & Lemieux, 2008; Lee &

Lemieux, 2010). We appoint bank size as the criterion that assigns banks into treatment or control groups. In all cases the treatment group contains banks just below or above the size specification as mentioned by Dodd-Frank. Our first focus uses $1 billion in assets to determine each group. In this case, the treatment group contains banks just below the cutoff, while the control groups are the banks just above the threshold. Additionally, we analyze banks exceeding $10 billion in assets as the treatment group for banks just below the same size cutoff[5].

As a first step, we select the RDD bandwidth for the cutoff. The RDD border selectors allows us to select a sample of comparable banks around specific, arbitrary size thresholds. As a consequence, banks immediately above and below the size cutoff could potentially have similar outcomes. We take advantage of this characteristic and with the RDD methodology we obtain an automatic bandwidth selection of banks, which includes a trade-off between bias and variance. The wider the bandwidth, greater will be the bias and thus, the smaller the variance. On this, the standard procedure is to choose a small enough bandwidth so that the bias is irrelevant. Bandwidth choice rules are based on maximum likelihood estimators to match potential outcomes given the established cutoff and an algorithm selects an optimal sampling border h. The frontier h defines the range values around the size cutoff. Consequently, the distance between the size observation and the size cutoff must be between –h and h. We use Calonico et al. (2014) bandwidth selector that gives a sample containing the most comparable individuals and, consequently, the lowest bias.

We combine the features of RDD with a differences-in-differences (DID) model to circumvent clear violation of prior parallel trending assumption of the DID model. As pointed out by Leonardi and Pica (2013), smaller entities may be on a declining path in comparison to larger ones and may also be affected differently by the business cycle. In other words, banks in the different size groups probably have ex-ante differential trends, which violates the common time effects' assumption intrinsic to the standard differences-in-differences analysis. By combining these two techniques, we use the RDD to estimate the probability that the bank *i* is in the treatment group, while the DID estimates the time-series variation effect of Dodd-Frank regulation for the treatment group as specified by the RDD. In other words, differences-in-differences and research discontinuities designs allow us to control for the variation between the banks' size and the cutoff. In essence, the distance between the bank size and the cutoff. Therefore, our DID estimator is then the difference between the discontinuity at each bank size cutoff after Dodd-Frank and the discontinuity at the respective cutoff.

For our main analyses (where treated banks are either those with assets up to $1B, or those exceeding $10B), and two specifications (profitability and growth as dependent variable), we use the following DID specification:

$$\begin{aligned} y_{it} = \alpha + \beta_1 TREAT_i + \beta_2 SIZEDIST_{it} + \beta_3 TREAT_i.DODD_t + \beta_4 DODD_t \\ + \beta_5 SIZEDIST_{it}.DODD_t + \beta_6 SIZEDIST_{it}.TREAT_i \\ + \beta_7 SIZEDIST_{it}.TREAT_i.DODD_t + \sum_{k=1}^{N} \beta_k \boldsymbol{C}_{it} + \omega_i + \boldsymbol{\theta}_t + \varepsilon_{it} \end{aligned} \quad (1)$$

The dependent variable y_{it} for bank *i* at quarter *t*, represents banks' profitability proxied as ROA or Deposit Growth.. $TREAT_i$ is a dummy variable that takes the value of one if the bank *i* is considered treated (based on the size cutoff specification). $DODD_t$ is the post-Dodd period indicator (2010Q3-2012Q4) for quarterly data between 2008-2012. $SIZEDIST_{it}$ is the size distance for each bank *i* at quarter *t*.

Our first variable of interest is $TREAT_i * DODD_t$ and is a dummy variable assuming a value of one after the post-Dodd-Frank period if bank *i* is in the treatment group at quarter *t* and zero otherwise. β_3 captures the Dodd-Frank marginal effect for the treatment group with the

[5] It is not feasible to test effects around the $ 50 billion in assets banks because of the characteristic of this sample: they are outliers, and the few number of observations prevented us to perform the tests.

respect to the banks that are not in the treatment size threshold. β_5 measures the marginal effect of Dodd-Frank in profitability or growth as the bank size moves away from the size cutoff point. β_6 measures the difference between the treatment group as the bank size moves away from the size cutoff point compared to those banks that are in the control group. Finally, we also include a triple interaction term $SIZEDIST_{it} * TREAT_i * DODD_t$ that includes the size distance, and the dummies for treatment group and post Dodd-Frank period. In this case, β_7 measures the difference in discontinuity variation after the post-Dodd-Frank period as the bank size moves away from the size cutoff point.

Since the DID estimator is an interaction between to variables, we need to guarantee that the effect is related to changes in banking regulation and not due to possible changes in the size levels (rule that assigns banks into treatment). To guarantee the accuracy of the diff-in-disc estimate, we fixed the pre-Dodd size level. For example, if the cutoff is $10 billion in assets, we classified the bank i as treated one if it exceeded this total assets amount in 2008 or in 2009, two years before the legislation was enacted.

3.2. Empirical Proxies

To act as controls, we construct CAMEL to measure the bank condition. The acronym CAMEL stands for Capital Adequacy, Asset Quality, Management, Earnings and Liquidity (Berger & Roman, 2015; Liu et al., 2013). Our database is the Federal Deposit Insurance Corporation (FDIC) Call Reports. This database offers branch-level information by American state, so we aggregated the data in a bank holding level using the unique number assigned by the Federal Reserve Board to the regulatory high holding company of the institution (RSSDHCR), and, in the absence of it, the FDIC unique identification (CERT).

Capital adequacy is the ratio of total equity capital divided by gross total assets. Asset Quality is the non-performing loans divided by the total loans. Non-performing loans represents the total loans that are close to being in default or are already in default. Management is the standard deviation of total assets in three consecutive years, a forward-looking indicator of bank's ability to diagnose and respond to financial stress. Earnings are the ratio of net income over total assets. Finally, liquidity is the ratio of cash over bank total deposits. We also control for the number of branches by banking holding, and the number of deposits[6] received by bank holding. Moreover, we use TARP and SBLF dummies to control for access to government funding[7]. All the variables are defined in Table 1.

Table 1
Variables Description

Variables		Description
Deposit growth		Percentage change in the dollar amount of deposits from quarter q-1 to q
Dodd		Indicator one if date is equal to or greater than the third quarter of year 2010; zero, otherwise
Treat	For cutoff of US$ 1 billion in assets	Indicator one if bank size is equal to or smaller than the natural log of $ 1 billion in assets; and zero, if bank size is greater than $ 1 billion and smaller than $ 10 billion. The treat dummy is defined in the pre-Dodd period: if a bank is up to $ 1 billion in assets in 2008, in 2009 or in 2010 (until the third quarter), it is part of the treatment group
	For cutoff of US$ 10 billion in assets	Indicator one if bank size is equal to or greater than the natural log of $ 10 billion in assets; zero, if bank size is greater than $ 1 billion and smaller than $ 10 billion. The treat dummy is defined in the pre-Dodd period: if a bank exceeds US$ 10 billion in assets in 2008, in 2009 or in 2010 (until the third quarter), it is part of the treatment group

[6] The number of branches and number of deposits is not available by quarter, only by year. We then repeated the year-end available information for every quarter of that respective year.
[7] The information about TARP and SBLF comes from the U.S. Department of the Treasury.

CAMEL	Capital Adequacy	Ratio of total equity capital divided by total assets
	Asset Quality	Non-performing loans (NCLNLS) divided by total loans (IDLNLS)
	Management Quality	Standard deviation of total assets (ASSET) in three consecutive quarters
	Earnings	Return on Assets (ROA): Ratio of annualized net income (NETINC) over Gross total assets (ASSET)
	Liquidity	Ratio of Cash (CHBAL) over bank total deposits (DEP)
	Size	Natural log of the bank's total assets (ASSETS)
Sizedist	For the cutoff of US$ 1 billion in assets	Distance between the total asset observation and the threshold defined by $ 1 billion in assets. We present it in USD or as a normalized statistic, which is Sizedist divided by the sample standard-deviation.
	For the cutoff of US$ 10 billion in assets	Distance between the total asset observation and the threshold defined by $ 10 billion in assets. We present it in USD or as a normalized statistic, which is Sizedist divided by the sample standard-deviation.
Number of deposits	Deposits	Natural log of number of domestic deposits (using DEPSUM) made in the quarter, without considering the withdrawals
Number of branches	Branches	Natural log of number of branches (using the office identifier UNINUM) aggregated by bank holding in the quarter
Lerner Index	Market power	Ratio of the difference of prices and marginal costs over the price (Following Berger et al., 2013)
	Higher market power	Indicator that takes the value of 1 if the bank has a Lerner Index greater or equal than the sample median; zero, otherwise. We used the CCT (Calonico, Cattaneo, and Titiunik, 2014) sample median.
Funding	TARP fund	Indicator that takes the value of 1 after the bank received TARP funds; zero, otherwise
	SBLF fund	Indicator that takes the value of 1 after the bank received SBLF funds; zero, otherwise

To observe market concentration trends, we follow Berger and Roman (2015) and apply the Lerner Index (Lerner, 1934), constructed as the difference in a bank's price and marginal cost of total gross assets over its price; e.g. $Lerner_{it} = (P_{TA_{it}} - MC_{TA_{it}})/P_{TA_{it}}$. $P_{TA_{it}}$ is the price of bank's *i* gross total assets at time *t* proxied by total revenues to total assets, and $MC_{TA_{it}}$ is the bank's marginal cost estimated from differentiating its cost function. The Lerner index, $P_{TA_{it}}$ and $MC_{TA_{it}}$ are calculated following Anginer et al. (2014). We estimate the parameters by bank in the pre-Dodd years (2008Q1-2009Q4). We use quaterly data and OLS and robust standard errors to do so. We consider the pre-2010 sample to avoid endogeneity issues, since Dodd-Frank may affect a bank's average cost. The Lerner Index overcomes other well-known competition metrics used in banking literature, such as the Herfindahl-Hirschman Index (Akins et al., 2016), since the Lerner Index can be calculated in bank-level and not necessarily in industry-level. It is also argued to be less restricted than the H-Statistic (Dick & Hannan, 2010), since the Lerner Index does not require the assumption of long-run equilibrium. A bank with Lerner Index near to zero operates in a perfect competition condition.

3.3. Data Description and Bandwidth Selection

Our entire sample has quarterly 135,187 observations in our five years of study (2008-2012). We eliminated data if: (i) the bank had missing information on any of the dependent or independent variables; (ii) the bank only appears after 2010Q3, not allowing us to verify the ex-ante value of the bank's total assets; (iii) if the information is duplicated per bank and

quarter.

We use the Calonico et al. 2014 (henceforth CCT) bandwidth selector algorithm to the pre-Dodd sample (2008Q1-2010Q2) of 70,445 observations in order to match banks' potential outcomes (ROA and Deposit Growth) given our selected criterion bank's size. The purpose is to select comparable banks assigned to treatment and control groups. The matched banks are obtained through the nearest-neighbor-based variance-covariance matrix estimator. We used three matches per observation and a triangular kernel function to construct the local first polynomial estimators. The algorithm chooses the frontiers *h* using the CCT method for each outcome and each size cutoff. The resultant frontiers *h*, the range value that defines a neighborhood around the total asset cutoff. The four different samples chosen by the algorithm are shown in Table 2.

Table 2

Descriptive Statistics per Size Group and Outcome Variable

This table presents descriptive statistics of the main variables between 2008 and 2012. The summary statistics are presented for two size groups: banks around $1 billion in assets and banks around $10 billion in assets. We also report the optimal h for each size cutoff, that is, the optimal range value (in one million dollars) that defines a neighborhood around each size cutoff. The frontier his calculated using CCT bandwidth selector based on Calonico, Cattaneo, and Titiunik (2014). ROA is return on assets and deposit growth is the percentage change in the total deposits amount from one period to another. Sizedist is the dollar distance between the total asset observation and the asset cutoff, in million dollars or divided by the sample standard deviation. All the variables are defined in table 1.

Panel A: Size below $1B in assets

Variables	*CCT for ROA: optimal h = $ 207.3029*			*CCT for DG: optimal h = $ 421.1132*		
	Mean	SD	Median	Mean	SD	Median
Sizedist	-32.555	115.855	-47.622	-130.000	224.849	-180.000
Normalized Sizedist	-0.001	0.003	-0.001	-0.003	0.006	-0.005
Asset Quality	0.033	0.050	0.020	0.032	0.046	0.020
Deposit Growth	0.011	0.072	0.009	0.013	0.068	0.010
Liquidity	0.076	0.082	0.052	0.079	0.164	0.053
ROA	0.002	0.012	0.003	0.003	0.011	0.003
Capital Adequacy	0.101	0.034	0.096	0.101	0.032	0.097
Management	0.030	0.042	0.020	0.030	0.041	0.021
Market power	0.805	0.674	0.779	0.794	0.692	0.781
TARP fund	0.129	0.335	0.000	0.130	0.336	0.000
SBLF fund	0.013	0.113	0.000	0.016	0.127	0.000
Branches	2.571	0.749	2.708	2.456	0.762	2.565
Deposits	13.535	0.188	13.537	13.410	0.281	13.387
Observations		**5,619**			**12,806**	

Panel B: Size above $10B in assets

Variables	*CCT for ROA: optimal h = 1,483.071*			*CCT for DG: optimal h = 4,067.244*		
	Mean	SD	Median	Mean	SD	Median
Sizedist	-100.000	856.255	-210.000	-730.000	2300.000	-1100.000
Normalized Sizedist	-0.003	0.022	-0.005	0.018	0.060	-0.029
Asset Quality	0.046	0.074	0.020	0.043	0.065	0.023
Deposit Growth	0.018	0.083	0.006	0.019	0.084	0.008
Liquidity	0.083	0.157	0.041	0.091	0.217	0.047
ROA	0.003	0.014	0.004	0.002	0.016	0.004
Capital Adequacy	0.119	0.039	0.114	0.117	0.044	0.108
Management	0.046	0.086	0.023	0.039	0.063	0.022
Market power	1.752	4.624	0.952	1.292	3.511	0.910
TARP fund	0.236	0.425	0.000	0.251	0.434	0.000
SBLF fund	-	-	-	0.005	0.068	0.000
Branches	4.088	1.576	4.554	4.019	1.545	4.522
Deposits	15.744	0.368	15.789	15.626	0.510	15.671
Observations		**416**			**1,305**	

Table 2 presents summary statistics on the border samples for each size cutoff and outcome variables. The first three columns of Panel A shows the summary statistics for the $1B size cutoff and using banks' profitability as the outcome variable. In this case, the optimal distance *h* equals to approximately $207.3M dollars. Thus, the banks in the sample selected by the algorithm are in the range of $792M and $1.207B of total assets. The resultant sample has 5,619 observations. For the same size group, the sample for the deposit growth as the outcome variable has an optimal distance *h* of $421.1M dollars, selecting banks with total assets between $579M and $1.421B. The final sample for this group has 12,806 observations. Although the optimal size distance and sample sizes for deposit growth doubles the ROA sample, these are comparable in terms of banks health condition, measured in the CAMEL, as well as the outcome variables themselves. Around 14% of the banks in both samples received government funds (either by the TARP or SBLF programs).

Panel B shows the summary statistics for the sample with the $10B assets cutoff. As in panel A, the first five columns show the summary statistics using banks' profitability as the outcome variable that determines the sample. The optimal distance *h* is $1.483B, thus making the sample of those banks with assets between $8.516B and $11.483B in assets, which leads to 416 bank-quarter observations. Using deposit growth as the outcome variable, the algorithm shows an optimal *h* of $4.067B in assets that results in 1,305 bank-quarter observations. In this case the banks selected are those in the range of $5.932B and $14.067B of total assets. As with Panel A, both selected samples are comparable in terms of bank's health, as well as the outcome variables. Not surprisingly lower amount of banks received government funds through the SBLF program and the percentage receiving TARP funds for these samples is around 25%.

To further measure differences between our control and treatment groups in the pre-Dodd period, in Table 3 we show mean comparison tests for all variables in our models. As in Table 2, Panel A, shows the comparison for $1B size cutoff sample, whereas Panel B shows the comparison for the $10B size cutoff sample. Overall, in both panels we show that the samples are comparable with similar characteristics. In most of the cases, the p-value shows that the mean-difference between control and treatment groups is not significant, which is a desirable condition for a difference-in-difference approach.

Table 3

Treatment-Control Comparison Tests

This table presents two-group mean-comparison tests between treatment and control groups of the main variables, in the year immediately pre-Dodd-Frank took act (2009). CCT is the bandwidth selector (Calonico, Cattaneo, and Titiunik, 2014). The statistics are presented for two size cutoffs: banks around $1B in assets and banks around $10B in assets. The column "Control" shows the mean for the control group. The column "Treatment" shows the mean of the treatment group. The column "P-value" shows the null hypothesis probability value that the means between the treatment and control groups are statistically different from each other. All the variables are defined in table 1.

Panel A: Size below $1B in assets

Variables	Return on Assets			Deposit Growth		
	Treatment	Control	P-value	Treatment	Control	P-value
Sizedist	-64.154	119.601	0.000	-195.855	234.437	0.000
Normalized Sizedist	-0.002	0.003	0.000	-0.005	0.006	0.000
Asset Quality	0.039	0.035	0.530	0.036	0.038	0.551
Deposit Growth	0.018	0.012	0.454	0.018	0.014	0.395
Liquidity	0.071	0.078	0.364	0.076	0.066	0.553
ROA	-0.002	-0.001	0.145	0.000	-0.003	0.001
Capital Adequacy	0.095	0.099	0.113	0.096	0.097	0.597
Management	0.038	0.025	0.021	0.035	0.029	0.032
Market power	0.772	0.803	0.591	0.783	0.740	0.240
TARP fund	0.137	0.086	0.068	0.146	0.159	0.488
Branches	2.557	2.549	0.899	2.416	2.679	0.000
Deposits	13.497	13.664	0.000	13.338	13.764	0.000

Panel B: Size above $10B in assets

Variables	Return on Assets			Deposit Growth		
	Treatment	Control	P-value	Treatment	Control	P-value
Sizedist in USD	320.369	-808.024	0.000	1076.661	-2305.162	0.000
Normalized Sizedist	0.008	-0.021	0.000	0.028	-0.060	0.000
Asset Quality	0.040	0.039	0.961	0.044	0.046	0.803
Deposit Growth	0.013	0.032	0.369	0.027	0.025	0.862
Liquidity	0.092	0.091	0.978	0.090	0.078	0.370
ROA	-0.005	0.001	0.131	-0.005	-0.001	0.059
Capital Adequacy	0.119	0.123	0.756	0.116	0.103	0.030
Management	0.056	0.057	0.972	0.048	0.043	0.509
Market power	2.519	1.015	0.272	1.605	0.828	0.102
TARP fund	0.270	0.464	0.070	0.329	0.336	0.899
Branches	3.675	4.226	0.183	3.786	4.148	0.065
Deposits	15.765	15.613	0.114	15.719	15.474	0.000

4. RESULTS

4.1. Main Tests

We apply the differences-in-discontinuities approach to each CCT sample to assess the Dodd-Frank impact on treated banks in terms of deposit growth and profitability. All regressions use panel with bank fixed effects, bank clusters and robust standard errors by bank. Table 4 presents the basic results for the $1B cutoff sample and Table 5 shows the results for $10B cutoff sample. As before, we have two outcome variables to assess Dodd-Frank impact: Profitability, measured as Return of Assets, and Deposit Growth. We run our analyses using two time windows: A long window of five years (2008Q1-2012Q4), and in a short window of three years (2009Q1-2011Q1) around Dodd-Frank implementation. For all the regressions, we run Eq. (1) and the coefficient of interest is $TREAT_i * DODD_t$, a dummy variable assuming a value of one after the post-Dodd-Frank period if bank *i* is in the treatment group at quarter *t* and zero otherwise. This DID estimator captures the Dodd-Frank marginal effect for the treatment group with respect to comparable banks that are not in the treatment size threshold.

Table 4

Dodd-Frank Effect on Smaller Banks

This table presents estimated parameters using DID linear regressions on Profitability (ROA) and Deposit Growth (percentage change in the deposit amounts) for small banks. Sizedist in the difference between the asset observation and the asset cutoff, divided by the asset sample standard deviation. CCT is the bandwidth selector. Long window columns present the results for the entire sample period (2008-2012), while short window columns present for a subsample period (2009-2011), for both samples around $1B in assets. All regressions include a set of year dummies and bank fixed effects, unreported. Lines with blanks means that there is no information about the respective variable in the sample. *, **, and *** represents 10%, 5% and 1% of statistical significance, respectively. Robust errors are reported in parenthesis. We use panel with fixed effects regressions and bank clusters. All the variables are defined in table 1.

Variables	**Profitability**		**Deposit Growth**	
	Long window	**Short window**	**Long window**	**Short window**
Sizedist	1.622***	1.481**	13.17***	12.21***
	(0.489)	(0.578)	(1.434)	(1.355)
Treat*Sizedist	-0.614	0.0651	2.403**	1.758
	(0.511)	(0.616)	(1.157)	(1.306)
Dodd	0.00477**	0.00209	0.00192	0.0112
	(0.00199)	(0.00236)	(0.00560)	(0.00708)
Sizedist*Dodd	-1.150**	-0.311	-0.556	-1.709
	(0.539)	(0.552)	(0.874)	(1.061)
Treat*Dodd	**-0.00439****	**-0.00153**	**-0.0156*****	**-0.0237*****
	(0.00200)	**(0.00241)**	**(0.00585)**	**(0.00729)**
Treat*Dodd*Sizedist	1.027*	0.0784	-0.866	0.552
	(0.556)	(0.566)	(0.955)	(1.130)

Asset Quality	-0.0785***	-0.0614***	-0.314***	-0.367***
	(0.0184)	(0.0198)	(0.0565)	(0.0548)
Deposit Growth	-0.00419	-0.000439	0.0543*	0.0768*
	(0.00363)	(0.00315)	(0.0291)	(0.0462)
Liquidity	-0.00981	-0.0203**	-0.500***	-0.511***
	(0.00821)	(0.00891)	(0.109)	(0.0993)
Capital Adequacy	0.193***	0.169***	-0.0469	0.108
	(0.0374)	(0.0437)	(0.181)	(0.130)
Management	-0.0118	-0.0382***	0.0688	0.238***
	(0.00881)	(0.0102)	(0.164)	(0.0691)
Market power	0.00912***	0.0126***	0.0235***	0.0312***
	(0.00227)	(0.00277)	(0.00618)	(0.00914)
Branches	-0.000249	0.00136	-0.0296**	-0.0284**
	(0.00278)	(0.00377)	(0.0145)	(0.0141)
Deposits	-0.0190***	-0.0288***	-0.278***	-0.213***
	(0.00387)	(0.00485)	(0.0376)	(0.0376)
Observations	5,619	3,399	12,806	7,731
N_banks	543	450	986	872

In Table 4, with the exception of the short window case for the profitability outcome, the DID estimators for the small banks are negative and statistically significant for profitability and deposit growth. The negative value and statistical significance for the estimated coefficient of the $Treat * Dodd$ regressor is consistent with the results shown in Figures 1-4 and with the conjecture that Dodd Frank imposed some tightened regulations, reducing small banks' ability to grow and be profitable. This effect in the long-window time frame is -0.44% for profitability and -1.56% for deposit growth with significance at the 5% and 1% respectively. The specification indicates that the profitability for banks with less than $1B on assets, after Dodd-Frank were on average 44 basis points lower than banks with more than $1B on assets. By the same token, the growth of deposits for those banks with less than $1B on assets, after Dodd-Frank were on average 1.56% lower than banks with more than $1B on assets.

The results remain qualitatively the same in the short window (2009-2011), except to the profitability effect: albeit not significant, the effect for the short-window time frame is -0.15%. In the case of deposit growth the coefficient is -2.37%, significant at the 1% level. The difference in the effect in profitability could be consequence of the Treasury programs providing relief to the regulatory burden in the short term.

Additionally, consistent with previous literature, all the other bank-level controls show statistically significant relationships on the determination of banks' profitatility and deposit growth. An increase in non-performing loans and volatility in firms assets measured as asset and management quality respectively, decreases banks profitability and deposit growth; Capital adequacy and market power are associated with increases profitability and deposit growth. The $Sizedist$ multiplier (the distance between the banks asset and the size cutoff) shows a positive relationship between returns on assets and the distance between the banks' assets and the size cutoff. In other words, the larger the bank, the more profitable it seems to be. However, when we look at the size effect on profitability after Dodd-Frank's passage, the coefficient is the opposite. Moreover, the $Sizedist * Dodd$ multiplier is negative and significant at 5% level for the long window specification.

Table 5
Dodd-Frank Effect on Bigger Banks

This table presents estimated parameters using DID linear regressions on Profitability (ROA) and Deposit Growth (percentage change in the deposit amounts) for bigger banks. Sizedist in the difference between the asset observation and the asset cutoff, divided by the asset sample standard deviation. CCT is the bandwidth selector. Long window columns present the results for the entire sample period (2008-2012), while short window columns present for a subsample period (2009-2011), for both samples around $10B in assets. All regressions include a set of year dummies and bank fixed effects, unreported. Lines with blanks means that there is no information about the respective variable in the sample. *, **, and *** represents 10%, 5% and 1% of statistical significance, respectively. Robust errors are reported in parenthesis. We use panel with fixed effects regressions and bank clusters. All the variables are defined in table 1.

Variables	**Profitability**		**Deposit Growth**	
	Long window	**Short window**	**Long window**	**Short window**
Sizedist	-0.0231	0.0649	1.494***	1.711***
	(0.101)	(0.131)	(0.324)	(0.428)
Treat*Sizedist	0.157*	0.0551	-0.891**	-0.744
	(0.0930)	(0.152)	(0.350)	(0.468)
Dodd	0.000586	0.000216	-0.0270*	-0.0210
	(0.00323)	(0.00397)	(0.0140)	(0.0158)
Sizedist*Dodd	-0.0394	-0.0606	-0.133	0.0395
	(0.102)	(0.136)	(0.178)	(0.229)
Treat*Dodd	**0.00123**	**0.00100**	**0.0335****	**0.0371****
	(0.00307)	**(0.00407)**	**(0.0147)**	**(0.0183)**
Treat*Dodd*Sizedist	-0.162	-0.115	-0.0968	-0.454
	(0.129)	(0.167)	(0.223)	(0.312)
Asset Quality	-0.110***	-0.136**	-0.385***	-0.436**
	(0.0367)	(0.0628)	(0.113)	(0.188)
Liquidity	0.00326	0.00821	-0.0658***	-0.116
	(0.0101)	(0.0121)	(0.0178)	(0.187)
Capital Adequacy	-0.0285**	-0.0453*	-0.0349	0.0774
	(0.0124)	(0.0235)	(0.267)	(0.325)
ROA	0.179*	0.00899	-0.678**	-0.594
	(0.0984)	(0.0786)	(0.283)	(0.430)
Management	0.0388	-0.00363	0.207	0.328**
	(0.0232)	(0.00982)	(0.171)	(0.151)
Market power	-0.00131	-0.000196	-0.00476	-0.00606**
	(0.00152)	(0.000825)	(0.00398)	(0.00251)
Branches	0.0152	0.00488	-0.00911	-0.00319
	(0.0126)	(0.0126)	(0.0164)	(0.0406)
Deposits	-0.0284***	-0.0312**	-0.119***	-0.156***
	(0.00999)	(0.0136)	(0.0166)	(0.0261)
Observations	416	264	1,305	789
N_banks	61	48	106	89

In Table 5, we present the results for bigger banks. Although we find no evidence for profitability, the DID estimator for bigger banks is positive for deposit growth rates, around 3.35% and 3.71% for the long and short time windows respectively. The results suggest that those banks exceeding $10B in assets overperform in terms of deposit growth comparable banks just below $10B in assets after the Dodd-Frank Act. Specifically, the growth of deposits for those banks with more than $10B on assets, after Dodd-Frank were on average 3.35% (3.71% for the short window) higher than banks with less than $10B on assets. Moreover, the *Sizedist* multiplier remains positive for the deposit growth specifications. All the other bank-level controls have the expected coefficients for the regressors as in Table 4.

So far, our results suggest that Dodd-Frank Act had different effects on banks profitability and deposit growth, depending on their size. These results are economically and statistical significant. A null effect in profitability for bigger banks could be explained through

the ex-ante cost advantage hold by bigger banks compared to smaller banks. Bigger institutions are able to absorb compliance costs in a large scale since they can manage the already existing personnel resources and their extensive base of tangible assets, whereas smaller banks face a restrict degree of flexibility in managing expenses. In this sense, a number of papers found evidence of scale economies in larger banks. These have lower operating costs as they can spread the overhead in information technology, accounting, advertising, and management over a larger asset or revenue base (Kovner et al., 2014). They also benefit from scale economies via increased cost efficiency (Biswas et al., 2017; Hughes & Mester, 2013). Economies of scale are a plausible reason for the growth in average bank size in recent years (Wheelock & Wilson, 2012).

The question remains of why depositors would migrate from smaller to bigger banks and what would be the role of the Dodd-Frank Act on this. There are three plausible explanations: First, bigger banks are able to spread compliance costs over a large asset base through consolidation and scale economies, which increases their cost advantage. They have more reasonable capital access to boost loan loss reserves, absorb credit losses and smooth new legislation compliance costs, as the Dodd-Frank disclosure costs (Hughes & Mester, 2013; Kroszner, 2016; Hunter et al., 1990). Second, smaller banks could be perceived as riskier as the *stigma channel* provided in Berger and Roman (2013). Although they focus on governmental intervention, smaller banks could lose customers that may be reluctant to do business with these banks due to limited oversight. In this context, the *stigma effect* comes via one mandatory regulation: Dodd-Frank may work as a selection criterion for "healthy, viable institutions". Even though Dodd-frank was a regulation for all banks, the act has escalating oversight based solely on the size of the bank, thus increasing the *safety or riskiness* perception for these banks[8]. Finally, as pointed by Peirce et al. (2014), smaller banks discontinued popular product lines after the legislation passage, such as residential mortgages. Reducing their profitability and their chance to increase their customer portfolios, jeopardizing their growth opportunities.

In sum, our results imply that the negative Dodd-Frank effect on small banks, in both returns and deposit growth ratios, holds although the funding programs created specifically to support these financial institutions, such as the earlier mentioned SBLF. Our conjecture is that these programs did not suffice as a government subsidy to avoid distortions in the absorption of Dodd's compliance costs in the long term.

We also investigate the effect of Dodd-Frank for low and high market concentration levels, by dividing our CCT samples in two subgroups, using Lerner Index. If Dodd-Frank was effective for systemic dangerous banks, it should have negatively effects for highly concentrated banks, since one of the legislation's goal is to reduce the power of the bigger banks over the economy. We measure Lerner Index for each size cutoff sample in the pre-Dodd period (2008Q1-2010Q2). We present the results only for the deposit growth, since all the relevant estimators for the ROA analyses were not significant.

Table 6
Dodd-Frank Effect and Market Power

This table presents estimated parameters using DID linear regressions on deposit growth, using $1B and $ 10B in assets banks with different market power levels. Higher market power is a dummy one if a bank has Lerner Index greater or equal than the median of each CCT sample in the pre-Dodd period; zero (lower market power), otherwise. Sizedist in the difference between the asset observation and the asset cutoff, divided by the asset sample standard deviation. We use panel with fixed effects regressions and bank clusters. Robust errors are reported in parentesis. All regressions include a set of year dummies and controls, untabulated. *, **, and *** represents 10%, 5% and 1% of statistic significance, respectively. All the variables are defined in table 1.

Variables	$1B in assets	$10B in assets

[8] For example, some provisions affected only banks with over $10B in asset, from risk committees to annual stress tests.

	Lower market power	Higher market power	Lower market power	Higher market power
Sizedist	15.89***	11.79***	1.444***	1.127**
	(2.413)	(1.706)	(0.378)	(0.546)
Treat*Sizedist	1.776	2.178	-0.998**	-0.601
	(1.915)	(1.398)	(0.451)	(0.584)
Dodd	0.00919	-0.00292	-0.0530**	0.00380
	(0.00956)	(0.00652)	(0.0250)	(0.0123)
Sizedist*Dodd	-2.647*	0.350	-0.379	0.235
	(1.585)	(1.007)	(0.238)	(0.194)
Treat*Dodd	**-0.0251****	**-0.0113**	**0.0509***	**0.0123**
	(0.00984)	**(0.00699)**	**(0.0296)**	**(0.0128)**
Treat*Dodd*Sizedist	1.168	-1.666	0.236	-0.488*
	(1.662)	(1.125)	(0.368)	(0.258)
Observations	5464	7342	591	714
Observations Treated	4623	6127	257	348
Observations Non-Treated	841	1215	334	366
N_banks	476	510	53	53

The results in Table 6 emphasizes the inefficiency generated by Dodd-Frank. Although the mandate of the law to end "too big to fail", the DID estimators are negative for smaller banks with lower market power. The coefficient is -2.51%, significant at the 5% level. Conversely, our result shows some evidence that bigger banks with *ex-ante* lower market power improved their market position after Dodd-Frank passage, the coefficient is 5.09%, significant at 10% level. Furthermore, banks with *ex*-ante higher market power did not experience a Dodd effect, regardless of their size. This result is interesting since the objective of the law was to focus in not only the financial stability of the system, but arguably to discourage market concentration. Our results indicate that the negative effect was for smaller banks in lower concentrated markets, becoming less profitable and having impediment to growth.

4.2 Robustness and Sensitivity Checks

A Research Discontinuity Design (RDD) can be invalid if individuals can somehow manipulate the assignment variable (Lee & Lumieux, 2010), also called the running variable, which is bank size in our case. In other words, banks assigned to the treatment group can manage their total assets (self-selection problem), in order to avoid the overregulation in the Dodd-Frank pre-announcement period. McCrary (2008) developed a test to verify the existence of manipulation of the assignment variable. The proposed test is based on an estimator for the discontinuity at the cutoff in the density function of the assignment variable. It is a Wald test of the null hypothesis that the discontinuity is zero. A significant t-statistic would suggest that there is a discontinuity in the total assets density for the pre-Dodd period, indicating size manipulation, banks managing their resources to fit in determined group and avoid compliance costs.

Table 7

Discontinuity estimates for bank size

This table shows the test outlined in McCrary (2008), based on an estimator for the discontinuity at the cutoff in the density function of the running variable, which is bank total assets. The test is implemented as a Wald test of the null hypothesis that the discontinuity is zero. The estimated parameter captures the magnitude and the direction of the discontinuity. Panel A implements the McCrary Test in the pre-Dodd period (2008Q1-2010Q2), while Panel B does the test for the out-of-the-sample quarterly data (2005Q1-2007Q4). The tests consider the entire sample (and not only the matched sample using CCT algorithm).

Panel A: McCrary Tests in Pre-Dodd sample period (2008Q1-2010Q2)

	Estimated parameter	Standard error	T-statistic
Banks around $10B in assets	0.049	0.126	0.387

Banks around $1B in assets	-0.178	0.045	-3.953

Panel B. Out-of-Sample McCrary Tests in pre-years Dodd (2005Q1-2007Q4)

	Estimated parameter	Standard error	T-statistic
Banks around $10B in assets	-0.118	0.043	-2.738

Table 7 presents the estimated discontinuities and its associated t-statistics from the McCrary test for manipulation of the running variable around each size threshold (McCrary, 2008), $1B and $10B billion in assets. We ran the McCrary test in the pre-Dodd period (2008Q1-2010Q2). On the one hand, the distribution of bank size along the running variable seems to be smooth around the threshold of $10B bank size, with a t-statistic of 0.387. In other words, the evidence suggests that there is no discontinuity around this threshold and no sign of size self-selection. On the other hand, the density function of the bank size is discontinuous at the $1B bank total assets, with a t-statistic of a 3.953. If banks are manipulating assets to avoid costs of regulation, they should run away from the right to the left side of the distribution, because they would receive a softer Dodd-Frank enforcement, in theory, once they belong the smaller size banks side. Consistent with Bouwman et al. (2018) this is what we find in our results for the $1B asset group. However, we argue that the results are due to previous market trends than a self-selection to avoid compliance costs. In an out-of-sample previous to the crisis and the Dodd-Frank legislation agenda period (see Panel B of Table 7), using the sample period of 2005Q1-2007Q4, we show that the discontinuity around $1B total assets group have t-statistics of -2.7. Furthermore, the signal of the estimated discontinuity remains similar if we compare the sample test and the out-of-sample test: -0.1780 and -0.1184. Overall, this evidence suggests the market trend of bank concentration instead of avoidance of compliance costs.

As a final test, we create an artificial shock to check if our results are driven by other events, such as the 2008 financial crisis, but not by the Dodd-Frank Act. The positive effect on some bigger banks' profitability, for instance, would be a consequence of an increasing market share post-crisis (more banks failures, less competition). We created the dummy $Dodd2008$ that takes the value of one when the sample year is greater than the first quarter of 2008, and it is equal to zero, otherwise. We chose 2008Q1 as the period in which the crisis started since this was the beginning of the U.S. recession in the 2008 financial crisis.[9].

In order to keep comparability, we used in the placebo tests the same bandwidth frontiers *h*, selected by the CCT method for each outcome variable (profitability and deposit growth), specified in the prior regressions (see Table 2). In all placebo tests for the $1B cutoff sample, the *Treat*Dodd* coefficient is not statistically significant, suggesting that the prior results were not driven by the economic recession. Moreover, in the profitability regression for the case of $10B cutoff sample, the coefficient is negative and significant at 5% level. This result is not surprising, since the crisis started after this period.

5. CONCLUSION

This study investigates the Dodd-Frank effect over U.S. banks in terms of profitability and growth opportunities. Difference-in-differences models combined with research discontinuity designs show that that the Dodd-Frank Act provided a positive effect on bigger banks deposit growth rates. In contrast, the smaller banks experienced a negative effect in their return on asset ratios and deposit growth rates. We also find evidence that the negative effect on smaller banks comes from those with ex-ante lower market power, which emphasizes unintended negative consequences of the Dodd-Frank legislation. Conversely, the legislation benefited bigger banks, giving them room to enhance costumer portfolios, in an already existing

[9] In 2007Q4, the real Gross Domestic Product (GDP) growth was a positive 1.5%., and it reversed to a negative performance of -2.7% in 2008Q1, according to a report released by the U.S. Department of the Treasury

trend of market concentration. These key findings add to the evidence that the Dodd-Frank generated inefficiencies in the banking system, whereas it jeopardized smaller businesses, impeding them from growing. Consequently, this study contributes to the existent literature that banking regulations should be based more on business complexity and individual risk profiles rather than merely on the size of banks.

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