Watch what they do, not what they say: Estimating regulatory costs from revealed preferences*

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Abstract

We show that distortion in the size distribution of banks around regulatory thresholds can be used to identify costs of bank regulation. We build a structural model in which banks can strategically bunch their assets below regulatory thresholds to avoid regulations. The resulting distortion in the size distribution of banks reveals the magnitude of regulatory costs. Using U.S. bank data, we estimate the regulatory costs imposed by the Dodd–Frank Act. Although the estimated regulatory costs are substantial, they are significantly lower than those in self-reported estimates by banks.

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1 Introduction

Financial regulators are mandated by law to perform a cost-benefit analysis (CBA) on regulations. In a CBA, the social benefits of regulations, such as those arising from a reduced probability of financial crisis, are compared with the regulatory costs, which are mainly borne by financial institutions that must comply with them. CBA is crucial for regulators' rule-making and forms the basis for judicial review and Congressional oversight of regulatory actions. Although there is a growing body of research on quantifying regulatory benefits to the public, quantifying regulatory costs borne by financial institutions is often viewed as a mundane task for regulators and has received less academic scrutiny.

Quantifying the costs of financial regulation, however, is far from trivial. Financial regulators generally do not have enough information to gauge the regulatory impacts on complex financial institutions. Instead, they often have to rely on self-reported estimates from financial institutions to guide their policies. However, these self-reported estimates may be inflated by financial institutions to justify regulatory relief. For instance, Parker (2018) finds that a highly influential estimate of regulatory costs cited by the 2016 House Concurrent Budget Resolution comes from studies "funded by organizations having a strong financial or institutional stake in the outcome of their studies" and the methodologies used to estimate regulatory costs are "fundamentally flawed." Nevertheless, these self-reported estimates are widely cited in policy debates and have promoted efforts to roll back financial regulations enacted after the 2008 financial crisis.[1] The lack of independent and rigorous assessment of regulatory costs highlights the need for academic research in this area (Posner and Weyl, 2013; Coates, 2014).

This paper proposes a revealed preference approach to infer regulatory costs from the

[1]For instance, in January 2017, the Trump administration issued an Executive Order that mandates "for every one new regulation issued, at least two prior regulations be identified for elimination." In May 2018, Congress passed the Economic Growth, Regulatory Relief, and Consumer Protection Act, which scales back many financial regulations enacted after the crisis.

regulatory distortion on the size distribution of financial institutions. To illustrate our approach, consider the Dodd–Frank Act of 2010, which imposes stringent regulations on banks when their assets cross the $10 billion and $50 billion thresholds.[2] As shown in Figures 1a and 1b, many banks shrink their assets to avoid these regulations, creating excess densities around these thresholds. Such distortions are not present in the pre-Dodd–Frank period, or around other round numbers that are not regulatory thresholds, such as $20 billion or $40 billion, as shown in Figure 2a and Figure 2b. We show that the extent of such regulatory distortions can reveal the regulatory costs faced by banks.

To formalize this idea, we develop a structural model of the size distribution of banks. In the model, banks are endowed with heterogeneous productivity, which affects the quantity of deposits each bank can raise for a given deposit rate. Banks then use the deposits to make loans to firms. Regulatory costs are modeled as a tax on banks' profits in the spirit of Posner (1971). The tax rate jumps discretely at regulatory thresholds, reflecting the regulations that come into effect at the regulatory thresholds.[3] The discrete jumps in the tax rate create an incentive to bunch. Banks that are just above the regulatory threshold shrink their size to avoid regulation. Banks that are far above the regulatory threshold do not bunch because the costs of bunching outweigh the costs of regulation.

We use the model to guide our estimation of the regulatory costs. In the absence of regulatory distortions, the size distribution of banks is determined by the underlying productivity and should not display any excess density around a particular threshold. In the presence of regulation, however, banks bunch to avoid regulation, creating excess densities around regulatory thresholds. The magnitude of the excess densities then reveals the regulatory costs borne by banks. Using this idea, we derive a maximum likelihood estimator and apply it to U.S. bank size data to estimate the regulatory costs imposed by the Dodd–Frank Act.

[2] We provide a more detailed discussion on the regulations triggered by each threshold in Section 2.

[3] This formulation also allows for the possibility that certain regulations may generate private value for banks that comply with them. In this case, the tax rate should be interpreted as the net regulatory burden. See Section 4.2 for a more detailed discussion.

The estimation shows that the regulation costs triggered at the \$10 billion threshold are equivalent to a 0.41% tax on banks' annual profits. The additional regulatory costs triggered at the \$50 billion threshold are equivalent to a 0.11% tax. The estimated regulatory costs are economically significant. For a bank with \$50 billion assets, the regulatory costs amount to \$4.16 million per year,[4] which is equivalent to the salary expenses of hiring 52 additional compliance officers, assuming the average annual compensation for a compliance officer is around \$80,000 (Feldman, Heinecke, and Schmidt, 2013).

Practitioners often point to the low franchise values in the post-crisis period as evidence of high regulatory costs imposed by the Dodd–Frank Act. Although this argument is appealing, it remains unclear how much regulations can explain the decline in bank values (Sarin and Summers, 2016; Chousakos and Gorton, 2017). Our structural model can study this question quantitatively by simulating bank values with and without the estimated regulatory costs. We find the estimated regulatory costs only explain a small fraction of the decrease in bank franchise value in the post-crisis period. Our result suggests non-regulatory factors, such as ultra-low interest rate environment (Calomiris and Nissim, 2014; Whited, Wu, and Xiao, 2021), market reassessment of risks (Sarin and Summers, 2016), and the removal of too-big-to-fail subsidies (Atkeson, d'Avernas, Eisfeldt, and Weill, 2019; Berndt, Duffie, and Zhu, 2020) may also have contributed to the decline in bank values.

The Dodd–Frank Act also has distributional implications in the cross-section of banks. One may expect the market shares of big banks (>\$50 billion) would shrink after the Dodd–Frank Act because they face the most-stringent regulations. Surprisingly, the counterfactual simulation suggests that the market share of big banks would expand after the Dodd–Frank Act. The reason for the expansion of big banks is twofold. First, medium banks (\$10 billion to \$50 billion) engage in regulatory avoidance, which reduces their average asset size. Second,

[4] The regulatory costs introduced by the Dodd–Frank Act for a \$50 billion bank are equivalent to a $0.41\% + 0.11\% = 0.52\%$ tax. The ratio of annual profits to assets is 1.6%. So the dollar value of regulatory costs per year is $\$50,000 \times 1.6\% \times 0.52\% = \$4.16$ million.

heightened regulatory costs depress bank value across the size spectrum, which reduces the entry of small banks (<$10 billion). This result suggests a possible unintended consequence of regulation on the bank industry's market structure.[5]

Regulation not only imposes compliance costs for banks but also leads to indirect costs for the rest of the economy. As banks shrink their size to avoid regulation, bank-dependent firms can be adversely affected. Regulation can also affect aggregate credit supply from the extensive margin of bank entry and exit. Quantifying the indirect costs of regulation requires solving the full market equilibrium. To this end, we calibrate parameters that govern the equilibrium supply and demand of bank credit using either values in the prior literature or the corresponding moments in the data. We then simulate counterfactual economies with and without the direct regulatory costs estimated from our maximum likelihood estimator. We quantify the indirect costs of regulation as the lost output of bank-dependent firms due to the regulation. We find that the indirect costs of Dodd–Frank Act appear to be modest: the indirect regulatory costs are equivalent to a 0.02% tax on the output of bank-dependent firms.

We compare our estimated regulatory costs with those from other methodologies. We show that reduced-form methods such as difference-in-differences and regression-discontinuity design are likely to underestimate the direct regulatory costs because banks can strategically avoid regulation. Furthermore, these methods cannot capture implicit regulatory costs that are not measured in banks' financial statements. Indeed, these reduced-form methods usually find little evidence of changes in regulatory costs after the Dodd–Frank Act. In contrast, estimates based on self-reported surveys from banks are usually much larger than our estimates, consistent with anecdotal evidence that these estimates may be inflated to lobby regulators for regulatory relief (Hinkes-Jones, 2017; Parker, 2018).

[5]This result does not imply that the Dodd–Frank Act has worsened the too-big-to-fail problem because we do not explicitly model how regulation affects big banks' risk-taking and their reliance on the implicit government guarantee.

We conduct several extensions and robustness checks on our results. First, we extend our analysis to the 2018 Economic Growth, Regulatory Relief, and Consumer Protection Act of 2018, which rolled back many regulatory requirements imposed by the Dodd–Frank Act. In the data, the excess densities around the Dodd–Frank thresholds have decreased significantly after the 2018 regulatory relief, suggesting the incentive to avoid regulation has weakened since then. Indeed, the estimated regulatory costs in the post-relief period are significantly smaller than those in the post-Dodd–Frank period. We also find that the number of banks in the steady state increases after the 2018 regulatory relief, consistent with an increase in bank entry observed in the data.

Second, our maximum likelihood estimator assumes the undistorted bank assets follow a power law distribution. Although this assumption is motivated by the data, we want to assess the robustness of our estimation to alternative distributions. To this end, we re-estimate the regulatory costs using an alternative distribution assumption for the maximum likelihood estimator and find the results are robust. Our estimates are not sensitive to the distribution assumption because the regulatory costs are mainly identified from the local abnormal densities around the threshold and are insensitive to the global property of the distribution.

Third, our model takes regulatory costs as exogenous parameters without stipulating the social benefits that motivate these regulations. One may worry whether our estimates of the regulatory costs will be biased if some unspecified social benefits of regulation, such as a reduction in the probability of financial crisis, can affect bank size in the general equilibrium. We show that our identification strategy still holds in the presence of the general equilibrium effects of regulatory benefits because our estimates of the direct regulatory costs are identified from the local bunching patterns resulting from the discontinuities in regulatory costs. The general equilibrium effects of regulatory benefits are likely to be smooth around the threshold and do not affect bunching at the regulatory thresholds.

Finally, we conduct several placebo tests by applying our estimator to the pre-Dodd–Frank sample and find no regulatory costs triggered by the thresholds in this sample. We also conduct placebo tests on round numbers that are not regulatory thresholds in the post-Dodd–Frank period. Again our estimator correctly indicates null results.

Our paper relates to the literature on cost-benefit analysis (CBA) of regulation. There is extensive literature on regulatory CBA in environmental economics and industrial organization (Harberger, 1964; Viscusi and Aldy, 2003). However, analogous literature has been conspicuously missing in financial economics until recently (Posner and Weyl, 2013). The existing research focuses on quantifying the benefits of financial regulation.[6] However, quantifying regulatory costs has received less attention so far. A contribution of our paper is a revealed preference approach to quantify regulatory costs.[7] This approach can be applied in many other settings in which the regulation is threshold-based. Our revealed preference approach is also less prone to potential bias in self-reported surveys. Our approach complements reduced-form methods to estimate regulatory costs such as difference-in-differences and regression discontinuity, for which endogenous selection around the threshold is an impediment for identification. Additionally, our approach is broadly related to the bunching literature in public finance and labor economics, which uses tax kinks to identify labor supply elasticity (Saez, 2010; Chetty, Friedman, Olsen, and Pistaferri, 2011; Kleven and Waseem, 2013).[8] In comparison, we show that the bunching pattern can also be used to identify regulatory costs. Our paper adds to a growing body of literature that employs structural techniques to study financial markets (Koijen and Yogo, 2015; Egan, Hortaçsu, and Matvos, 2017; Buchak, Matvos, Piskorski, and

[6]Coates (2014) surveys the literature on the estimation of the GDP losses due to financial crisis and how much bank regulation can reduce such losses. Posner and Weyl (2013) propose and estimate a parameter called the statistical cost of a crisis (SCC), which allows regulators to translate the reduced probability of a crisis into a dollar value with certainty.

[7]Some researchers have developed indices of regulatory costs based on textual analysis of the regulatory provisions or compliance-related spending (Al-Ubaydli and McLaughlin, 2017; Calomiris, Mamaysky, and Yang, 2020; Simkovic and Zhang, 2020). These indices are helpful for understanding the cross-section variations in regulatory exposure, but they are difficult to be translated into monetary values in a CBA.

[8]See also DeFusco and Paciorek (2017), Dagostino (2018), Bachas, Liu, and Yannelis (2019), Alvero and Xiao (2020), Bachas, Kim, and Yannelis (2020), and Antill (2020) for applications of the bunching approach in finance.

Seru, 2018; Benetton, 2018; Nelson, 2018; Robles-Garcia, 2019; Darmouni, 2020; Xiao, 2020; Corbae and D'Erasmo, 2020; Begenau and Landvoigt, 2021).

This paper also relates to the vast literature on financial regulation. The aftermath of the 2008–2009 financial crisis witnessed one of the most active periods of financial regulation in U.S. history. The unprecedented wave of financial regulation has stimulated a fast-growing body of research. The existing literature shows from a variety of perspectives how the new regulations affect the financial system (Buchak, Matvos, Piskorski, and Seru, 2018; Acharya, Berger, and Roman, 2018; Cortés, Demyanyk, Li, Loutskina, and Strahan, 2020; Fuster, Plosser, and Vickery, 2018; Carletti, Goldstein, and Leonello, 2020; Kashyap, Tsomocos, and Vardoulakis, 2020). We contribute to this literature by quantifying the costs of Dodd–Frank regulations on banks. This question is crucial because the narrative of repressive regulatory costs has made many Dodd–Frank regulations targets of repeal. We find that the self-reported estimates from the finance industry are usually much larger than the estimates from the revealed preference approach, consistent with the anecdotal evidence that regulatory costs are often "hyped" by the finance industry (Hinkes-Jones, 2017, p.1). Furthermore, we study the impacts of the Dodd–Frank regulations on bank size, productivity, and profit distribution. By doing so, our paper contributes to the literature on the distortionary effects of size-based regulation, which has mainly focused on the labor market so far (Garicano, Lelarge, and Van Reenen, 2016; Gourio and Roys, 2014; Ando, 2021).

2 Institutional background

We first discuss the cost-benefit analysis of financial regulation. Then we discuss the Dodd–Frank Act and its impact on the size distribution of banks.

2.1 Cost-benefit analysis (CBA) of regulation

Regulators are mandated by law to conduct a cost-benefit analysis (CBA) on regulations. CBA entails an economic or statistical assessment of the social benefits of the regulation and the compliance costs borne by the regulated parties. If a regulation is likely to spill over to other agents in the economy, then the indirect regulatory costs should also be estimated. The major statutes that apply to financial regulators include (1) the Paperwork Reduction Act (PRA), which requires regulators to justify the collection of information from the public to minimize its burden and maximize the utility of information collected;[9] (2) the Regulatory Flexibility Act (RFA), which requires regulators to assess and consider alternatives to the burden of regulation on small entities;[10] and (3) the Congressional Review Act (CRA), which requires regulators to submit proposed rules—along with any cost-benefit analysis the agencies have conducted—to Congress and the Government Accountability Office (GAO).[11]

The goal of the cost-benefit analysis is to advance regulators' ability to increase welfare and allow the public to detect and push back against regulations that fail to do so. The cost-benefit analysis often forms the basis for judicial review and Congressional oversight of regulatory actions. For instance, in the 2002 SEC mutual fund governance reform, the regulator proposed to increase the required share of independent directors from 50% to 75% for mutual funds. Following the SEC's proposal, the Chamber of Commerce, a business-oriented interest group, sued the SEC for failure to quantify the costs of the rule. In its defense, the SEC argued that staffing would be discretionary and the SEC had no basis for knowing how many chairs would hire staff or how many staff each chair would hire. However, the court rejected this argument and maintained that "estimating the costs for an individual fund is pertinent to an assessment of the requirement."[12] In the end, the rule was struck

[9]Pub. L. No. 104–13, 109 Stat. 163 (1995) (codified at 44 U.S.C. §§ 3501-3520).
[10]Pub. L. No. 96-354, 94 Stat. 1164 (1980) (codified at 5 U.S.C. §§ 601–612).
[11]Pub. L. No. 104–121, 110 Stat. 847 (1996) (codified as amended in 5 U.S.C. § 801 et seq.).
[12]Chamber of Commerce v. SEC, 412 F.3d 133 (D.C. Cir. 2005).

down by the court.

CBA of financial regulations has emerged as an important point of policy debate since the passage of the Dodd–Frank Act. Proponents argue that financial regulators should be held accountable for more-stringent CBA to ensure their discretion on rule-making is not abused (Posner and Weyl, 2013). However, others caution about the inherent difficulties in CBA of financial regulations because of the complexity of financial institutions (Coates, 2014). A key issue faced by financial regulators is the lack of information on regulatory costs (Coates, 2014; Cochrane, 2014). This paper argues that regulators can extract valuable information by analyzing financial institutions' action around the regulatory threshold to gauge the magnitude of regulatory costs, at least from an ex-post perspective. This method can be used in many settings that feature regulatory thresholds. We do not attempt to provide a general method to quantify the benefits of financial regulation, which has received relatively more attention in the literature. Instead, we focus on estimating the costs of regulation, which is an important yet understudied component of CBA of financial regulations. Our estimates of regulatory costs can be used in conjunction with estimates of regulatory benefits in CBA.

2.2 The Dodd–Frank Act

The Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010 (Dodd–Frank) is the centerpiece of post-crisis financial reform. The Dodd–Frank Act takes a tiered regulatory approach: banks are classified into size categories based on several regulatory thresholds and banks in larger size categories are subject to stricter regulations. Specifically, banks whose assets exceed the $10 billion threshold are required to (1) conduct annual stress tests, (2) comply with the Durbin Amendment, which puts a cap on the fees charged to merchants for debit card transactions, (3) report to the Consumer Financial Protection Bureau (CFBP), a government agency created as part of Dodd–Frank, and (4) create risk committees with independent directors. Banks whose assets exceed \$50 billion are subject to additional risk-based capital and liquidity requirements, stress tests, and annual resolution plans. A detailed summary of the law can be found in Huntington (2010).

The tiered regulation creates discontinuities in the regulatory burden at the regulatory thresholds. In response to such discontinuities, banks around the thresholds strategically downsize their assets to avoid regulation. As shown by the red solid line in Figures 1a and 1b, the cumulative distribution function of bank size displays abnormal bulges around the \$10 billion and \$50 billion thresholds after the passage of the Dodd–Frank Act, suggesting that banks bunch their assets to avoid regulation.[13] This pattern is consistent with Bouwman, Hu, and Johnson (2018), who find that banks around the Dodd–Frank thresholds substantially reduce their assets. Such a pattern is not present in the pre-Dodd–Frank period, as shown by the blue dashed line in Figures 1a and 1b.

One may worry that banks may simply cluster around round numbers and do not necessarily try to avoid regulation. To address this concern, we examine round numbers that are not regulatory thresholds, such as \$20 billion or \$40 billion. We find no excess density around these round numbers, as shown in Figures 2a and 2b. This result suggests that the excess densities around \$10 billion and \$50 billion are not driven by banks' clustering at round numbers. Instead, they are the outcomes of banks' strategic response to the regulations imposed by the Dodd–Frank Act.

In addition to the distortion in the size distribution of banks around regulatory thresholds, bank franchise value has also been significantly depressed in the post-Dodd–Frank period, as shown in Figure 3a. The average franchise value of U.S. banks, measured by the market value of assets divided by the book value, decreased by 7% from the period of 2000-2010 to the period of 2011-2019. In addition, new bank entry has also been abnormally low since the

[13] Online Appendix Figure OA.1 shows the histograms of bank size around the regulatory thresholds.

Dodd-Frank Act is passed, as shown in Figure 3b. Although these patterns are consistent with heightened regulatory costs (Sarin and Summers, 2016; Chousakos and Gorton, 2017), they could also be driven by other confounding factors such as ultra-low interest rates, the removal of the too-big-to-fail subsidy, and market reassessment of risks (Calomiris and Nissim, 2014; Atkeson, d'Avernas, Eisfeldt, and Weill, 2019; Berndt, Duffie, and Zhu, 2020; Whited, Wu, and Xiao, 2021).

3 Model

This section introduces our theoretical framework. We first describe individual banks' optimal size choices in the presence of the size-based regulation in a partial equilibrium setting in which the distribution of productivity and the lending rate are given. We derive a sufficient statistic formula for the direct regulatory costs. Then, we endogenize the productivity distribution and the lending rate in a general equilibrium framework with firms, which allows us to quantify the indirect costs of bank regulation on the rest of the economy.

3.1 Bank size choice and direct cost of regulation

The economy is populated by heterogeneous banks indexed by their productivity z, which follows a distribution with probability density function $g(z)$. A bank can raise funding from depositors at a cost $r(q|z)$, where q is the log quantity of funds. Banks' funding cost is increasing in q and is decreasing in z, that is, $r_q > 0$ and $r_z < 0$. As a result, a more productive bank can raise more funding for a given funding cost r. A simple example of the funding cost function is $r(q|z) = \frac{1}{\theta}(q - z)$, where θ is the semi-elasticity of funding supply. Banks then lend to firms with a rate R. For now, the distribution of the productivity z and the lending rate R are taken as exogenous. We will endogenize these variables in Section 3.2.

Banks face a size-based regulation that classifies banks into $I+1$ categories based on I size thresholds, $\underline{q_i}$, where $i = 1, ..., I$. If a bank's assets cross threshold $\underline{q_i}$, it will incur an additional regulatory cost that is equivalent to τ_i fraction of its profits. Our approach of measuring regulatory costs as a tax is in a spirit similar to Posner (1971). One can translate the regulatory costs to an annual monetary value by multiplying them with the annual profits. One can also interpret τ_i as the fraction of bank value loss due to the present value of all future regulatory costs. This formulation of regulatory costs can be applied in many other settings where the specifics of regulations may differ.

Facing the size-based regulation, banks choose size q to maximize profits

$$\max_q \pi(q|z) = \max_q (R - r(q|z)) \exp(q) \cdot \prod_{i=1}^{I} (1 - \tau_i \mathbb{1}_{q \geq \underline{q_i}}). \tag{1}$$

As shown in the above formula, the regulatory costs increase discretely by τ_i once a bank crosses the i's threshold. τ_i captures the regulations that come into effect at the corresponding threshold. Note that τ_i does not include regulations that all banks need to comply with or regulations triggered by other thresholds. Neither does τ_i capture the potential indirect costs of regulation on the rest of the economy, in which we will discuss in Section 3.3.

Note that certain regulations may generate private value for banks in compliance with them. For instance, regulatory disclosure can reduce the cost of capital for banks above the threshold. In this case, the tax rate reflects a net regulatory cost, that is, the difference between the reporting burden and the private value from a lower cost of capital. We do not attempt to further separate the reporting burden and the private value to the regulated parties because it is sufficient to estimate the net costs for the purpose of CBA. Regulators can compare the estimated net costs borne by financial institutions with the social benefits of regulation (and social costs if there are any).

We first solve for the optimal undistorted log assets when there is no regulation by setting all τ_i to zero:

$$q_0(z) \equiv \arg\max_q (R - r(q|z)) \exp(q). \tag{2}$$

The optimal undistorted size is obtained by equalizing the profit margin to the inverse semi-elasticity of funding supply, $R - r(q_0(z)|z) = r_q(q_0(z)|z)$. If we assume the elasticity of funding supply is a constant, i.e., $r(q|z) = \frac{1}{\theta}(q - z)$, then the optimal undistorted size is given by

$$q_0(z) = z + \theta R - 1. \tag{3}$$

Now we solve for banks' optimal size when the regulation is present.[14] Regulation creates a discrete jump in regulatory costs as shown in the red dotted line in Figure 4a. Banks can avoid the regulation by bunching below the threshold. However, bunching is costly because banks give up profits they could have earned if they operated on their undistorted scale. The cost of bunching increases with the productivity z, as more-productive banks need to give up more assets to bunch, as shown by the blue dashed line in Figure 4a. As shown in Figure 4b, banks whose undistorted size just above the regulatory threshold find it more profitable to bunch because they only need to shrink by a little bit. Banks whose undistorted size far exceeds the regulatory threshold find it more profitable to operate at their undistorted scale. Formally, we can derive the optimal asset choice as a function of productivity:

$$q^*(z) = \begin{cases} \underline{q}_i & z \in [\underline{z}_i, \overline{z}_i] \\ q_0(z) & z \notin \cup [\underline{z}_i, \overline{z}_i] \end{cases}, \tag{4}$$

where $\underline{z}_i$ is the productivity of a bank whose undistorted assets are equal to the regulatory threshold

$$q_0(\underline{z}_i) = \underline{q}_i, \tag{5}$$

[14]We assume the regulatory thresholds are distant enough from each other so that banks only consider whether to avoid the nearest threshold.

and $\overline{z}_i$ is the productivity of a marginal bank that is indifferent between whether to bunch at the regulatory threshold or to pay the regulatory costs.

$$\pi(q_0(\overline{z}_i) \mid \overline{z}_i)(1-\tau_i) = \pi(\underline{q}_i \mid \overline{z}_i). \tag{6}$$

Banks with productivity between $\underline{z}_i$ and $\overline{z}_i$ bunch at the regulatory threshold, $\underline{q}_i$, while banks outside the bunching interval operate in their optimal scale.[15] Using the above indifference condition of the marginal bank, equation (6), we can derive a sufficient statistic formula (Chetty, 2009) for the regulatory costs.

Proposition 1: *The direct regulatory costs τ_i that come into effect at threshold i is given by the following sufficient statistic formula:*

$$\tau \simeq 1 - \left[\left(\overline{q_i} - \underline{q_i} + 1\right)\right] \exp\left(\underline{q_i} - \overline{q_i}\right), \tag{7}$$

where the approximation is exact when the semi-elasticity of the funding supply, r_q, is a constant.

Proof: See Appendix A.1.

Equation (7) shows that the regulatory cost τ_i only depends on the difference between the marginal bank's log assets, $\overline{q_i}$, and the regulatory threshold, $\underline{q_i}$. It does not depends on the lending and deposit rates, R and r. The intuition is the following. Banks trade off the costs of regulation and the costs of bunching, which are expressed as a percentage of banks' profits. Although a higher lending rate (or a lower deposit rate) increases the level of banks' profits, it does not change the relative magnitude of regulatory costs and the costs of bunching. In other words, if our goal is to estimate the tax-equivalent costs of regulation

[15] In our current model, banks choose their size to avoid regulation. It is equivalent to recast the model as banks choosing their funding rates to avoid regulation. Specifically, because the funding supply is upward sloping, banks can pay a low rate so that their size becomes smaller.

borne by banks, we only need the size distribution of banks as the data input. However, if we would like to translate the regulatory costs to a dollar value, we would need the lending and deposit rates to compute banks' profits.

3.2 Firms

We now endogenize the lending rate by introducing the firm sector, which borrows capital from banks and produces output using a Cobb-Douglas production function:

$$\max_{K} \Pi = AK^{\alpha} - RK, \tag{8}$$

where $Y = AK^{\alpha}$ is the output, K is the capital, and A is the total factor productivity.

The aggregate supply of capital is given by summing the credit supply among banks in the economy:

$$K^{s}(R) \equiv N \int \exp(q^{*}(z|R))g(z)dz, \tag{9}$$

where N is the number of banks, $g(z)$ is the probability density function of banks' productivity, and $q^{*}(z|R)$ is banks' optimal size choice defined in equation (4).

The equilibrium lending rate R is determined by the market-clearing condition in the lending market:

$$K^{s}(R) = \left(\frac{R}{A\alpha}\right)^{\frac{1}{\alpha-1}}. \tag{10}$$

3.3 Bank entry and the distribution of productivity

We endogenize the equilibrium distribution of banks' productivity $g(z)$ by introducing growth, entry, and exit. Banks' productivity z evolves following a Brownian motion: $dz_t = \mu_z dt +$

$\sigma_z dB_t$. The value function v of a bank with a current productivity z_0 is defined by

$$v\left(z_0\right) \equiv \mathbb{E}\left[\int_0^{\infty} e^{-(\rho+\lambda)t} \pi\left(q^*(z_t)|z_t\right) dt \mid z_0\right], \tag{11}$$

where ρ is the discount rate, λ is the exogenous exit rate, and π is the profits resulting from banks' optimal size choice as defined by equation (1).

New banks endogenously enter the economy. The entry rate is given by the following condition

$$m = \overline{m} \exp\left(\eta\left(\int v(z)\psi(z)dz - c_e\right)\right), \tag{12}$$

where c is the entry costs, $\psi(z)$ is the distribution of potential entrants' productivity, η is the entry elasticity, and $\overline{m}$ is the long-run entry mass when the expected value of entry equals entry costs. For simplicity, we assume the new entrants have the same starting productivity of z_n. The distribution of the productivity evolves according to the following Kolmogorov forward equation:

$$\frac{\partial g\left(z,t\right)}{\partial t} = -\frac{\partial}{\partial z}\left[\mu_z g\left(z,t\right)\right] + \frac{1}{2}\frac{\partial^2}{\partial z^2}\left[\sigma_z^2 g\left(z,t\right)\right] - \lambda g\left(z,t\right) + \frac{m}{N}\psi\left(z\right). \tag{13}$$

A stationary equilibrium exists in this economy, which is defined by bank value function $v(z)$, the probability density function of productivity $g(z)$, the number of banks N, the equilibrium lending rate R, and the aggregate capital K such that:

1. Incumbent banks optimally choose their credit supply given by equation (4).
2. Potential entrants optimally choose to enter the economy according to equation (12).
3. Firms optimally choose their credit demand given by equation (8).
4. Aggregate credit supply equals aggregate credit demand.
5. The distribution of banks reaches steady states $\frac{\partial g(z,t)}{\partial t} = 0, \forall z$.

Assuming the elasticity of funding supply is constant, we can show that bank assets in the stationary equilibrium follows a power law distribution.[16] The intuition is that bank assets follow proportional random growth in the absence of regulatory distortion, which generates a power law distribution in the stationary equilibrium (Gabaix, 2016).

3.4 Indirect cost of regulation

We define the indirect costs of regulation in the stationary equilibrium, $\tau_{indirect}$, as the percentage output change between the regulated and unregulated economy:

$$\tau_{indirect} = \frac{Y(0) - Y(\tau)}{Y(0)}. \tag{14}$$

where $Y(\tau)$ and $Y(0)$ are the equilibrium firm output in the regulated and unregulated economies, respectively:

$$\begin{aligned} Y(\tau) &= A\left(N(\tau)\int \exp(q^*(z|R(\tau),\tau))g(z|\tau)dz\right)^{\alpha}, \\ Y(0) &= A\left(N(0)\int \exp(q^*(z|R(0),0))g(z|0)dz\right)^{\alpha}. \end{aligned} \tag{15}$$

The above equation shows that the indirect costs of regulation can arise from both the intensive and extensive margins. First, regulation reduces the credit supply from incumbent banks, q^* (intensive margin). Second, regulation can affect banks' entry incentive, and consequently, the total number of banks, N (extensive margin). Note that the sign of the second effect is ambiguous. On the one hand, as regulation reduces the incumbent banks' credit supply, the incentive to enter may increase. On the other hand, because new entrants may eventually grow bigger and face the regulation, heightened regulation may reduce their incentive to enter. Therefore, whether regulation increases or decreases bank entry is an empirical question.

[16]See Appendix A.2 for the proof of the stationarity and the derivation of the stationary distribution.

4 Estimation

We estimate the model in two stages. First, we estimate the direct regulatory costs using a maximum likelihood estimator. Second, we estimate the indirect regulatory costs by comparing the total output of bank-dependent firms in counterfactual economies with and without regulation. Separating the estimation into two stages clarifies what assumptions and data are needed to quantify the direct and indirect costs of regulation. Estimating the direct costs of regulation only requires the data on the size distribution of banks as shown in Section 3.1. However, the indirect costs on the rest of the economy require parameters on the production functions of banks and firms, which are calibrated to either values in the prior literature or the corresponding moments in the data.

Note that we elect not to use the changes in bank values or bank entries to estimate regulatory costs. Although these two moments are related to the regulatory burden on banks, they can be driven by other factors such as a low interest rate environment, market perception of risks, and the size of the too-big-to-fail subsidy. Instead, we use the distortion in the size distribution of banks around the Dodd–Frank thresholds, which is unlikely to be driven by other factors as discussed in Section 2.2. Using the estimated regulatory costs from the bunching patterns, we can then quantify how much of the reduction in market valuation of bank shares and the entry rate can be explained by the regulation.

4.1 Data

We combine two main data sources: the Consolidated Reports of Condition and Income ("Call Reports," for commercial banks) and the Consolidated Financial Statements for Holding Companies ("FRY-9C reports," for bank holding companies). Since the Dodd–Frank Act applies to the highest holding entity, we only consider the total consolidated assets for the estimation.[17] The sample period is 2001–2019. We exclude banks with assets less than $1 billion from the sample.

Table 1 provides the summary statistics for our sample. The sample covers around 40,000 bank-quarter observations. The average asset size is $28 billion. The asset size distribution is highly skewed. As of 2010, small banks (<$10 billion) account for 84% of banks but only 6% of assets. Medium banks ($10 billion to $50 billion) account for 8% of banks but 4% of assets. Big banks (>$50 billion) account for 7% of banks but 89% of assets. The mean and standard deviation of the annual asset growth rate are 7.7% and 8.7%, respectively. The average profits per dollar of assets is 1.6%.

We also report a set of regulation-related administrative expense items, including legal, data processing, advisory, printing and supplies, auditing, communications, and labor expenses. Note that we do not use these expense items in our structural estimation because these expense items do not capture all regulatory costs. Instead, we will use these expense items when we compare our structural method with other methods of estimating regulatory costs in Section 4.4. In our sample, the average administrative expenses are 0.2 cents per dollar of assets. The number of employees per million of assets is 0.2. The average salaries are 1.6 cents per dollar of assets.

4.2 Stage 1: direct regulatory costs

We now illustrate how to estimate regulatory costs from the distortion in the size distribution. Following Garicano, Lelarge, and Van Reenen (2016), we assume log assets are observed with a structural error, $a = q + u$, which follows a normal distributions: $u \sim N(0, \sigma^2)$. This structural error accounts for any empirical departures from the model. Specifically, the theoretical model implies a sharp bunching exactly at regulatory thresholds. However, in

[17]See article 12 CFR § 252.13.

the data, the bunching pattern is more diffused because there are random deposit flows and fluctuations in asset values. The standard deviation of the structural error σ captures the extent of this diffusion.

We further assume the undistorted assets follow a power law distribution: $\exp(q) \sim c\exp(q)^{-\beta}$. This assumption is consistent with the equilibrium property of our model and can be verified in the data. Specifically, Figure 5a plots the log frequency versus the log size of banks in the pre-Dodd–Frank sample. The relationship is close to a straight line, which suggests that the distribution follows a power law (Gabaix, 2016). We will examine the robustness of the results to this assumption in Section 5.

We estimate the regulatory cost parameter using a maximum likelihood estimator:

$$\max_{\Theta} \mathcal{L}(\Theta) = \sum_{j=1}^{J} \ln f(a_j|\Theta), \tag{16}$$

where f is the likelihood function derived in Appendix A.3. a is the observed log assets. $\Theta = (\tau, \beta, \sigma)$ is the set of unknown parameters. τ is the direct regulatory cost. σ is the standard deviation of the structural error. β determines the curvature of distribution of undistorted assets. Note that the scale parameter c of the power law distribution enters the likelihood as a constant so it is unidentified by the data.

Figure 6 illustrates the intuition of the estimation. We simulate the size distribution of banks around the regulatory threshold for different regulatory costs and standard deviations of the structural error. A larger regulatory cost τ leads to a larger abnormal mass around the regulatory threshold. A larger standard deviation of the structural error σ makes the abnormal mass more diffused around the threshold. The goal of the maximum likelihood estimation is to find a set of parameters that can generate a similar distortion to what is observed in the data.

We conduct the estimation for each regulatory threshold separately using sub-samples of banks around the thresholds. Doing so is sensible because the thresholds are far apart and the bunching ranges are unlikely to overlap. We use banks in the $3 billion to $40 billion interval for the $10 billion threshold, and banks above $40 billion for the $50 billion threshold.[18] The sample period is from 2010Q3 to 2018Q2.

We present the result of the maximum likelihood estimation in Table 2. The point estimate for the annual regulatory costs triggered by the $10 billion threshold is 0.41% of annual profits. The estimate is statistically significant with a standard error of 0.066%. Note that this estimate captures the additional regulatory costs imposed by the Dodd–Frank Act that are triggered at the $10 billion threshold. It does not include the regulations that were already in place before the Dodd–Frank Act. Given this estimate, we calculate the undistorted assets of the marginal bank, $\exp(\overline{q})$, to be around $11 billion using equation (7). Next, we examine the $50 billion threshold in the second panel of Table 2. The point estimate of additional regulatory costs crossing the $50 billion threshold is 0.11%. Adding the 0.41% regulatory costs triggered by crossing the $10 billion threshold, the total regulatory cost imposed by the Dodd–Frank Act on banks above $50 billion is 0.52%. We also calculate that the undistorted assets of the marginal bank at this threshold are around $52 billion.

To put this number into perspective, we can calculate the dollar costs of the regulatory burden imposed by the Dodd–Frank Act on a bank with $50 billion assets. Given the profits are around 1.6% of total assets (Table 1), our estimate implies a dollar value of regulatory costs around $4.16 million per year. Our estimate is equivalent to the annual expense of hiring 52 additional compliance officers, assuming the average annual compensation for a compliance officer is around $80,000 (Feldman, Heinecke, and Schmidt, 2013).

[18] The results are robust to the estimation sample as shown in the Online Appendix Table OA.1.

4.3 Stage 2: indirect regulatory costs

So far, we have estimated the direct costs of regulation on banks. We now calibrate other model parameters that affect the indirect costs of regulation on firms that borrow from banks. We calibrate these parameters using either the corresponding moments in the data or the values in the prior literature. Table 3 presents the calibrated parameters. The mean and the standard deviation of the productivity growth, μ_z, and σ_z, are calibrated to match the mean and standard deviation of asset growth, which are 7.7% and 8.7%, respectively. We assume the funding supply function is $r(q|z) = \frac{1}{\theta}(q - z)$, where the elasticity of funding supply θ is calibrated to 61.7 to match the profits-to-assets ratio of 1.62% in the data. The constant funding supply elasticity assumption is consistent with the fact that banks' profit margins are quite similar across banks with vastly different sizes.[19] The productivity of new entrants, z_n, is calibrated to -3.470, such that the size of new entrants match its counterpart in the data, \$0.25 billion. The exit rate λ is calibrated to 4.4% to match the value observed in the data. The subjective discount rate of banks is calibrated to 7% to match the average ratio of market value of assets to the book value in the pre-Dodd–Frank data. The total factor productivity A is calibrated to match an average lending rate of 5%. Intuitively, higher total factor productivity drives up the demand for credit and the equilibrium lending rate. We calibrate the entry cost c_e to the pre-regulation market valuation of the new entrants, $v(z_n)$. These two values should be the same in the stationary equilibrium, as shown in equation (12). We normalize the mass of entry in the long-run $\overline{m}$ to 1. The curvature of the production function α is set to 0.3, as in Cooper, Haltiwanger, and Willis (2007). This parameter determines the aggregate elasticity of credit demand to the lending rate. We set the elasticity of entry η to a large number, 100, so that the equilibrium approximates the competitive entry in the long run (Moll, 2018).

Figure 5 compares the model-predicted stationary probability density function with that

[19] See Online Appendix Figure OA.2.

in the data. The model fits the data very well over the entire distribution. This result is quite remarkable because the size distribution is endogenously determined in the equilibrium and is not targeted in the calibration. We further zoom in to the region around the regulatory thresholds in Figure 7. Note that the probability density function is quite noisy in small samples. Consequently, we plot the cumulative distribution function instead. We find that the model generates similar departures from the power law distribution to the data as shown in Figure 1.

Table 4 presents the results of the counterfactual simulations. Column 1 presents prices and quantities in the baseline economy without the Dodd–Frank regulations. The asset size distribution is highly skewed, as in the data. Small banks (<\$10 billion) account for 88% of banks but only 6% of assets. Medium banks (\$10 billion to \$50 billion) account for 7% of banks and 7% of assets. Big banks (>\$50 billion) account for 5% of banks but 87% of assets. The average annual profits of the small, medium, and big banks are \$0.023 billion, \$0.358 billion, and \$6.150 billion, respectively.

We then simulate an economy with the Dodd–Frank Act and present the percentage change with respect to the baseline economy in column 2 of Table 4. We first examine how the Dodd–Frank Act affects the total number of banks in the stationary equilibrium. In theory, the Dodd–Frank Act can have two countervailing forces on bank entry. On the one hand, the regulation increases the profits of potential entrants because incumbent banks around the regulatory thresholds reduce their lending to avoid the regulation. On the other hand, the prospect of facing tightened regulation in the future for the potential entrants reduces their incentive to enter. The simulation suggests that the later force dominates. The total mass of banks decreases by 0.18% after the introduction of the Dodd–Frank Act. This prediction is consistent with the falling entry rates after the Dodd–Frank Act observed in the data, as shown in Figure 3b.

Practitioners often argue that high regulatory costs imposed by the Dodd–Frank Act leads to the decline in bank franchise values. Although the decline in franchise values is consistent with heightened regulatory costs, it could be driven by many other factors such as ultra-low interest rate environment (Calomiris and Nissim, 2014; Whited, Wu, and Xiao, 2021), market reassessment of risks (Sarin and Summers, 2016), and the removal of too-big-to-fail subsidies (Atkeson, d'Avernas, Eisfeldt, and Weill, 2019; Berndt, Duffie, and Zhu, 2020). As a result, we abstain from using the change in the bank franchise value to estimate regulatory costs. Instead, we use the regulatory costs estimated from bunching to evaluate how much the decline in bank values can be attribute to the Dodd–Frank Act. We find the estimated regulatory costs lead to a 0.22% decrease in bank values, which constitutes only a small fraction of the overall decline in bank franchise value in the post-crisis period. Our estimate suggests non-regulatory factors may have contributed to the decline in bank values.

Next, we investigate the distributional effects of the Dodd–Frank Act in the cross-section of banks. This question is motivated by the fact that big banks are subject to tighter regulation according to the Dodd–Frank Act. We find that big banks indeed suffer a greater decrease in profits than medium and small banks, as shown in Panel (b) of Table 4. Surprisingly, the heightened regulation on big banks does not translate into smaller market shares. Instead, the share of big banks increases in the stationary equilibrium with the Dodd–Frank Act. The reason is twofold. First, medium banks ($10 billion to $50 billion) engage in regulatory avoidance, which reduces their average asset size, as shown in Panel (c). Second, heightened regulatory costs depress bank valuation across the size spectrum, which reduces the entry of small banks (<$10 billion), as shown in Panel (d). This result does not imply that the Dodd–Frank Act has worsened the too-big-to-fail problem because we do not explicitly model how regulation affects big banks' risk-taking and their reliance on the implicit government guarantee. However, it does suggest a possible unintended consequence of regulation on the bank industry's market structure.

Finally, we examine the indirect costs of regulation on bank-dependent firms. We find that the Dodd–Frank Act increases the equilibrium lending rate by 0.046%, and decreases the lending quantity by 0.065%. Overall, the Dodd–Frank Act decreases the total output of bank-dependent firms by around 0.020%. These results suggest that the indirect regulatory costs are modest. One may worry that our estimates of the indirect regulatory costs may be sensitive to the parameters that we use to simulate the counterfactuals. In Table OA.2 of the Online Appendix, we simulate the baseline and counterfactual economies using alternative values of the discount rate, exit rate, and entry cost. We find the estimated indirect regulatory costs with alternative parameters are in the same order of magnitude as our baseline estimate.

4.4 Comparisons with existing methods

In this section, we compare our structural estimates with the existing methods of estimating regulatory costs. Note that the cost estimates surveyed in this section are about the direct compliance costs for banks. Therefore, they should be compared with the direct regulatory costs estimated in Section 4.2, which are 0.41%-0.52% of banks' profits.

4.4.1 Survey

One of the most commonly used methods of estimating regulatory costs is conducting surveys. We provide a summary of surveys on the regulatory costs of the Dodd–Frank Act for banks in Table 5. Many surveys only provide a qualitative indication of high regulatory costs but no quantitative estimates. Among surveys that do provide quantitative estimates, the magnitudes differ greatly. For instance, a survey conducted by the *Bank Director Magazine* suggests that the annual regulatory costs are around 9.9% of banks' annual profits. In contrast, a survey conducted by the American Action Forum estimates that the regulatory costs are around 1.8%. The survey estimates are usually much larger than the estimates obtained from our revealed preference approach.

4.4.2 Difference-in-differences

Some researchers also use the difference-in-differences approach to estimate regulatory costs. For instance, Hinkes-Jones (2017) estimate regulatory costs by comparing legal and administrative expenses of affected banks with those of unaffected banks. This methodology faces two challenges. The first challenge is measurement. Not all regulatory costs are reflected as expenses in banks' income statements. For instance, an increased capital requirement is costly but does not directly lead to higher expenses. The second challenge is endogeneity. Because banks can endogenously bunch below the threshold and avoid the regulatory costs, a difference-in-differences regression may lead to downward biases.

To illustrate the difficulty of using the difference-in-differences approach to estimate regulatory costs, we apply this methodology to estimate the regulatory costs imposed by the Dodd–Frank Act on banks with more than \$10 billion in assets. The regression model is as follows:

$$Expenses_{i,t} = \alpha_i + \alpha_t + \beta Treat_i \times Post_t + \beta X_{i,t} + \varepsilon_{i,t}, \tag{17}$$

where *Expenses* includes regulation-related expenses such as legal, data processing, advisory, printing, stationery and supplies, auditing, and communication costs. α_i and α_t are bank and time fixed effects, respectively. $X_{i,t}$ includes the log number of branches. The expenses are normalized by assets. We also include the number of employees and total salaries to account for the possibility that regulations may force banks to hire more compliance officers. The sample includes banks with assets between \$3 billion and \$40 billion as of 2010Q2. The sample period is from 2003Q1 to 2018Q2. *Treat* is a dummy equal to 1 if the bank's total assets is above \$10 billion as of 2010Q2, and 0 otherwise. *Post* is a dummy that equals 1 for years after the Dodd–Frank Act (after 2010Q3).

Table 6 reports the results. None of the expenses increases significantly for the treated banks. Some expenses, such as the communication expenses, actually have the wrong sign. This result is confirmed by plotting the rolling four-quarter average annualized expenses for the treated and control groups in Figure 8, which shows no significant increase for the treated group after the Dodd–Frank Act. However, these results should not be interpreted as evidence that the Dodd–Frank Act imposes no costs on banks because of the measurement issue and endogeneity concern discussed earlier.

4.4.3 Regression discontinuity

Another methodology that can be used to estimate regulatory costs is regression discontinuity design. This methodology is subject to the measurement and endogeneity concerns as discussed in Section 4.4.2. Nevertheless, we apply this approach to banks around the $10 billion threshold using the following regression model:

$$Expenses_{i,t} = \beta_0 + \beta_1 \mathbf{1}_{\left\{Q_{i,t} \geq \underline{Q}\right\}} + \beta_2 f\left(Q_{i,t} - \underline{Q}\right) + \beta_3 \mathbf{1}_{\left\{Q_{i,t} \geq \underline{Q}\right\}} f\left(Q_{i,t} - \underline{Q}\right) + \varepsilon_{i,t}, \quad (18)$$

where $Expenses_{i,t}$ include the same set of regulation-related expenses as in Section 4.4.2; $Q_{i,t}$ is the assets; $f(\cdot)$ is a polynomial function of degree one. β_1 is the increase in the regulation-related expenses when a bank's assets exceed the regulatory threshold, $\underline{Q}$. The sample period is from 2010Q3 to 2018Q2. Table 7 presents the estimated coefficients, and Figure 9 shows the results graphically. Again, most expenses do not exhibit significant changes above and below the thresholds. There is a small increase in the auditing costs for treated banks, but a small decrease in the communication costs.

4.4.4 Summary

The existing methods lead to inconsistent evidence on the regulatory costs of the Dodd–Frank Act. Surveys on banks typically suggest extremely large regulatory costs, consistent with the anecdotal evidence that survey estimates may be inflated to lobby regulators for regulatory relief (Hinkes-Jones, 2017; Parker, 2018). In contrast, reduced-form methods such as difference-in-differences and regression discontinuity designs find virtually no evidence of additional regulatory costs due to the Dodd–Frank Act, with the caveats of the endogeneity and measurement issues. Our revealed preference approach finds a modest level of regulatory costs. We view our approach as complementary to the existing methods because it relies on different assumptions and uses different data input to evaluate regulatory costs.

5 Extension and Robustness

Our revealed preference approach addresses some challenges faced by the existing methods, such as the lack of reliable data and the endogeneity concern. Nevertheless, this approach does require some structural assumptions, and the robustness of the results to these assumptions should be duly assessed. In this section, we conduct a few extensions and robustness checks on our results.

5.1 Regulatory relief in 2018

In 2018, the U.S. Congress passed the Economic Growth, Regulatory Relief, and Consumer Protection Act, reversing many regulations of the Dodd–Frank Act. This regulatory relief presents a good validity check for our approach because the estimated regulatory costs should decrease in the post-relief period. Indeed, we find that the estimated regulatory costs at the

$10 billion threshold decreases by around 50% relative to the pre-relief value, while the estimated regulatory costs at the $50 billion threshold almost completely disappeared, as shown in Table 8.[20] These estimates are consistent with the visual evidence in Figure 10 that the abnormal densities at the Dodd–Frank regulatory thresholds have significantly reduced or completely disappeared after the relief.

Then, we examine the effect of the 2018 regulatory relief on the indirect cost of regulation in column 3 of Table 4. We find that the regulatory relief alleviates the reduction in the number of banks. This result is consistent with the recovery in bank entries after 2018, as shown in Figure 3b. Similarly, the total output partially recovers but is still below the pre-Dodd–Frank Act equilibrium. Finally, the 2018 regulatory relief also partially reverses the distributional effects of the Dodd–Frank Act.

5.2 Alternative distribution assumption

In our baseline estimation, we assume that the undistorted assets follow a power law distribution. However, empirically it is difficult to distinguish a power law distribution from the upper tail of the log-normal distribution. Therefore, it is important to show that our estimates are not sensitive to a particular distribution assumption. To this end, we re-estimate the regulatory costs assuming the undistorted assets follow a log-normal distribution.[21] Table 9 presents the results. We find that the estimated regulatory costs are similar using this alternative distribution assumption. Our estimates are insensitive to the distribution assumption because regulatory costs are mainly identified by the local abnormal densities.

[20] Because there is only one year of data after the regulatory relief, we fix the exponent of the power law distribution and the structural error volatility to the baseline estimation value as these parameters are quite persistent.

[21] The derivation of the maximum likelihood estimator can be found in Appendix A.4.

5.3 Placebo tests

To further examine the robustness of our estimation, we conduct several placebo tests. First, we apply our maximum likelihood estimator to the pre-Dodd–Frank sample in Panels (a) and (b) of Table 10. We set the standard deviation of the structural error σ to the value from our baseline estimations because it is difficult to identify this parameter when there is no abnormal density created by regulation.[22] Nevertheless, the results are not sensitive to the value of this parameter. The results in Panels (a) and (b) show that banks incur no additional regulatory cost when they cross the \$10 billion or \$50 billion thresholds before the Dodd–Frank Act. We also apply our maximum likelihood estimator to round numbers that are not regulatory thresholds, such as \$20 billion and \$40 billion. Again our estimator correctly indicates null results as shown in Panels (c) and (d).

5.4 Social benefits of regulation and general equilibrium effects

We focus on estimating regulatory costs borne by banks rather than benefits of regulation to the public. So we take the regulatory costs as exogenous parameters without specifying the social benefits that motivate the regulation in the first place. However, there is still the question of whether one can identify costs if there are some unspecified social benefits, which might affect banks through some general equilibrium effects. We argue that the presence of unspecified social benefits does not affect our identification strategy. To elaborate, our identification strategy exploits the local bunching patterns caused by the discontinuities in regulatory costs. Even if regulatory benefits have some general equilibrium effects, they are likely to be smooth around the threshold and do not affect bunching at the regulatory thresholds. For instance, suppose regulation reduces the probability of systematic crisis,

[22]Intuitively, this parameter measures the extent to which the abnormal densities are diffused around the threshold, as shown in Figure 6. Therefore, it is difficult to identify this parameter if there is no abnormal density in the first place.

which lowers banks' exit rates. However, the resulting effects on the overall shape of the size distribution of banks are captured by the power law exponent, β, in equation (16).[23] They do not affect our estimate of the direct costs of regulation, τ, which is identified from the local departure from the new power law distribution.

6 Conclusion

In this paper, we propose a revealed preference approach to estimate regulatory costs borne by financial institutions. By focusing on banks' actions rather than their self-reported estimates, our approach circumvents the information obstacle faced by regulators. We use our approach to estimate the costs of the Dodd–Frank Act. We find that the regulation costs triggered at the \$10 billion threshold are equivalent to a 0.41% annual tax on banks' profits. The regulatory costs triggered at the \$50 billion threshold are equivalent to a 0.11% tax. In total, the regulatory costs introduced by the Dodd–Frank Act for a \$50 billion bank amount to \$4.16 million per year. We also examine the impacts of regulation on bank franchise value, entry and exits, and the output of bank-dependent firms. Although our estimated regulatory costs are substantial, they are significantly lower than those claimed by banks.

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[23] The power law exponent is a function of the exit rate as shown in Appendix A.2.

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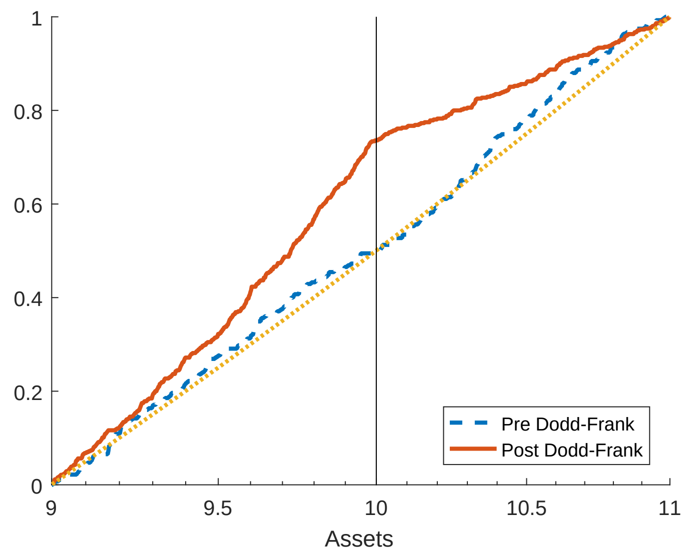
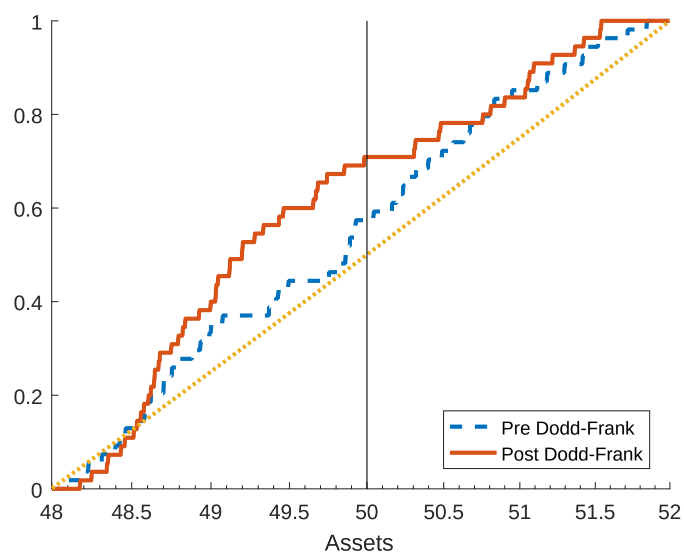
Figure 1: The Size Distribution of Banks Around Regulatory Thresholds Before and After Dodd–Frank

(a) $10 billion



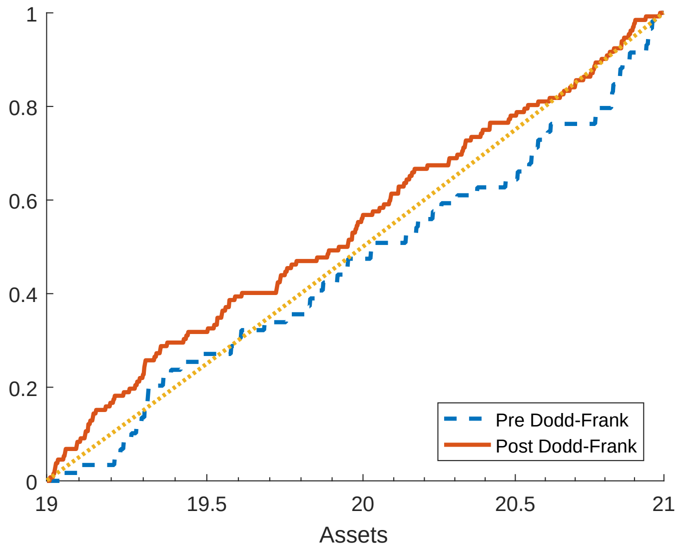
(b) $50 billion



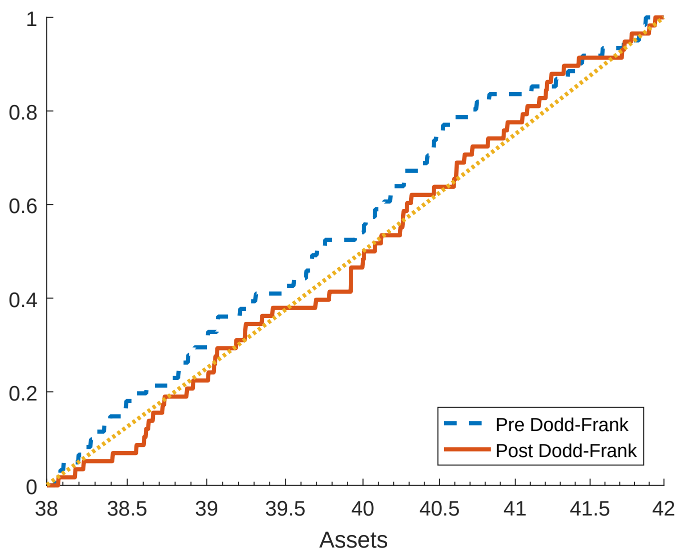
Note: This figure shows the size distribution of banks around the $10 billion and $50 billion regulatory thresholds. The blue dashed line and the red solid line represent the cumulative distribution functions before and after the Dodd–Frank Act.

Figure 2: The Size Distribution of Banks Around Non-regulatory Thresholds Before and After Dodd–Frank

(a) $20 billion



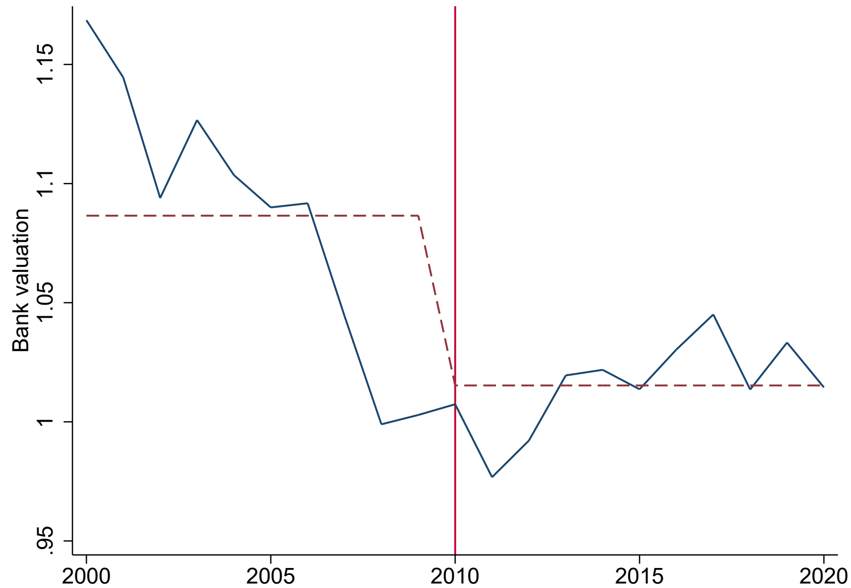
(b) $40 billion



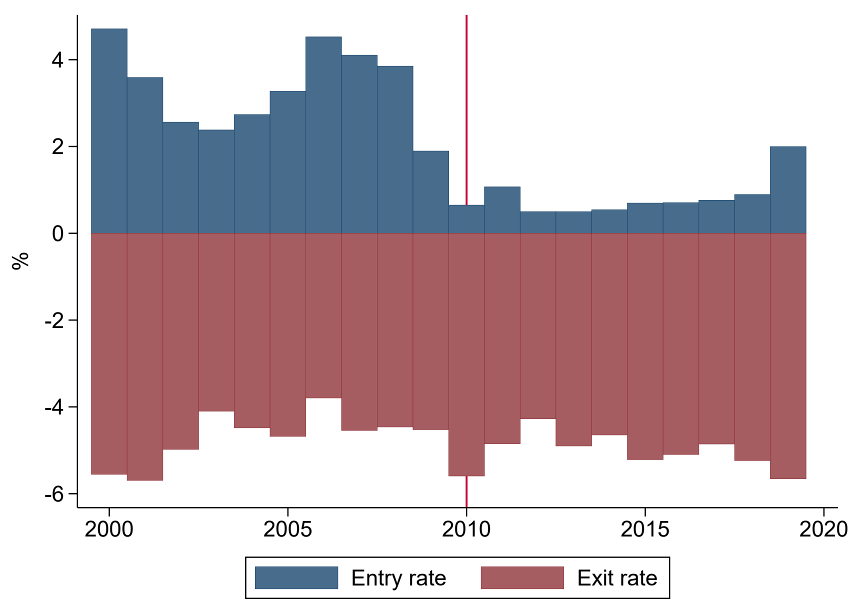
Note: This figure shows the size distribution of banks around $20 billion and $40 billion. The blue dashed line and the red solid line represent the cumulative distribution functions before and after the Dodd–Frank Act.

Figure 3: Entry, Exit, and Bank Valuation

(a) Market-to-book ratio



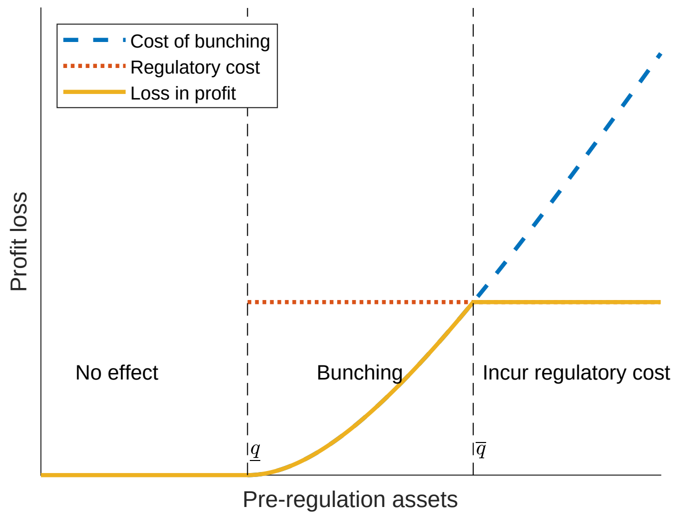
(b) Entry and exit rates



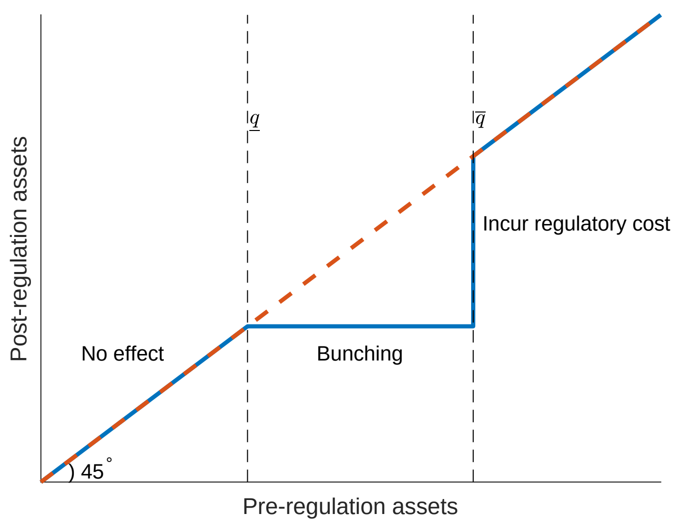
Note: Figure 3a shows the average ratio of market value of assets to the book value of assets for U.S. banks. Figure 3b shows entry and exit rates of U.S. banks before and after the Dodd–Frank Act. The entry (exit) rate is calculated by dividing the number of banks that enter the market (drop out from the market) in a year by the total number of banks in that year. Data source: CRSP, Computat, Call Reports, FR Y-9C.

Figure 4: Effects of Threshold-Based Regulation on Bank Assets and Profits

(a) Effects on profits



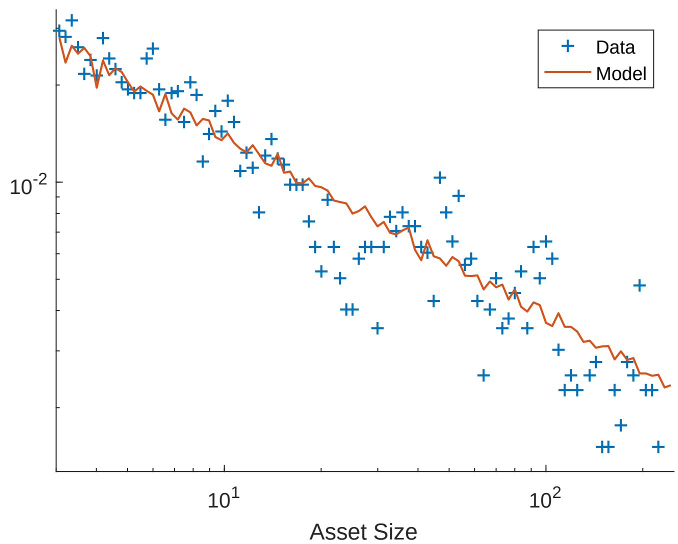
(b) Effects on assets



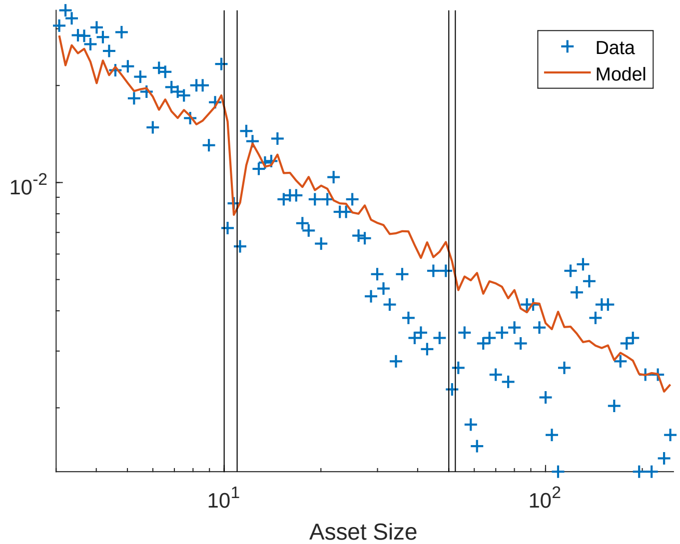
Note: The top panel shows regulatory costs and costs of bunching as functions of pre-regulation assets. The bottom panel shows the post-regulation assets as a function of pre-regulation assets.

Figure 5: The Size Distribution of Banks: Data vs. Model

(a) Pre Dodd–Frank Act

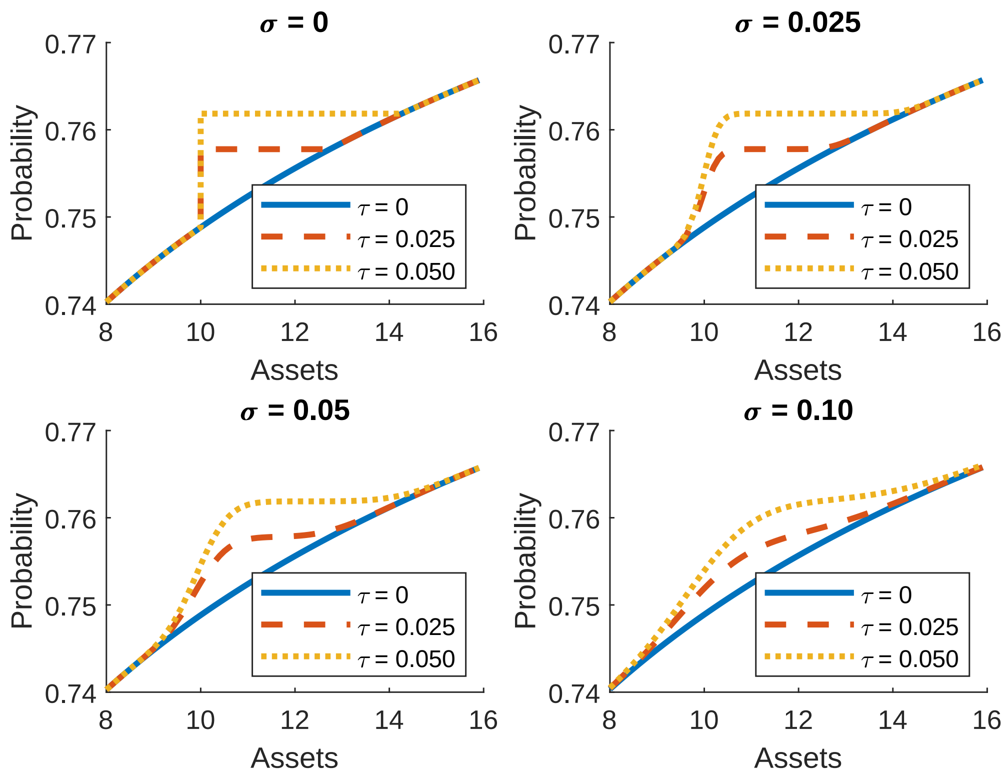


(b) Post Dodd–Frank Act



Note: This figure shows the probability density of bank size in the model and in the data before and after the Dodd–Frank Act, respectively. The vertical lines indicate the bunching range around the \$10 and \$50 billion thresholds.

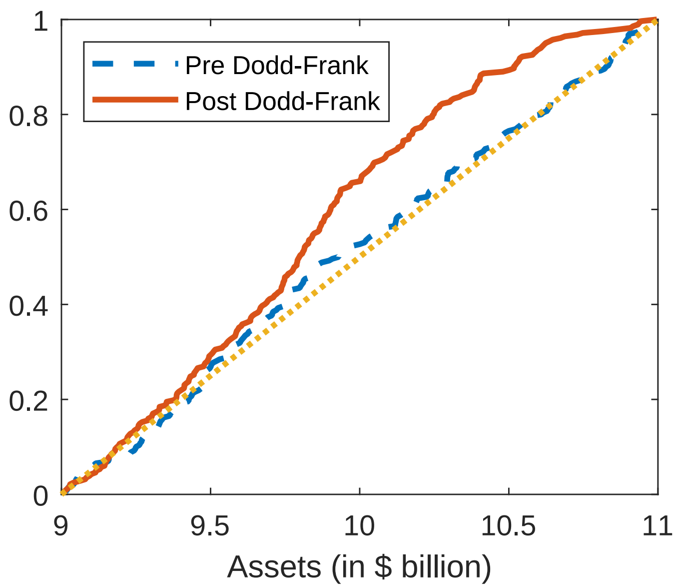
Figure 6: Theoretical Size Distribution Around Regulatory Thresholds



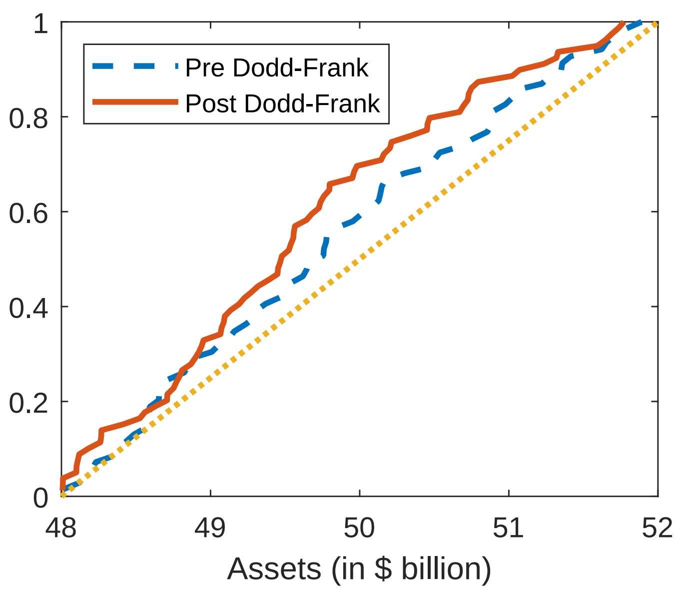
Note: This figure shows theoretical cumulative distributions of bank size under different values of regulatory costs τ and standard deviation of the structural errors σ.

Figure 7: Simulated Size Distribution Around Regulatory Thresholds

(a) \$10 billion

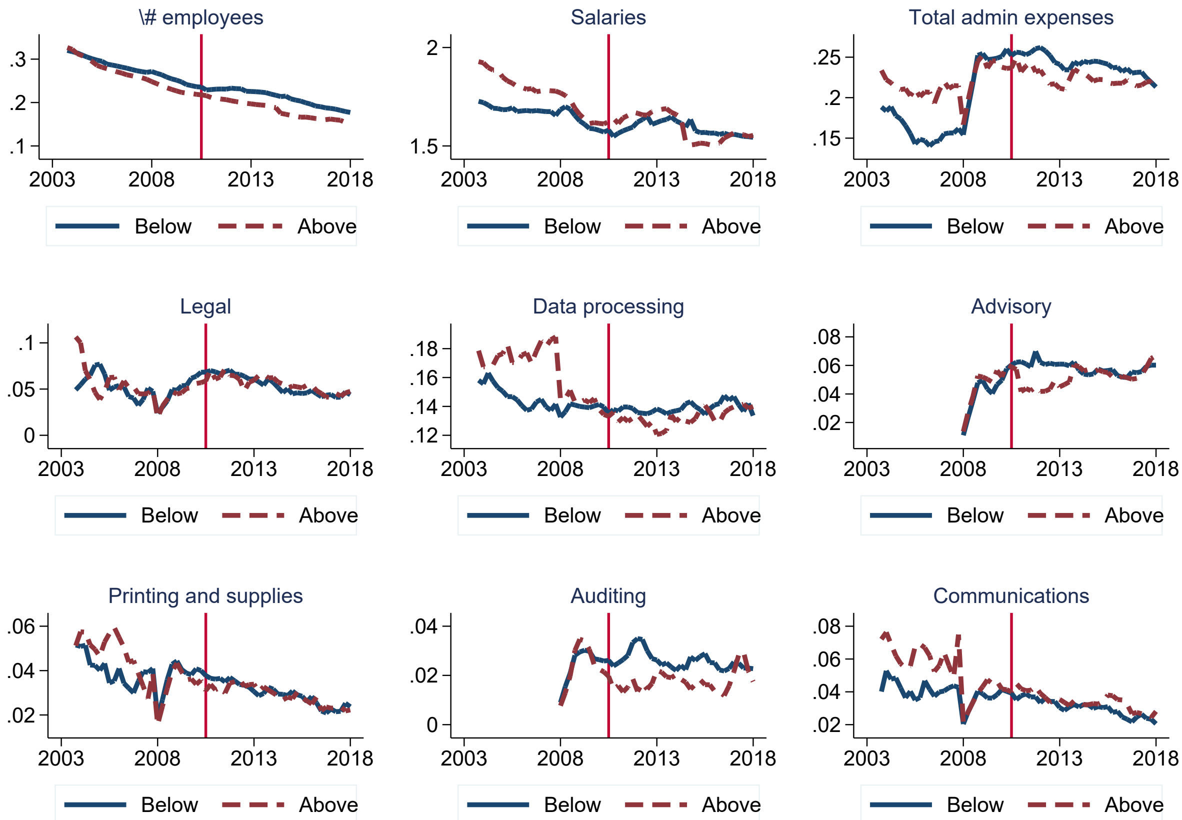


(b) \$50 billion



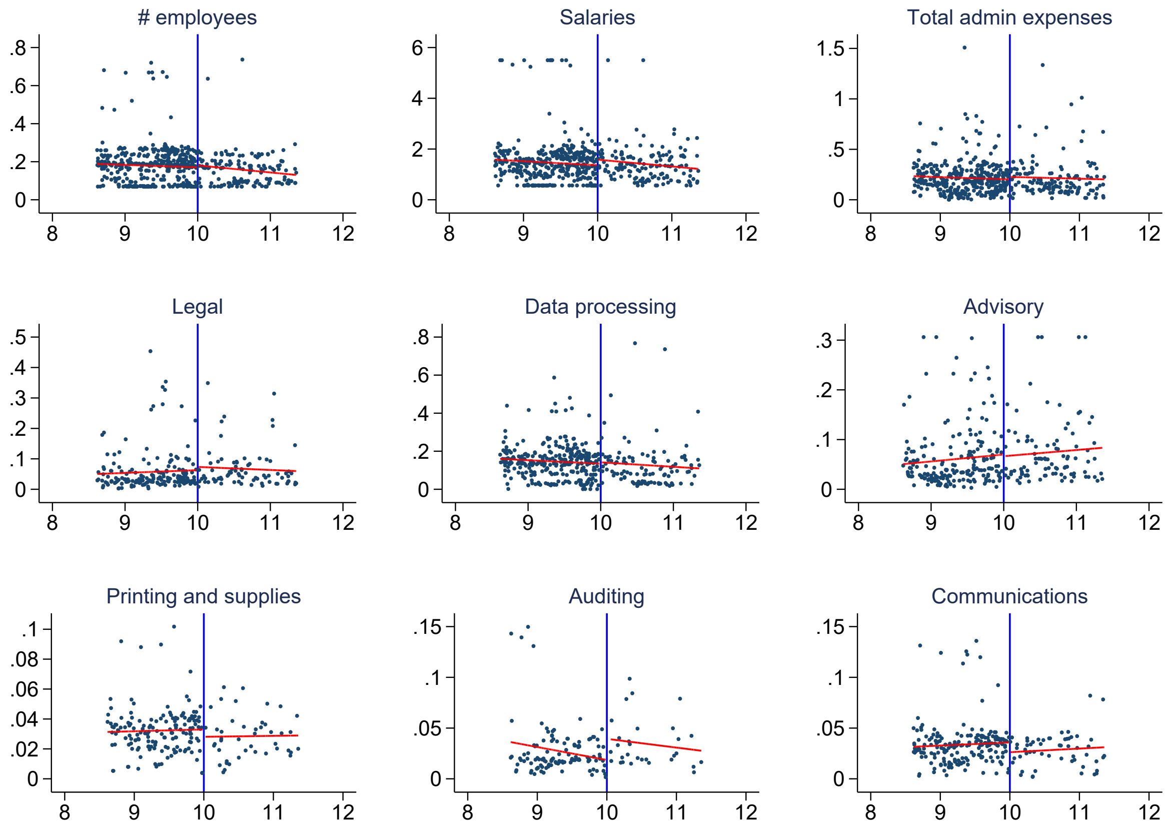
Note: This figure shows the size distribution of banks in the model around the \$10 billion and \$50 billion thresholds before and after the Dodd–Frank Act, respectively.

Figure 8: Average Expenses over Time by Bank Size



Note: This figure presents the evolution of average cost-related variables for banks in different size groups. Banks are classified as "below" ("above") if their total consolidated assets are between \$3 billion and \$10 billion (\$10 billion and \$40 billion) at the start of the Dodd–Frank Act in 2010. The dependent variables are normalized by assets.

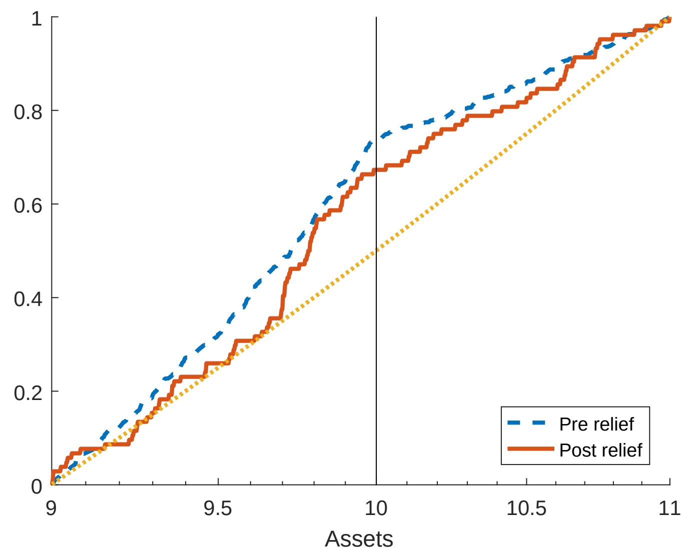
Figure 9: Bank Net Income Around the Regulatory Threshold



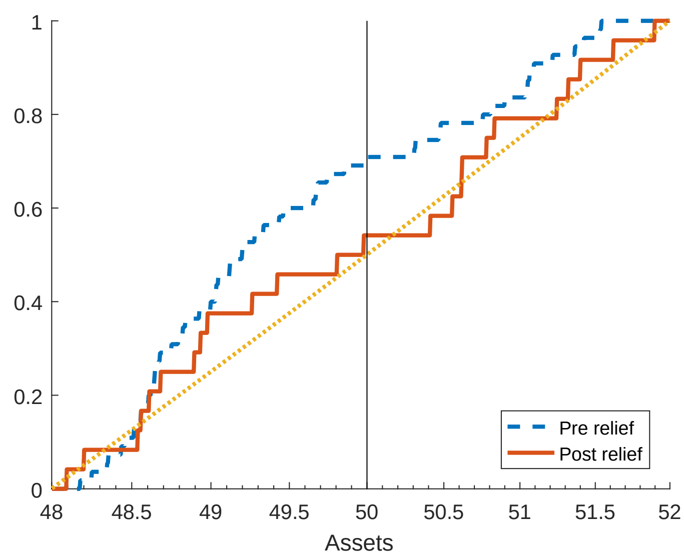
Note: This figure presents the scatter plot of the net income against total assets of banks around the $10 billion threshold. The sample includes all the bank-quarter observations from 2010Q3 to 2018Q2. The red lines represent the predicted values using the regression of equation (18). The dependent variables are normalized by assets.

Figure 10: The Size Distribution of Banks Around Regulatory Thresholds Before and After 2018 Regulatory Relief

(a) $10 billion



(b) $50 billion



Note: This figure shows the size distribution of banks around the $10 billion and $50 billion regulatory thresholds. The blue dashed line and the red solid line represent the cumulative distribution functions before and after the regulatory relief in 2018Q2.

Table 1: Summary Statistics

	N	mean	sd	p5	p25	p50	p75	p95
Assets	39228	27.905	163.363	1.056	1.376	2.232	5.845	81.776
Assets growth rate	33616	7.655	11.504	-7.081	1.484	5.809	11.632	29.310
Assets growth rate (sd)	38578	8.668	5.071	2.385	4.736	7.663	11.719	18.100
Profits	39228	1.624	1.328	0.223	1.074	1.503	1.948	3.063
Total admin expenses	39228	0.201	0.184	0.000	0.083	0.173	0.278	0.517
Legal	39228	0.026	0.051	0.000	0.000	0.000	0.037	0.129
Data processing	39228	0.101	0.110	0.000	0.000	0.083	0.149	0.295
Advisory	39228	0.028	0.055	0.000	0.000	0.000	0.039	0.132
Printing and supplies	39228	0.015	0.027	0.000	0.000	0.000	0.029	0.065
Auditing	39228	0.012	0.024	0.000	0.000	0.000	0.022	0.059
Communications	39228	0.013	0.025	0.000	0.000	0.000	0.025	0.059
# employees	39228	0.217	0.106	0.070	0.148	0.206	0.271	0.398
Salaries	39228	1.618	0.812	0.736	1.235	1.514	1.804	2.705

Note: This table reports the summary statistics of all the U.S. banks from 2001 to 2019. Assets are reported in billions. Profits and expenses are annualized and reported as a percentage of the assets. The number of employees are reported as per million of assets.

Table 2: Maximum Likelihood Estimation of Regulatory Costs

Panel A: $10 billion threshold

		Estimated value	S.E.
β	Exponent of the power law distribution	1.112	[0.001]
σ	Measurement error volatility (in %)	4.258	[0.386]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	10.973	[0.086]
τ	Cost of regulation (% of profit)	0.405	[0.066]

Panel B: $50 billion threshold

		Estimated value	S.E.
β	Exponent of the power law distribution	1.084	[0.002]
σ	Measurement error volatility (in %)	2.291	[0.498]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	52.393	[0.528]
τ	Cost of regulation (% of profit)	0.106	[0.046]

Note: This table presents the results of the maximum likelihood estimation of the regulatory costs using the power law distribution. The sample period is from 2010Q3 to 2018Q2. The estimation sample of Panel A includes banks with assets between $3 billion and $40 billion. The estimation sample of Panel B includes banks with assets above $40 billion. Standard errors are obtained via the inverse of the Hessian matrix.

Table 3: Calibrated Parameters for Policy Experiment

Parameter	Value	Definition
μ_z	7.700	Productivity growth
σ_z	8.700	Productivity diffusion
θ	61.728	Elasticity of funding supply
ρ	7.000	Discount rate
λ	4.400	Exit rate
z_n	-3.470	Productivity of new entrants
c_e	0.120	Entry costs
A	8.000	Total factor productivity
α	0.300	Curvature of the production function
η	100.000	Elasticity of entry

Note: This table reports the calibrated parameters for the counterfactual simulations.

Table 4: Counterfactual Simulation

Counterfactual	Baseline	Dodd-Frank	Regulatory relief
		Panel (a): all banks	
Mass of banks	11.836	-0.184 %	-0.094 %
Market-to-book	1.228	-0.221 %	-0.104 %
Lending quantity	257.805	-0.065 %	-0.032 %
Lending rate	0.049	0.046 %	0.023 %
Output	42.313	-0.020 %	-0.010 %
		Panel (b): annual profits by size group	
Small banks	0.023	0.068 %	0.033 %
Medium banks	0.358	-0.399 %	-0.221 %
Big banks	6.150	-1.268 %	-0.593 %
		Panel (c): asset shares by size group	
Small banks	0.057	-0.061 %	-0.034 %
Medium banks	0.073	-0.216 %	-0.123 %
Big banks	0.870	0.022 %	0.013 %
		Panel (d): shares of banks by size group	
Small banks	0.878	-0.012 %	-0.006 %
Medium banks	0.072	0.089 %	0.042 %
Big banks	0.050	0.075 %	0.042 %

Note: This table reports the results of counterfactual simulations. Column (1) reports the equilibrium quantities and prices in the baseline economy without the Dodd–Frank Act. Columns (2) and (3) report the simulated economies with the Dodd–Frank Act and the 2018 regulatory relief, respectively. The values are reported as percentage changes with respect to the baseline economy.

Table 5: Estimated Regulatory Costs of Dodd–Frank on Banks Based on Surveys

Source	Sample	Estimate	Date
Bank Director Magazine	Survey of 10 banks	9.9	1/1/2017
American Action Forum	Estimation from Federal Register	1.8	7/1/2016
JPMorgan and Citigroup	Survey of 2 banks	0.9	2012, 2014
Federal Reserve Bank of Minneapolis	Estimation of cost of new hires	1.1	3/1/2013
Bank Director and Grant Thornton LLP Survey	Survey of 130 senior executives	Qualitative	6/1/2013
KPMG 2013 Community Banking Survey	Survey of 100 senior executives	Qualitative	10/1/2013
Florida Chamber Fundation	Survey of 75 banks	Qualitative	7/1/2012
Mercatus Center's Small Bank Survey	Survey of 200 banks	Qualitative	2/1/2014
Risk Management Association Survey	Survey of 230 senior executives	Qualitative	3/1/2013

Note: This table presents a list of surveys on the regulatory costs of the Dodd–Frank Act on banks. For sources with quantitative estimates, we translate the estimates into percentages of net income.

Table 6: Regulatory Costs of the Dodd–Frank Act Estimated by Difference-in-Differences

	(1) # employees	(2) Salaries	(3) Total admin expenses	(4) Legal	(5) Data processing	(6) Advisory	(7) Printing	(8) Auditing	(9) Com-munications
Treat * Post	-0.012	-0.043	-0.012	0.008	0.001	-0.003	0.001	0.000	-0.009**
	[0.012]	[0.081]	[0.018]	[0.008]	[0.014]	[0.008]	[0.004]	[0.005]	[0.004]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,816	6,816	5,931	3,135	5,067	2,429	2,476	1,323	2,643
Adj. R-squared	0.515	0.039	0.115	0.063	0.006	0.037	0.197	0.043	0.302

Note: This table presents the estimated regulatory costs from the difference-in-difference regression shown in equation (17). The sample includes U.S. banks with assets between 3 billion and 40 billion at the time of the introduction of Dodd-Frank and covers the period of 2003Q1–2018Q2. The dependent variables are normalized by assets. *Post* is a dummy equal to 1 for all years after the Dodd–Frank Act (after 2010Q3). *Treat* is a dummy equal to 1 if the bank's total consolidated assets are above $10 billion as of 2010Q2, and 0 otherwise. Robust standard errors clustered at the bank level are showed in brackets. All regressions include bank and time fixed effects, and control for the log of number of bank branches

Table 7: Regulatory Costs of the Dodd–Frank Act Estimated by Regression Discontinuity

	# employees	Salaries	Total admin expenses	Legal	Data processing	Advisory	Printing	Auditing	Communications
Treatment Effect	0.010	0.222	0.025	0.011	0.007	-0.003	-0.005	0.021**	-0.010*
	[0.024]	[0.182]	[0.030]	[0.021]	[0.023]	[0.015]	[0.005]	[0.010]	[0.005]
Observations	559	559	505	256	400	296	203	148	256
Adj. R-squared	0.011	0.004	-0.004	-0.005	0.006	0.008	-0.003	0.028	0.003
Bandwidth	1.38	1.38	1.38	1.38	1.38	1.38	1.38	1.38	1.38

Note: This table presents the estimated regulatory costs from the regression discontinuity design shown in equation (18). The sample includes U.S. banks with assets between 8.62 and 11.38 billion from 2010Q3 to 2018Q2. The dependent variables are normalized by assets. Robust standard errors clustered at the bank-level are showed in brackets.

Table 8: Maximum Likelihood Estimation of Regulatory Costs: Post 2018 Regulatory Relief

$10 billion threshold

		Estimated value	S.E.
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	10.701	[0.159]
τ	Cost of regulation (% of profit)	0.219	[0.095]

$50 billion threshold

		Estimated value	S.E.
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	50.138	[3.707]
τ	Cost of regulation (% of profit)	0.003	[0.012]

Note: This table presents the results of the maximum likelihood estimation of the regulatory costs using the power law distribution. The sample period is from 2018Q2 to 2019Q4. The estimation sample of Panel A includes banks with assets between $3 billion to $40 billion. The estimation sample of Panel B includes banks with assets above $40 billion. Standard errors are obtained via the inverse of the Hessian matrix.

Table 9: Maximum Likelihood Estimation of Regulatory Cost: Log Normal Distribution

Panel A: $10 billion threshold

		Estimated value	S.E.
μ_q	Average undistorted log(asset)	1.999	[0.007]
σ_q	Undistorted log(asset) std.	0.674	[0.005]
σ	Measurement error volatility (in %)	4.027	[0.378]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	10.888	[0.086]
τ	Cost of regulation (% of profit)	0.342	[0.062]

Panel B: $50 billion threshold

		Estimated value	S.E.
μ_q	Average undistorted log(asset)	5.040	[0.022]
σ_q	Undistorted log(asset) std.	1.062	[0.016]
σ	Measurement error volatility (in %)	2.355	[0.533]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	52.552	[0.533]
τ	Cost of regulation (% of profit)	0.120	[0.048]

Note: This table presents the results of the maximum likelihood estimation of the regulatory costs using the log normal distribution. The sample period is from 2010Q3 to 2018Q2. The estimation sample of Panel A includes banks with assets between $3 billion to $40 billion. The estimation sample of Panel B includes banks with assets above $40 billion. Standard errors are obtained via the inverse of the Hessian matrix.

Table 10: Regulatory Cost Estimates: Placebo Tests

Panel A: $10 billion threshold, pre Dodd–Frank

		Estimated value	S.E.
β	Exponent of the power law distribution	1.112	[0.002]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	10.002	[0.239]
τ	Cost of regulation (% of profit)	0.005	[0.003]

Panel B: $50 billion threshold, pre Dodd–Frank

		Estimated value	S.E.
β	Exponent of the power law distribution	1.085	[0.003]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	51.221	[0.717]
τ	Cost of regulation (% of profit)	0.029	[0.034]

Panel C: $20 billion threshold, post Dodd–Frank

		Estimated value	S.E.
β	Exponent of the power law distribution	1.112	[0.001]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	20.016	[0.618]
τ	Cost of regulation (% of profit)	0.004	[0.003]

Panel B: $40 billion threshold, post Dodd–Frank

		Estimated value	S.E.
β	Exponent of the power law distribution	1.085	[0.002]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	40.509	[1.546]
τ	Cost of regulation (% of profit)	0.008	[0.071]

Note: This table presents the results of the maximum likelihood estimation of the regulatory costs using the power law distribution. The sample periods of Panels A and B are from 2001Q1 to 2007Q4. The sample periods of Panels C and D are from 2010Q3 to 2017Q4. The estimation sample of Panels A and C includes banks with assets between $3 billion and $40 billion. The estimation sample of Panels B includes banks with assets above $40 billion. The estimation sample of Panel D includes banks with assets above $30 billion. Standard errors are obtained via the inverse of the Hessian matrix.

A Appendix

A.1 Derivation of Regulatory Costs

Provided the different regulatory thresholds are far enough from each other, we can derive the regulatory cost (i.e., fraction of profits lost) τ_i in the same manner for all i. Therefore, we drop the subscript i in the following derivation. We know from the profit indifference condition of the marginal bank in equation (7) that τ can be written as follows:

$$1 - \tau = \frac{(R - r(\underline{q}|\overline{z}))\exp\left(\underline{q}\right)}{(R - r\left(\overline{q}|\overline{z}\right))\exp\left(\overline{q}\right)}. \tag{19}$$

We conduct a Taylor expansion for $r(\underline{q}|\overline{z})$ at the optimal size, $\overline{q}$, so the numerator becomes

$$\begin{aligned} R - r(\underline{q}|\overline{z}) &= R - r(\overline{q} - (\overline{q} - \underline{q})|\overline{z}) \\ &= R - (r(\overline{q}|\overline{z}) - r_q\left(\overline{q}|\overline{z}\right)\left(\overline{q} - \underline{q}\right) + o(\overline{q} - \underline{q})) \\ &= R - (r(\overline{q}|\overline{z}) - (R - r(\overline{q}|\overline{z}))(\overline{q} - \underline{q}) + o(\overline{q} - \underline{q})) \\ &= (R - r(\overline{q}|\overline{z}))(1 + \overline{q} - \underline{q}) - o(\overline{q} - \underline{q}), \end{aligned} \tag{20}$$

where the third equality uses the result of equation (2) that the profit margin at the optimal size equals the inverse semi-elasticity $R - r\left(\overline{q}|\overline{z}\right) = r_q\left(\overline{q}|\overline{z}\right)$. Plugging in equation (20) into equation (19), we get

$$1 - \tau = \left(\overline{q} - \underline{q} + 1\right)\exp\left(\underline{q} - \overline{q}\right) + o(\overline{q} - \underline{q}) \simeq \left(\overline{q} - \underline{q} + 1\right)\exp\left(\underline{q} - \overline{q}\right). \tag{21}$$

When the funding supply has a constant semi-elasticity, the higher-order term $o(\overline{q} - \underline{q})$ in the Taylor expansion disappears and the approximation becomes exact.

A.2 Derivation of the stationary distribution

Guess $g(z) = c_z \exp(z)^{-\beta}$ and plug it to the Kolmogorov forward equation (13):

$$0 = -\frac{\partial}{\partial z}\left[\mu_z c_z \exp(z)^{-\beta}\right] + \frac{1}{2}\frac{\partial^2}{\partial z^2}\left[\sigma_z^2 c_z \exp(z)^{-\beta}\right] - \lambda c_z \exp(z)^{-\beta}, \tag{22}$$

for $z \neq z_n$. This leads to a quadratic equation

$$0 = -\mu_z \beta + \frac{1}{2}\sigma_z^2 \beta(\beta + 1) - \lambda. \tag{23}$$

This quadratic equation always has two real roots $\beta_+ > 0$ and $\beta_- < 0$ as long as $\lambda > 0$. The general solution to the Kolmogorov forward equation is

$$g(z) = c_- \exp(z)^{-\beta_-} + c_+ \exp(z)^{-\beta_+}. \tag{24}$$

g(z) is integrable, which implies that $c_- = 0$ for $z > z_n$ and $c_+ = 0$ for $z < z_n$ (Moll, 2018). Therefore, the stationary distribution of the productivity is a double power law distribution.

$$g(z) = \begin{cases} c_z \exp(z - z_n)^{-\beta_-} & z < z_n \\ c_z \exp(z - z_n)^{-\beta_+} & z > z_n, \end{cases} \tag{25}$$

where z_n is the productivity of the new entrants.

Assuming the elasticity of funding supply is constant, the undistorted log asset is a linear function of productivity according to equation (3). The stationary distribution of bank size is also a double power law distribution in the absence of regulatory distortion.

A.3 Derivation of maximum likelihood estimator: power law

Define h and H as the probability density function and cumulative distribution function of the undistorted bank log-assets q. Using banks' optimal size choice described in equation (4), the theoretical density function of banks' log-assets with one regulatory threshold is given by the following distribution function

$$q \sim \begin{cases} h(q) & q \in (-\infty, \underline{q}) \\ H(\overline{q}) - H(\underline{q}) & q = \underline{q} \\ 0 & q \in (\underline{q}, \overline{q}] \\ h(q) & q \in (\overline{q}, \infty). \end{cases} \tag{26}$$

The empirical bank size a is observed with a structural error $u = \sigma v$ with $v \sim N(0, 1)$. Denote $\mathbb{P}(x \leq a|v)$ as the probability of observing log assets x below a given value a for a given realization of the structural error v. We have:

$$\mathbb{P}(x \leq a|v) = \mathbb{P}(q + \sigma v \leq a|v) = \mathbb{P}(q \leq a - \sigma v|v). \tag{27}$$

The above equation shows that the probability of observing size x below a given value a for a given realization of the structural error σv is the same as the probability that the theoretical size q is below $a - \sigma v$.

Using equations (26) and (27), the conditional cumulative distribution of the observed size a is given by:

$$\mathbb{P}\left(x \leq a|v\right) = \begin{cases} H(a-\sigma v) & a-\sigma v \in (-\infty, \underline{q}) \\ H(\overline{q}) & a-\sigma v \in [\underline{q}, \overline{q}] \\ H(a-\sigma v) & a-\sigma v \in (\overline{q}, \infty). \end{cases} \tag{28}$$

We can change the conditions such that they are written with respect to the structural error, v:

$$\mathbb{P}\left(x \leq a|v\right) = \begin{cases} H(a-\sigma v) & v \in (\frac{1}{\sigma}(a-\underline{q}), \infty) \\ H(\overline{q}) & v \in [\frac{1}{\sigma}(a-\overline{q}), \frac{1}{\sigma}(a-\underline{q})] \\ H(a-\sigma v) & v \in (-\infty, \frac{1}{\sigma}(a-\overline{q})). \end{cases} \tag{29}$$

The unconditional cumulative distribution function of observed size a can be written as the convolution of the conditional CDF of q and the distribution of the structural error v:

$$\begin{aligned} \mathbb{P}\left(x \leq a\right) =& \mathbb{E}\left[\mathbb{P}\left(x \leq a \mid v\right)\right] \\ =& \int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} H(a-\sigma v)\phi\left(v\right) dv \\ &+ H(\overline{q}) \left[\Phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right) - \Phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)\right)\right] \\ &+ \int_{-\infty}^{\frac{1}{\sigma}(a-\overline{q})} H(a-\sigma v)\phi\left(v\right) dv. \end{aligned} \tag{30}$$

We take the derivative of equation (30) to get the probability density function of the observed size a:

$$
\begin{aligned}
f\left(a\right) =&\frac{d}{da}\mathbb{E}\left[\mathbb{P}\left(x \leq a \mid v\right)\right] \\
=&\frac{d}{da}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} H(a-\sigma v)\phi\left(v\right)dv \\
&+\frac{d}{da}H(\overline{q})\left[\Phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)-\Phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)\right)\right] \\
&+\frac{d}{da}\int_{-\infty}^{\frac{1}{\sigma}\left(a-\overline{q}\right)} H(a-\sigma v)\phi\left(v\right)dv.
\end{aligned}
\tag{31}
$$

The second term in equation (31) is straightforward to compute:

$$
\begin{aligned}
&\frac{d}{da}H(\overline{q})\left[\Phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)-\Phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)\right)\right] \\
=&\frac{1}{\sigma}H(\overline{q})\left[\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)-\phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)\right)\right].
\end{aligned}
$$

For the first and third terms in equation (31), we use the Leibniz formula:

$$
\frac{d}{da}\int_{t_1(a)}^{t_2(a)} f\left(a,v\right)dv = f\left(a,t_2\left(a\right)\right)t_2'\left(a\right) - f\left(a,t_1\left(a\right)\right)t_1'\left(a\right) + \int_{t_1(a)}^{t_2(a)} f_a\left(a,v\right)dv.
$$

Using the Leibniz formula, the first term in equation (31) becomes:

$$
\frac{d}{da}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} H\left(a-\sigma v\right)\phi\left(v\right)dv = -\frac{1}{\sigma}H\left(\underline{q}\right)\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right) + \int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} h\left(a-\sigma v\right)\phi\left(v\right)dv,
$$

given that $\frac{1}{\sigma}H\left(-\infty\right)\cdot\phi\left(\infty\right)=0$.

The third term in equation (31) becomes:

$$
\frac{d}{da}\int_{-\infty}^{\frac{1}{\sigma}\left(a-\overline{q}\right)} H\left(a-\sigma v\right)\phi\left(v\right)dv = \frac{1}{\sigma}H\left(\overline{q}\right)\phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)\right) + \int_{-\infty}^{\frac{1}{\sigma}\left(a-\overline{q}\right)} h\left(a-\sigma v\right)\phi\left(v\right)dv,
$$

given that $\frac{1}{\sigma}H\left(\infty\right)\cdot\phi\left(\infty\right)=0$. In summary, the probability density of the observed bank size is given by:

$$
\begin{aligned}
f(a) = & -\frac{1}{\sigma} H\left(\underline{q}\right) \phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right) + \int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} h(a-\sigma v)\,\phi(v)\,dv \\
& + \frac{1}{\sigma} H(\overline{q}) \left[\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right) - \phi\left(\frac{1}{\sigma}(a-\overline{q})\right)\right] \\
& + \frac{1}{\sigma} H(\overline{q}) \phi\left(\frac{1}{\sigma}(a-\overline{q})\right) + \int_{-\infty}^{\frac{1}{\sigma}(a-\overline{q})} h(a-\sigma v)\,\phi(v)\,dv.
\end{aligned}
$$

By simplifying the terms and plugging in the standard normal pdf $\phi(v) = \exp(-\frac{1}{2}v^2)/\sqrt{2\pi}$, we have:

$$
\begin{aligned}
f(a) = & \underbrace{\frac{1}{\sigma}\left[\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)\right]\left(H(\overline{q}) - H\left(\underline{q}\right)\right)}_{\text{Term 1}} \\
& + \underbrace{\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} h(a-\sigma v)\,\phi(v)\,dv}_{\text{Term 2}} \\
& + \underbrace{\int_{-\infty}^{\frac{1}{\sigma}(a-\overline{q})} h(a-\sigma v)\,\phi(v)\,dv,}_{\text{Term 3}}
\end{aligned}
\tag{32}
$$

We now assume the undistorted bank assets follow a power-law distribution, $\exp(q) \sim c\exp(q)^{-\beta}$ over the strictly positive support $[q_{min}, \infty]$, where q_{min} corresponds to the minimum theoretical log-asset of a bank that could be observed. Given that we defined q as log-assets of a bank (see Section 3), the probability density function of q is:

$$
\begin{aligned}
h(q) &= \frac{d}{dq}\mathbb{P}\left(\exp(x) \leq \exp(q)\right) \\
&= \frac{d}{dq}\left(\frac{c}{1-\beta}e^{(1-\beta)q}\right) \\
&= c\exp\left((1-\beta)q\right),
\end{aligned}
\tag{33}
$$

for $q \geq q_{min}$, and $h(q) = 0$ for $q < q_{min}$. The scaling parameter c is constrained to be equal to $(\beta-1)/\exp\left((1-\beta)q_{min}\right)$ such that the distribution integrates to one.

Plugging in equation (33) into equation (32), we can derive the first term of equation (32) as:

$$\text{Term 1} = \frac{1}{\sigma}\frac{c}{1-\beta}\left[\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)\right]\left(\exp\left(\left(1-\beta\right)\overline{q}\right)-\exp\left(\left(1-\beta\right)\underline{q}\right)\right).$$

The second term of equation (32) is:

$$\begin{aligned}\text{Term 2} = &\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty}\mathbf{1}_{\{a-\sigma v\geq q_{min}\}}c\exp\left(\left(1-\beta\right)\left(a-\sigma v\right)\right)\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}v^2\right)dv\\ =&c\exp\left(\left(1-\beta\right)a+\frac{1}{2}\left(\beta-1\right)^2\sigma^2\right)\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty}\mathbf{1}_{\left\{v\leq\frac{1}{\sigma}\left(a-q_{min}\right)\right\}}\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\left(v-\left(\beta-1\right)\sigma\right)^2\right)dv\\ =&c\exp\left(\left(1-\beta\right)a+\frac{1}{2}\left(\beta-1\right)^2\sigma^2\right)\cdot\\ &\left(\Phi\left(\frac{1}{\sigma}\left(a-q_{min}\right)-\left(\beta-1\right)\sigma\right)-\Phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)-\left(\beta-1\right)\sigma\right)\right).\end{aligned}$$

The third term of equation (32) is:

$$\begin{aligned}\text{Term 3} = &\int_{-\infty}^{\frac{1}{\sigma}\left(a-\overline{q}\right)}\mathbf{1}_{\{a-\sigma v\geq q_{min}\}}c\exp\left(\left(1-\beta\right)\left(a-\sigma v\right)\right)\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}v^2\right)dv\\ =&c\exp\left(\left(1-\beta\right)a+\frac{1}{2}\left(\beta-1\right)^2\sigma^2\right)\Phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)-\left(\beta-1\right)\sigma\right).\end{aligned}$$

To summarize, the probability density of the observed bank size is given by:

$$\begin{aligned}f\left(a\right) = &\frac{1}{\sigma}\frac{c}{1-\beta}\left[\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)\right]\left(\exp\left(\left(1-\beta\right)\overline{q}\right)-\exp\left(\left(1-\beta\right)\underline{q}\right)\right)\\ &+c\exp\left(\left(1-\beta\right)a+\frac{1}{2}\left(\beta-1\right)^2\sigma^2\right)\cdot\\ &\left(\Phi\left(\frac{1}{\sigma}\left(a-q_{min}\right)-\left(\beta-1\right)\sigma\right)-\Phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)-\left(\beta-1\right)\sigma\right)+\Phi\left(\frac{1}{\sigma}\left(a-\overline{q}\right)-\left(\beta-1\right)\sigma\right)\right).\end{aligned} \tag{34}$$

Taking the log of equation (34), we can get the log-likelihood function for the MLE. Note that when $\tau=0$, we have $\overline{q}=\underline{q}$. The first term of equation (34) equals 0 and this equation simplifies to:

$$f(a) = c \exp\left((1-\beta) a + \frac{1}{2} (\beta - 1)^2 \sigma^2 \right) \Phi\left(\frac{1}{\sigma} (a - q_{min}) - (\beta - 1) \sigma \right).$$

A.4 Derivation of maximum likelihood estimator: log-normal

The derivation of the maximum likelihood estimator under the log-normal distribution is the same as the power-law distribution until equation (33), where the undistorted asset size follows a log-normal distribution instead. As a result, the undistorted log-assets q follows a normal distribution with probability density function:

$$h(q) = \frac{1}{\sigma_q} \phi\left(\frac{q - \mu_q}{\sigma_q} \right), \tag{35}$$

where μ_q denotes the mean undistorted log-assets, and σ_q denotes the standard deviation. Plugging in equation (35) into equation (32), we can derive the first term of equation (32) as:

$$\text{Term 1} = \frac{1}{\sigma} \left[\phi\left(\frac{1}{\sigma} (a - \underline{q}) \right) \right] \left(\Phi\left(\frac{\overline{q} - \mu_q}{\sigma_q} \right) - \Phi\left(\frac{\underline{q} - \mu_q}{\sigma_q} \right) \right).$$

The second term of equation (32) is:

$$
\begin{aligned}
\text{Term 2} =& \int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} \frac{1}{\sigma_q}\phi\left(\frac{a-\sigma v-\mu_q}{\sigma_q}\right)\phi\left(v\right)dv \\
=& \frac{1}{2\pi}\frac{1}{\sigma_q}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{a-\sigma v-\mu_q}{\sigma_q}\right)^2-\frac{1}{2}v^2\right)dv \\
=& \frac{1}{2\pi}\frac{1}{\sigma_q}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} \exp\left(-\frac{1}{2}\frac{\left(\sigma^2+\sigma_q^2\right)v^2-2\left(a-\mu_q\right)\sigma v+\left(a-\mu_q\right)^2}{\sigma_q^2}\right)dv \\
=& \frac{1}{2\pi}\frac{1}{\sigma_q}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} \exp\left(-\frac{1}{2}\frac{\left(\sigma^2+\sigma_q^2\right)\left(v-\frac{a-\mu_q}{\sigma^2+\sigma_q^2}\sigma\right)^2-\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\sigma^2+\left(a-\mu_q\right)^2}{\sigma_q^2}\right)dv \\
=& \frac{1}{\sigma_q}\exp\left(\frac{\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\sigma^2-\left(a-\mu_q\right)^2}{2\sigma_q^2}\right)\frac{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}{\sqrt{2\pi}} \\
&\cdot\frac{1}{\sqrt{2\pi\frac{\sigma_q^2}{\left(\sigma^2+\sigma_q^2\right)}}}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} \exp\left(-\frac{1}{2}\left(\frac{v-\frac{a-\mu_q}{\sigma^2+\sigma_q^2}\sigma}{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}\right)^2\right)dv \\
=& \frac{1}{\sigma_q}\frac{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\right) \\
&\cdot\frac{1}{\sqrt{2\pi\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}\int_{\frac{1}{\sigma}\left(a-\underline{q}\right)}^{\infty} \exp\left(-\frac{\sigma^2+\sigma_q^2}{2\sigma_q^2}\left(v-\sigma\frac{a-\mu_q}{\sigma^2+\sigma_q^2}\right)^2\right)dv \\
=& \frac{1}{\sqrt{2\pi\left(\sigma^2+\sigma_q^2\right)}}\exp\left(-\frac{1}{2}\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\right)\left\{1-\Phi\left(\frac{\frac{1}{\sigma}\left(a-\underline{q}\right)-\sigma\frac{a-\mu_q}{\sigma^2+\sigma_q^2}}{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}\right)\right\}.
\end{aligned}
$$

The third term of equation (32) is computed similarly:

$$
\begin{aligned}
\text{Term 3} =& \int_{-\infty}^{\frac{1}{\sigma}\left(a-\bar{q}\right)} \frac{1}{\sigma_q}\phi\left(\frac{a-\sigma v-\mu_q}{\sigma_q}\right)\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{1}{2}v^2\right)dv \\
=& \frac{1}{\sqrt{2\pi\left(\sigma^2+\sigma_q^2\right)}}\exp\left(-\frac{1}{2}\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\right)\Phi\left(\frac{\frac{1}{\sigma}\left(a-\bar{q}\right)-\sigma\frac{a-\mu_q}{\sigma^2+\sigma_q^2}}{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}\right).
\end{aligned}
$$

To summarize, the probability density of the observed bank log-assets is given by:

$$\begin{aligned}f(a) =& \frac{1}{\sigma}\phi\left(\frac{1}{\sigma}\left(a-\underline{q}\right)\right)\left(\Phi\left(\frac{\bar{q}-\mu_q}{\sigma_q}\right)-\Phi\left(\frac{\underline{q}-\mu_q}{\sigma_q}\right)\right)\\ &+\frac{1}{\sqrt{2\pi\left(\sigma^2+\sigma_q^2\right)}}\exp\left(-\frac{1}{2}\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\right)\left\{1-\Phi\left(\frac{\frac{1}{\sigma}\left(a-\underline{q}\right)-\sigma\frac{a-\mu_q}{\sigma^2+\sigma_q^2}}{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}\right)\right\}\\ &+\frac{1}{\sqrt{2\pi\left(\sigma^2+\sigma_q^2\right)}}\exp\left(-\frac{1}{2}\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\right)\Phi\left(\frac{\frac{1}{\sigma}\left(a-\bar{q}\right)-\sigma\frac{a-\mu_q}{\sigma^2+\sigma_q^2}}{\sqrt{\frac{\sigma_q^2}{\sigma^2+\sigma_q^2}}}\right).\end{aligned} \tag{36}$$

Taking log of equation (36), we can get the log-likelihood function for the MLE. Note that when $\tau = 0$, we have $\overline{q} = \underline{q}$. The first term of equation (36) equals 0 and this equation simplifies to:

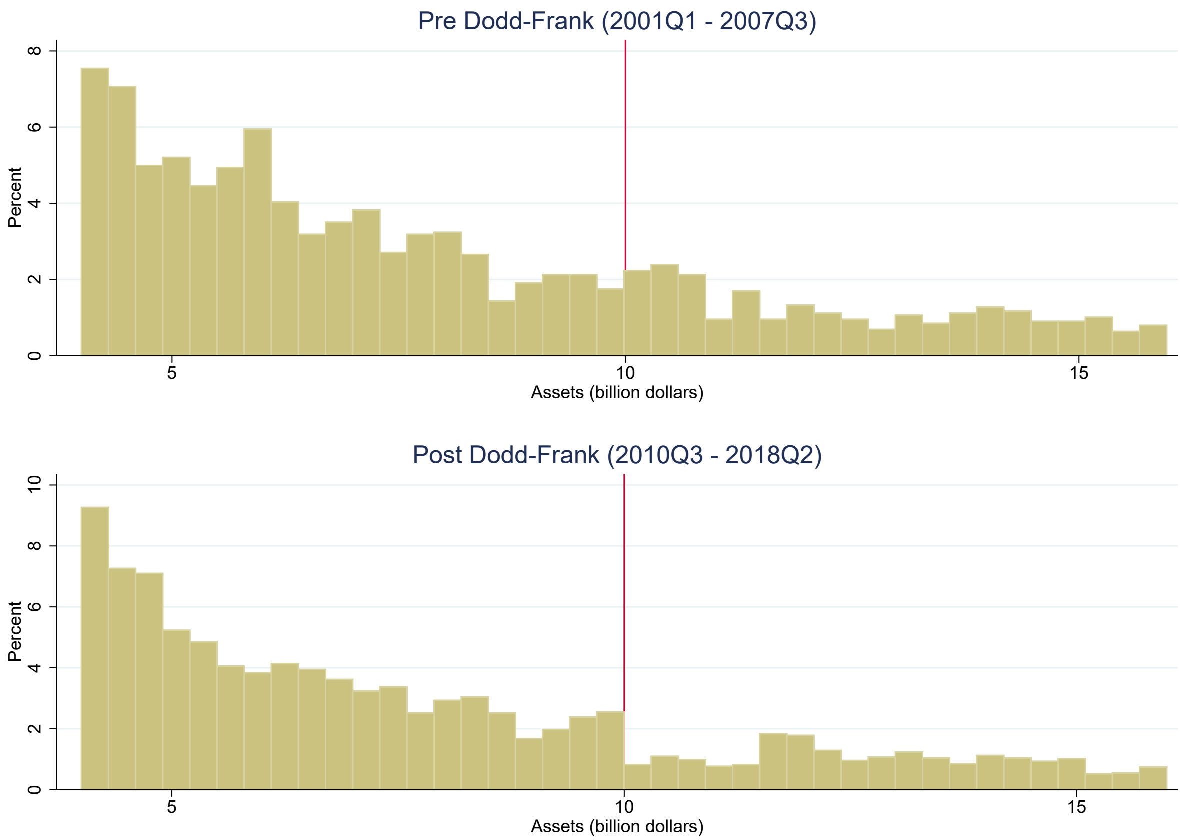
$$f(a) = \frac{1}{\sqrt{2\pi\left(\sigma^2+\sigma_q^2\right)}}\exp\left(-\frac{1}{2}\frac{\left(a-\mu_q\right)^2}{\sigma^2+\sigma_q^2}\right).$$

Watch what they do, not what they say:

Estimating regulatory costs from revealed preferences

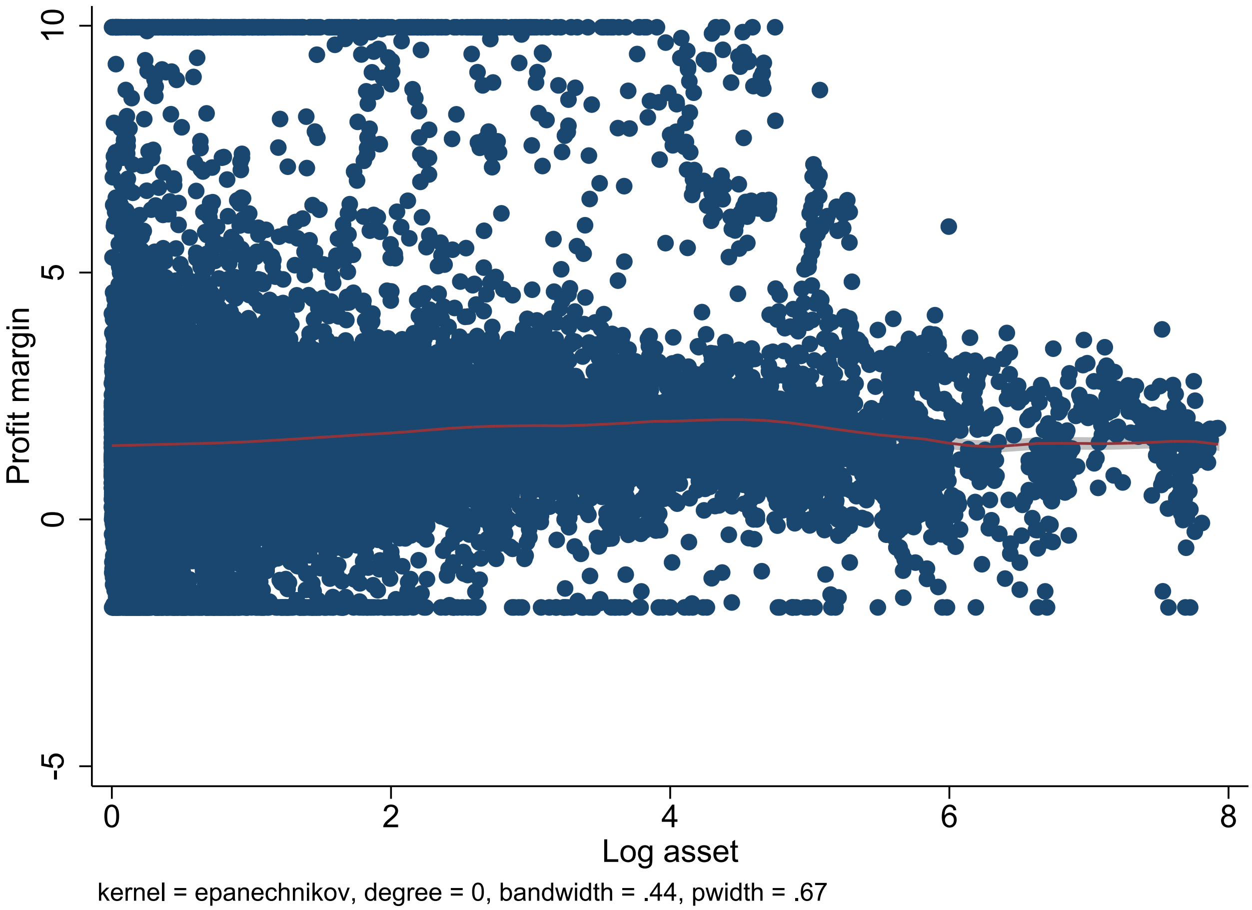
Online Appendix

Figure OA.1: Histogram of Bank Size Around Regulatory Threshold



This figure shows the histogram of bank size around the $10 billion threshold before and after the Dodd–Frank Act, respectively.

Figure OA.2: Bank Profit Margin Across Size Distribution



This figure shows the kernel regressions of the bank profit margin on the log assets. The sample period is 2001Q1–2019Q4. Each dot is a bank-quarter observation.

Table OA.1: Maximum Likelihood Estimation of Regulatory Costs with Different Assets Interval

Panel A: $10 billion threshold

		Estimated value	S.E.
β	Exponent of the power law distribution	1.113	[0.001]
σ	Measurement error volatility (in %)	4.258	[0.386]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	10.973	[0.086]
τ	Cost of regulation (% of profit)	0.405	[0.066]

Panel B: $50 billion threshold

		Estimated value	S.E.
β	Exponent of the power law distribution	1.085	[0.002]
σ	Measurement error volatility (in %)	2.291	[0.498]
$\exp(\overline{q})$	Assets of marginal bank ($ Billion)	52.393	[0.547]
τ	Cost of regulation (% of profit)	0.106	[0.046]

Note: This table presents the results of the maximum likelihood estimation of the regulatory costs using the power law distribution. The sample period is from 2010Q3 to 2018Q2. The estimation sample of Panel A includes banks with assets between $3 billion and $30 billion. The estimation sample of Panel B includes banks with assets above $30 billion. Standard errors are obtained via the inverse of the Hessian matrix.

Table OA.2: Counterfactual Simulation: Robustness

Counterfactual	Lower discount rate	Higher entry cost	Higher exit rate
		Panel (a): all banks	
Mass of banks	-0.236%	-0.193 %	-0.153 %
Market-to-book	-0.234%	-0.223 %	-0.214 %
Lending quantity	-0.085%	-0.067 %	-0.054 %
Lending rate	0.060%	0.047 %	0.038 %
Output	-0.026%	-0.020 %	-0.016 %
		Panel (b): annual profits by size group	
Small banks	0.096%	0.076 %	0.069 %
Medium banks	-0.395%	-0.399 %	-0.393 %
Big banks	-1.246%	-1.272 %	-1.276 %
		Panel (c): asset shares by size group	
Small banks	-0.067%	-0.063 %	-0.038 %
Medium banks	-0.247%	-0.230 %	-0.215 %
Big banks	0.028%	0.022 %	0.024 %
		Panel (d): shares of banks by size group	
Small banks	-0.012%	-0.012 %	-0.009 %
Medium banks	0.086%	0.083 %	0.073 %
Big banks	0.100%	0.083 %	0.073 %

Note: This table reports the results of the robustness of counterfactual simulations with respect to alternative parameter values. The values are expressed as the percentage changes from the baseline economy without the Dodd–Frank Act to the the economy with the Dodd–Frank Act. Column (1) reports the results when the discount rate is decreased by 10% relative to the baseline value. Columns (2) reports the results when the entry cost is increased by 10% relative to the baseline value. Column (3) reports the result when the exit rate is increased by 10% relative to the baseline value.