Funding and Incentives of Regulators: Evidence from Banking

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October 2018

Abstract

Regulation is often funded with fees paid by regulated firms, potentially creating incentive problems. We use this feature to study the incentives of regulators and their ability to affect firm behavior. Theoretically, we show that firms that pay higher fees may face more lenient regulation, when leniency increases regulatory budgets in the short term. Our identification approach uses multiple kinks in fee schedules of federal bank regulators as a source of exogenous variation. Using a novel dataset on fees and regulatory actions, we find that firms that pay higher fees face more lenient regulation, which leads to a buildup of risk. Higher fee-paying banks are allowed higher leverage and asset risk, and in the longer term have more loan defaults and a higher likelihood of regulatory actions, which tend to follow banking crises.

Disclosure Statements

Roni Kisin declares that he has no potential conflicts of interest, as identified by the Disclosure Policy of the Journal of Finance.

Asaf Manela declares that he has no potential conflicts of interest, as identified by the Disclosure Policy of the Journal of Finance.

1   Introduction

Incentives and abilities of regulators are frequently called into question, especially following periods of economic turmoil and high-profile accidents. Recent examples of industries where regulatory agencies became subjects of controversies and allegations of regulatory capture include pharmaceuticals (withdrawal of painkiller Vioxx), offshore drilling (BP oil spill), and finance (financial crisis of 2008). But empirical work on the incentive schemes of regulators and their consequences is scarce, leaving an important policy debate on the incentive structure of regulatory agencies largely unaided by evidence.[1]

We study the effect of the funding structure on regulatory incentives and outcomes in a setting where regulation is funded by regulated firms. "User-fee" models of regulation are present in many industries (including those mentioned above), but the underlying economic tradeoffs have not been studied empirically. We show theoretically that a potential consequence of the user-fee system is that regulators may become more lenient toward firms that pay higher fees. Therefore, variation in fees can be used to study the effect of monetary incentives on regulatory leniency in the user-fee model, and, more generally, shed light on the regulatory process.

We test this idea using a novel dataset on regulatory assessment fees charged by two primary regulators of national banks in the US: The Office of Thrift Supervision (OTS) and The Office of the Comptroller of the Currency (OCC). Using exogenous variation in fees generated by kinks in the fee schedules of these agencies we provide new evidence on the interaction between regulators and firms, as well as on the consequences of the user-fee model of regulation.

Banking is an appealing setting for a study of regulatory incentives and potential effects of the user-fee model. Both the OCC and the OTS get essentially all of their funding from

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[1]Following withdrawal of Vioxx, an FDA epidemiologist testified that Vioxx was a "profound regulatory failure," and that the FDA "is incapable of protecting America against another Vioxx." (Senate Committee on Finance, 2004). The BP Oil Spill Commission Report (2011) calls the incident an "inexcusable, shortfall in supervision." The offshore oil drilling regulator (Minerals Management Service) was reorganized following the Deepwater Horizon spill. Following the 2008 financial crisis, the Office of Thrift Supervision—regulator of such institutions as WaMu, IndyMac, and AIG—was accused of failure and abolished. OTS itself was preceded by the Federal Home Loan Bank Board, which also closed following the Savings and Loans Crisis (Senate Permanent Subcommittee on Investigations, 2010).

supervised banks and receive no appropriations from Congress.[2] Moreover, banking regulators have a significant influence over bank risk—a primary focus of regulation. Therefore, the main outcomes of the supervisory process, as well as outcomes of risk-taking, such as failures, enforcement actions, and asset performance can be measured with publicly available data.

To clarify the theoretical implications of regulation funded with user fees, we present a stylized model of a regulator who negotiates the choice of risk with a firm. The firm has bargaining power because it can deprive the regulator of its fees: it could switch regulators, forgo the project, relocate, or even exit. In finance, such a threat is far from hypothetical—many academics and policy makers are concerned with the ability of banks to avoid regulation by switching regulators (Rosen, 2003, 2005), moving assets off-balance sheet (Acharya, Schnabl, and Suarez, 2013; Kisin and Manela, 2016), or, more generally, shift operations into the unregulated "shadow banking" sector (e.g., Gorton, 1994; Adrian and Shin, 2009; Gorton and Metrick, 2010; Gorton, 2010).

We show that when the regulator and firm pull in opposite directions around the agreed upon risk, regulators accept higher risk in higher fee-paying firms. Intuitively, higher fee income alleviates the cost of higher risk. The model, therefore, clarifies how exogenous variation in fees can be used to identify the effects of monetary incentives on regulation.

Empirically isolating the effect of fees is difficult, because they are determined by bank size, and therefore correlated with unobserved bank characteristics. Moreover, fees are a deterministic function of size, which precludes the use of conventional instrumental variable techniques. To address this, we use the "kinked" structure of the fee schedule. Fees are a non-decreasing piece-wise linear function of bank size, with decreasing slopes in the relevant sample. Bank size affects fees differently depending on which side of a kink a bank happens to be. This discontinuity in slopes allows us to identify a treatment effect of fees, applying the sharp regression kink design ("RKD," Card, Lee, Pei, and Weber, 2015). Intuitively, we look for kinks in the relationship between measures of bank risk outcomes and bank size, which coincide with kinks in the fee schedule.

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[2]These regulators oversee 65% of the banking assets in the US during our sample period. About 95% of their funding comes from supervised banks, and the remainder from interest on their past budget surpluses.

Importantly, although our identifying variation comes from changes in the slope of the fee function with respect to size, what we estimate is the effect of fees on bank risk. The RKD estimator recovers the effect of fees on risk from the ratio of the change in the slope of the risk measure around the kink to the change in the slope of the fee function. Drawing a parallel to two-stage least squares for intuition, if a large slope decrease in the risk function with respect to size (the "reduced form"), coincides with a modest slope decrease in the fee function with respect to size (the "first stage"), then fees must have a large positive effect on risk, that can be measured by the ratio of the two effects.

Several features make RKD especially attractive for our setting. First, the locations of kinks in the fee schedules stayed practically constant over time, which removes potential concerns regarding the endogenous adjustment of kink points by regulators.

Second, kinks significantly affect regulatory revenues. A relevant measure for our analysis is the difference in the elasticity of fees with respect to size for banks on two sides of a kink. For an average kink, a one percent increase in assets has a 0.17 percentage point higher effect on fees on the left side of the kink than on its right. Because the average elasticity on the left is 0.76, the first stage effect is a 22 percent decrease in the elasticity of fees to bank size.

Third, the fee schedules feature multiple kinks along the distribution of bank sizes, providing variation at different points in the size distribution. Moreover, while the elasticity differences vary between 0.05 and 0.88 (depending on the kink and the schedule), kinks with large elasticity changes are present at various points of the distribution. This ensures that our analysis is not limited *a priori* to a small group of banks from a particular part of the size distribution. The existence of multiple kinks, however, together with changes in kinks across regulators and time, also complicates a straightforward application of the RKD in our setting. Therefore, we extend the basic framework to account for multiple kinks and time variation in kink positions and slopes.

We find that banks that pay higher fees take more risks, as measured by leverage and by riskiness of assets. A 1% increase in regulatory fees paid by a bank increases its regulatory leverage (assets over equity) by approximately 2%, which, on average, translates to an increase from 11.8 to 12 for core leverage, and 7.1 to 7.28 for tier 1 risk-based leverage. Fees also lead to an increase in asset risk, as evidenced by an increase of 3% in loan loss reserves.

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These findings suggest that the user fee system significantly affects the regulatory process. Banks that pay higher fees face more lenient regulation.

Having established the effect of fees on bank risk-taking, we take a closer look at the economic mechanism behind this result. In particular, we investigate what makes large regulatory organizations respond to changes in individual bank fees. A closer look at the institutional environment clarifies the mechanism. First, supervision of a majority of banks (mid-size and small) is delegated to local field offices with significant decision-making authority. Budgets and employment in these offices relies on banks under their supervision, and fees paid by individual banks can capture a sizable share of their budgets. For example, the departure of a median (mean) bank would reduce their budget by about \$54,000 (\$230,000).[3] We find that our results are indeed concentrated in the group of mid-size banks.

Second, we examine the effect of competition between regulators. We show theoretically that competition increases the effective bargaining power of banks, and find empirically that the effects are particularly large when a bank's treatment by its regulator may affect the charter choice of its holding company peers. Therefore, even small changes in fees can be important for the relevant supervisory unit, and the effect of fees can be further magnified by the firm's bargaining power.[4]

Next, we study the dynamic effects of fees on risk and other outcomes. While regulation may affect some outcomes immediately (e.g., leverage), other outcomes, such as realized defaults, loss reserves adjustments, and regulatory actions following past risk-taking, are likely to respond slowly to changes in regulatory strictness. Moreover, fees may affect banks' future assignment around the kinks, which could bias estimates from a regression of future outcomes on current fees. We explore the delayed effects of fees by adapting the dynamic regression discontinuity (RD) design developed by Cellini, Ferreira, and Rothstein (2010) to the regression kink setting. This approach allows estimating both the effect of current fees on future outcomes that includes their indirect effect through interim fees (intent-to-treat), and the pure effect of current fees on future outcomes (treatment-on-treated).

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[3]As mentioned above, banks have other, readily-available tools to significantly affect the local office's budget (e.g., moving assets off balance sheet). Subsequent work documents the importance of field level interaction, by studying the effects of field office closures on bank risk (Gopalan, Kalda, and Manela, 2016).

[4]Another way to assess the magnitudes of our estimates is to quantify the value of the estimated change in risk, relative to a one-percentage-point increase in fees for banks. We discuss this exercise in Section 5.3.4.

We find that fees have significant effects on future regulatory enforcement actions and loan default rates. Higher fees increase enforcement actions after two quarters, and increase noncurrent loans after 5–6 quarters. We document that regulators tend to initiate corrective actions mostly following banking crises, which implies that higher fees lead to a buildup of risk in regulated banks. The results on regulatory actions and loan defaults capture delayed consequences of risks taken in response to lax regulatory treatment.

Our paper contributes to several strands of literature on the economics of regulation. To the best of our knowledge, we provide the first causal evidence on the effect of regulatory fees on the outcomes of regulation. Besides providing rare evidence on the effects of regulators' incentives, we directly relate regulatory outcomes to the user-fee model of regulation. As mentioned above, this model is used in many industries, such as aviation, oil and gas, pharmaceuticals, and antitrust, and is commonly motivated by efficiency improvements and a reduced burden on taxpayers. It is often feared, however, that the user-fee model can lead to regulatory capture and favoritism. Our paper provides the first empirical evidence for the existence of such effects.[5]

In the context of financial regulation, our study is related to Agarwal, Lucca, Seru, and Trebbi (2014) and Kroszner and Strahan (1996; 1999). Agarwal, Lucca, Seru, and Trebbi exploit exogenous rotations between federal and state supervisors of state-chartered banks to show inconsistency in regulatory outcomes. In addition, they document that larger bank size is associated with regulatory leniency, but do not identify the effect of fees. Kroszner and Strahan (1996) show that during the S&L crisis in the 80s, regulators kept insolvent thrifts alive by influencing the allocation of private capital. Kroszner and Strahan (1999) find that pressure from interest groups affected the implementation of interstate branching deregulation.[6]

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[5]For the benefits, see President's FY 2014 Budget Analytical Perspectives. Philipson, Berndt, Gottschalk, and Sun (2008) provide evidence of efficiency gains. They document shorter drug approval times by the FDA after user fees were introduced, but point out that other events may have led to this result. See BP Oil Spill Commission Report (2011) for a critique of the user-fee model of regulation.

[6]See also Lucca, Seru, and Trebbi (2014) and Shive and Forster (2013) on the "revolving door" between regulatory agencies and the industry, and Lambert (2015) on lobbying and regulatory outcomes. Eisenbach, Lucca, and Townsend (2016) and Hirtle, Kovner, and Plosser (2016) study the costs and benefits of bank supervision using data on work hours of Federal Reserve supervisors. More broadly, there is a similarity between user fee-funded government regulators and private auditors, e.g., credit rating agencies and self-regulatory organizations (see, e.g., Bolton, Freixas, and Shapiro, 2012, for a theoretical treatment). Duflo,

This literature convincingly shows that regulation depends on the identities and incentives of regulators, and not just driven by laws and rules. We complement and extend this literature by measuring the effects of the structure and sources of regulatory revenues. The sensitivity of regulatory conduct to monetary incentives implies that effective design of regulatory agencies should take this issue into account. Our evidence is particularly informative for studies on the design of regulatory agencies, since we examine variation in incentives *within* agencies. This allows isolating the effect, holding constant other characteristics of regulators and firms.

Our focus on revenues is particularly advantageous for the external relevance of our findings. Revenue structure is a generally available policy tool with a clear interpretation. Its power stems from general economic tradeoffs, and does not hinge on the particular features of a given sector. Two recent examples of alleged conflicts of interest in similarly-structured agencies—the Federal Aviation Agency (FAA) and the Mineral Management Service (MMS)—suggest that the "leniency-for-fees" channel could be operating in other settings.[7]

Another related literature focuses on the ability of banks to choose regulators by choosing charters. Blair and Kushmeider (2006) note that reliance on fees may exacerbate the competition between regulators. The empirical evidence on the effect of competition is mixed: Rosen (2003; 2005) documents that switching charters is associated with an increased return on equity, but not risk. Rezende (2014) studies the effect of charter switching on regulatory ratings. Using fees to instrument for switching between OCC and state regulators, he finds more favorable regulatory ratings and a higher probability of failure after switching. We show that the effect of fees on regulation does not require competition between regulators, but could be exacerbated by it. We do not find a significant difference in the effect of fees

Greenstone, Pande, and Ryan (2013) study private pollution auditors in India, who are paid by firms. They find that audit quality can be improved by altering auditors' incentives.

[7]Similar to banking, the FAA and the MMS are user-fee-financed and rely on local supervisory units. The FAA was blamed in April 3, 2008 congressional hearings for succumbing to excessively "cozy" relationships with the airlines, routinely failing to take proper enforcement action, and allowing non-compliant airlines to escape penalties by using the voluntary disclosure programs without fixing their underlying safety problems. The MMS, the US offshore oil drilling regulator, was reorganized following the 2010 Deepwater Horizon incident. The BP Oil Spill Commission Report (2011), which calls the incident an "inexcusable, shortfall in supervision," traces the origins of MMS to a political compromise.

across agencies, and our tests are consistent with Agarwal, Lucca, Seru, and Trebbi (2014) who find that bank and time effects deal effectively with the issue of charter shopping. We do find, however, that competition magnifies the effect of fees—regulators respond particularly strongly to fees of banks when they are interested in attracting their holding company peers.

Methodologically, we contribute to a growing literature that applies RKD to important economic questions, following the seminal contributions of Nielsen, Sørensen, and Taber (2010) and Card, Lee, Pei, and Weber (2015).[8] Often, the method is applied in settings with multiple and time-varying kinks. While this feature may provide an important advantage—in our setting, it increases statistical power and allows estimating the effects from across the size distribution—it also introduces heterogeneity across kinks and over time. We show that pooling data across kinks, while ignoring such heterogeneity may lead to severe bias. We provide a parsimonious and easily implementable adjustment of the RKD that accommodates kink heterogeneity, while still allowing researchers to pool observations across multiple kinks in estimating treatment effects. Our extensions of RKD to multiple kinks and dynamic effects could prove useful in future applications.

The paper proceeds as follows. Section 2 describes our theoretical framework and derives its empirical predictions. Section 3 describes banking regulation in the United States, the roles of OCC and OTS, and our data on regulatory fees. Section 4 describes our empirical approach and the application of the RKD in our setting. Section 5 reports our empirical results. Section 6 examines their robustness. Section 7 concludes.

2   Model

Our goal in this section is to provide a simple economic framework for the empirical analysis of the effects of user-fee models on regulatory incentives. We start by modeling the objective of a regulator with respect to firm risk. There is little theoretical or empirical work to guide us in the choice of the regulator's objective function.[9] Since we want to analyze incentives

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[8]See Landais (2015) for a recent application and Ganong and Jäger (2014) for a survey.

[9]The theoretical literature on optimal regulation often considers a benevolent planner maximizing social welfare. See, e.g, Baron and Myerson (1982) and Laffont and Tirole (1986). Boot and Thakor (1993) consider a self-interested bank regulator concerned with its reputation. Bank regulators in Bond and Glode (2014) aim to maximize the number of useful reports they can generate within their budget. Dewatripont and Tirole

generated by the fee structure, the regulator in our model has a preference over net fee income, $r(x, q) = f(q) - c(x, q)$, where $f(q)$ is fee revenue. As in our institutional setting, the fees are determined by firm size q.[10] The cost of regulation $c(x, q)$ may include the regulator's private cost of supervision, and the social costs net of benefits from a firm of size q bearing risk x. For the moment, we do not need to specify the exact measure of risk or its units, and only require that it is real-valued, $x \in X \subset \mathbb{R}$. Our results apply to continuous outcomes, such as leverage ratios, as well as discrete outcomes, such as supervisory ratings and enforcement actions. Fees and outside options are assumed to belong, respectively, to convex subsets $F \subset \mathbb{R}$ and $O \subset \mathbb{R}$.

This objective could raise two immediate questions. First, why would regulators care about fee income? This assumption is motivated by the fact that for the banking regulators we study labor costs take up 70–80% of the fee income, as we show below in Figure 1. Therefore, in our stylized model, the fees in the objective function play the role of labor income and job security. Second, this objective may appear to ignore other factors that could be valued by the regulator, such as social welfare from bank lending, which could mitigate the effect of fees. Note, however, that the regulator's cost $c(x, q)$ can be thought of as net of such benefits. We abstract from these factors since our goal in this section is to highlight a potential mechanism for the effect of fees on incentives in the simplest possible setting. Importantly, our empirical application does not impose specific preferences and we estimate the equilibrium net effect of fees nonparametrically. Specifically, we use a nonparametric identification framework developed by Card, Lee, Pei, and Weber (2015), which allows for nonseparability between f, q, and the error term, and for nonlinearities in the dependency of risk on size.

The regulator and the firm negotiate the choice of risk x. The firm cares about its profits net of regulatory fees $\pi(x, q) - f(q)$. Firm size q is set by the time of the negotiation and

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(1994) allow banking regulators that care more about the value of deposits than social welfare. A separate literature relates prevailing forms of regulation to political bargains and institutions. See for example, Stigler (1971); Peltzman (1976); Shleifer and Vishny (2002), and more recently Calomiris and Haber (2014).

[10]Fees are completely determined by size for a vast majority of banks. For banks with CAMELS ratings of 3 and above, however, there is a discrete increase in fees. We ignore this feature in the model, because, as we explain in Section 3.2.1, it does not complicate our empirical analysis. Theoretically, we can easily allow fees to also depend on risk, but such a modification would not change the comparative statics below, all of which ask how risk would change following an *exogenous* increase in fees.

is known to both parties. This assumption reflects the regulatory practice in our setting.[11]

While the objectives of the regulator and the firm may be aligned over some range of q and x, we assume that around the agreed choice of risk, they would want to move risk in opposing directions. This assumption ensures an interior solution for risk. Intuitively, if this was not the case, the parties would change the risk until they reach a point where their preferences differ. Specifically, we assume that both regulatory costs and firm profits are strictly increasing in risk. That is, for any q, and for any $x^L, x^H \in X$ such that $x^L < x^H$, we have $c\left(x^L, q\right) < c\left(x^H, q\right)$ and $\pi\left(x^L, q\right) < \pi\left(x^H, q\right)$. The assumption that regulatory costs depend on size and are increasing in risk is consistent with recent empirical findings that more supervisory resources are spent on larger and riskier banks (Eisenbach, Lucca, and Townsend, 2016; Hirtle, Kovner, and Plosser, 2016). Because none of the following results depends on predetermined size directly, we omit it unless necessary.

Assume a Nash bargaining solution, so that firm risk x maximizes the regulator and the firm's bilateral Nash product with bargaining power parameter $\rho \in (0, 1)$

$$x^*\left(f, o\right) = \arg\max_x \left[f - c\left(x\right)\right]^\rho \left[\pi\left(x\right) - f - o\right]^{1-\rho}. \tag{1}$$

This setup is widely used in empirical bargaining models (e.g., Crawford and Yurukoglu, 2012), and nests the limiting cases where the choice of risk is made solely by the regulator ($\rho \to 1$) or by the firm ($\rho \to 0$).

The firm's outside option is denoted by $o\left(q\right)$ and can potentially depend on size. This parameter allows us to analyze the effects of competition among regulators. US banks, in particular, can often *choose* their regulator by selecting a charter, which could result in competition among regulators (Rosen, 2003; Calomiris, 2006), thereby potentially exacerbating the effects of fees. We normalize the regulator's outside option to zero, without loss of generality, because the regulator's cost $c\left(x, q\right)$ can be thought of as net of its disagreement

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[11]End-of-last-period $t-1$ book assets q_{t-1} determine regulatory fees f_t paid at time t, in the case of the banking regulators we study. Therefore, future fees are mostly known before period t actions take place. Importantly, a bank can leave its federal regulator in favor of a state charter up until the last day of period $t-1$. Whether this simple bargaining channel applies to other industries where regulators are funded by firms, depends on the ability of the firm to walk away from the negotiating table, by leaving for a competing regulator, by exiting, or by reducing the size of a project.

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payoff.[12]

The optimal choice of risk x^* trades off the benefit to the firm from increased risk against the cost to the regulator. We next establish several monotone comparative static results about risk. The first result establishes that, all else equal, an exogenous increase in fees increases firm risk.

Proposition 1 (Risk is increasing in fees). *For a firm of any size q, with any outside option o, and faced with regulatory fees $f^L, f^H \in F$, such that $f^L < f^H$, the agreed level of risk x^* is increasing in fees:*

$$x^* \left(f^L, o, q \right) \leq x^* \left(f^H, o, q \right). \tag{2}$$

Proof. First note that conditional on agreement, $f - c(x, q) > 0$ and $\pi(x, q) - f - o > 0$, otherwise the parties would walk away. Applying logs to both sides of the objective (1) does not change the solution x^* but results in a more convenient expression,

$$x^* (f, o, q) = \arg \max_x u(x, f, o, q) \equiv \rho \log [f - c(x, q)] + (1 - \rho) \log [\pi(x, q) - f - o]. \tag{3}$$

Establishing that x^* is increasing in f is equivalent to showing that u has *increasing differences* in (x, f) for any o and q (Vives, 2001, Theorem 2.3). Because u is continuously differentiable in $f \in F$, and F is convex, it suffices that the partial derivative w.r.t. f,

$$u_f (x, f, o, q) = \frac{\rho}{f - c(x, q)} - \frac{1 - \rho}{\pi(x, q) - f - o}, \tag{4}$$

is nondecreasing in x. That is, for any f, o and q, and for any $x^L, x^H \in X$ such that $x^L < x^H$, we need $u_f \left(x^H, f, o, q \right) \geq u_f \left(x^L, f, o, q \right)$. Using (4) and collecting terms we require,

$$\rho \left[\frac{1}{f - c(x^H, q)} - \frac{1}{f - c(x^L, q)} \right] \geq (1 - \rho) \left[\frac{1}{\pi(x^H, q) - f - o} - \frac{1}{\pi(x^L, q) - f - o} \right]. \tag{5}$$

Because $c\left(x^L, q \right) < c\left(x^H, q \right)$ and $\pi\left(x^L, q \right) < \pi\left(x^H, q \right)$, the term in brackets on the left is positive while the term in brackets on the right in negative. Because $\rho \in (0, 1)$ the inequality holds, which concludes the proof. $\square$

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[12]The firm's outside option is the net profit it would earn under the next best regulator with risk $\tilde{x}$, fees $\tilde{f}$, and a switching cost κ, that is $o(q) \equiv \pi(q, \tilde{x}) - \tilde{f}(q) - \kappa$. If exit is the only alternative, then $o(q) = 0$.

This result clarifies that all we need for risk to increase in fees is that the regulator and firm pull in opposite directions around the agreed upon risk. The intuition is that higher fees increase the regulator's utility in the short-term, so that the cost increase from higher risk is smaller in percentage terms. At the same time, higher fees decrease the firm's profits, so it cares even more about increasing its risk. As a result, the agreed level of risk increases.

A second implication of the model is that risk is increasing in the firm's outside option. The intuition for this result, which implicitly motivates a growing literature on regulatory shopping, is that a higher outside option raises the effective bargaining power of the firm. The monotonicity of the firm's profits in risk then implies that agreed risk increases in its outside option, as we establish next.

Proposition 2 (Risk is increasing in the firm's outside option). *For a firm of any size q, faced with regulatory fees $f \in F$, with outside option $o^L, o^H \in O$ such that $o^L < o^H$, the agreed level of risk x^* is increasing in the outside option:*

$$x^* \left(f, o^L, q \right) \leq x^* \left(f, o^H, q \right). \tag{6}$$

Proof. As in Proposition 1, it suffice to show that the partial derivative w.r.t. o,

$$u_o \left(x, f, o, q \right) = -\frac{1 - \rho}{\pi \left(x, q \right) - f - o}, \tag{7}$$

is nondecreasing in x. That is, for any f, o and q, and for any $x^L, x^H \in X$ such that $x^L < x^H$, we need $u_o \left(x^H, f, o, q \right) \geq u_o \left(x^L, f, o, q \right)$. From (7) we have,

$$-\frac{1 - \rho}{\pi \left(x^H, q \right) - f - o} > -\frac{1 - \rho}{\pi \left(x^L, q \right) - f - o}, \tag{8}$$

because $\rho \in (0, 1)$ and $\pi \left(x^L, q \right) < \pi \left(x^H, q \right)$, which concludes the proof. □

A corollary to these two results is that an exogenous increase in fees increases risk even more when the outside option is higher.

Corollary 1 (Risk is increasing in fees even more when the outside option is higher). *For a firm of any size q, faced with regulatory fees $f^L, f^H \in F$ such $f^H > f^L$, and an outside*

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option $o^L, o^H \in O$ such that $o^H > o^L$, the agreed level of risk x^* satisfies

$$x^* \left(f^L, o^L, q \right) \leq x^* \left(f^H, o^L, q \right) \leq x^* \left(f^H, o^H, q \right). \tag{9}$$

Proof. The first and second inequalities follow from Propositions 1 and 2, respectively. □

The weak inequalities in the propositions and corollary above is all we can hope for while allowing for discrete risk measures. These inequalities become strict if we additionally assume that (a) c and π are continuously differentiable (and increasing as before) in x, and (b) x^L or x^H is in the interior of X (Van Zandt, 2002). For better intuition, and because most of our empirical measures of risk are continuous financial ratios, we adopt these two additional assumptions in what follows.

The agreed risk x^* equates the bilateral marginal benefit and marginal cost, weighted by each party's bargaining power:

$$\rho \frac{c_x \left(x^*, q \right)}{f \left(q \right) - c \left(x^*, q \right)} = (1 - \rho) \frac{\pi_x \left(x^*, q \right)}{\pi \left(x^*, q \right) - f \left(q \right) - o \left(q \right)}. \tag{10}$$

The marginal cost of an increase in risk is the percent decrease in the regulator's net fees, while the marginal benefit is the percent increase in the bank's net profit.

Equation (10) clarifies the effect of fees on risk. Higher fees increase the regulator's payoff, therefore offsetting the impact of higher costs. Moreover, on the right-hand side of (10), higher fees increase the marginal benefit because of the decrease in profits (net of fees). While both effects increase the resulting risk, we expect the former to be much stronger because fees are a major source of regulator revenue but only a minor cost for banks.

The following proposition shows that the effect of an exogenous increase in fees on risk, measured by the fee elasticity of risk, is positive.

Proposition 3 (Fee elasticity of risk is strictly positive)**.** *Assuming that c and π are continuously differentiable in x, the fee elasticity of risk is positive and given by the expression:*

$$\phi \left(q \right) \equiv \frac{d \log x^*}{d \log f} = \frac{\frac{f(q)}{f(q) - c(x^*, q)} + \frac{f(q)}{\pi(x^*, q) - f(q) - o(q)}}{\frac{1}{1-\rho} \frac{c(x^*, q)}{f(q) - c(x^*, q)} \epsilon_{cx} + \sigma_{cx} - \sigma_{\pi x}} > 0, \tag{11}$$

where $\sigma_{\pi x} \equiv \frac{\pi_{xx}(x^*,q)x^*}{\pi_x(x^*,q)}$, $\sigma_{cx} \equiv \frac{c_{xx}(x^*,q)x^*}{c_x(x^*,q)}$, *and* $\epsilon_{cx} \equiv \frac{c_x(x^*,q)x^*}{c(x^*,q)}$.

Proof. Differentiating the first-order condition (10) with respect to f and rearranging gives

$$\frac{dx^*}{df} = \frac{(1-\rho)\frac{\pi_x(x^*,q)}{[\pi(x^*,q)-f-o]^2} + \rho\frac{c_x(x^*,q)}{[f-c(x^*,q)]^2}}{-\frac{\partial}{\partial x}\left\{(1-\rho)\frac{\pi_x(x,q)}{\pi(x,q)-f-o} - \rho\frac{c_x(x,q)}{f-c(x,q)}\right\}_{|x=x^*}}. \tag{12}$$

The numerator is positive because $\rho \in (0,1)$, $c_x > 0$, $\pi_x > 0$, and the benefits from agreement are positive for both parties ($\pi(x^*,q) - f(q) > o(q)$ and $f(q) > c(x^*,q)$). Moreover, the denominator is positive whenever x^* characterizes a local maximum, as this is the second-order condition for optimality, which establishes the sign. Specifically, we require

$$\frac{\pi_{xx}(x^*,q)}{\pi_x(x^*,q)} < \frac{c_{xx}(x^*,q)}{c_x(x^*,q)} + \left(\frac{1}{1-\rho}\right)\frac{c_x(x^*,q)}{f(q)-c(x^*,q)}, \tag{13}$$

which holds, for example, if regulatory costs are weakly more convex in risk than firm profits. Completing elasticities and using the first-order condition (10) yields the stated result. □

Equation (11) shows that the treatment effect of fees is determined by the importance of fees in the payoffs of the regulator and the firm, and by the effect of risk on these payoffs. The elasticity of risk with respect to fees is larger when fees are large relative to the payoffs of the regulator or the firm, when the regulator has little bargaining power ρ, when the elasticity of costs to risk ϵ_{cx} is small, or when the relative convexity of the cost function σ_{cx} is not much larger than that of the profit function $\sigma_{\pi x}$.

2.1 Taking the Model to the Data

Equation (11) also highlights identification challenges in estimating the effect of regulatory fees. Since fees are determined by size q, any variable that affects fees f, will also affect q, thereby violating the independence assumptions required for an instrument. Moreover, unobserved factors can be correlated with the sensitivity of profits to risk, firm size, and fees. Our implementation of the RKD addresses these issues.

We next provide an intuitive explanation for how a kink in the fee function can overcome this identification challenge, within a relatively simple version of our theoretical model and

under somewhat restrictive empirical assumptions, which we relax in Section 4.

We therefore momentarily consider the special case of the model where both costs and profits are linear in risk. Specifically, $\pi(x, q) = \pi_0(q) + \pi_x(q) x$ and $c(x, q) = c_0(q) + c_x(q) x$, for some positive functions of size, $\pi_x(q)$ and $c_x(q)$. In this case, agreed risk has a closed-form solution, which is linear in fees:

$$x^*(f(q), q) = \chi_0(q) + \chi_f(q) f(q), \tag{14}$$

where $\chi_0(q) \equiv -(1 - \rho)\frac{c_0(q)}{c_x(q)} - \rho\frac{\pi_0(q)}{\pi_x(q)} + \frac{\rho}{\pi_x(q)} o(q)$, and $x_f(q) \equiv \frac{1-\rho}{c_x(q)} + \frac{\rho}{\pi_x(q)}$.

The fee elasticity of risk in this linear case,

$$\phi(q) = \frac{x_f(q) f(q)}{\chi_0(q) + \chi_f(q) f(q)}, \tag{15}$$

is large when risk is costly for the regulator and the firm only profits by small amounts, relative to their counterparty's bargaining power ($x_f(q)$ is large), when fees $f(q)$ are large, or when the regulatory cost and firm profits of a riskless firm are small ($\chi_0(q)$ is small).

We specify our empirical model in logs because the bank size distribution is highly skewed, and because it allows us to estimate a fee elasticity of risk that is potentially more homogeneous across size groups. Suppose therefore a multiplicative error term so that realized log risk y as a function of log assets $v \equiv \log q$, and log fees $b(v)$ is

$$y = \log x^* = \log\left[\chi_0(e^v) + \chi_f(e^v) e^{b(v)}\right] + \varepsilon. \tag{16}$$

The identification challenge is that bank size v is likely endogenous ($E[\varepsilon|v] \neq 0$). In this case, a simple regression of risk on fees would result in biased estimates of the fee elasticity of risk because unobservables in the error term determine both size and fees. Instead, consider the derivative of the conditional expectation of risk with respect to bank size

$$\frac{dE[y|v]}{dv} = \frac{\chi_0'(q) + \chi_f'(q) f(q)}{\chi_0(q) + \chi_f(q) f(q)} q + \frac{\partial E[\varepsilon|v]}{\partial v} + \phi(q) \times \frac{f'(q) q}{f(q)}. \tag{17}$$

The first and second terms are the direct effect of size on risk, holding fees constant. The

third term is the indirect effect of size, which operates through an increase in fees.

To identify the elasticity of risk to fees $\phi(q)$, we exploit the fact that a kink in the fee schedule $f(q)$ at a point $q = q_k$ generates variation in the elasticity of fees with respect to size. Let $\Delta(q_k) \equiv \left[f'\left(q_k^+\right) - f'\left(q_k^-\right) \right] \frac{q_k}{f(q_k)}$ denote this change in the size elasticity of fees at q_k. The key identifying assumption is that the effects of both size and fees on bank risk are smooth near the kink, and that the density of size conditional on the residual is smooth as well. It follows that the only source for a discontinuous change in slopes of risk conditional on size at a kink point $q_k = e^k$ is due to the kink in the fee function:

$$\lim_{v_0 \downarrow k^+} \frac{dE[y|v]}{dv}\Big|_{v=v_0} - \lim_{v_0 \uparrow k^-} \frac{dE[y|v]}{dv}\Big|_{v=v_0} = \phi(q_k) \times \Delta(q_k). \tag{18}$$

This "reduced form" effect, can be estimated from the mean change in the slope of bank risk as a function of size at a given kink point. Scaling it by the known "first stage" change in the size elasticity of fees, $\Delta(q_k)$, we recover the fee elasticity of risk. This intuition extends to the case where the error in (16) is nonseparable and y is an arbitrary but smooth function of fees and size, and to cases with multiple time-varying kinks, as we elaborate in Section 4.

3   Institutional Background and Data

3.1   Regulation of Banks and Thrifts in the United States

A depository institution can choose between a bank or a thrift charter, and whether it is a federal or state charter. This choice determines their primary regulator. Federally-chartered banks are regulated by the Office of the Comptroller of the Currency (OCC). Federally-chartered thrifts were regulated by the Office of Thrift Supervision (OTS), until 2011 when it was closed and subsumed by the OCC. State-chartered banks and thrifts are regulated jointly by each state's chartering authority and by either the Federal Deposit Insurance Corporation (FDIC) or the federal reserve system (Fed). Moreover, the Fed supervises bank-holding companies and the FDIC has backup authority over all depository institutions.[13]

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[13]Blair and Kushmeider (2006) review the history and challenges of this "dual banking system." White (2011) describes the history of the user-fee system at the OCC and documents that some concerns about the incentives effects of the early version of the system were voiced as early as 1894.

We focus on the regulators of nationally chartered banks and thrifts—the OCC and the OTS. Unlike other federal banking regulators (Fed and FDIC), these agencies are almost entirely funded with assessment fees paid by the regulated banks and receive no appropriations from congress. Figure 1 shows the breakdown of revenues and costs of these agencies over time. On average, assessment fees account for 96 percent of the OCC's revenues. A small addition to its revenue comes from interest income on its accumulated savings from historical budget surpluses. The bulk of its supervisory costs, 67 percent on average, cover labor costs (personnel compensation and benefits). The data from OTS show similar patterns.[14]

3.2 Data

We collected a novel dataset of all fee schedules for OCC from 1985 to 2014, and for OTS from 1990 to 2012. A Notice of OCC or OTS Fees for each year is usually published towards December of the previous year, though in some years fees are kept constant, or change midyear. These regulatory bulletins specify semi-annual assessment fees due January 31 and July 31 based on call report information as of December 31 and June 30, respectively. Older bulletins were retrieved from the Westlaw legal research database and recent ones online.[15]

We merged this information with the Research Information System database maintained by the FDIC, which contains bank-level quarterly call/thrift reports for the entire period. Importantly, the FDIC records the identity of the primary regulator of each insured depository institution. Over our sample, on average, the OCC regulates 2,800 banks holding 50 percent of US bank assets. The OTS regulates 1,600 banks holding 15% of the assets. Our analysis omits, on average, about 7,000 state-chartered banks holding 35% of the market, because their fee structures are somewhat heterogeneous, increasing substantially the data collection and classification effort. Panel (a) of Table 1 presents summary statistics for our sample.

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[14]State-chartered depository institutions pay assessment fees to state regulators, which are often cheaper because a portion of the costs of the supervision are borne by the FDIC and Fed. The FDIC is funded by deposit insurance premiums, and the Fed is funded by interest earned on its securities holdings.

[15]Rescinded bulletins were accessed at http://www.occ.gov/news-issuances/bulletins/rescinded/occ-rescinded.html and http://www.occ.gov/news-issuances/bulletins/rescinded/ots-thrift-bulletins-rescinded.html.

3.2.1 Fee Schedules

An example fee schedule for OCC appears in Panel (b) of Table 1. Fees are a deterministic function of total balance-sheet assets of the regulated bank. Specifically, fees are a non-decreasing piece-wise linear function of bank size, with mostly decreasing slopes. This regressive fee schedule implies that the marginal cost of regulation per-dollar of assets decreases in bank size. Such a fee structure makes sense if, for example, the costs of regulating banks are increasing but concave in bank size. OTS fee schedules follow the same structure, but use different cutoffs and marginal rates. The summary statistics in Table 1 show that from a regulated bank's perspective, regulatory fees account for 1.3 percent of its noninterest expense, or 0.7 percent of its operating expense.

Our identification strategy exploits kinks in the regulatory fee functions. Panel (c) of Table 1 reports the average differences in the elasticity of fees to balance-sheet assets moving from the left to the right of each kink. The table shows that kinks 1, 3 and 9 (for the OCC) and kinks 1, 2, and 3 (for the OTS) have the largest slope changes. Our analysis pools information from all kinks in the fee functions of the OCC and OTS over the entire sample. Figure 2b shows that the average kink is substantial. A one percent increase in assets on the left of the average kink yields a 0.17 percentage point higher fees than on its right. Because the average elasticity on the left is 0.76, the first stage effect is a 22 percent decrease in elasticity. Note that in a sharp RKD setting as this one, the strength of the instrument is not an issue, as we know precisely the assets that assign banks to the sides of each kink.

Figure 2a shows that the values of the balance sheet assets at kinks, our "assignment variable," remain flat over our sample period. Both agencies keep kink points fixed in nominal terms and adjust schedules mostly by periodic indexing of fees at kink points to inflation.[16] As we discuss in Section 4.4, this is a particularly attractive feature as it ensures that the assignment of banks to treatment is not altered by regulators on an ongoing basis.

Fees also change with the regulatory assessment of a bank's risk and the structure of its holding company. The OCC and OTS include a surcharge for banks with high (bad)

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[16]In a representative example, the FY 2002 OCC notice of fees mentions that "marginal rates of the OCC's assessment schedule continue to be indexed to reflect inflation, as measured by the Gross Domestic Product Implicit Price Deflator (GDPIPD) for the previous June-to-June period."

CAMELS ratings (50 percent for 3-rated and 100 percent for 4- and 5-rated banks). The OCC also gives a 12 percent reduction in fees to non-lead banks belonging to a multiple national bank organization. These proportional fee changes do not affect our analysis, however, since they preserve both kink locations and fee elasticities.[17] Moreover, empirically, only very few banks may potentially get this special fee treatment: the mean OCC bank has a mean (median) CAMELS rating of 1.92 (2) (Gopalan, Kalda, and Manela, 2016), and only 8 percent of commercial banks have a rating of 3 and above (Falato and Scharfstein, 2016).

3.2.2 Outcome Measures

The theoretical model of Section 2 predicts a positive relationship between bank risk and regulatory fees. In practice, risk can be increased by holding riskier assets and by increasing financial leverage. Therefore, we examine risk measures from both sides of the balance sheet separately in our empirical work. We focus on a representative set of risk measures from the multitude of complementary economic and regulatory measures studied in the literature (e.g. Falato and Scharfstein, 2016).

The first set of risk measures are leverage ratios (assets over equity). A bank with a higher leverage is more risky in that it is more likely to default on its debt. Importantly, while there are rules that define minimum capital ratios, regulators have substantial leeway in determining appropriate capital ratios.[18] Consistent with the existence of such leeway, Agarwal, Lucca, Seru, and Trebbi (2014) find that state supervisors assign more lenient (lower) supervisory CAMELS rating to the same bank, even though the same laws and regulations apply. Gopalan, Kalda, and Manela (2016) document that bank examiners exert considerable discretion by assigning different capital adequacy ratings to banks with identical capital ratios, and by setting bank-specific minimum capital ratio plans, which are often significantly higher than minimum capital requirements set by law.

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[17]To see this, consider two banks of the same size q, a bank with good CAMELS rating that pays $f(q)$, and a high-CAMEL bank subject to a surcharge s, that pays $\tilde{f}(q) = (1+s) f(q)$. The size elasticity of fees for the safe bank is mechanically the same as that of the risky bank, $\tilde{f}'(q) \frac{q}{\tilde{f}(q)} = (1+s) f'(q) \frac{q}{(1+s)f(q)} = f'(q) \frac{q}{f(q)}$. Similarly, the change in elasticity around the kink point q_k is the same for both banks.

[18]The relevant rules state, "banks should maintain capital commensurate with the level and nature of risks, including the volume and severity of adversely classified assets, to which they are exposed" (12 CFR Part 325, Appendix B).

Following the literature, we measure financial leverage by core leverage and tier 1 risk-based leverage ratios. Both measures are the reciprocals of the corresponding regulatory capital ratios: core leverage is defined as balance sheet assets divided by tier 1 capital, and risk-based leverage is risk-based assets divided by tier 1 capital. Risk-based assets, introduced by regulators after the first Basel accord, are intended to adjust the regulatory capital ratios for the riskiness of the bank's assets. They are calculated by applying a weight to each asset of a particular risk group.[19]

We capture changes in asset risk with commonly-used measures of realized and expected loan losses. In addition, we capture the increase in asset risk indirectly through the difference between the effect of fees on risk-based and core leverage ratios.[20] The first measure of asset risk is the ratio of noncurrent loans to total loans, which captures the realized performance of assets. Noncurrent loans are over 90 days past due or not accruing interest. Our dynamic RKD methodology accommodates the fact that it takes time for the asset risk to become reflected in realized performance, and that this lag is not known a priori.

The second measure of asset risk is the ratio of loss reserves to total outstanding loans. According to accounting standards, loss reserves should reflect "imminent and probable losses," which means they increase with the riskiness of assets. Therefore regulatory leniency should lead to an increase in loss reserves. On the other hand, previous literature has documented that *conditional* on the riskiness of assets, supervisors often wish to increase loss reserves more than dictated by accounting rules, while banks wish to decrease them (see, e.g., Balla and Rose, 2011, for a review). Since we are interested in loss reserves as a measure of asset risk, we expect an increase in loss reserves if lenient regulation allows banks to take on riskier assets. If, as documented by previous literature, lax regulation also leads to smaller reserves than justified by the true asset risk, we may find delayed adjustments or even a negative short-term effect of fees on loss reserves. Our empirical approach allows us to

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[19]There are four major risk weights: 0%, 20%, 50%, and 100%. For example, cash gets a weight of zero, claims guaranteed by OECD governments 20%, residential mortgages 50%, and standard assets 100%. Off-balance-sheet items are converted into balance-sheet equivalents by multiplying their risk-weighted value by a conversion factor. Since risk-based capital ratios were not used in the first five years of our sample, unless otherwise noted, we use the period when both measures were available to make the analysis comparable across risk measures. Including the rest of the sample does not significantly change our results.

[20]Since the only difference between the core and risk-based leverage ratio is the risk-weighting of assets in the numerator, the differences in the measured effects have to be due to changes in the average risk weights.

reconcile these views by looking at contemporaneous and delayed effects of fees on reserves.

Bank regulators also take enforcement actions against banks, and impose monetary penalties. We use these actions as an additional measure of the outcomes of risk-taking. Figure 3 plots the fraction of banks under corrective actions imposed by OCC and OTS.[21] A striking pattern that emerges is the clustering of regulatory actions following banking crises. To take a closer look at this relationship, we add the fraction of failed/assisted banks—a frequently-used measure of ex post outcomes of risk-taking. Actions tend to follow spikes in bank failures, suggesting these variables are closely related. Corrective actions, however, occur much more frequently than failures. This makes them especially useful in our setting, since our methodology restricts the estimating sample to a small neighborhood around the kinks, making it hard to reliably estimate the probability of rare events. Echoing these facts, below we document a strong dynamic effect of fees on corrective actions: prior risk taking increases the probability that regulators take action against a bank during the crisis.

4   Nonparametric Regression Kink Design with Multiple Time-Varying Kinks and Dynamic Effects

We begin by describing the single-kink regression kink design (RKD). We then show how to apply RKD in our setting, which has two distinctive features. First, there are multiple kinks in the assessment fee schedules, and their location and magnitude vary over time and across regulators. Second, we adjust the estimation strategy for potential dynamic effects of regulation on the outcome variables. Our extension gives us more power to estimate the treatment effects, and highlights some pitfalls that could occur if one ignored cross-sectional or time-series heterogeneity in kink slopes.

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[21]Our definition of "corrective actions" includes prompt corrective actions, cease and desist orders, safety and soundness orders, decision/opinion orders, capital directives, securities enforcement actions, and formal supervisory agreements. Monetary penalties and personal actions are not included in this definition. Proceeds from monetary penalties are deposited into the Treasury general fund. See 12 U.S.C. 1818(i)(2) and 12 U.S.C. 1467a(i)(2).

4.1 RKD with a Single Kink

Our identification strategy uses kinks in the fee function as a source of exogenous variation in fees to identify their treatment effect on risk. Importantly, the estimates reflect the effects of higher fees on the dependent variable and not the effects of the kinks themselves.

We build on a nonparametric identification framework of Card, Lee, Pei, and Weber (2015), which allows non-separability of the error term, and for nonlinear effects of firm size. We do so because even in our simplified model, the effects of higher size q on risk x are potentially nonlinear. Moreover, this specification allows for unobservables to enter the risk equation in a flexible way.

Card, Lee, Pei, and Weber (2015) study a general single kink model, specifying that for each observation i, the outcome y_i conditional on the regressor of interest $b(v_i)$, the assignment variable v_i, and an unobservable shock ε_i

$$y_i = y\left(b\left(v_i\right), v_i, \varepsilon_i\right),$$

where the outcome can be a non-separable function of $b(v)$, v, and ε. The key identifying assumption is that a kink in the function $b(v)$ around a kink point k is the only source of discontinuity. That is, the response function $y(b, v, \epsilon)$ is continuous and partially differentiable with respect to its first and second arguments, and these partial derivatives are both continuous around k. In our setting, this means that in a close neighborhood around the kink, there are no kinks in the *direct* effect of size and fees on risk. Additionally, the estimator requires a "smooth density assumption," i.e., the density of v conditional on ε is continuously differentiable in v for all v and ε. That is, the assignment variable v (bank size in our case) cannot have kinks that coincide with the kinks in the fee function. Under these assumptions, the treatment-on-the-treated (TOT) parameter takes the following form:

$$\beta^{\text{TOT}} = \frac{\lim_{v_0 \downarrow k^+} \frac{dE[y|v]}{dv}\big|_{v=v_0} - \lim_{v_0 \uparrow k^-} \frac{dE[y|v]}{dv}\big|_{v=v_0}}{\lim_{v_0 \downarrow k^+} b'(v_0) - \lim_{v_0 \uparrow k^-} b'(v_0)}. \tag{19}$$

In our setting, (19) says that the effect of fees $b(v_i)$ on risk y (e.g., leverage ratio) is identified from the discontinuous change in the slope of mean risk $E[y|v]$ as a function of

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bank size v. In other words, the treatment effect is identified when the kink in the relationship between size and leverage coincides with the kink in the fee schedule. Under the "exclusion restriction" that the direct effects of size and fees on risk are locally smooth, such a kink in observed risk as a function of size would arise only because of the kink in the fee function and because fees directly affect bank risk.

To estimate (19), Card, Lee, Pei, and Weber (2015) suggest a local polynomial regression:

$$y_i = \sum_{p=1}^{P} \beta_p \left(v_i - k\right)^p D\left(v_i > k\right) + \sum_{p=0}^{P} \alpha_p \left(v_i - k\right)^p + \varepsilon_i. \tag{20}$$

In our case, $(v - k)$ represents the distance of a bank from the kink (the forcing variable is centered around the kink), $D\left(v_i > k\right)$ is a dummy variable that gets a value of one if an observation is to the right of the kink, and p correspond to a polynomial degree. P polynomial terms in $\sum_{p=0}^{P} \alpha_p \left(v_i - k\right)^p$ absorb any smooth effect of v on the outcome, while the terms in $\sum_{p=1}^{P} \beta_p \left(v_i - k\right)^p D\left(v_i > k\right)$ identify the incremental effect of fees. The observations are weighted by a kernel $K\left(\frac{v-k}{h}\right)$ over a bandwidth h, giving relatively more weight to observations closer to the kink.

To gain a better intuition, it may be helpful to compare this estimator to two-stage least squares. Intuitively, $\hat{\beta}_1$ represents the "reduced form"—the effect of size on risk. To recover the treatment effect of fees, however, we need to account for the effect of size on fees (the "first stage"). Here, the "first stage" is the deterministic change in slopes of the fee function at the kink: $\Delta \equiv b'\left(k^+\right) - b'\left(k^-\right)$. So the treatment-on-treated is captured by:

$$\hat{\beta}^{\text{TOT}} \equiv E\left[\frac{\partial y\left(b, k, \varepsilon\right)}{\partial b}\right] = \frac{\hat{\beta}_1}{\Delta}. \tag{21}$$

Note that if the treatment-on-treated—the effect of fees on risk—is positive, we should see a negative coefficient $\hat{\beta}_1$ because $\Delta < 0$.

4.2 RKD With Multiple Time-Varying Kinks

In many applications of RKD, the kinked function $b\left(v\right)$ is not constant. In our setting, while the fee schedules are deterministic and known for each observation, they change over time and

across regulators. In addition, there are multiple kinks in each regulator's fee function, which allow us to estimate the treatment effect using firms across the size distribution. Another important advantage is that this feature increases statistical power—a common problem with discontinuity designs—by pooling observations across kinks. In order to do this, however, the basic RKD methodology needs to be adjusted to account for the heterogeneity across kinks. As we show in Section 6.3, ignoring such heterogeneity, may lead to severe misspecification and biased estimates.[22]

We therefore extend the single-kink specification (20) to allow for multiple kinks:

$$y_{ij} = \sum_{p=1}^{P} \beta_p \Delta_j^p \left(v_{ij} - k_j\right)^p D\left(v_{ij} > k_j\right) + \sum_{p=0}^{P} \alpha_{jp} \left(v_{ij} - k_j\right)^p + \varepsilon_{ij}, \tag{22}$$

where j indexes observations in the neighborhood of the same kink j of a unique regulatory fee schedule. Since bank regulatory fee schedules change about once a year and differ across regulators, observations with the same j subscript have the same regulator, and roughly the same year and size. The model assumes a constant treatment effect but properly allows the controlling polynomial coefficients α_{jp} to vary across kinks. Intuitively, a P-th order Taylor expansion around each kink k_j involves different coefficients for every kink j. Moreover, we include $\Delta_j \equiv b'\left(k_j^+\right) - b'\left(k_j^-\right)$ in the "instrument" and recover the treatment-on-treated effect directly as $\hat{\beta}^{\text{TOT}} = \hat{\beta}_1$.

Finally, several practical considerations arise with respect to the choices of bandwidth, polynomial degree, and kernel. As a starting point, we follow the recommendations of Card, Lee, Pei, and Weber (2015) and Calonico, Cattaneo, and Titiunik (2014). Owing to the large size of our dataset, we are able to use a tight bandwidth around the kink and experiment with different choices to ensure that our estimates are not driven by bandwidth choice. In our empirical application and simulations, we find that controlling for nonlinearities with a local quadratic estimator is more important at larger bandwidths. After adjusting for nonlinearities, however, larger bandwidths provide similar results. Conversely, the required bandwidth increases proportionally with polynomial order due to a larger number of param-

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[22]The problem is similar to what happens when the true model depends on real dollar values, but the econometrician uses nominal explanatory variables unadjusted for inflation. A trend in inflation can overwhelm the true effect and lead one to draw the opposite conclusions from the data.

eters. Similar to Card et al. (2015), we find that at lower bandwidths, quadratic (or higher order) estimators result in a significant loss in precision and often implausible magnitudes. Therefore, our preferred specification is a local linear regression with a 0.1 bandwidth.[23]

4.3 RKD with Dynamic Effects

Fees may have dynamic or delayed effects on the outcomes of regulation for two reasons. First, outcomes may respond slowly to regulatory intensity. This is most relevant for long-term outcomes (e.g., noncurrent loans and regulatory actions) and variables prone to delayed reporting and adjustment (e.g., loss reserves). Intuitively, while financial leverage may adjust quickly to reflect regulatory leniency, it takes time for asset risk to become detectable in noncurrent loans (if only because these are loans that are over 90 days past due), and loss reserves may adjust over time to reflect new information about assets. Similarly, it may take a considerable amount of time for prior risk-taking to generate result in a corrective enforcement action. Therefore, fees may affect these variables with lags.

Second, potential sources of autocorrelation in fees and risk could complicate the interpretation of the simple static estimator. For example, fees may affect the treatment assignment of a bank *in future periods*. This could happen if lax regulation affects the future size of the bank by allowing riskier behavior.

To address these issues, we follow Cellini, Ferreira, and Rothstein (2010), who extend the regression discontinuity design (RD) and show how to identify both intent-to-treat (ITT) and treatment-on-treated (TOT) effects in a dynamic setting.[24] The ITT is the *total effect* of exogenous variation in fees on outcomes over multiple quarters. This effect is comprised of the direct treatment effect of the lagged fee on current outcomes (bank risk), and the indirect effect of the lagged fee through its impact on the assignment of the banks to treatments in the interim periods (e.g. bank risk leads to larger future size and fees). It is called "intent

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[23]Card et al. (2015) provide a detailed discussion of these issues and advocate choosing an estimator based on simulations that approximate the data generating process, or the asymptotic mean squared error criterion. The bandwidth of 0.1 is smaller than suggested by Calonico et al. (2014) for our data. We also report the results for a bandwidth of 0.2 and a local quadratic estimator. Finally, like Card et al. (2015) we use a uniform kernel. A triangular kernel produces similar estimates.

[24]While Cellini, Ferreira, and Rothstein (2010) study RD and not RKD, the relevant features of their approach are directly applicable in our setting.

to treat", because while treatment is guaranteed contemporaneously, it is not guaranteed to induce future treatment. The ITT effect of the τ-th lag on the outcome at time t is

$$\beta_\tau^{\text{ITT}} \equiv \frac{\partial y_{ijt}}{\partial b_{ijt-\tau}} + \sum_{s=1}^{\tau} \left(\frac{\partial y_{ijt}}{\partial b_{ijt-\tau+s}} \times \frac{\mathrm{d}b_{ijt-\tau+s}}{\mathrm{d}b_{ijt-\tau}} \right) = \beta_\tau^{\text{TOT}} + \sum_{s=1}^{\tau} \beta_{\tau-s}^{\text{TOT}} \pi_s, \tag{23}$$

where π_s is the effect of past treatment $b_{ijt-\tau}$ on future treatment $b_{ijt-\tau+s}$.

Following Cellini, Ferreira, and Rothstein (2010), we use our discontinuity approach to recover the total effect of fees at time t on current and future periods. Intuitively, we get a number of overlapping estimates for each quarter because the regression estimates a separate effect of fees at each lag. Simultaneously, we estimate the autocorrelation in fees π. Then, Equation (23) can be used to recursively extract τ-specific TOT estimates:

$$\beta_\tau^{\text{TOT}} = \beta_\tau^{\text{ITT}} - \sum_{s=1}^{\tau} \beta_{\tau-s}^{\text{TOT}} \pi_s, \tag{24}$$

which is the treatment effect of fees at a given lag τ, but purged from the indirect effect of future treatment. The contemporaneous effect is simply the $\tau = 0$ special case.

Specifically, the estimation is done in two steps. First, we jointly estimate β_τ^{ITT} and π_τ:

$$y_{ijt+\tau} = \sum_{p=1}^{P} \beta_{p\tau} z_{ijt}^p D_{ijt} + \sum_{p=0}^{P} \alpha_{jp\tau} (v_{ijt} - k_{jt})^p + \theta_\tau + \psi_t + \varepsilon_{ijt+\tau}, \tag{25}$$

$$z_{ijt+\tau} D_{ijt+\tau} = \sum_{p=1}^{P} \pi_{p\tau} z_{ijt}^p D_{ijt} + \sum_{p=0}^{P} \tilde{\alpha}_{jp\tau} (v_{ijt} - k_{jt})^p + \tilde{\theta}_\tau + \tilde{\psi}_t + \tilde{\varepsilon}_{ijt+\tau}, \tag{26}$$

where $y_{ijt+\tau}$ is an outcome variable at time $t + \tau$ of an observation in the neighborhood of kink j at time t, $z_{ijt} \equiv \Delta_j (v_{ijt} - k_{jt})$ is the slope-change-adjusted distance from the kink, D_{ijt} is a shorthand for $D(v_{ijt} > k_{jt})$—an indicator of the position of the bank relative to the kink at time t, θ_τ is a fixed effect for the number of quarters relative to t, and ψ_t is a year fixed effect. All coefficients, including those on the controlling polynomial are τ-specific.

Intuitively, regression (25) estimates the total effect of time τ treatment on time $t+\tau$ bank outcomes ($\beta_\tau^{\text{ITT}} = \beta_{1\tau}$), while (26) estimates its effect on time $t + \tau$ treatment ($\pi_\tau = \pi_{1\tau}$). In the second step, we use these ITT estimates and their covariance matrix estimated via Equations (25) and (26) to recover β_τ^{TOT} for each lag τ via Equation (24). Standard errors

for these estimates are computed using the delta method.[25]

4.4 Potential Threats to Identification

Two potential concerns that may arise in our setting are systematic sorting of banks around the kinks and endogenous manipulation of the fee schedules by regulators.

Systematic sorting would occur if banks could perfectly position themselves at a particular side of the kink, which would invalidate the smooth density assumption. Banks are unlikely, however, to have perfect control over their end-of-period assets, which are largely funded with demandable debt. Moreover, in our setting, such sorting is less plausible than in a more common RD application, simply because fees are continuous at the kink, which lessens the bank's incentive to sort. Absent a level discontinuity, there is essentially no gain to a bank from *positioning* itself just to the right of a kink as opposed to just to its left ($\lim_{v_0 \downarrow k^+} E\left[y|v\right]|_{v=v_0} = \lim_{v_0 \uparrow k^-} E\left[y|v\right]|_{v=v_0}$). The change in slope we rely on, instead, means that the gain to the bank from *increasing* its size is different on the two sides of the kink ($\lim_{v_0 \downarrow k^+} \frac{dE[y|v]}{dv}|_{v=v_0} \neq \lim_{v_0 \uparrow k^-} \frac{dE[y|v]}{dv}|_{v=v_0}$). This is not to say that the kink generates no incentive to sort, just that it is likely weaker than in the RD case.

Smooth density is a key identifying assumption for the RKD, and it is therefore important to verify that it is not compromised in our data. We follow McCrary (2008), which provides a smooth density test for the RD, and adapt this test for an RKD setting with multiple time-varying kinks. This amounts to testing for a kink in the histogram of the assignment variable using a local polynomial regression similar to the one used to estimate our main effect, which explains the height of the bins using the bin midpoints. This test, described in detail in Appendix A.3, fails to reject the smooth density hypothesis in our data.

Endogenous fee-setting would pose a problem for identification if regulators could manipulate the assignment variable in a way that was correlated with (or depended on) unobserved determinants of risk-taking. In practice, this is not a significant concern, since regulators keep kink points fixed in nominal terms (Figure 2a). As discussed in Section 3, most adjust-

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[25]In all our specifications, standard errors are adjusted for two-way clustering at the year and bank levels, which, in this case also accounts for the fact that each bank-quarter observation (i, t) may be used multiple times.

ments to the schedules are periodic inflation adjustments of the level of fees at kink points, and do not violate the identification conditions (Card, Lee, Pei, and Weber, 2015).

5   Results

We start with a graphical presentation of our regression kink design in leverage ratios. As we show below, leverage ratios respond to contemporaneous fees, which makes it easy to see the effect of the fees in the raw data. Next we present the results of static RKD estimation. Finally, we examine a dynamic RKD model, which allows us to study delayed outcomes such as loan loss reserves, loan defaults, and enforcement actions.

5.1   Discontinuity Plots: Kinks in the Outcome Data

Figure 4 shows that risk-taking, as measured by leverage ratios exhibits kinks that coincide with kinks in the fee schedules. This pattern supports the prediction that higher fees increase risk-taking. The figures capture the reduced form effect—the effect of size on leverage around the kink. This effect is expected to be *negative* if higher fees lead to higher leverage. As we show in Equation (21), a negative reduced form ($\hat{\beta}_1$) corresponds to a positive treatment effect of fees since the first stage (Δ) is negative (the slope on the right side of the kink is lower than the slope on the left side).[26]

To reduce the noise from multiple time-varying kinks at different points in the size distribution, we adjust the raw data for kink-year fixed effects, and plot the residuals from this regression against distance from the kink. This allows showing both the average change in the slopes and the average relationship between risk and size. The plots are robust to the choice of bandwidth and polynomial degree.[27]

Because our estimates rely on changes in slopes, the figures may be less intuitive than the plots commonly reported in regression discontinuity studies. To see the intuition, consider

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[26]There is no statistically-significant discontinuity in levels at the kink point (see Appendix A.1).

[27]The bandwidth in Figure 4 is the same as the one used in our benchmark RKD tests. In Figure A.1, we plot the data over the longest possible bandwidth (0.3 log-points on each side of the kink). Those plots show a strong positive correlation between size and leverage, as expected in banking data (see, e.g., Kisin and Manela, 2016), and a clear discontinuity in the slopes at the kink.

the data generating process in Equation (20) and ignore multiple kinks and higher-order polynomials. The slopes to the left and to the right of the kink are α_1 and $\alpha_1 + \beta^{\text{TOT}}\Delta$, respectively. We know that the size elasticity of fees is negative ($\Delta < 0$), because the slope of the fee schedule is decreasing. Therefore, if the treatment effect is positive ($\beta^{\text{TOT}} > 0$), the slope to the right will be smaller than the slope to the left. In other words, our model predicts that leverage would increase faster in size to the left of the kink than to its right.[28]

Interestingly, the change in the slope is more pronounced for the risk-based leverage ratio. This stronger effect reflects an increase in the riskiness of assets in addition to the change in financial leverage, because the difference between the two leverage ratios is entirely due to risk-weighting. In other words, banks increase leverage and take on riskier assets. We confirm the latter conclusion with evidence from loss reserves and long term asset performance in the dynamic regressions below.

Finally, it is worth mentioning that in unreported tests we find no graphical evidence for contemporaneous effect of fees on noncurrent loans and regulatory actions, and find weak evidence for loan loss reserves. This is consistent with the evidence in Section 5.4, where we find delayed effects of fees on these variables. As we show below, loss reserves exhibit both contemporaneous and delayed effects, consistent with the intuition that banks partially adjust loss reserves when they take on risky assets and adjust them again when these assets start showing signs of higher default probabilities.

5.2   Static Regression Kink Design Estimates

Table 2 reports the estimated elasticities of bank risk to regulatory fees, $\hat{\beta}_1$, from the static RKD model in Equation (22) for two leverage ratios, and loan loss reserves. Loan loss reserves is the only measure of asset risk examined in this section, because, in principle, it should adjust contemporaneously to reflect expectations of future losses from risky assets.[29]

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[28]In these reduced form figures, the prediction is that the slope to the right of the kink is smaller than the slope to its left. In Figure A.1 we show that the residuals after controlling for polynomials in size exhibit a pronounced change in the sign of the slope at the kink point, which is consistent with a positive treatment effect of fees on risk.

[29]We defer the analysis of loan performance and regulatory actions to Section 5.4. As discussed in Section 4.3, the static framework is not well-suited for slow-adjusting variables, and the dynamic model results include the static estimator as a special case. We also omit the results on the total risk-based leverage, which are almost identical to the tier 1 risk-based ratio in all specifications.

We find statistically and quantitatively significant positive effects of fees on all three measures of risk. To help interpret the results, we report the magnitudes of the estimated effects (the effect of a one percent increase in fees on the level of the dependent variable), as well as the means of fees and the outcome variables in the estimation samples. The effects are quite large: a one percent increase in fees increases the core leverage ratio by two percent, or approximately 0.24 and the tier 1 risk-based leverage ratio by 0.18. Increasing the estimation bandwidth and the polynomial degree does not substantially change our inferences, but results in larger magnitudes.

Turning to the asset risk results (columns (5)-(6)) of Table 2, we find that a 1 percent increase in regulatory fees increases loan loss reserves ratio by around 3 percent. It appears that higher loss reserves are driven by higher expected losses from riskier loans—an indirect consequence of softer regulation. In other words, lax regulation allows banks to invest in riskier assets, which is, at least partially, reflected in this measure of risk. In line with the evidence in Figure 4, this effect is not as pronounced as the effect of fees on leverage. As discussed above, however, information about assets may take time to get incorporated in loss reserves. Moreover, as documented by previous literature, banks may avoid increasing reserves to fully reflect the new asset risk, especially under lax regulation. Therefore, we revisit the dynamics of this risk measure in Section 5.4.

5.3   A Closer Look at Economic Magnitudes and the Mechanism

Table 2 shows sizable effects of fees on bank risk-taking. For the mean bank in the sample, the results imply that banks that pay a 1 percent higher fee are allowed to increases their core leverage from 11.7 to 12, and the tier 1 risk-based leverage from 7.1 to 7.28. This is comparable to issuing additional debt equal to 1.7% of balance sheet assets (or 2.8% of risk-based assets).

One may still wonder, why an organization like the OCC, with roughly $1 billion in annual fee revenues, would respond to relatively modest increases in fees? To answer this question, we take a closer look at the way the agencies operate, and use this information to motivate empirical tests of the economic mechanisms that may shed more light on the magnitudes of the effects. Econometrically, this means introducing heterogeneity in the treatment effect

along dimensions suggested by the institutional details and the theoretical model.

5.3.1 Supervision is Done at the Local Level

Much of the apparent puzzle regarding the magnitudes of the fee effect is resolved once we note that most of the supervisory work is done locally at the level of a field office, which has substantial decision-making authority and whose budget is determined by banks under its supervision. In particular, at the OCC much of the supervision of midsize and small banks is delegated to local field offices (around 70 in number, depending on the time period), and the OTS has a similar setup.[30] Therefore, the appropriate benchmark for the variation in fees is the budget of a local supervisory entity, as opposed to the agency as a whole. The fee revenues of the mean OCC field office are about $8 million a year (Gopalan, Kalda, and Manela, 2016), which significantly increases the potential importance of individual bank fees.

This observation suggests that the effects should be more pronounced in the subsample of small/mid-sized banks, because field offices are more likely to pay heed to fees, and their discretion is limited primarily to small/mid-size banks. We examine this hypothesis in Panel (a) of Table 3. We find that the effects of fees on leverage ratios and loss reserves are most pronounced in this sub-population of banks, both in terms of the economic magnitudes and in terms of the statistical significance.

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[30]Consider, for example, the quote from the OCC: "*We have built the supervision of community banks around local field offices where local Assistant Deputy Comptroller (ADC) has responsibility for the supervision of a portfolio of community banks.[...] We give our ADCs considerable decision-making authority, [...] and we expect them to make most supervisory decisions locally.*" (Testimony of Toney Bland, Senior Deputy Comptroller for Midsize and Community Bank Supervision, OCC, before the Subcommittee on Financial Institutions and Consumer Credit, House Committee on Financial Services US House of Representatives. See also "OCC Announces District Office Restructuring to Meet Challenges of the Future", September 25, 2002, which quotes the then Comptroller, stating that "*National bankers told us in interviews that they almost always contact their local field office, rather than the District Office, when they have a question or an issue, [...] The strong relationship between our banks and the local ADC or examiner-in-charge is a hallmark of the national banking system and it will not change.*" At the OTS, deputy directors and assistant regional directors, as opposed to the central office, are in charge of specific areas of regional operations including examinations. Assistant regional directors who oversee examinations, in turn, monitor groups of field managers, who are responsible for a caseload of financial institutions. Field examiners report directly to a field manager. See Statement of John M. Reich, Director Office of Thrift Supervision Oversight Hearing on the Office of Thrift Supervision before the Subcommittee on Oversight and Investigations of the Committee on Financial Services US House of Representatives, May 25, 2006. Empirically, Gopalan, Kalda, and Manela (2016) document that following the closure of OCC field offices, the banks they previously supervised distribute cash, increase leverage, and increase their risk of failure, more than similar banks in the same time and place, which suggests that field level interaction is an important part of regulation.

5.3.2 Inter-agency Heterogeneity

Given the turbulent history of the OTS (both in its recent form and as the Federal Home Loan Bank Board), it is not surprising that this organization was often considered less competent than other regulatory institutions, until it was finally terminated and subsumed by the OCC. Therefore, from a policy perspective, it is important to examine whether our results are artifacts of some particular failings of the OTS model.

The results in Panel (b) of Table 3 do not support the hypothesis that the effect of fees is special to the OTS. The effect on the core leverage ratio in the OTS is of a similar magnitude, but statistically weaker than the result for the OCC. The effect of tier 1 risk-based leverage is stronger in OTS, and the effects on the loss reserves are both indistinguishable from zero, but none of the differences are statistically significant.

5.3.3 Competition Over Banks And Bank Bargaining Power

As mentioned, US banks can choose their regulator by selecting a charter, which could result in competition among regulators (Rosen, 2003; Calomiris, 2006), thereby potentially exacerbating the effects of fees.

Two recent contributions related to the multi-charter system that are most closely related to our analysis are Agarwal, Lucca, Seru, and Trebbi (2014) and Rezende (2014). Rezende documents that banks with a higher ratio of fees to assets are more likely to switch charters. This approach does not directly rely on kinks for identification, as it retains variation in fees due to differences across regulators, time, and bank size. The advantage of this approach is that it allows using more data, which may be necessary for the estimation of a discrete choice model of charter switching, especially since switches are rare. In our setting, however, it is crucial to include kink-by-regulator-specific controlling polynomials and fixed effects, to remove all size effects and persistent differences across fee schedules, regulators and banks that select them. Not surprisingly, we do not find a significant local effect of fees on the probability of switching, which is consistent with Agarwal, Lucca, Seru, and Trebbi who find that bank and time effects effectively deal with the issue of charter shopping. While in general this is an attractive feature of our approach, it makes it harder to see whether

competition magnifies the effects of fees.

Therefore, to examine the importance of regulatory competition, we take a different approach by noting that competition increases the effective bargaining power of banks. Specifically, according to Corollary 1, a higher outside option for the firm may exacerbate the effects of fees. This implies that we should see magnified effects of fees in banks that are attractive to regulators for competitive reasons. In our data one such bank characteristic is the composition of the bank's holding company. We conjecture that banks' bargaining power may improve if the way they are treated by their regulator affects the charter choices of other banks in their holding companies.

We test this hypothesis in Panel (c) of Table 3.[31] In the first three columns, we show the results of splitting the data by banks from single- and multi-bank holding companies and standalone banks. All three groups show a similar effect of fees on the core ratio. The fact that fees have a significant impact in banks that belong to holding companies is interesting in its own right, because holding companies are supervised by the Federal Reserve, providing an additional layer of supervision. In columns (3)-(6) we focus on multi-bank holding companies, and find that the effect of fees on leverage is most pronounced in banks whose peers within a holding company are regulated by different regulators, especially when a lead bank in the company is not regulated by the OCC. We conclude that regulatory competition is likely to have magnified the effect of fees. This finding also explains the economic magnitudes of the estimates—the impact of small differences in fees is magnified by regulatory competition.

5.3.4   How Valuable is Leniency for Banks?

Another way to gauge the economic magnitudes of our estimates is to compare banks' willingness to pay for the implied increases in risk against the corresponding changes in fees. Intuitively, the estimated effect of fees on risk is large if banks are willing to pay much more than an increase in fees would achieve.

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[31]This panel uses the OCC data, since we do not have a reliable thrift holding company identifier for OTS, and very few OTS banks belonged to bank holding companies. To preserve space, we only present the results for the core leverage ratio, which also has the advantage of an increased sample size (risk-based ratios were not used in the first five years of our sample). Because of the smaller sample size, the optimal bandwidth in this panel is 0.2 and we use a quadratic local polynomial. The results for other leverage ratios are similar for the splits in columns (1)-(3), and have higher standard errors in columns (4)-(6), where sample size becomes more of an issue.

The estimates from Kisin and Manela (2016) can be used to perform such a back-of-the-envelope calculation. Kisin and Manela use a regulatory loophole to estimate that the annualized shadow cost of bank capital requirements for the largest US banks is 0.0025 for the core leverage ratio per dollar of assets. From Table 1, the median treated bank in our setting has $148 million in assets, which implies it would be willing to pay $3,693 ($= 0.0025 \times 147,700,000 \times 0.01$) a year, to reduce its regulatory capital ratio by one percentage point, or equivalently, to increase its leverage by 12.7% (from 11.3 to 12.7). Our estimate of the core leverage fee elasticity implies that for a median bank such an increase in leverage could be achieved by increasing its annual regulatory fees by about 6.2% ($= 12.7\%/2.069$), or $3,325 for the median bank.[32] Therefore, by paying higher fees banks spend roughly their willingness to pay for the increase in leverage. The magnitudes of these costs and benefits are quite similar, which implies that the magnitude of the corresponding effect on risk is economically reasonable.

5.4 Dynamics of Leverage, Asset Risk and Regulatory Actions

In Table 4 we present intent-to-treat and treatment-on-treated estimates from the dynamic RKD model of Section 4.3 for 12 lags ($\tau = 0 \ldots 11$).[33] Figures 5 and 6 show these results graphically. As shown in Equation (23), ITT measures the effect of a contemporaneous exogenous variation in fees τ quarters later, without controlling for fees in the interim periods. The TOT, on the other hand, isolates the impact of each τ'th lag.

Columns (1)-(6) show the results for potentially slow-moving variables, such as loss reserves, noncurrent loans, and regulatory actions. Loss reserves, as we have already seen in Table 2, show some contemporaneous adjustment. Banks continue adjusting loss reserves in the next quarter. Interestingly, there is an additional adjustment of the reserves 5–6 quarters later—by about a third of the initial effect—presumably when more information about the

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[32]Medians are more relevant for our estimates, which mostly come from small/mid-size banks, though means yield similar conclusions. The mean bank in our sample would be willing to pay $51,193 ($= 0.0025 \times 2,047,700,000 \times 0.01$) to increase its core leverage by 13.3%, and could achieve this by increasing its regulatory fees by about 6.4% ($14,730). One caveat for these back-of-the-envelope calculations is that the banks' willingness to pay for higher leverage may be different for the large banks studied in Kisin and Manela (2016).

[33]In our empirical specification we allowed for a full set of possible lags for each bank. We report the first 12 lags in the table and 16 in the figures to simplify the exposition.

assets becomes available. This timing coincides with the changes in the noncurrent loans ratio (columns (3)-(4)). As expected, noncurrent loans do not respond to the variation in fees immediately, as it takes time for the assets to stop performing, but it increases sharply 5–6 quarters after the exogenous increase in fees.

Columns (5)-(6) present the results for regulatory enforcement actions. Again, there is no contemporaneous effect, but we see a sharp increase in actions two quarters after the increase in fees. That is, banks that pay higher fees are allowed to take more risks, which results in a higher probability of regulatory actions in the future.[34]

Next we turn to leverage ratios (columns (7)-(10) of Table 4 and Figure 6). The strong contemporaneous response to fees that we saw in the static setting (Table 2), can be seen here again in the first line for each specification ($\tau = 0$). Contrary to the slow-adjusting variables in columns (1)-(6), however, the effect on leverage diminishes rapidly over time. The TOT elasticity drops from 2 to 0.45 for the core leverage within the first quarter, and disappears completely after two quarters. Tier 1 risk-based ratio (column (10)) shows a similar drop in the estimated fee elasticity, which goes to zero within a quarter. It appears that banks respond to lax regulation immediately by increasing financial leverage and the riskiness of assets, which carry long-term future consequences.

6   Robustness

6.1   Bandwidth Sensitivity

A common feature of local polynomial regression is that the choice of bandwidth is important. We investigate the sensitivity of our estimates to this choice by gradually shrinking the bandwidth from 0.3 down to 0.05 fixing the polynomial degree at either 1 or 2. Figure 7 shows that point estimates of the elasticity of leverage ratios to fees increase in magnitude and mostly remain significant as we shrink the bandwidth. Of course, in the limit as the bandwidth shrinks to zero, no observations are left and the confidence interval blows up.

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[34]In unreported tests we find no statistically significant effect on bank failure rates, which are both rare and clustered around banking crises. By contrast, closely-related enforcement actions, which tend to follow both failures and near failures (Figure 3), are more frequent and therefore provide a more powerful test of the leniency-for-fees channel.

Similarly, the estimated effect of fees on loan loss reserves is robust and remains significant as we shrink the bandwidth. As discussed in Section 4.2, the estimates from the local quadratic polynomial specification become too noisy at smaller bandwidth because the additional parameters that need to be estimated require more data. Also, consistent with the results in Table 2, the effect on loan loss reserves is only marginally statistically significant in this static specification.

6.2 Placebo Tests

We investigate whether our results are spurious by using round-numbered kink points that are of the same magnitude but different from the true kinks, while retaining the slopes of the true fee schedules. This procedure uses "fake kinks" where no kink is known to exist. If our methodology is biased toward rejecting the null, we would expect the placebo tests to identify significant treatment effects. We pick round-numbered kink points because regulators may respond differently to banks that cross such round number thresholds.[35]

Placebo test results using leverage ratios and loan loss reserve ratios as dependent variables are reported in Table 5. As expected, none of the effects is statistically significant at the 5 percent level. The only marginally significant result for loss reserves with a linear specification loses significance when moving to a quadratic polynomial. We also find no significant placebo effects in alternative tests (unreported), where we create placebo kink points by shifting all kink points from k_j to $k_j + 0.1$.

6.3 Monte Carlo Simulations

Another way to test whether a particular choice of empirical specification (e.g., bandwidth and polynomial degrees) is likely to bias the RKD estimates, is by Monte Carlo simulation. We simulate the dependent variable as $\log y_i = 8 + \beta_0^{TOT} \times \log Fees_i - 0.7 \times \log Assets_i + 0.1 \times (\log Assets_i)^2 + w_i$. We generate random samples of similar size as our real sample, by sampling from the assets and kinks distribution and drawing independent shocks (w_i) from the distribution of residuals from a preliminary OLS regression of log leverage ratios on log

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[35]We thank a referee for this suggestion. In a previous version of the paper we generated placebo kink points by shifting all kinks by 0.1.

fees and log assets. We then apply the exact same multiple kink regression specification as before.

The simulations show that our empirical implementation of the RKD method is well-suited for our data. Table 6 shows that when the true effect is zero, the mean estimates reported in Panel (a) are zero as well. Moreover, Panel (b) shows that, as expected, a test with $p = 0.05$ significance falsely rejects the null in a 0.04 to 0.08 fraction of the simulated samples. Panels (c) and (d) repeat the exercise, but this time when the true effect is 2, roughly corresponding to our leverage ratio effects. The mean estimates and the rejection rates are about right when we use a $P = 1$ degree polynomial with a $h = 0.1$ bandwidth, but this bandwidth provides insufficient power to reject the false null with a higher degree polynomial. The additional parameters require a wider bandwidth to achieve a reasonable rejection rate.

6.3.1 The Importance of Adjusting for Multiple and Time-varying Kinks

In Section 4, we extended the local polynomial regression specification of Card, Lee, Pei, and Weber (2015) to include regulator-time, and kink-specific controlling polynomials. As we discussed, this allows us to increase statistical power, provided that the estimating equations are properly adjusted to account for the heterogeneity across kinks. In this section, we study the importance of this adjustment and show that a failure to account for kink heterogeneity would result in severely biased estimates, and false rejections of the null hypothesis.

Table 7 shows the results of an estimation that does not properly account for heterogeneity across kinks. The simulated samples are identical to those of Table 6, but pool all kinks without properly allowing for kink-specific controlling polynomials as we advocate in Section 4. Panels (a) and (b) show that even when the true effect is zero, this specification essentially always rejects the null regardless of the polynomial degree or bandwidth. Panels (c) and (d) show that when the true effect is positive 2, single-kink RKD estimates are significantly negative.

7 Conclusion

We provide the first causal evidence that funding of regulatory agencies affects the implementation of regulatory policies. In many sectors regulation is funded by regulated firms. We show how variation in user-fees can be used to study regulatory incentives and the effects of incentives on regulatory outcomes. Using a simple model where stricter regulation reduces regulators' income by pushing firms to forgo projects, scale down, or shift activity to the unregulated sector, we show that firms that pay higher fees face more lenient regulation. Intuitively, higher fee income alleviates the negative effect of higher risk.

Empirical tests of this channel face significant identification challenges, which we address using kinks in the fee schedules of federal banking regulators. We find strong evidence that banks that pay higher fees get more lenient regulatory treatment. Higher fees increase bank leverage and the riskiness of assets. Moreover, banks that pay higher fees are more likely to experience future enforcement actions and loan defaults. We conclude that regulators have the ability to regulate firm behavior, but financial incentives of regulatory agencies matter for the implementation of regulation. Our findings imply that this issue should be taken into account in an effective regulatory design.

The "leniency-for-fees" channel identified in this paper applies broadly, outside of the banking sector. Given the pervasiveness of this model of regulation and the availability of data on regulatory budgeting policies, it should be possible to quantify these effects in other industries. Anecdotal evidence discussed in this paper suggests that similar conflicts of interest due to fee income arise in other important regulated industries, where regulators are funded by regulated firms and supervision relies on local supervisory units. Our framework and extensions of the regression kink design to allow multiple kinks and dynamic effects could be useful in such future research, and other applications of the regression kink design.

Appendix

A   Smoothness Assumptions

As explained in Section X, the identifying assumptions for RKD ensure that the slope discontinuity of the fee function is the only source for discontinuity at the kink point. We next provide evidence that these assumptions are reasonable in our setting.

A.1   Discontinuity in Levels

Consistent with our identifying assumptions, our main specifications reported in Table 2 implicitly assume that the outcome measures of risk are continuous functions of size and fees around kink points in the fee function. Rather than impose that the intercepts are the same on both sides of the average kink, here we allow for a discontinuity in levels by adding the term $\beta_0 D (v_{ij} > k_j)$ to the regressions. The results reported in Table A.1 show that we cannot reject the null that the intercepts are the same on both sides of the average kink at the 5 percent significance level. Moreover, the point estimates for the fee elasticity of risk, β_1, are essentially unchanged.

A.2   Kinks in the Raw Data: Robustness

The raw data plots in Figure 4 provide clear evidence that kinks in regulatory leverage coincide with kinks in regulatory fee schedules. As a robustness test, in Figure A.1, we show that kinks are visible even if we zoom out and plot the data over the longest possible bandwidth (0.3 log-points on each side of the kink). Those plots show a strong positive correlation between size and bank risk, as expected in the banking data (see, e.g., Kisin and Manela, 2016), and a clear discontinuity in the slopes at the kink.

Moreover, the right-hand-side panels show a discontinuity in slopes after controlling for polynomials in size, which has a stronger prediction about the sign of the slopes: if the treatment effect is positive, the slope must be positive to the left of the kink and negative to its right, regardless of the magnitude of the effect. To see the reason for this, suppose that the data generating process is given by Equation (20), but we ignore the kinks and regress $y_i =$

$\tilde{\alpha}_0 + \tilde{\alpha}_1 (v_i - k) + \epsilon_i$. Then the slope of the residual in $v_i - k$ will be $\beta_1 \left[D_i - \frac{\text{cov}[(v_i - k) D_i, v_i - k]}{\text{var}[v_i - k]} \right]$. Because the term in the brackets is negative (positive) to the left (right) of the kink and the treatment effect is positive ($\beta_1 < 0$), the residuals will be increasing to the left of the kink and decreasing to its right. This intuition carries over to our regression setting.

A.3 Smooth Density Tests

We follow McCrary (2008), which provides a smooth density test for the regression discontinuity design (RD), and adapt this test for an RKD setting with multiple time-varying kinks.

We construct frequency "observations" of equally-spaced bins of length $w \ll h$ around each kink-year j. We assign to each such bin region the discretized version of the assignment variable v_{ij} around kink k_j[36]

$$G_j (v_{ij}) = \left\lfloor \frac{v_{ij} - k_j}{w} \right\rfloor w + \frac{w}{2} \in \left\{ \ldots, -5\frac{w}{2}, -3\frac{w}{2}, -\frac{w}{2}, \frac{w}{2}, 3\frac{w}{2}, 5\frac{w}{2}, \ldots \right\}$$

Define the (normalized) cell size for the s-th bin of kink j,

$$Y_{js} = \frac{1}{nw} \sum_{i=1}^{n} 1 (G_j (v_{ij}) = X_{js}) \times 1 (|v_{ij} - k_j| \leq h),$$

where X_{js} are the equi-spaced grid points of the support of $G_j (v_{ij})$.

The first-histogram is the scatter plot (X_{js}, Y_{js}). The second step smooths the histogram using a local polynomial regression similar to the one used to estimate our main effect, which explains the height of the bins using the bin midpoints:

$$Y_{js} = \sum_{p=1}^{P} \beta_p X_{js}^p D (X_{js} \geq 0) + \sum_{p=0}^{P} \alpha_{jp} X_{js}^p + v_{js} \tag{27}$$

weighted by a kernel $K (X_{js}/h)$ and tests whether β_1 is different from zero to identify a kink in the density $f (v)$ at $v = k$.

The smooth density hypothesis is not rejected in our data. Figure A.2 shows that the

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[36]McCrary adds the discontinuity point (c in his notation) back to the normalized grid points, but since we would like to center various kinks around zero we do not.

histogram of log assets is quite smooth around the kinks. The regression results do not reject the null of a smooth density with t-statistic 0.92 for a polynomial of degree 1 (0.31 for a polynomial of degree 2).

B Dynamic Model of Bargaining with a Regulator

Dynamic considerations about future fees, regulatory costs and firm profits can easily be incorporated into the static model in Section 2. Suppose the period-t payoff to the regulator from fees $f_t = f(q_t)$ when the bank takes risk x_t is $r(x_t, f_t, q_t) = f_t - c(x_t, q_t)$ as before. Similarly, let $b(x_t, f_t, o_t, q_t) = \pi(x_t, q_t) - f_t - o(q_t)$ denote the bank's per-period payoff, net of its disagreement payoff $o(q_t)$. The time-t persistent state of the bank is summarized by q_t, which can be simply interpreted as bank size, but is potentially a vector of state variables. The main departure from the static setting is that now, higher risk may alter the survival probability of the bank, denoted by $p(x_t, q_t)$, which in turn affects the dynamic tradeoff between contemporaneous risk and future expected net fees to the regulator and profits to the bank.

The expected present value to the regulator given risk x_t and a discount factor $\delta_r \in (0,1)$ can be represented by the following Bellman equation,

$$R(x_t, f_t, q_t) = \max\left\{ r(x_t, f_t, q_t) + \delta_r p(x_t, q_t) E\left[R\left(A(q_{t+1}), q_{t+1}\right) | q_t\right], 0\right\} \tag{28}$$

$$= \max\left\{ f_t - C(x_t, q_t), 0\right\}, \tag{29}$$

where $C(x_t, q_t) \equiv c(x_t, q_t) - \delta_r p(x_t, q_t) E\left[R\left(A(q_{t+1}), q_{t+1}\right) | q_t\right]$.

The maximization in (28) reflects the regulator's ability to revoke the charter of a bank with whom it disagrees about the level risk it poses.

Similarly, the expected present value of the bank's payoffs in excess of its outside option o and using its discount factor $\delta_b \in (0,1)$ is

$$B(x_t, f_t, q_t) = \max\left\{ b(x_t, f_t, o_t, q_t) + \delta_b p(x_t, q_t) E\left[B\left(A(q_{t+1}), q_{t+1}\right) | q_t\right], 0\right\} \tag{30}$$

$$= \max\left\{ \Pi(x_t, q_t) - f_t - o(q_t), 0\right\}, \tag{31}$$

where $\Pi(x_t, q_t) \equiv \pi(x_t, q_t) + \delta_b p(x_t, q_t) E[B(A(q_{t+1}), q_{t+1}) | q_t]$. The maximization here reflects the bank's choice to remain regulated under the same charter or to exit or switch charters and get the disagreement payoff $o(q_t)$.

Agreed risk each period maximizes the Nash bargaining objective with bargaining power coefficient $\rho \in (0, 1)$

$$x^*(f_t, q_t) = \arg\max_{x_t} R(x_t, f_t, q_t)^\rho B(x_t, f_t, q_t)^{1-\rho}.$$

Because the functional form of this objective is identical to that in (1), after replacing assumptions about per-period profits and costs with their expected present values, the comparative static results of Section 2 go through. For example, Propositions 1 and 2 and Corollary 1 would simply require that around the optimum, uppercase $\Pi(x_t, q_t)$ and $C(x_t, q_t)$ are increasing in x_t for all q_t.

Given the maintained assumption that the per-period cost $c(x_t, q_t)$ is increasing in x_t, $C(x_t, q_t)$ is increasing under the natural assumption that the survival probability is decreasing with bank risk. The dynamic model allows us to consider reputation concerns of the regulator, which are absent from our static model. A regulator with a high reputation would have a relatively low cost of regulation $c(x, q)$ so that its per-period payoff from fees net of cost is large. For such a high-reputation regulator the expected present value of future payoffs would be large relative to a low-reputation regulator. Higher bank risk would decrease the survival probability $p(x, q)$, and therefore provide a greater incentive to reduce risk. That is C_x would be positive and increasing in the regulator's reputation.

For the bank's present value of profits $\Pi(x_t, q_t)$ to increase with risk, it suffices that the increase in short-term profits $\pi(x_t, q_t)$ is greater than the reduction in the discounted expected value of future payoffs due to the lower survival probability. Short-termism by bank management, or a partial internalization of such risk due to explicit or implicit creditor insurance can generate such an effect.

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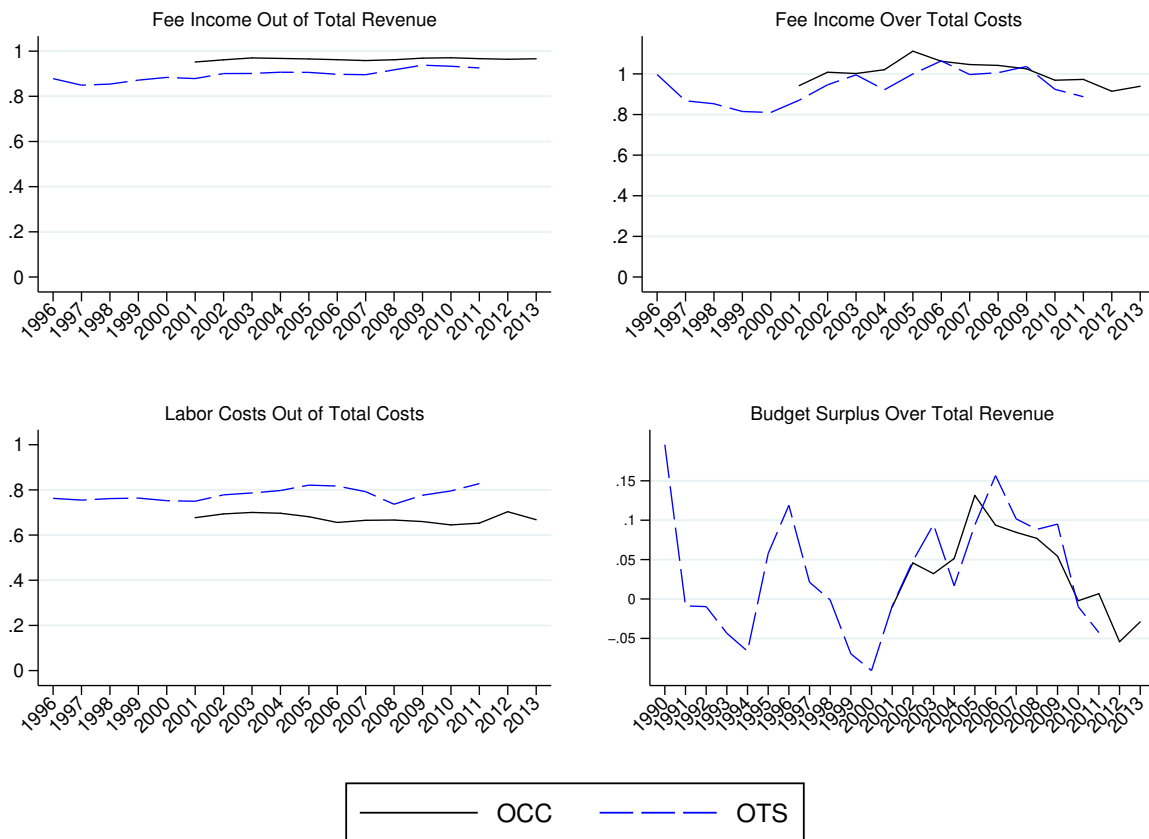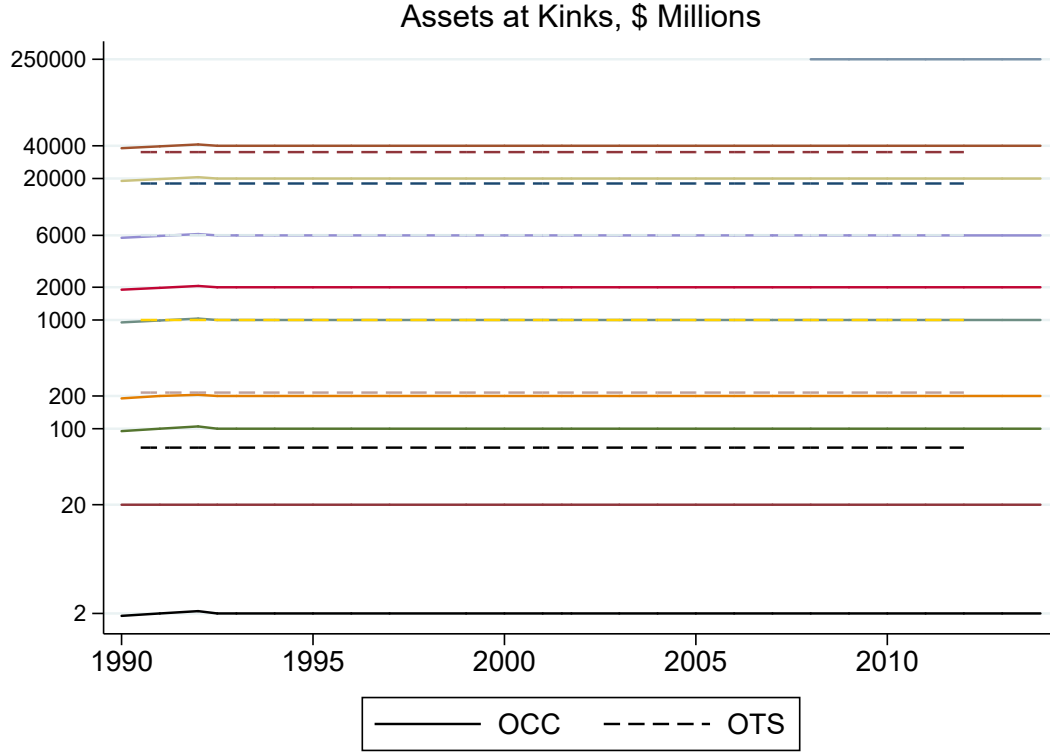
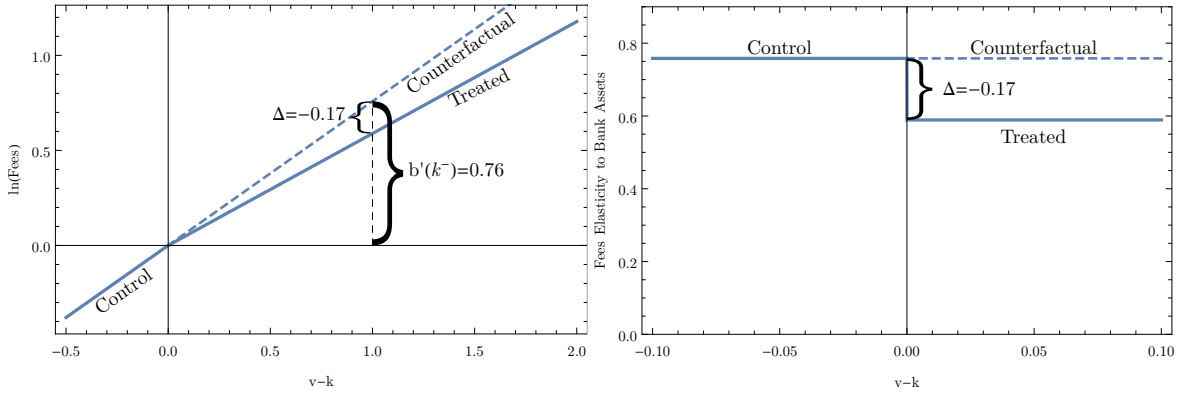Figure 1: **Revenues, Costs and Budget Surplus of Bank Regulators**

Source: The Office of the Comptroller of the Currency (OCC) annual reports for fiscal years 2001-2013 and The Office of Thrift Supervision (OTS) financial statements for 1990-2011.

(a) Balance Sheet Assets at Kinks

(b) Average Elasticity of Fees with respect to Size

Figure 2: **Kinks in Regulatory Fee Schedules**

Notes: Panel (a) shows the position of kinks in the fee schedules over time, in terms of the balance sheet assets that determine the fees, for OCC and OTS. Panel (b) shows the mean difference in elasticities estimated with a regression $b\left(v_{ij}\right) \equiv \log Fees_{ij} = \alpha_j + \beta\left(v_{ij} - k_j\right) + \Delta\left(v_{ij} - k_j\right)D\left(v_{ij} > k_j\right) + \gamma D\left(v_{ij} > k_j\right) + \varepsilon_{ij}$, where v_{ij} is the log assets of bank i in kink-year j, and k_j is log assets at the kink. The figure on the left shows the average slopes. The figure on the right shows the mean difference in elasticities. The interpretation of $\Delta = -0.17$ is that a one percent increase in assets has a 0.17 percentage point higher effect on fees on the left side of the average kink than on the right. Because the average elasticity on the left is 0.76, this represents a 22 percent decrease in elasticity.
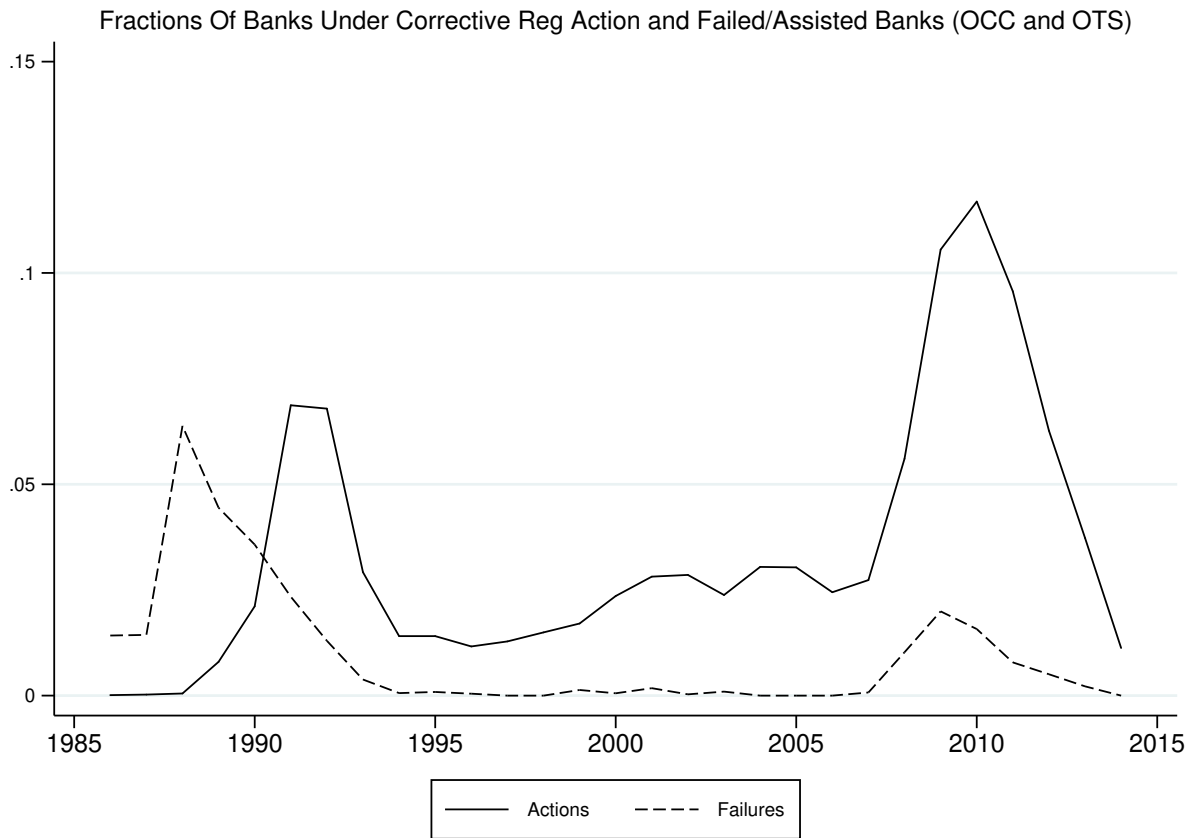
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Figure 3: **Fraction of Failing/Assisted Banks and Banks Under Corrective Actions**

Notes: The solid line is the fraction of banks under corrective enforcement actions initiated by their primary regulator. The dashed line is the fraction of banks that failed or received assistance from the FDIC. The sample includes all banks regulated by OTS and OCC.
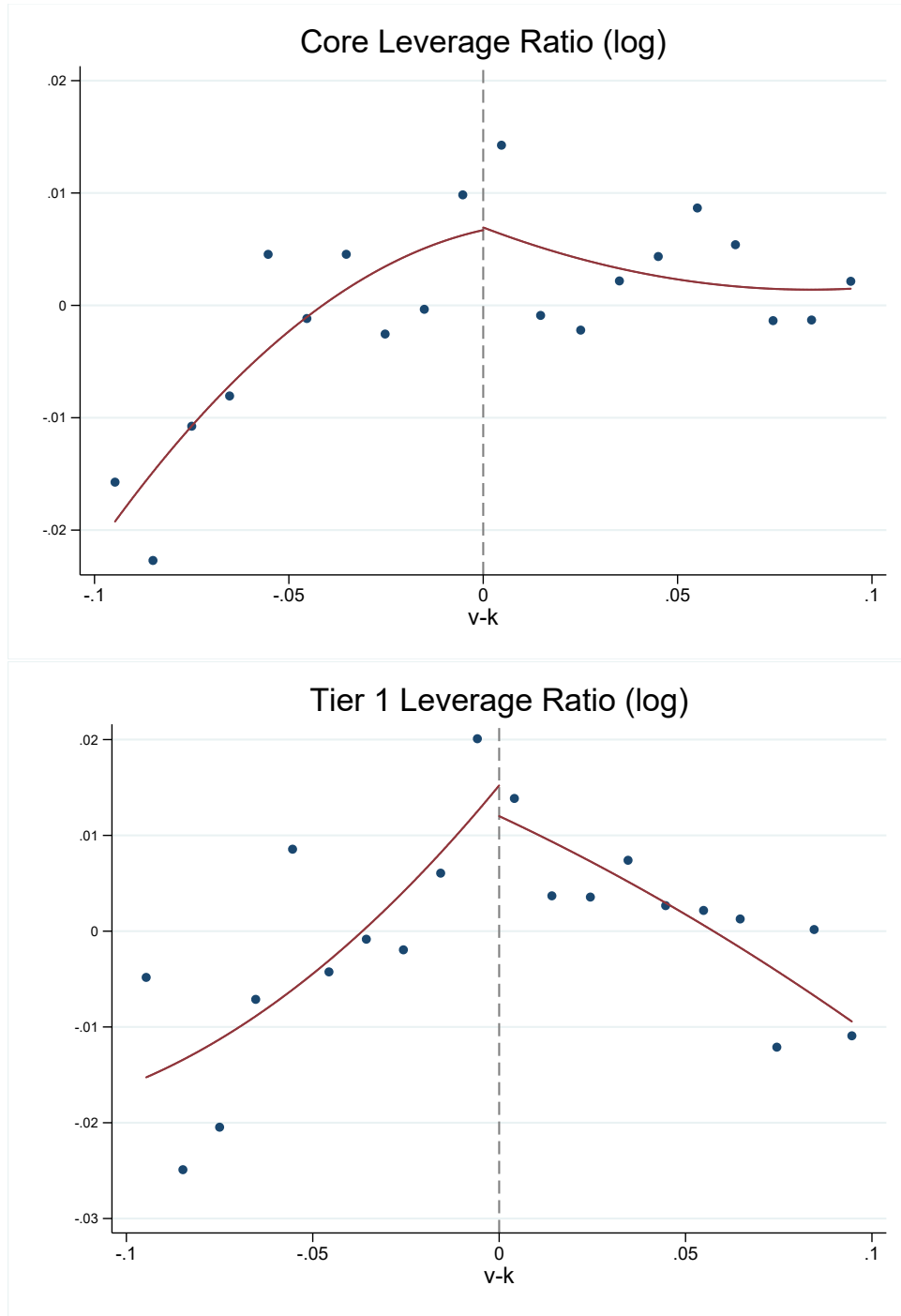
Figure 4: **Discontinuity Plots: Kinks in the Outcome Data**

Notes: The figure shows two regulatory leverage ratios (defined as the reciprocal of the corresponding capital ratio), around kinks in the regulatory fee schedules. For each variable, the figure shows residuals from the regression $y_{ij} = \theta_j + \varepsilon_{ij}$, plotted against distance from the kink $v_{ij} - k_j$, where v_{ij} is the log assets of bank i in kink-year j, k_j is log assets at the kink, and θ_j are kink-year fixed effects. The data is grouped into 20 bins and the average for each bin is plotted. Solid lines show the quadratic fit, estimated separately on each side of the kink, using the underlying data. The sample is national banks and thrifts regulated by OCC or OTS (1990–2014).
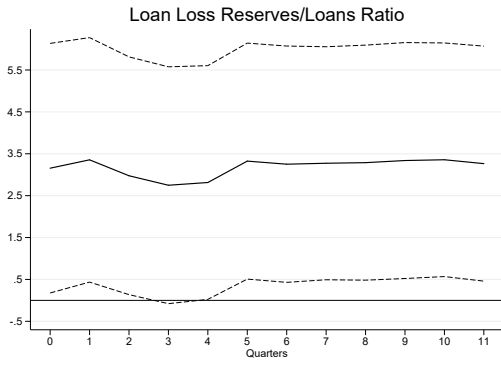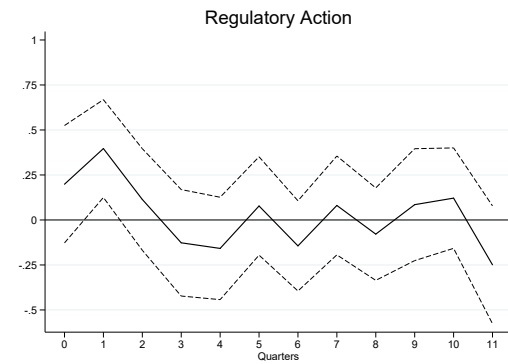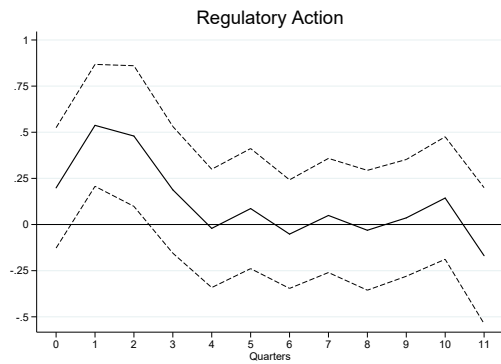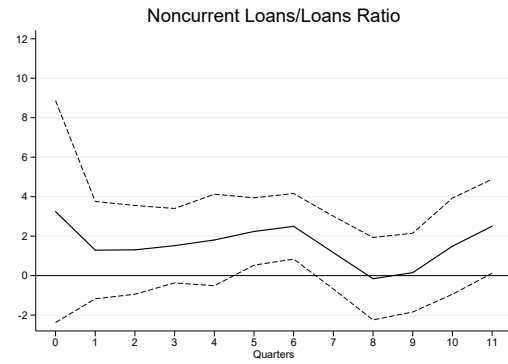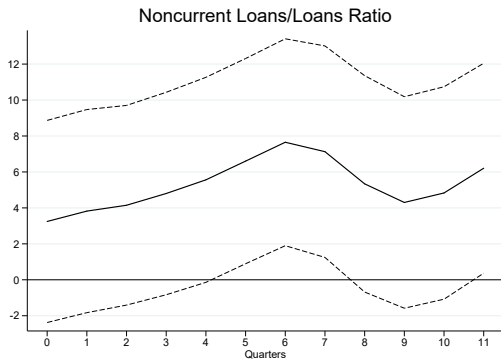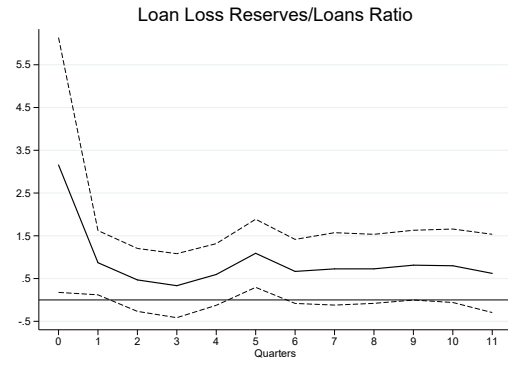
Figure 5: **Dynamic RKD: Slow-adjusting Variables**

Notes: ITT and TOT estimates from Table 4 (with 95% confidence intervals) of the effect of the exogenous variation in lagged assessment fees paid by national banks and thrifts to OCC and OTS. Quarter 0 is the contemporaneous effect of fees on the outcomes. ITT is estimated with Equation (25) and TOT with Equation (24). Standard errors are adjusted for two-way clustering on a bank and a quarterly level.
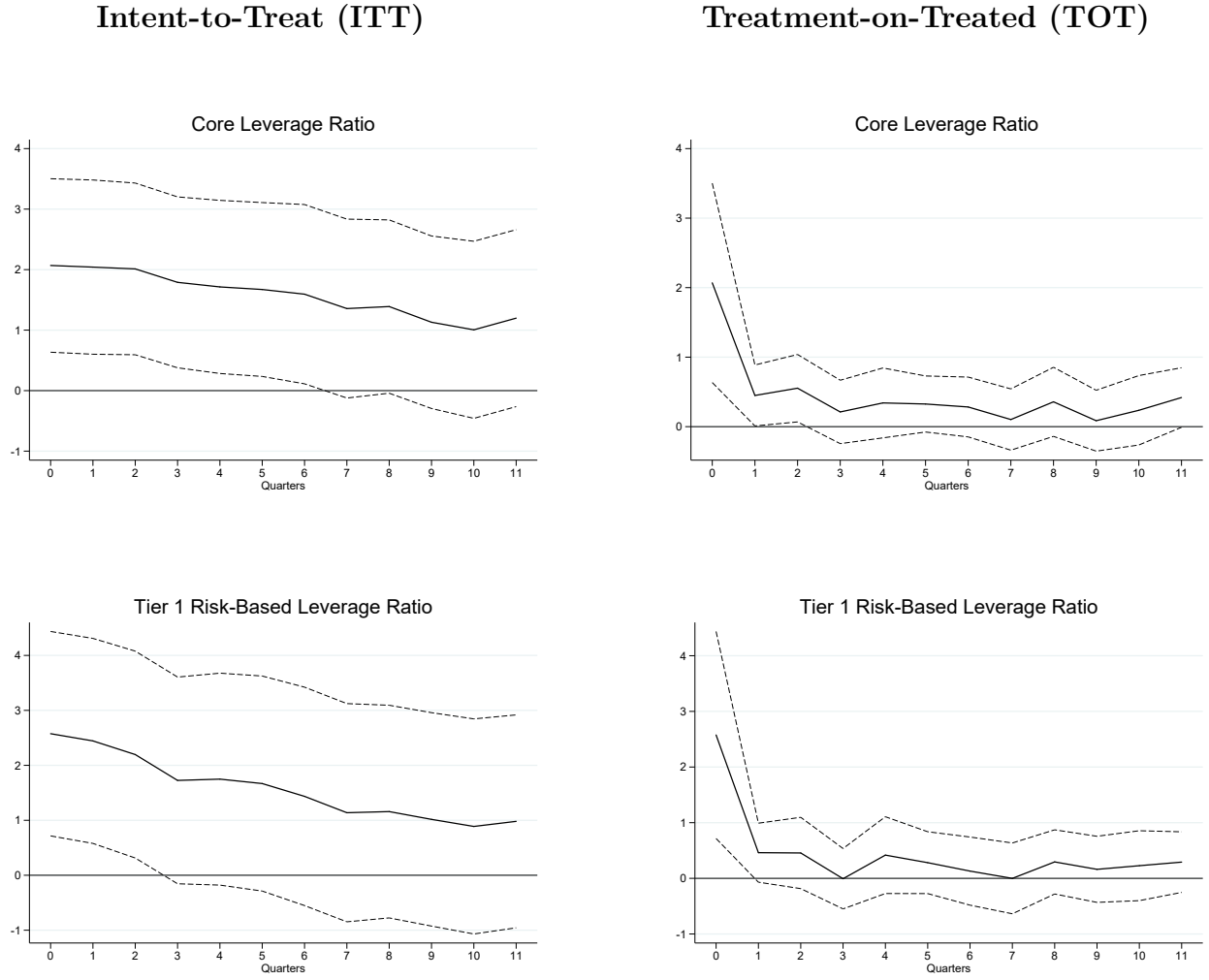
Figure 6: **Dynamic RKD: Leverage Ratios**

Notes: ITT and TOT estimates from Table 4 (with 95% confidence intervals) of the effect of the exogenous variation in lagged assessment fees paid by national banks and thrifts to OCC and OTS. Quarter 0 is the contemporaneous effect of fees on the outcomes. ITT is estimated with Equation (25) and TOT with Equation (24). Standard errors are adjusted for two-way clustering on a bank and a quarterly level.
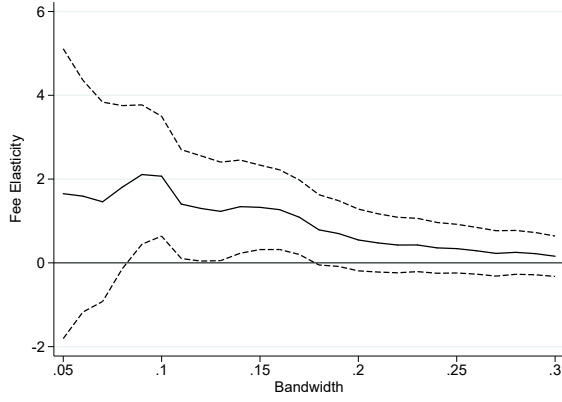
(a) Core Leverage Ratio, $P = 1$
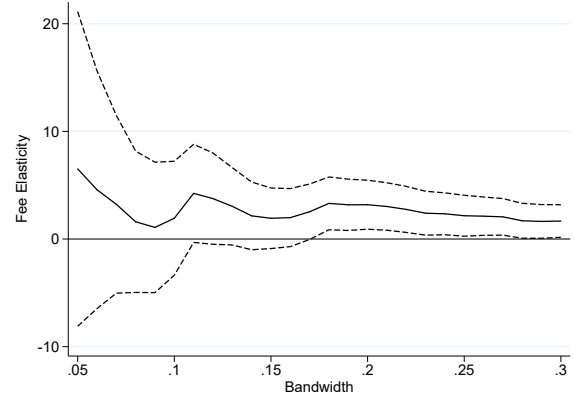
(b) Core Leverage Ratio, $P = 2$
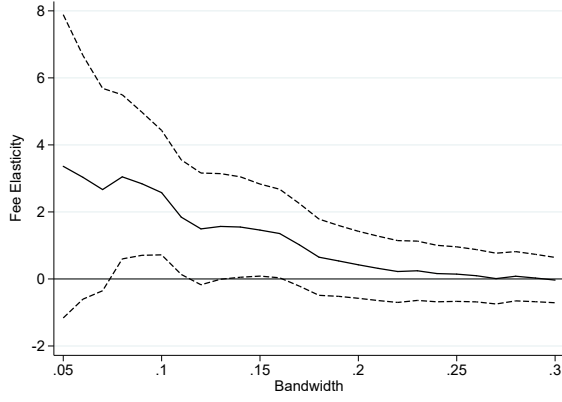
(c) Tier 1 Risk-Based Leverage Ratio, $P = 1$
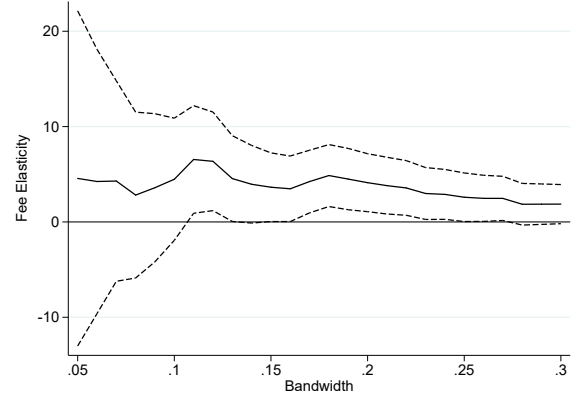
(d) Tier 1 Risk-Based Leverage Ratio, $P = 2$
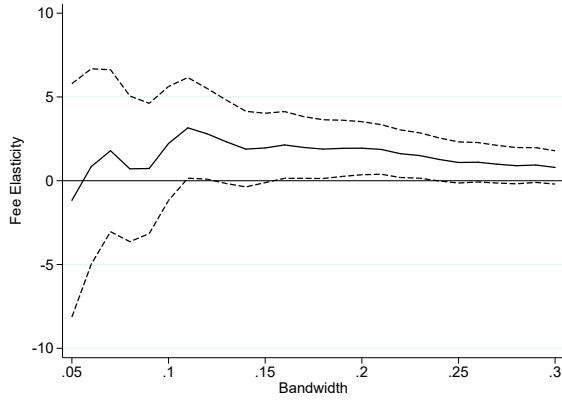
(e) Loan Loss Reserve / Loans, $P = 1$
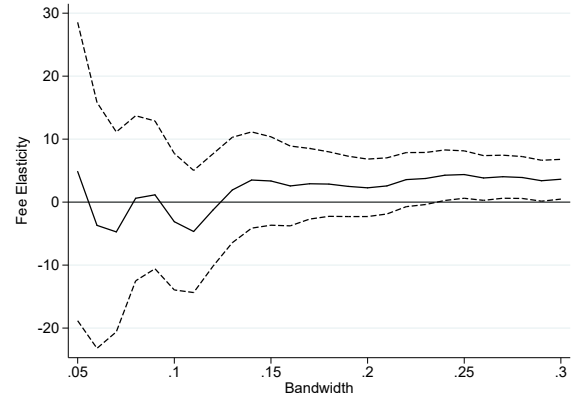
(f) Loan Loss Reserve / Loans, $P = 2$

Figure 7: **Bandwidth Sensitivity: Effects of Fees on Leverage and Loan Losses**

Notes: Solid lines show point estimates (β^{TOT}) of the elasticity of each of the dependent variables to regulatory fees, as we vary the bandwidth (h) between 0.05 and 0.30 log points. We report estimates from the regression kink design with first ($P = 1$) and second degree ($P = 2$) polynomials. Dashed lines are the 95% confidence interval. Standard errors are adjusted for two-way clustering by bank and quarter.

	Mean	Stdev	p1	p50	p99	N
Assets, $ Mil.	2047.7	31538.0	12.3	147.7	24396.6	331,614
Regulatory Fees, $ Mil.	0.23	2.14	0.0085	0.054	2.96	326,933
Fees as percent of Operating Expense	0.68	2.84	0.11	0.57	2.15	326,866
Fees as percent of Noninterest Expense	1.36	3.57	0.15	1.22	3.60	326,853
Core (Tier 1) Leverage	11.7	4.35	3.34	11.3	29.9	331,544
Tier 1 Risk-Based Leverage	7.11	2.97	1.67	6.93	16.8	331,614
Loan Loss Reserves as percent of Loans	1.41	1.03	0.050	1.21	6.05	329,531
Noncurrent Loans as percent of Loans	1.53	2.07	0.0100	0.83	11.3	329,531

(a) **Summary Statistics**

If balance-sheet assets are ($ Mil.)		The semiannual fee ($) is		
Over	But Not Over	This Amount	Plus	Of Excess Over ($ Mil.)
0	2	0	0.001574233	0
2	20	3,148	0.000196781	2
20	100	6,691	0.000157424	20
100	200	19,284	0.000102325	100
200	1,000	29,517	0.000086582	200
1,000	2,000	98,783	0.000070840	1,000
2,000	6,000	169,623	0.000062971	2,000
6,000	20,000	421,507	0.000053579	6,000
20,000	40,000	1,171,613	0.000050403	20,000
40,000		2,179,673	0.000033005	40,000

(b) **Example Fee Schedule: OCC 1999 Fees Schedule**

Kink	Fees Elasticity Diff.		Assets ($M)		Fees, Annualized ($M)	
	OCC	OTS	OCC	OTS	OCC	OTS
1	-0.51	-0.25	3	94	0.01	0.03
2	-0.11	-0.24	27	302	0.02	0.09
3	-0.28	-0.23	137	1404	0.05	0.29
4	-0.10	-0.10	274	8464	0.08	1.23
5	-0.16	-0.16	1368	25265	0.27	3.24
6	-0.09	-0.17	2735	49126	0.47	5.65
7	-0.13		8206		1.16	
8	-0.09		27357		3.21	
9	-0.31		54713		5.87	

(c) **Average Kinks in Fee Schedules**

Table 1: **Summary Statistics for Banks and Kinks in Fee Schedules**

Notes: Panel (a): Summary statistics for nationally chartered banks and thrifts regulated by OCC and OTS (1990–2014). The unit of observation is bank-quarter. Dollar amounts are measured in constant year-2012 dollars. Leverage ratios are reciprocals of the regulatory capital ratios: balance sheet assets (core) or risk-based assets (risk-based) over tier 1 capital. Loss reserves and noncurrent loans are normalized by the total outstanding loans. Ratios are winsorized at 0.01 level. Panel (b): Example fee schedule from the OCC. Source: OCC Bulletin 98-54, *Office of the Comptroller of the Currency Fees for 1999*, dated December 1, 1998. Panel (c): Average differences in the elasticity of fees to balance-sheet assets moving from the left to the right of each kink, as well as the levels of assets and fees at the kink point.

Risk Measure:	Core Leverage		Risk-Based Leverage		Loss Reserves	
	(1)	(2)	(3)	(4)	(5)	(6)
Fee Elasticity of Risk, β_1	2.069***	3.022***	2.576***	3.809**	3.156**	4.273**
	(2.87)	(2.72)	(2.75)	(2.54)	(2.09)	(2.12)
Effect at Mean	0.241	0.352	0.184	0.274	0.000460	0.000618
Mean Dep. Var.	11.63	11.64	7.160	7.186	0.0146	0.0145
Mean Fee	180,829	182,957	180,807	182,946	183,392	184,281
Bandwidth	0.1	0.2	0.1	0.2	0.1	0.2
Poly. Degree	1	2	1	2	1	2
R-Squared	0.22	0.22	0.19	0.19	0.30	0.31
Observations	51,797	108,429	51,804	108,439	56,707	123,097

Table 2: **Effects of Regulatory Fees on Bank Risk**

Notes: Regression kink estimates of the effect of regulatory fees on leverage ratios (columns (1)-(4)) and loan loss reserves (column (5)-(6)) for nationally chartered banks and thrifts, 1990-2014. The fee elasticity of risk, β_1, is the percentage change in a risk measure as a result of a one percent change in fees, estimated from the nonparametric local polynomial regression (22) that controls for a polynomial in size (distance from the kink) interacted with kink-date fixed effects,

$$y_{ij} = \sum_{p=1}^{P} \beta_p \Delta_j^p \left(v_{ij} - k_j\right)^p D\left(v_{ij} > k_j\right) + \sum_{p=0}^{P} \alpha_{jp} \left(v_{ij} - k_j\right)^p + \varepsilon_{ij},$$

of each risk measure (in logs) y_{ij} on slope-change-adjusted distance from the kink $\Delta_j\left(v_{ij} - k_j\right)$ times a kink crossing indicator $D\left(v_{ij} > k_j\right)$, where v_{ij} is the log assets of bank i in kink-year j, and k_j is log assets at the kink. Effect at mean is the effect of a one percent change in fees on bank risk calculated at the sample mean. Leverage ratios are reciprocals of the regulatory capital ratios: balance sheet assets (core) or risk-based assets (risk-based) over tier 1 capital. Loss reserves are normalized by the total outstanding loans. The choice of optimal bandwidths and polynomial degrees is described in Section 4.2. All specifications use a uniform kernel. Standard errors are adjusted for two-way clustering on a bank and a quarterly level and t-statistics are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Core Leverage			Risk-Based Leverage			Loss Reserves		
	(1) Small/Mid-Size		(2) Large		(3) Small/Mid-Size		(4) Large		(5) Small/Mid-Size
Fee Elasticity	2.421***	(3.01)	1.956	(1.66)	3.106***	(3.04)	2.887*	(1.86)	2.823*
Effect at Mean	0.275		0.236		0.208		0.215		0.000386
Mean Dep. Var.	11.36		12.09		6.686		7.435		0.0137
Mean Fee	49,262		275,292		49,256		275,292		49,256
Obs	32,963		30,523		32,970		30,523		36,011

(Panel (a) columns (5) Small/Mid-Size and (6) Large continued):

	(5) Small/Mid-Size		(6) Large	
Fee Elasticity	2.823*	(1.76)	1.543	(0.45)
Effect at Mean	0.000386		0.000204	
Mean Dep. Var.	0.0137		0.0132	
Mean Fee	49,256		277,039	
Obs	36,011		27,290	

(a) **Leverage and Asset Risk by Bank Size Category**

	Core Leverage				Risk-Based Leverage				Loss Reserves			
	(1) OCC		(2) OTS		(3) OCC		(4) OTS		(5) OCC		(6) OTS	
Fee Elasticity	1.956**	(2.74)	2.285	(1.71)	2.051*	(2.04)	3.581**	(2.15)	1.481	(1.01)	6.398*	(1.95)
Effect at Mean	0.223		0.282		0.150		0.243		0.000246		0.000576	
Mean Dep. Var.	11.38		12.32		7.293		6.800		0.0166		0.00901	
Mean Fee	181,469		179,087		181,439		179,087		183,849		182,146	
Obs	37,876		13,921		37,883		13,921		41,504		15,203	

(b) **Leverage and Asset Risk by Regulatory Agency**

	Holding Company Type						Regulators within Holding Company					
	(1) None		(2) Single-Bank		(3) Multi-Bank		(4) OCC Only		(5) Multiple Regulators		(6) Lead Non-OCC	
Fee Elasticity	3.886*	(1.71)	2.763**	(2.02)	4.100**	(2.55)	2.081	(0.65)	4.760***	(2.74)	10.94**	(2.55)
Effect at Mean	0.413		0.318		0.523		0.256		0.616		1.320	
Mean Dep. Var.	10.64		11.51		12.76		12.28		12.94		12.06	
Mean Fee	61,281		97,196		292,676		355,607		272,311		137,187	
Obs	25,679		45,749		38,008		10,054		29,812		8,099	

(c) **Core Leverage in OCC Banks**

Table 3: **Effects of Regulatory Fees Across Regulators and Bank Types**

Notes: Regression kink estimates of the effect of regulatory fees on leverage and loss reserves for national banks and thrifts, 1990-2014. Fee elasticity is the percentage change in the outcome due to a 1 percent change in fees. Effect at mean is the effect on the level of the outcome. Leverage is the reciprocal of regulatory capital ratio: balance sheet assets (core) or risk-based assets (risk-based) over tier 1 capital. Loss reserves are normalized by the total outstanding loans. Panel (a) separates small/midsize and large banks. Panel (b) reports the estimates by agency. Panel (c) col. (1)-(3) separates holding company types for OCC. Col. (4)-(6): multi-bank companies in OCC. "OCC Only:" all banks in the company are regulated by the OCC. "Multiple Regulators:" some banks in the company are with other regulators. "Lead Non-OCC:" the largest bank in the company is with another regulator. All specifications include a local linear polynomial in the distance from the kink interacted with kink-date fixed effects, using 0.1 bandwidth and a uniform kernel, except Panel (c) which uses 0.2 bandwidth and a quadratic polynomial to account for the smaller subsamples. Standard errors are adjusted for two-way clustering on a bank and a quarter level and t-statistics are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

	Loss Reserves		Noncurrent Loans		Regulatory Actions		Core Leverage		Risk-Based Leverage	
	(1) ITT	(2) TOT	(3) ITT	(4) TOT	(5) ITT	(6) TOT	(7) ITT	(8) TOT	(9) ITT	(10) TOT
Elasticity Qtr t	3.156** (2.08)	3.156** (2.08)	3.245 (1.13)	3.245 (1.13)	0.199 (1.19)	0.199 (1.19)	2.069*** (2.83)	2.069*** (2.83)	2.576*** (2.71)	2.576*** (2.71)
Qtr t+1	3.355** (2.25)	0.871** (2.27)	3.821 (1.33)	1.291 (1.02)	0.537*** (3.19)	0.397*** (2.86)	2.042*** (2.78)	0.449** (2.01)	2.445** (2.57)	0.461* (1.70)
Qtr t+2	2.975** (2.05)	0.468 (1.25)	4.147 (1.46)	1.305 (1.14)	0.479** (2.47)	0.114 (0.79)	2.012*** (2.78)	0.554** (2.24)	2.196** (2.29)	0.456 (1.39)
Qtr t+3	2.749* (1.91)	0.333 (0.87)	4.801* (1.67)	1.517 (1.58)	0.188 (1.07)	-0.127 (-0.84)	1.790** (2.48)	0.212 (0.91)	1.726* (1.80)	-0.00681 (-0.02)
Qtr t+4	2.814** (1.98)	0.596 (1.62)	5.561* (1.91)	1.805 (1.53)	-0.0209 (-0.13)	-0.158 (-1.09)	1.714** (2.35)	0.342 (1.33)	1.749* (1.78)	0.417 (1.19)
Qtr t+5	3.325** (2.31)	1.091*** (2.69)	6.602** (2.27)	2.236** (2.57)	0.0864 (0.52)	0.0777 (0.56)	1.672** (2.28)	0.326 (1.59)	1.669* (1.67)	0.282 (0.99)
Qtr t+6	3.251** (2.26)	0.667* (1.75)	7.653*** (2.61)	2.498*** (2.95)	-0.0519 (-0.35)	-0.144 (-1.13)	1.594** (2.11)	0.283 (1.29)	1.436 (1.42)	0.130 (0.42)
Qtr t+7	3.274** (2.31)	0.727* (1.68)	7.128** (2.37)	1.165 (1.24)	0.0492 (0.31)	0.0806 (0.58)	1.356* (1.80)	0.103 (0.46)	1.138 (1.12)	-0.000732 (-0.00)
Qtr t+8	3.288** (2.30)	0.727* (1.77)	5.338* (1.74)	-0.157 (-0.15)	-0.0311 (-0.19)	-0.0787 (-0.60)	1.390* (1.90)	0.357 (1.41)	1.158 (1.17)	0.295 (1.00)
Qtr t+9	3.339** (2.32)	0.813* (1.95)	4.302 (1.43)	0.151 (0.15)	0.0360 (0.22)	0.0850 (0.54)	1.130 (1.55)	0.0858 (0.38)	1.017 (1.03)	0.162 (0.53)
Qtr t+10	3.357** (2.36)	0.800* (1.83)	4.830 (1.60)	1.491 (1.20)	0.144 (0.85)	0.121 (0.85)	1.005 (1.35)	0.235 (0.92)	0.888 (0.89)	0.227 (0.71)
Qtr t+11	3.265** (2.28)	0.621 (1.33)	6.207** (2.08)	2.504** (2.06)	-0.169 (-0.90)	-0.249 (-1.49)	1.198 (1.61)	0.419* (1.92)	0.981 (0.99)	0.292 (1.05)

Table 4: **Dynamic Effects of Fees: Leverage, Asset Risk, and Regulatory Actions**

Notes: Intent-to-treat (ITT) and treatment-on-treated (TOT) elasticities—percentage change in the outcome due to a one percent change in fees. ITT includes the direct effect (TOT) and the indirect effect through the impact on future assignments (Equation (23)). TOT is recursively recovered via Equation (24). Leverage is the reciprocal of regulatory capital ratio: balance sheet assets (core) or risk-based assets (risk-based) over tier 1 capital. Loss reserves and noncurrent loans are normalized by total loans. All regressions include kink-group, year, and lag fixed effects. t-statistics are in parentheses, and the standard errors are adjusted for two-way clustering at the bank and quarterly level. Sample: banks and thrifts regulated by OCC and OTS (1990–2014) $^*p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

Risk Measure:	Core Leverage		Risk-Based Leverage		Loss Reserves	
	(1)	(2)	(3)	(4)	(5)	(6)
Fee Elasticity of Risk, β_1	-0.0724	-0.308	0.00618	0.0967	-0.842*	-0.683
	(-0.21)	(-0.64)	(0.02)	(0.21)	(-1.87)	(-1.22)
Effect at Mean	-0.00841	-0.0357	0.000445	0.00695	-0.000123	-0.000100
Mean Dep. Var.	11.60	11.59	7.211	7.190	0.0146	0.0147
Mean Fee	184,770	191,351	184,752	191,333	186,077	194,889
Bandwidth	0.1	0.2	0.1	0.2	0.1	0.2
Poly. Degree	1	2	1	2	1	2
R-Squared	0.24	0.23	0.22	0.21	0.31	0.31
Observations	53,573	112,101	53,579	112,113	58,705	126,140

Table 5: *Placebo Tests*: **Effects of Regulatory Fees on Bank Risk**

Notes: Regression kink estimates of the effect of regulatory fees on leverage ratios (columns (1)-(4)) and loan loss reserves (column (5)-(6)) for nationally chartered banks and thrifts, 1990-2014. We construct a placebo test for the instrument by using round-numbered kink points that are of the same magnitude but different from the true kinks, while retaining the slopes of the true fee schedules. For OCC we set placebo kinks at 10, 50, 150, 250, 2,500, 5,000, 10,000, 30,000, 60,000 and 300,000 million dollars. For OTS we set placebo kinks at 50, 250, 2,500, 5,000, 10,000 and 30,000 million dollars. The fee elasticity of risk, β_1, is the percentage change in a risk measure as a result of a one percent change in fees, estimated from the nonparametric local polynomial regression (22) that controls for a polynomial in size (distance from the kink) interacted with kink-date fixed effects,

$$y_{ij} = \sum_{p=1}^{P} \beta_p \Delta_j^p (v_{ij} - k_j)^p D (v_{ij} > k_j) + \sum_{p=0}^{P} \alpha_{jp} (v_{ij} - k_j)^p + \varepsilon_{ij},$$

of each risk measure (in logs) y_{ij} on slope-change-adjusted distance from the kink $\Delta_j (v_{ij} - k_j)$ times a kink crossing indicator $D (v_{ij} > k_j)$, where v_{ij} is the log assets of bank i in kink-year j, and k_j is log assets at the kink. Effect at mean is the effect of a one percent change in fees calculated at the sample mean. Leverage ratios are reciprocals of the regulatory capital ratios: balance sheet assets (core) or risk-based assets (risk-based) over tier 1 capital. Loss reserves are normalized by the total outstanding loans. The choice of optimal bandwidths and polynomial degrees is described in Section 4.2. All specifications use a uniform kernel. Standard errors are adjusted for two-way clustering on a bank and a quarterly level and t-statistics are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	-0.08	-0.14	-0.16	-0.20	-0.23	-0.27
2	0.08	-0.02	-0.08	-0.05	-0.06	-0.03
3	0.15	-0.10	-0.07	-0.07	-0.05	-0.05

(a) Mean TOT Estimate. True Regulatory Fees Elasticity $= 0$

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	0.05	0.07	0.08	0.17	0.40	0.76
2	0.04	0.08	0.06	0.05	0.05	0.05
3	0.05	0.05	0.07	0.07	0.05	0.07

(b) Rejection Rate $p < 0.05$. True Regulatory Fees Elasticity $= 0$

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	1.82	1.69	1.54	1.43	1.33	1.21
2	2.63	2.18	1.88	1.88	1.85	1.91
3	2.79	2.29	2.37	2.10	1.92	1.90

(c) Mean TOT Estimate. True Regulatory Fees Elasticity $= 2$

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	0.24	0.89	1.00	1.00	1.00	1.00
2	0.07	0.18	0.40	0.74	0.94	1.00
3	0.07	0.09	0.21	0.37	0.64	0.83

(d) Rejection Rate $p < 0.05$. True Regulatory Fees Elasticity $= 2$

Table 6: **Simulated Samples**

Notes: Reported are mean treatment-on-treated estimates and the fraction of the 1000 simulated random samples where the regression kink design rejects the null hypothesis of zero effect. Each entry corresponds to a different RKD regression specification with a polynomial degree P and bandwidth h. We simulate the dependent variable as $\log y_i = 8 + \beta_0^{TOT} \times \log Fees_i - 0.7 \times \log Assets_i + 0.1 \times (\log Assets_i)^2 + w_i$. We generate the random samples by sampling from the assets and kinks distribution and drawing independent shocks (w_i) from the distribution of residuals from a preliminary OLS regression of log leverage ratios on log fees and log assets.

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	-14.00	-6.35	-4.50	-3.49	-3.05	-2.49
2	-49.41	-24.19	-15.06	-12.83	-11.51	-9.90
3	-48.73	-22.42	-14.63	-11.27	-10.55	-9.48

(a) Mean TOT Estimate. True Regulatory Fees Elasticity $= 0$

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	1.00

(b) Rejection Rate $p < 0.05$. True Regulatory Fees Elasticity $= 0$

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	-88.08	-42.28	-27.25	-20.24	-15.84	-12.13
2	-340.21	-176.53	-116.60	-95.17	-80.93	-67.78
3	-311.90	-145.49	-105.77	-82.05	-72.83	-62.95

(c) Mean TOT Estimate. True Regulatory Fees Elasticity $= 2$

P \ h	0.05	0.10	0.15	0.20	0.25	0.30
1	1.00	1.00	1.00	1.00	1.00	1.00
2	1.00	1.00	1.00	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	1.00

(d) Rejection Rate $p < 0.05$. True Regulatory Fees Elasticity $= 2$

Table 7: **Ignoring Kink Heterogeneity Leads to Severe Biases**

Notes: Reported are mean treatment-on-treated estimates and the fraction of the 1000 simulated random samples where the regression kink design rejects the null hypothesis of zero effect. The simulated samples are identical to those of Table 6, but pool all kinks without properly allowing for kink-specific controlling polynomials as we advocate in Section 4. Each entry corresponds to a different RKD regression specification with a polynomial degree P and bandwidth h. We simulate the dependent variable as $\log y_i = 8 + \beta_0^{TOT} \times \log Fees_i - 0.7 \times \log Assets_i + 0.1 \times (\log Assets_i)^2 + w_i$. We generate the random samples by sampling from the assets and kinks distribution and drawing independent shocks (w_i) from the distribution of residuals from a preliminary OLS regression of log leverage ratios on log fees and log assets.
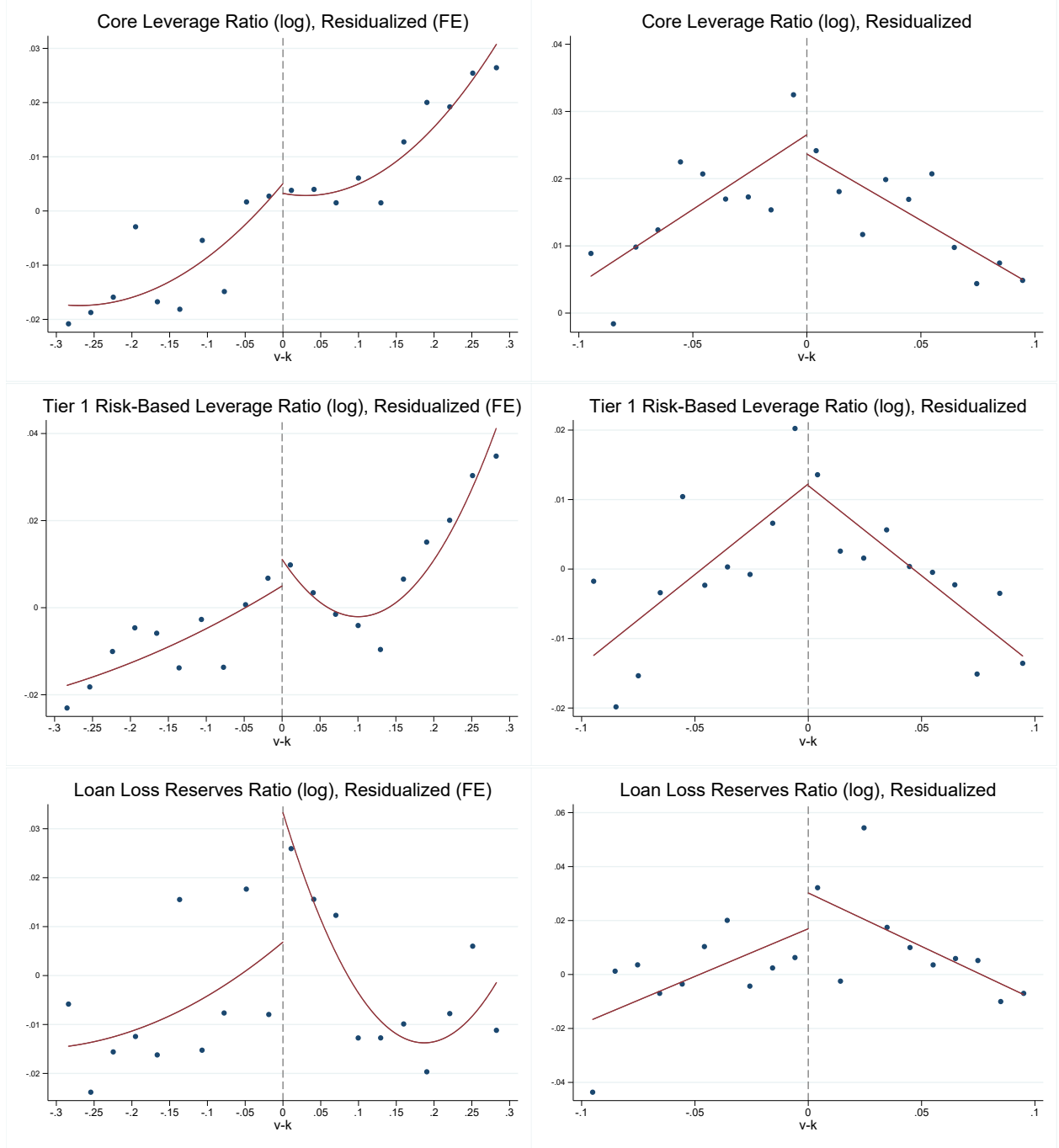
Figure A.1: **Discontinuity Plots: Robustness**

Notes: The figure shows two regulatory leverage ratios (defined as the reciprocal of the corresponding capital ratio) and loss reserves normalized by total loans, around kinks in the regulatory fee schedules. For each variable, the figure on the left shows residuals from the regression $y_{ij} = \theta_j + \varepsilon_{ij}$, plotted against distance from the kink $v_{ij} - k_j$, where v_{ij} is the log assets of bank i in kink-year j, k_j is log assets at the kink, and θ_j are kink-year fixed effects. The figures on the right show residuals from a regression on the *smooth* assignment variable (distance from the kink) interacted with kink-year fixed effects, $y_{ij} = \theta_j + \tilde{\alpha}_j (v_{ij} - k_j) + \varepsilon_{ij}$. The data is grouped into 20 bins and the average for each bin is plotted. The solid lines show the quadratic or linear fit, estimated using the underlying data. The sample is national banks and thrifts regulated by OCC or OTS (1990–2014).
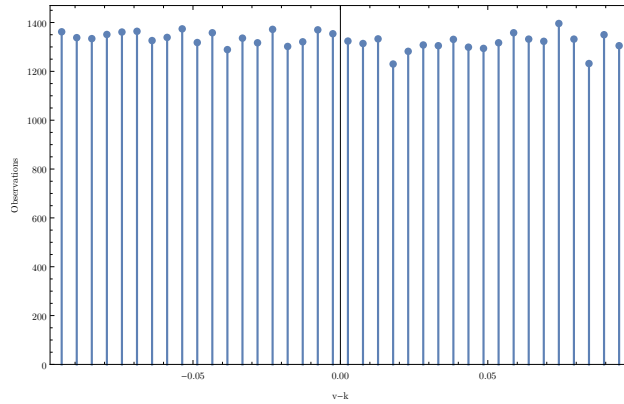
Figure A.2: **Histogram of Assignment Variable** ($\ln Assets$) **Around Kinks**

Notes: The histogram shows that the density of the assignment variable, log assets, is continuous and smooth around the kinks. We aggregate observations around all kinks j belonging to the fee schedule effective at time t by reporting the histogram of $v_{itj} - k_{tj}$. We test for a kink in the histogram of the assignment variable using a local polynomial regression similar to the one used to estimate our main effect, which explains the height of the bins using the bin midpoints. Further details are provided in Section A.3. The regression results do not reject the null of a smooth density with t-statistic 0.92 for a polynomial of degree 1.

Risk Measure:	Core Leverage		Risk-Based Leverage		Loss Reserves	
	(1)	(2)	(3)	(4)	(5)	(6)
Level Change at Kink, β_0	-0.00409	-0.0137*	-0.000277	-0.0120	0.0106	0.0201
	(-0.51)	(-1.84)	(-0.03)	(-1.20)	(0.69)	(1.30)
Fee Elasticity of Risk, β_1	2.065***	3.005***	2.576***	3.794**	3.166**	4.294**
	(2.87)	(2.70)	(2.76)	(2.53)	(2.09)	(2.12)
Effect at Mean	0.240	0.350	0.184	0.273	0.000461	0.000621
Mean Dep. Var.	11.63	11.64	7.160	7.186	0.0146	0.0145
Mean Fee	180,829	182,957	180,807	182,946	183,392	184,281
Bandwidth	0.1	0.2	0.1	0.2	0.1	0.2
Poly. Degree	1	2	1	2	1	2
R-Squared	0.22	0.22	0.19	0.19	0.30	0.31
Observations	51,797	108,429	51,804	108,439	56,707	123,097

Table A.1: **Testing for a Discontinuity in Levels**

Notes: Regression kink estimates of the effect of regulatory fees on leverage ratios (columns (1)-(4)) and loan loss reserves (column (5)-(6)) for nationally chartered banks and thrifts, 1990-2014. Here we allow for free intercepts on both sides of the average kink to test for a level change at the mean kink point, β_0. The fee elasticity of risk, β_1, is the percentage change in a risk measure as a result of a one percent change in fees, estimated from the nonparametric local polynomial regression (22) that controls for a polynomial in size (distance from the kink) interacted with kink-date fixed effects,

$$y_{ij} = \beta_0 D\left(v_{ij} > k_j\right) + \sum_{p=1}^{P} \beta_p \Delta_j^p \left(v_{ij} - k_j\right)^p D\left(v_{ij} > k_j\right) + \sum_{p=0}^{P} \alpha_{jp} \left(v_{ij} - k_j\right)^p + \varepsilon_{ij},$$

of each risk measure (in logs) y_{ij} on slope-change-adjusted distance from the kink $\Delta_j \left(v_{ij} - k_j\right)$ times a kink crossing indicator $D\left(v_{ij} > k_j\right)$, where v_{ij} is the log assets of bank i in kink-year j, and k_j is log assets at the kink. Effect at mean is the effect of a one percent change in fees on bank risk calculated at the sample mean. Leverage ratios are reciprocals of the regulatory capital ratios: balance sheet assets (core) or risk-based assets (risk-based) over tier 1 capital. Loss reserves are normalized by the total outstanding loans. The choice of optimal bandwidths and polynomial degrees is described in Section 4.2. All specifications use a uniform kernel. Standard errors are adjusted for two-way clustering on a bank and a quarterly level and t-statistics are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.