Funding and Incentives of Regulators: Evidence from Banking

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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.

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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 failure 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 effectiveness is scarce, leaving such policy debates largely unaided by evidence.[1]

To study the effects of regulators' incentives, we use the fact that in many industries (including those mentioned above) regulation is funded with fees paid by regulated firms. We show that variation in fees from individual firms can be used to study the incentives of regulators, their ability to alter enforcement in response to monetary incentives, and, generally, shed light on the regulatory process. We test this idea using a novel dataset on regulatory assessment fees and regulatory actions in the US banking sector. Using exogenous variation in these fees, generated by kinks in the fee schedules, 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 provides a useful laboratory. First, banking data includes measures of risk—a primary concern for regulators—and measures of potential outcomes of risk-taking, such as bank failures, enforcement actions, and loan defaults. Second, as we discuss below, regulators have leeway in determining bank risk. Finally, kinks in fee schedules faced by banks provide a previously unexplored source of exogenous variation in the revenues of regulatory agencies.

Our data covers all banks supervised by the two primary regulators of national banks and thrifts: The Office of Thrift Supervision (OTS) and The Office of the Comptroller of the Currency (OCC). During our sample period, which spans almost three decades, these agencies oversaw 65% of US banking assets. About 95% of their funding comes from supervised banks, and the remainder from interest on their past budget surpluses. They received no appropriations from Congress.

[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).

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 under plausible conditions, regulators accept higher risk in higher fee-paying firms. Intuitively, higher fee income alleviates the negative effect 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 hard, because they are determined by bank size, and therefore correlated with unobserved bank characteristics. Moreover, fees are a deterministic piecewise-linear function of size, which precludes the use of conventional instrumental techniques. To address this, we use the "kinked" structure of the fee schedule. Bank size affects fees differently depending on which side of a kink a bank happens to be located. 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 an outcome variable (e.g., bank risk) and bank size, which coincide with kinks in the fee schedule.

The kinks significantly affect regulatory revenues; 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 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. Another way to gauge the importance of kinks for regulatory budgets, is to ask, how much would the budget change if instead of one average-sized bank, the regulator would be in charge of two banks half its size. Intuitively, the change would be zero if there were no kinks in the fee schedule.[2] For the mean bank in our sample, such an exercise would raise its fees by sixty thousand dollars, or 17 percent. For the median bank it would raise the fees by sixteen thousand dollars, or 29 percent.

Another attractive feature of our empirical setup is that the fee schedules feature multiple kinks

[2]We thank Luigi Zingales for suggesting this exercise.

along the distribution of bank sizes. This ensures that the reliance on kinks does not a priori limit the analysis 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 the riskiness of assets. A 1% increase in regulatory fees paid by a bank increases its regulatory leverage 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. 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 mechanisms behind this result. In particular, we would like to understand why a large regulatory organization responds to changes in individual bank fees. A closer look at the institutional environment resolves this apparent puzzle. First, supervision of a majority of banks (mid-size and small) is delegated to local field offices, which have significant decision-making authority. Budgets and employment in these local offices relies on banks under their supervision, and fees paid by individual banks can capture a sizeable share of their budgets.[3] We show 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 would increase 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 reduced form effect of fees can be further magnified by the firm's bargaining power.[4]

We further extend the RKD framework to study possible dynamic effects of fees on bank outcomes. While regulation may affect some outcomes immediately (e.g., leverage), other outcomes,

[3]For example, a departure of a median (mean) bank would reduce the budget by about $54,000 ($230,000). As mentioned above, banks have other, more 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 understand the magnitude of our estimates is to ask how reasonable is 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.

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). 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).

We find that fees have significant effects on future regulatory enforcement actions and loan default rates. Higher fees increase enforcement actions after 3 quarters, and increase non-current loans after 7–8 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—in finance and elsewhere—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. 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 is the first causal evidence on this issue.[5] More broadly, our findings expose a similarity between user fee-funded government regulators and private auditors, such as credit rating agencies and self-regulatory organizations (see, e.g., Bolton, Freixas, and Shapiro, 2012, for a theoretical treatment). Duflo, Greenstone, Pande, and Ryan (2013) study private pollution auditors in India, who are chosen and paid by firms. They find that the existing system is corrupted, but audit quality can be improved by altering auditors' incentives.

[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.

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]

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 the 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 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;

[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. In a more recent contribution, Eisenbach, Lucca, and Townsend (2016) study the costs and benefits of bank supervision using data on work hours of Federal Reserve supervisors.

[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.

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 across agencies, and our tests are consistent with Agarwal, Lucca, Seru, and Trebbi (2014) who find that bank and time effects effectively deal 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 bank 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 the estimating equations. 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.

[8] Ganong and Jäger (2014) survey more than 20 RKD applications in the last 5 years.

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 generated by the fee structure, the regulator in our model has a preference over net fee income, $u(q,x) = f(q) - c(q,x)$, where $f(q)$ is fee revenue. As in our institutional setting, the fees are determined by firm size. The cost of regulation $c(q,x)$ may include the regulator's private cost of supervision, and the social costs net of social benefits from a firm of size q bearing risk x.

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 ignores other factors that could be valued by the regulator, such as social welfare from bank lending. Such preferences may introduce additional tradeoffs, potentially mitigating the effect of fees. 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 non-parametrically. Specifically, we use a nonparametric identification framework developed by Card, Lee, Pei, and Weber (2015), which allows for non-separability 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 is assumed to maximize its profits net of regulatory fees $\pi(q,x) - f(q)$. We assume that q is set by the time of the negotiation and it is known to both parties. This assumption reflects the regulatory practice in our setting.[10]

[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 (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] End-of-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

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

$$\max_{x} \left[f(q) - c(q,x)\right]^{\beta} \left[\pi(q,x) - f(q)\right]^{1-\beta}. \tag{1}$$

This setup is widely used in empirical bargaining models (e.g., Crawford and Yurukoglu, 2012), and nests the special cases where choice of risk is made solely by the regulator ($\beta = 1$) or the firm ($\beta = 0$). While the objective of both the regulator and the firm may be aligned over some range of firm size q and risk x, we assume that around the optimal choice of risk, they pull in different directions, so that the optimal risk is an interior solution (i.e. the second-order conditions hold). We normalize the outside options to zero, without loss of generality, since both regulatory costs and firm profits can be thought of as net of each party's disagreement payoff.

The optimal choice of x equates the bilateral marginal benefit and marginal cost, weighted by each party's bargaining power:

$$\beta \frac{c_x(q,x)}{f(q) - c(q,x)} = (1-\beta) \frac{\pi_x(q,x)}{\pi(q,x) - f(q)}. \tag{2}$$

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

The effect of an increase in fees on the equilibrium risk is apparent from (2). Higher fees increase the regulator's payoff, therefore diminishing the effect of higher costs in percentage terms. Moreover, higher fees increase the marginal benefit because the percent increase in firm profits is relative to profits net of fees. Both effects work to increase the resulting risk, although we expect the first to be much stronger than the latter in our setting because fees are a major source of regulator revenue but only a minor cost for banks.

Assuming that higher risk increases both firm profits and the cost of regulation, the effect of an exogenous increase in fees on risk is positive:

$$\frac{d\log x}{d\log f} = \frac{\frac{f(q)}{f(q)-c(q,x)} + \frac{f(q)}{\pi(q,x)-f(q)}}{\frac{1}{1-\beta}\frac{c(q,x)}{f(q)-c(q,x)}\epsilon_{cx} + \sigma_{cx} - \sigma_{\pi x}} > 0, \tag{3}$$

bargaining channel applies in other settings depends on the ability of the firm to walk away from the negotiating table, either directly by leaving for a competing regulator, or by reducing the size of a project.

where $\sigma_{\pi x} \equiv \frac{\pi_{xx}(q,x)x}{\pi_x(q,x)}$, $\sigma_{cx} \equiv \frac{c_{xx}(q,x)x}{c_x(q,x)}$, and $\epsilon_{cx} \equiv \frac{c_x(q,x)x}{c(q,x)}$. Equation (3) 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 β, 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 $\sigma_{\pi x}$.

Equation (3) 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 firm size 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.

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.[11]

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 accounted for 96 percent of the OCC's revenues. A small addition to its revenue

[11] 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.

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.[12]

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 keep 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.[13]

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 regulated 2,800 banks holding 50 percent of US bank assets. The OTS regulated 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.

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

[12] 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.

[13] Recinded 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.

fees account for 1.3 percent of its noninterest expense, or 0.7 percent of its operating expense.[14]

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 exhibit the largest slope changes while the remaining kinks are rather small. It turns out that our results are mostly due to these larger kinks, though our main analysis pools information from all kinks in the fee functions of the OCC and OTS over the entire sample. Both agencies mostly keep the kink points fixed in nominal terms, but change the marginal rates at times, mostly to index them to inflation.

Figure 2 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.

The theoretical model of Section 2 predicts a positive relationship between bank risk and regulatory fees. Since there is no unified definition for bank risk-taking, we examine two separate sets of risk measures: financial leverage and asset risk.

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. It is well known that the raw relationship between the regulatory leverage ratios and bank size is decreasing Kisin and Manela (e.g., 2016). This correlation, however, does not uncover the effect of fees on leverage ratios since size is potentially correlated with other bank characteristics, such as profitability. Bank regulators supervise leverage to make sure that capital ratios, the reciprocals of leverage, match the risks taken by banks. As a result, regulators have substantial leeway in determining the appropriate capital ratios.[15]

We focus on two leverage ratios: core and tier 1 risk-based. 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 the 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

[14]The OCC and OTS also include a surcharge for banks with high (bad) CAMELS ratings above 2. The OCC gives a 12 percent reduction in fees to non-lead banks belonging to a multiple national bank organization. These proportional fee changes preserve both kink locations and fee elasticities and therefore do not affect our analysis.

[15]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).

weight to each asset of a particular risk group.[16] Since risk-based capital ratios were not used in the first five years of our sample, unless otherwise noted, we limit our sample to the period when both measures were available to make the analysis comparable across risk measures.[17]

To measure banks' asset risk, we examine two commonly-used measures of realized or expected loan losses. The first is noncurrent loans, which accounts for loans that are over 90 days past due or not accruing interest. Following common practice, we normalize this variable by total outstanding loans.

The second measure of asset risk is the loss-reserve, also normalized by total outstanding loans. It captures allowances for expected losses that banks are obligated to set aside. According to accounting standards, loss reserves should account for "imminent and probable losses," which means that it should increase if banks increase the riskiness of their assets. It is, therefore, a useful complement to the information on realized loan performance since it reflects banks' and regulators' expectations, and, at least in principle, should adjust immediately to incorporate new information about asset risk.[18]

Bank regulators can also take enforcement actions against banks or individuals employed by banks, and impose monetary penalties. Figure 3 plots the fraction of banks under corrective actions imposed by OCC and OTS.[19] A striking pattern that emerges from these data 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 to Figure 3. Corrective actions appear to follow spikes in bank failures, with a delay of approximately four quarters. Echoing this stylized fact, in our analysis below we document a strong dynamic pattern in the effect of fees on corrective actions: prior risk taking increases the probability that regulators will have to take an action against a bank during

[16] 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.

[17] Including the rest of the sample does not significantly change our results.

[18] Previous literature has documented a tension between accounting rules and regulatory treatment of loss reserves (see, e.g., Balla and Rose, 2011, for a review). To increase banks stability, supervisors often wish to increase these reserves more than the banks would like, and more than dictated by the accounting standards. This has interesting implications for our setting. On the one hand, banks with riskier loans would expect higher losses and therefore would increase reserves. This would predict a positive effect of fees on loss reserves ratio. On the other hand, if lax regulation leads to smaller reserves, we may see a negative effect.

[19] 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).

the crisis.

4 Empirical Methodology: Regression Kink Design with Multiple Time-Varying Kinks and Dynamic Effects

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.

We begin by describing the single-kink regression kink design (RKD). We then show how to apply this estimator 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.

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 to identification is a "smooth density assumption," stating that, 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 of its own. In these models, one can identify the treatment-on-the-treated (TT) parameter as

$$\beta^{\mathrm{TT}} = \frac{\lim_{v_0 \downarrow k^+} \frac{dE[y|v]}{dv}|_{v=v_0} - \lim_{v_0 \uparrow k^-} \frac{dE[y|v]}{dv}|_{v=v_0}}{\lim_{v_0 \downarrow k^+} b'\left(v_0\right) - \lim_{v_0 \uparrow k^-} b'\left(v_0\right)}. \tag{4}$$

In our setting, (4) says that the effect of fees ($b(v_i)$) on y (e.g., capital ratio) is identified from the discontinuous change in the slope of y as a function of v (bank size). In other words, the treatment effect is identified when the kink in the relationship between size and capital coincides with the kink in the fee schedule.

Card, Lee, Pei, and Weber (2015) suggest using a local polynomial regression for estimation:

$$y_i = \sum_{p=1}^{P} \beta_p (v_i - k)^p D(v_i > k) + \sum_{p=0}^{P} \alpha_p (v_i - k)^p + \varepsilon_i, \tag{5}$$

where 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. The treatment-on-treated is identified by the scaled regression coefficient

$$\hat{\beta}^{\mathrm{TT}} \equiv E\left[\frac{\partial y(b,k,\varepsilon)}{\partial b}\right] = \frac{\hat{\beta}_1}{\Delta},$$

where $\Delta \equiv b'(k^+) - b'(k^-)$ is the change in slopes at the kink. Intuitively, if the regression finds a large change in slopes of y as a function of v at the kink (β_1 is large), when the change in slope in the assignment function $b(v)$ at the kink is small, then the effect of b on y must be larger than in the case when Δ is large. Note that in this single kink setting Δ is constant across observations.

4.1 RKD With Multiple Time-Varying Kinks

In many applications of RKD, the kinked function $b(v)$ 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 fee function. This is highly advantageous, as it allows us to estimate the treatment effect using firms across the size distribution. Another important advantage is that this feature can be used to increase 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.[20]

[20] 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.

We therefore extend the single-kink nonparametric specification (5) to allow for multiple kinks:

$$y_{ij} = \sum_{p=1}^{P} \beta_p \Delta_j^p \left(v_{ij} - k_j\right)^p D\left(v_{ij} > k_j\right) + \sum_{p=0}^{P} \alpha_{jp} \left(v_{ij} - k_j\right)^p + \varepsilon_{ij}, \tag{6}$$

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 $\hat{\beta}^{\mathrm{TT}} = \hat{\beta}_1$.

We specify our empirical model in logs because the bank size distribution is highly skewed. The assignment variable is therefore $v_{ij} = \log q_{ij} = \log Assets_{ij}$ of bank i, which belongs to kink $k_j = \log q_j = \log Assets_j$. The changes in slope multipliers in the log specifications are the changes in elasticities of fees $f(q)$ with respect to book assets q, that is $\Delta_j \equiv \left[f'\left(q_j^+\right) - f'\left(q_j^-\right)\right] \frac{q_j}{f(q_j)}$ as reported in the lower panel of Table 1.

Finally, several practical considerations arise with respect to the choices of bandwidth, polynomial degrees, and a kernel function. 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 very tight bandwidth around the kink and experiment with different choices to ensure that our estimates are not driven by bandwidth selection. In our empirical application and simulations, we find that controlling for nonlinearities with a local quadratic estimator becomes more important at higher 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 parameters. 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 uses a bandwidth of 0.1 and a local linear regression in size.[21]

[21] 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. 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

4.2 RKD with Dynamic Effects

Regulation may have dynamic effects on banks for two reasons. First, outcomes may respond slowly to regulatory intensity. This is most relevant for risk measures that use realized 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 an impact that would warrant a corrective enforcement action. Therefore, fees may affect these variables with (unknown) lags, which may bias the static estimates. Second, fees may affect the treatment assignment of a bank *in future periods*. For example, lax regulation could affect the future size of the bank (by allowing riskier behavior), which also complicates the identification of the treatment-on-the-treated (TT) effect.

To address these issues, we follow Cellini, Ferreira, and Rothstein (2010), who extend the regression discontinuity design (RD) and show how to identify both the intent-to-treat (ITT) and the TT effects in a dynamic setting. 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, and the indirect effect of the lagged fee through its impact on the assignment of the banks to treatments in the interim periods. The ITT effect of the τ-th lag on the outcome at time t is

$$\beta_{\tau}^{\mathrm{ITT}} \equiv \frac{\partial y_{ijt}}{\partial b_{ijt-\tau}} + \sum_{s=1}^{\tau} \left(\frac{\partial y_{ijt}}{\partial b_{ijt-\tau+s}} \times \frac{\mathrm{d}b_{ijt-\tau+s}}{\mathrm{d}b_{ijt-\tau}} \right) = \beta_{\tau}^{\mathrm{TT}} + \sum_{s=1}^{\tau} \beta_{\tau-s}^{\mathrm{TT}} \pi_s, \tag{7}$$

where π_s is the ITT effect of $b_{ijt-\tau}$ on $b_{ijt-\tau+s}$. Equation (7) can be used to recursively extract τ-specific TT estimates $\beta_{\tau}^{\mathrm{TT}}$:

$$\beta_{\tau}^{\mathrm{TT}} = \beta_{\tau}^{\mathrm{ITT}} - \sum_{s=1}^{\tau} \beta_{\tau-s}^{\mathrm{TT}} \pi_s. \tag{8}$$

the asymptotic mean squared error criterion. Finally, like Card et al. (2015) we use a uniform kernel. A triangular kernel produces similar estimates.

The estimation is done in two steps. First, we estimate β_τ^{ITT} and π_s simultaneously from

$$y_{ijt+\tau} = \sum_{p=1}^{P} \beta_{p\tau} \Delta_j^p \left(v_{ijt} - k_{jt}\right)^p D_{ijt} + \sum_{p=0}^{P} \alpha_{jp\tau} \left(v_{ijt} - k_{jt}\right)^p + \theta_\tau + \psi_t + \varepsilon_{ijt+\tau}, \tag{9}$$

where $y_{ijt+\tau}$ is an outcome variable at time $t+\tau$ of an observation in the neighborhood of kink j at time t, D_{ijt} is a shorthand for $D\left(v_{ijt} > k_{jt}\right)$—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. In the second step, we use the ITT estimates (β_τ^{ITT} and π_s) and their covariance matrix estimated via Equation (9) to recover β_τ^{TT} for each lag τ via Equation (8). Standard errors for these estimates are computed using the delta method.[22]

4.3 Smooth Density Tests

Since the smooth density assumption is a key identifying assumption in the RKD setting, we test whether it holds in the data. 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 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 Appendix A, which show that the smooth density hypothesis is not rejected in our data.

5 Results

We start with a graphical presentation of our regression kink design in several raw outcome variables: leverage ratios and loan loss reserves (our measures of risk), followed by statistical tests based on the multiple kink design developed above. We then report estimates of the dynamic model, which additionally include delayed outcome variables such as bank failures and enforcement actions.

[22] 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.

5.1 Discontinuity Plots: Kinks in the Outcome Data

Before applying the RKD framework, in Figure 4 we examine whether the raw outcome variables exhibit kinks which coincide with kinks in the fee schedules. We focus on regulatory leverage ratios and loan loss reserves. In addition to the raw data, we plot the residuals from a regression of risk measures on a smooth flexible polynomial function of bank size interacted with kink-year effects. This reduces the noise in the data by adjusting for the fact that there are multiple kinks that vary over time and cover a wide range of bank sizes.[23]

Since we plot changes in slopes, the figures may be somewhat less intuitive than the plots commonly reported in the regression discontinuity design literature. To see the intuition, consider the data generating process in Equation (5). Ignoring higher order polynomials and multiple kinks, the slope to the right of the kink is the sum of the treatment effect of fees and the effect of size on leverage ($\alpha_1 + \beta^{\mathrm{TT}}\Delta$). It will be smaller than the slope to the left of the kink (α_1) if the treatment effect (β^{TT}) is positive, because the slope of the fee schedule is decreasing ($\Delta < 0$). If leverage increases in size ($\alpha_1 > 0$), and fees further increase leverage, we would expect leverage to the left of the kink to increase faster than to the right. The slope to the right of the kink will be negative if the local effect of bank size is relatively small ($\alpha_1 < \beta^{\mathrm{TT}}\Delta$), and positive otherwise.

This intuition carries over to the case of residuals, with a stronger prediction about the sign of the slopes. Suppose the true data generating process is given by Equation (5), but we ignore the kinks and run $y_i = \tilde{\alpha}_0 + \tilde{\alpha}_1 (v_i - k) + \epsilon_i$. Then, by standard omitted variables arguments, the slope of the residual in $v_i - k$ will be $\beta_1 \left[D_i - \frac{\mathrm{cov}[(v-k)D, v-k]}{\mathrm{var}[v-k]} \right]$. Therefore, if the treatment effect is positive ($\beta_1 < 0$), the slope must be positive to the left of the kink and negative to the right.[24]

Figure 4 shows the behavior around the kinks of two regulatory leverage ratios (tier 1 risk-based and core), as well as the loan loss reserves ratio. All plots plots indicate that higher fees increase risk. There is a clear discontinuity at the kink, and the slopes before the kink are higher than after. The plots of residuals show a predicted reversal in signs. The raw data shows a similar reversal for the risk-based ratios. The kinks in the loss reserves appear weaker than the kinks in the leverage ratios. In Section 5.4 we document a delay in the effect of fees on loss reserves, likely due to delays

[23] The regression used to estimate the residuals for Figure 4 is $y_{ij} = \sum_{p=0}^{2} \tilde{\alpha}_{jp} (v_{ij} - k_j)^p + \varepsilon_{ij}$.

[24] Note that $\mathrm{plim}\tilde{\alpha}_1 = \alpha_1 + \beta_1 \frac{\mathrm{cov}[(v-k)D, v-k]}{\mathrm{var}[v-k]}$ and $0 < \frac{\mathrm{cov}[(v-k)D, v-k]}{\mathrm{var}[v-k]} < 1$.

in compliance, which leads to a weaker contemporaneous effect.[25]

5.2 Static Regression Kink Design Estimates

Table 2 reports the estimated elasticities from the static RKD model in Equation (6)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.[26]

We find statistically and quantitatively significant 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. This exercise shows that 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, at least partially, gets 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. Since the information about assets may take time to get incorporated in the loss reserves, we will revisit the behavior of this measure of risk in a dynamic setting in Section 5.4.

5.3 A Closer Look at the 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

[25]The residual plots are robust to the choice of bandwidth and a polynomial specification. Not surprisingly, the raw data become too noisy for a clear visualization at larger bandwidths, and the effect of fees gets overwhelmed by a strong correlation between leverage and size.

[26]We defer the the analysis of loan performance and regulatory actions to Section 5.4. As discussed in Section 4.2, the static framework is not well-suited for slow-adjusting variables, and the dynamic model results will include the static estimator as a special case for $\tau = 0$. 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.

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 a 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.[27] 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 suggests that the effects should be more pronounced in the subsample of small/mid-sized

[27] 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.

banks, because the 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.

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

So far we have mostly ignored the issue of competition among regulators. US banks, however, can *choose* their regulator by selecting a charter, which could result in competition among regulators (Rosen, 2003; Rezende, 2014; Calomiris, 2006), thereby potentially exacerbating the effects of fees.

Empirically, the necessary inclusion of kink-by-regulator-specific controlling polynomials and fixed effects remove most of the persistent differences across regulators and the banks that select them. Not surprisingly, we do not find a significant effect of fees on the probability of changing regulators, which is consistent with Agarwal, Lucca, Seru, and Trebbi (2014) who report that bank and time effects effectively deal with the issue of charter shopping. While in general this is an attractive feature, it makes it harder to see whether regulatory 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.[28] 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.[29] 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 serves to explain the remaining apparent puzzle regarding the economic magnitudes of the estimates—the impact of small differences in fees appears to be magnified by the regulatory competition.

[28] To see this, consider a simple extension of our model with multiple regulators and bargaining over risk x

$$\max_{x} \left[f(q) - c(q,x)\right]^{\beta} \left[\pi(q,x) - f(q) - o(q)\right]^{1-\beta},$$

where $o(q) \equiv \pi(q,\tilde{x}) - \tilde{f}(q) - \kappa$ is the firm's outside option—the net profit it would earn under the next best regulator with risk $\tilde{x}$ ($o(q) = 0$ in case of exit), and κ is a switching cost. The optimal x solves

$$\beta \frac{c_x(q,x)}{f(q) - c(q,x)} = (1-\beta) \frac{\pi_x(q,x)}{\pi(q,x) - f(q) - o(q)},$$

where $o(q)$ is the the main difference relative to Equation (2). Therefore, regulatory competition could improve the firm's outside option, thereby increasing its effective bargaining power. Only under strong assumptions, such as linearity of costs and profits in risk, the effect of fees on risk does not depend on $o(q)$.

[29] 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.

5.3.4 How Valuable is Leniency for Banks?

Another way to understand the economic magnitudes of our estimates, is to ask whether the *effect on risk* is disproportionately large relative to the corresponding changes in fees? One way to get a benchmark for the magnitude of the change in risk is to examine banks willingness to pay for similar increases in regulatory leverage ratios.

The estimates from Kisin and Manela (2016) can be used to perform such a back-of-the-envelope calculation. Kisin and Manela (2016) 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 average treated bank in our setting has \$2 billion in assets, which implies it would be willing to pay $\$51,193$ ($= 0.0025 \times 2,047,700,000 \times 0.01$), to reduce its regulatory capital ratio by one percentage point, or equivalently, to increase its leverage by 13.3% (from 11.7 to 13.3). Our estimate of the core leverage fee elasticity implies that for an average bank such an increase in leverage could be achieved by increasing its annual regulatory fees by about 6.4% ($= 13.3\%/2.069$), or $\$14,730$ for the mean bank.[30] Therefore, by paying higher fees banks spend less than their willingness to pay for the increase in leverage. More importantly, the magnitudes of these costs and benefits are quite similar, which implies that while a one-percentage-point increase in fees may appear relatively modest, the magnitude of the corresponding effect on risk is economically quite reasonable.

5.4 Dynamic Effects: 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 4.2 for 12 lags ($\tau = 0 \ldots 11$).[31] Figures 5 and 6 show these results graphically. As shown in Equation (7), ITT measures the effect of a contemporaneous exogenous variation in fees τ quarters later, without controlling for fees in the interim periods. The TT, 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,

[30] Similarly, the median bank in our sample would be willing to pay $\$3,693$ ($= 0.0025 \times 147,700,000 \times 0.01$) to increase its core leverage by 12.7%, and it could achieve this by increasing its regulatory fees by about 6.2% ($\$3,325$). One caveat for this back-of-the-envelope calculation is that the banks' willingness to pay for higher leverage may be different for large banks studied in Kisin and Manela (2016).

[31] 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.

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. Perhaps more interesting is the additional adjustment of the reserves 5-6 quarters later—by about a third of the initial effect—presumably when more information about the assets becomes available. This timing coincides with the changes in the noncurrent loans ratio (columns (3)-(4)). As expected, the noncurrent loans ratio does 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 against banks. Again, there is no contemporaneous effect, but we see a sharp increase in actions 2 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.

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 TT 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 point estimate, and the effect goes to zero within a quarter. It appears that banks respond to lax regulation immediately by increasing financial leverage and the riskiness of assets, with the long-term consequences to follow.

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. Similarly, the estimated effect of fees on loan loss

reserves is robust and remains significant as we shrink the bandwidth. As discussed in Section 4.1, 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 shifting all kink points from k_j to $k_j + h$ for all fee schedules and kinks j. 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.

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.

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 $\log y_i = 8 + TT_0 \times \log Fees_i - 0.7 \times \log Assets_i + 0.1 \times (\log Assets_i)^2 + w_i$. 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 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 less likely to be closed by their regulators, and 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 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 j of group g. We assign to each such bin region the discretized version of the assignment variable v_{ij} around kink k_j[32]

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

Define the (normalized) cell size for the sth bin of kink j,

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

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

The first-histogram is the scatterplot (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:

$$Y_{js} = \sum_{p=1}^{P} \beta_p X_{js}^p D\left(X_{js} \geq 0\right) + \sum_{p=0}^{P} \alpha_{jp} X_{js}^p + \upsilon_{js} \tag{10}$$

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

The smooth density hypothesis is not rejected in our data. Figure A.1 shows that the 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.

[32] 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.

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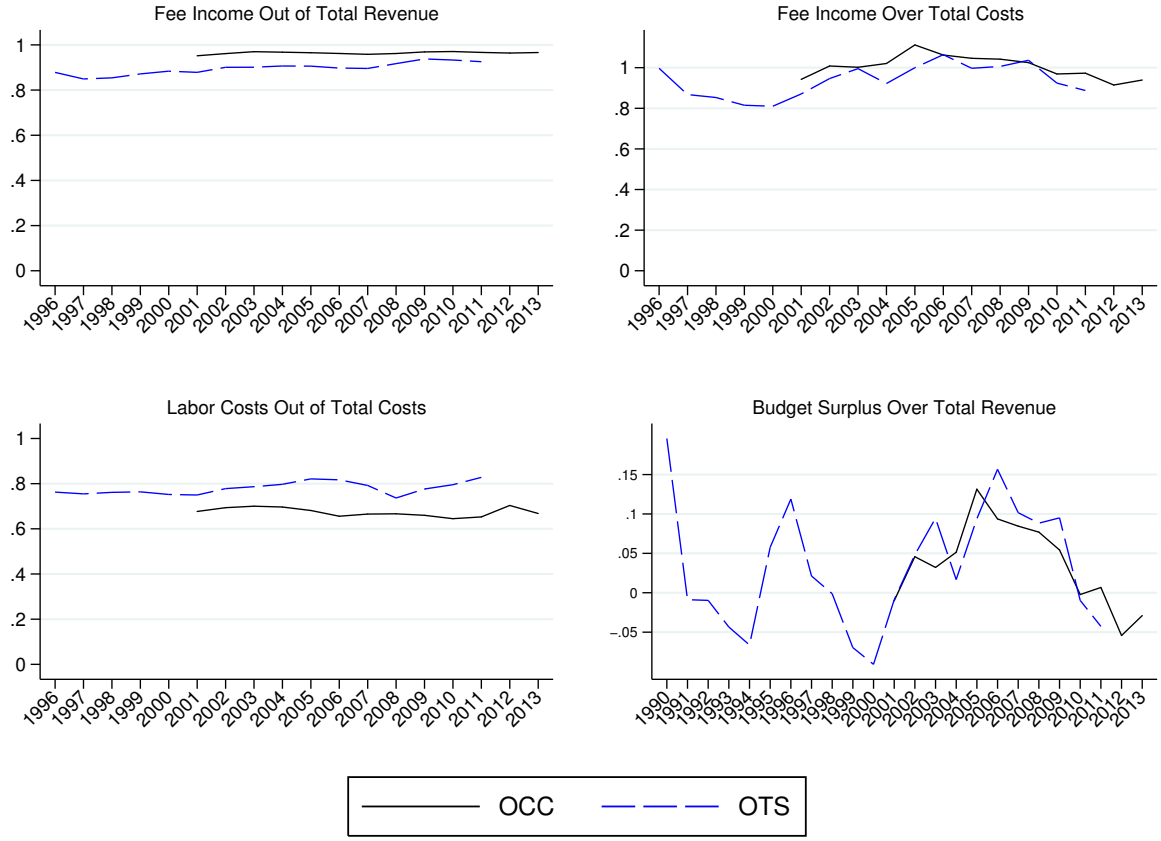


Figure 1: **Revenues, Costs and Budget Surplus of Bank Regulators**
Source: The Office of the Comptroller of the Currency (OCC) annual reports for fiscal years 2001-2013 and The Office of Thrift Supervision (OTS) financial statements for 1990-2011.

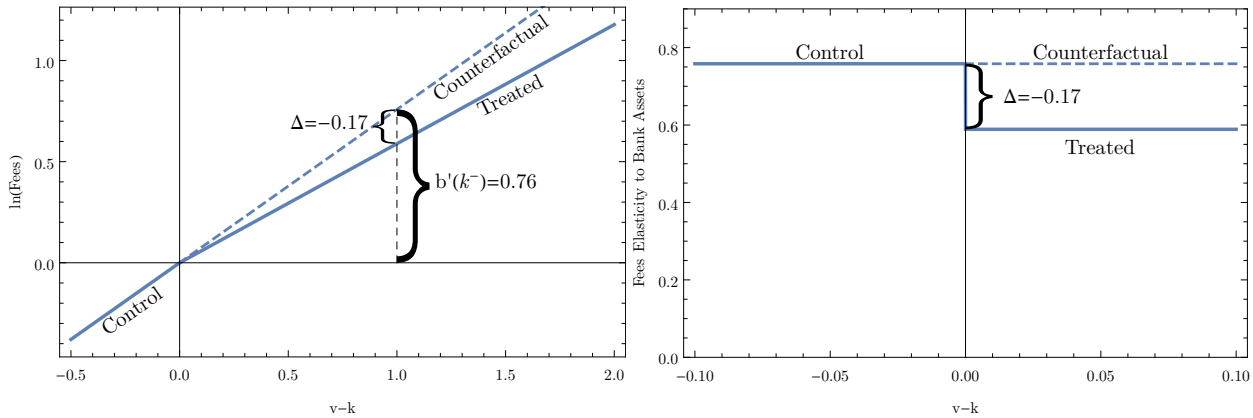


Figure 2: **Kinks in Regulatory Fee Schedules**

Notes: The figures show the mean difference in elasticities estimated with a local linear regression $b(v_{ij}) \equiv \log Fees_{ij} = \alpha_j + \beta(v_{ij} - k_j) + \Delta(v_{ij} - k_j) D(v_{ij} > k_j) + \gamma D(v_{ij} > k_j) + \varepsilon_{ij}$, 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 illustrates the mean slopes ignoring the levels α_j. The figure on the right illustrates our "first-stage" effect, which is 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 its right. Because the average elasticity on the left is 0.76, the "first-stage" estimated effect represents a 22 percent decrease in elasticity. Our dataset includes all fee schedules for national banks and thrifts regulated by OCC (1985–2014) and OTS (1990–2012). Table 1 shows an example fee schedule.

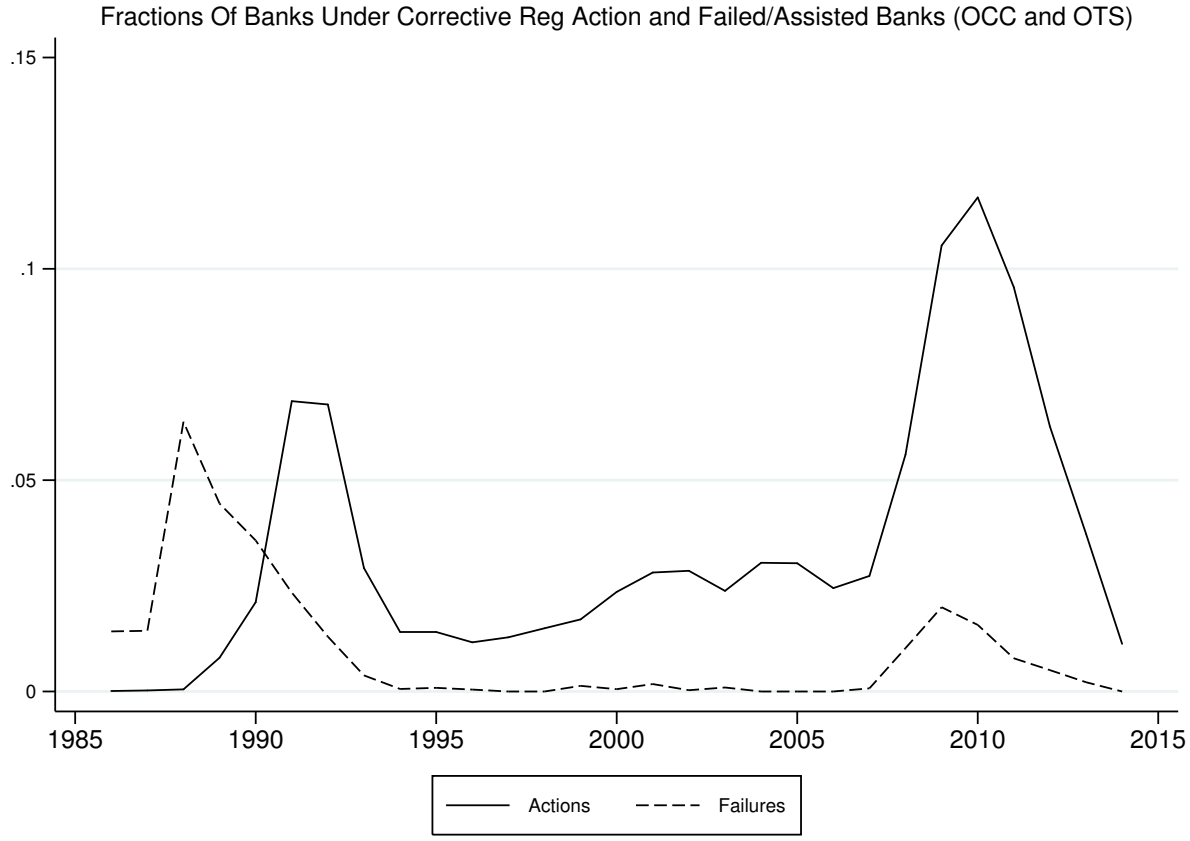


Figure 3: **Fraction of Failing/Assisted Banks and Banks Under Corrective Actions**

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.

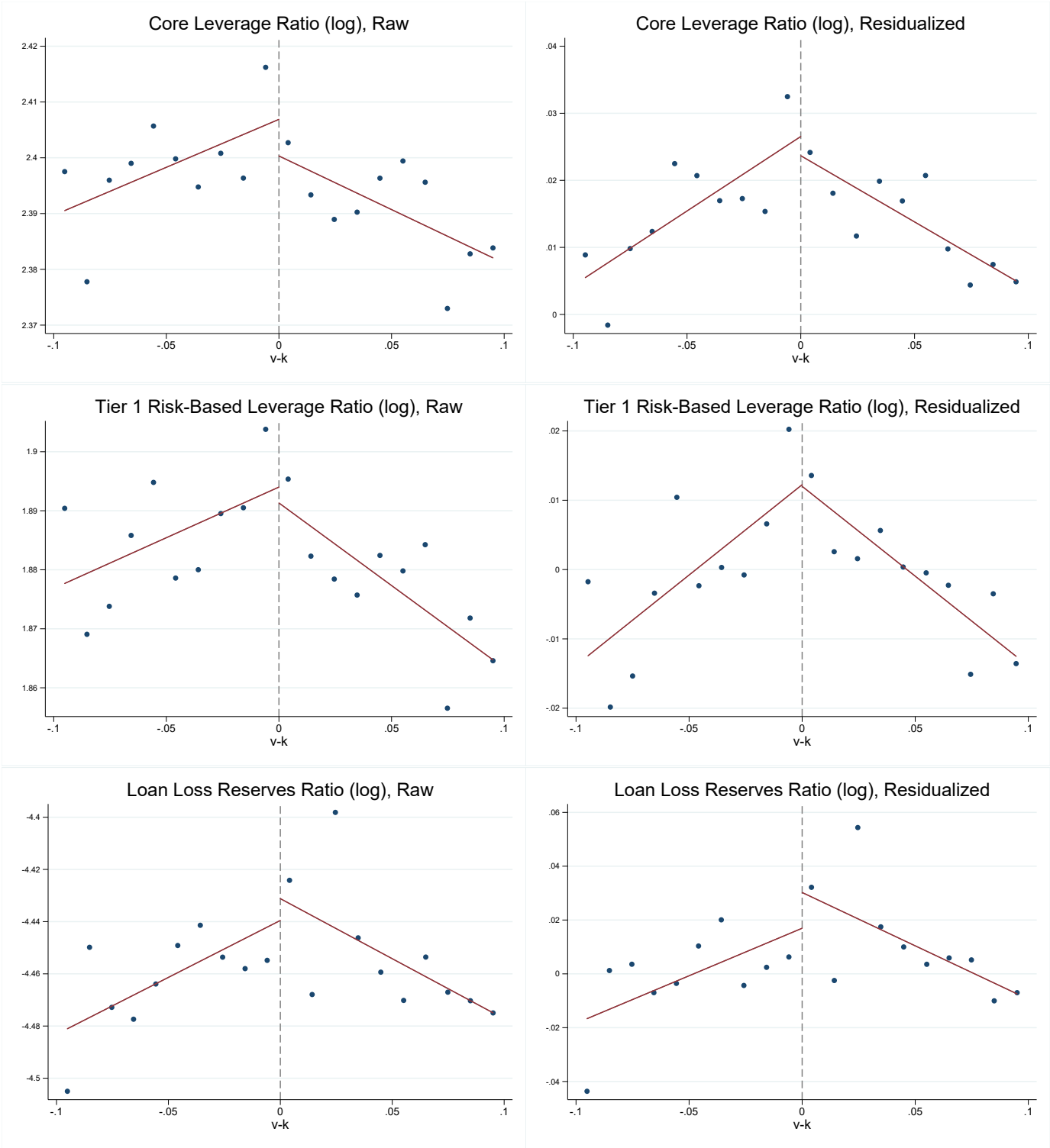


Figure 4: **Fees and Leverage—Kinks in Raw Outcomes**

Notes: The figure shows two regulatory leverage and loss reserves ratios around kinks in the regulatory fee schedules. Leverage is defined as the reciprocal of the corresponding regulatory capital ratio. Loss reserves are normalized by total outstanding loans. Residualized variables are estimated with a regression on a smooth flexible function of the assignment variable interacted with kink-year fixed effects: $y_{ij} = \sum_{p=0}^{2} \alpha_{jp} (v_{ij} - k_j)^p + \varepsilon_{ij}$, where v_{ij} is the log assets of bank i in kink-year j, k_j is log assets at a kink. The data is grouped into 20 bins and the average for each bin is plotted. The solid lines show the linear fit in $v - k$, estimated using the underlying data. The sample: national banks and thrifts regulated by OCC or OTS (1990–2014).

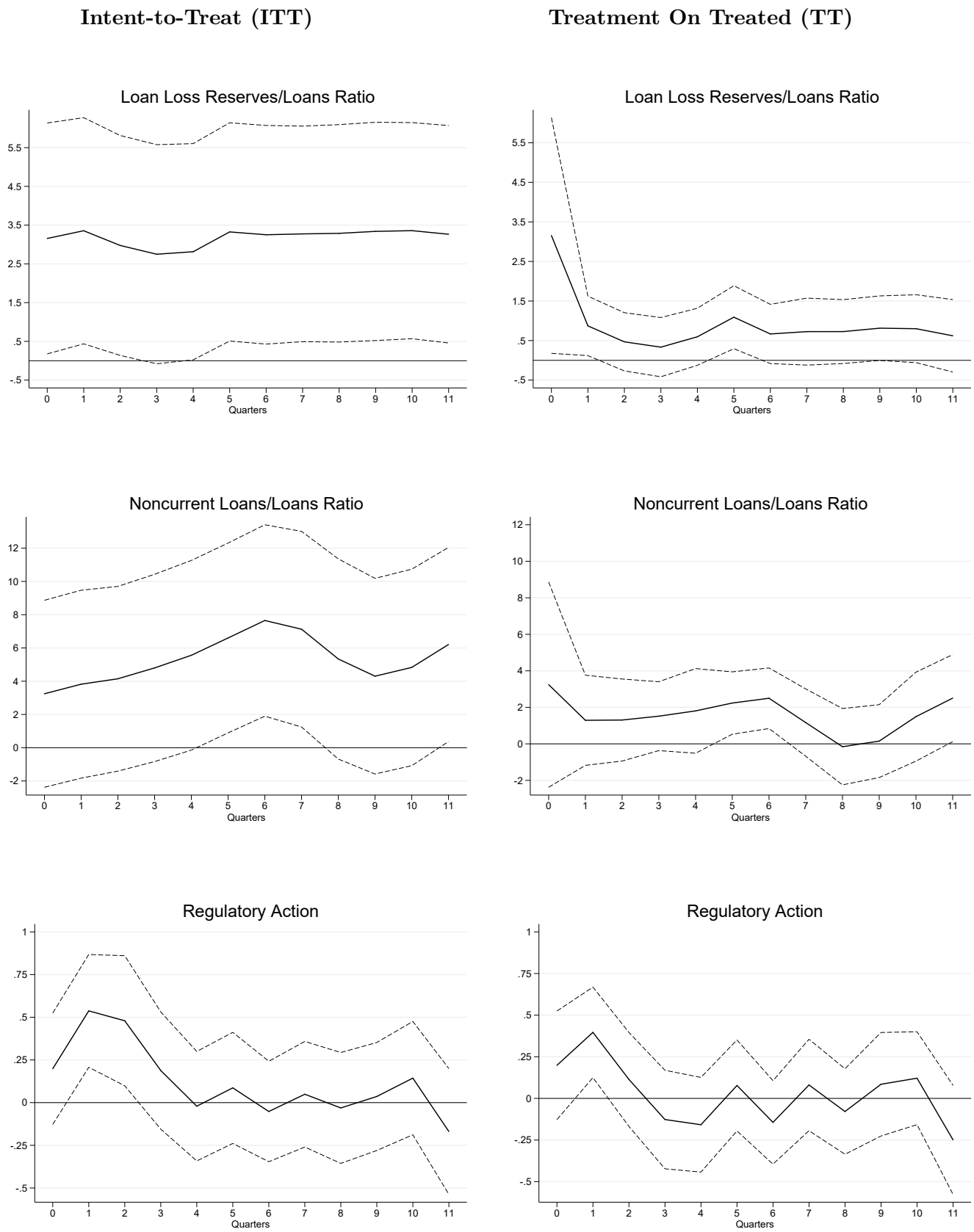


Figure 5: **Dynamic RKD: Slow-adjusting Variables**

Notes: ITT and TT 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 (9) and TT with Equation (8). Standard errors are adjusted for two-way clustering on a bank and a quarterly level.

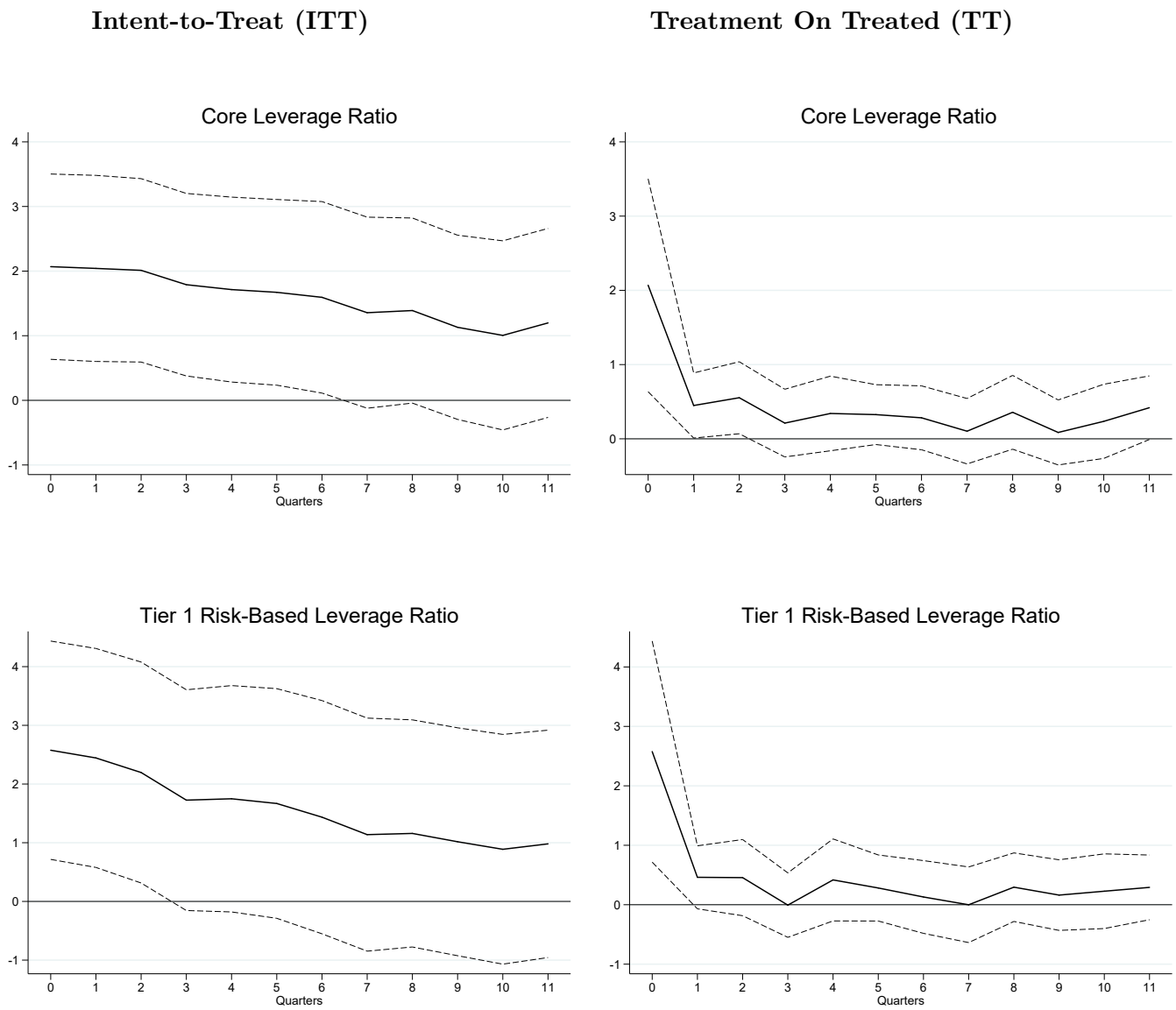
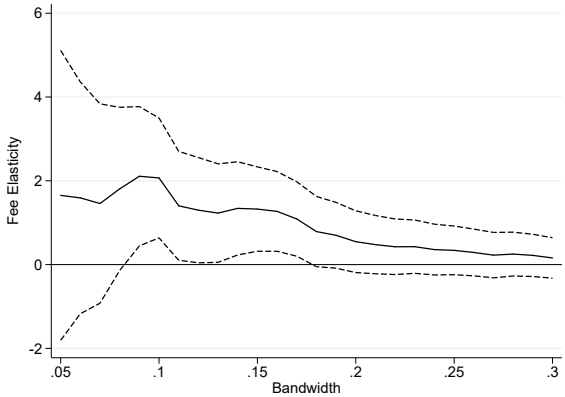
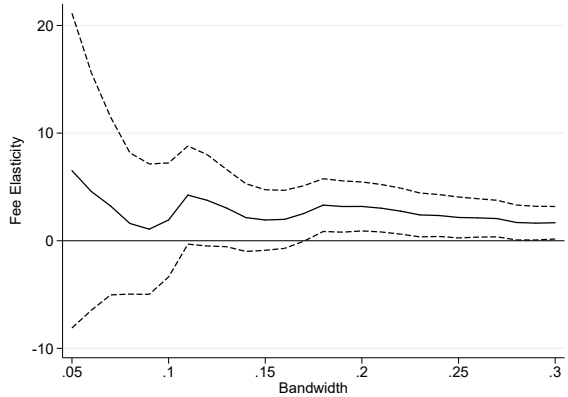


Figure 6: **Dynamic RKD: Leverage Ratios**

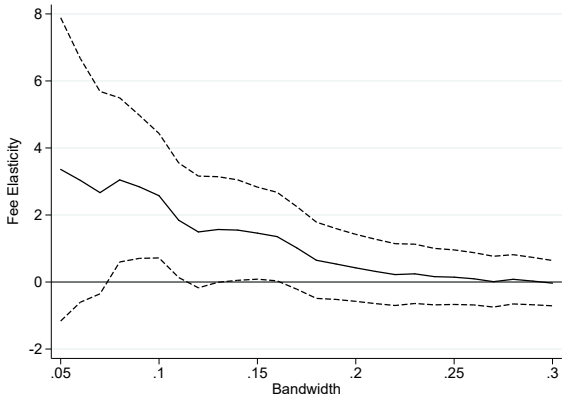
Notes: ITT and TT estimates from Table 4 (with 95% confidence intervals) of the effect of the exogenous variation in lagged assessment fees paid by national banks and thrifts to OCC and OTS. Quarter 0 is the contemporaneous effect of fees on the outcomes. ITT is estimated with Equation (9) and TT with Equation (8). Standard errors are adjusted for two-way clustering on a bank and a quarterly level.



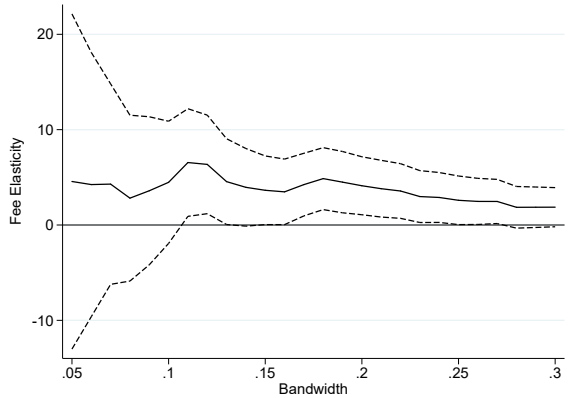
(a) Core Leverage Ratio, $P = 1$



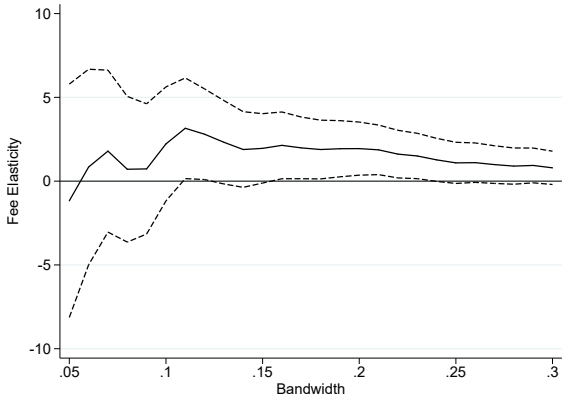
(b) Core Leverage Ratio, $P = 2$



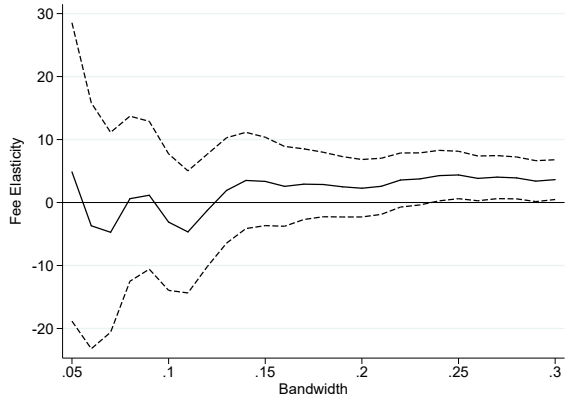
(c) Tier 1 Risk-Based Leverage Ratio, $P = 1$



(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 Bank Capital and Loan Losses**

Notes: Solid lines show how point estimates ($\hat{\beta}_1$) of the elasticity of each of the dependent variables to regulatory fees change 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 on a bank and a quarterly level.

	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: tier 1 capital over balance sheet assets (core) or over risk-based assets (tier 1 risk-based). 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.

	Core Leverage		Risk-Based Leverage		Loss Reserves	
	(1)	(2)	(3)	(4)	(5)	(6)
Fee Elasticity	2.069***	3.022***	2.576***	4.154***	3.156**	4.273**
	(2.87)	(2.72)	(2.75)	(2.72)	(2.09)	(2.12)
Effect at Mean	0.241	0.352	0.184	0.298	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-Sq	0.22	0.22	0.19	0.19	0.30	0.31
Obs	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. Fee elasticity is the percentage change in a dependent variable as a result of a one percent change in fees. 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: tier 1 capital over balance sheet assets (core) or over risk-based assets (tier 1 risk-based). Loss reserves are normalized by the total outstanding loans. All specifications are based on Equation (6) in Section 4.1, and control for a polynomial in size (distance from the kink) interacted with kink-date fixed effects. The choice of optimal badnwidths and polynomial degrees is described in Section 4.1. 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		(6) Large	
Fee Elasticity	2.421***	(3.01)	1.956	(1.66)	3.106***	(3.04)	2.887*	(1.86)	2.823*	(1.76)	1.543	(0.45)
Effect at Mean	0.275		0.236		0.208		0.215		0.000386		0.000204	
Mean Dep. Var.	11.36		12.09		6.686		7.435		0.0137		0.0132	
Mean Fee	49,262		275,292		49,256		275,292		49,256		277,039	
Obs	32,963		30,523		32,970		30,523		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: tier 1 capital over balance sheet assets (core) or over risk-based assets (risk-based). 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. 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) TT	(3) ITT	(4) TT	(5) ITT	(6) TT	(7) ITT	(8) TT	(9) ITT	(10) TT
Elasticity Qtr t	3.156**	3.156**	3.245	3.245	0.199	0.199	2.069***	2.069***	2.576***	2.576***
	(2.08)	(2.08)	(1.13)	(1.13)	(1.19)	(1.19)	(2.83)	(2.83)	(2.71)	(2.71)
Qtr t+1	3.355**	0.871**	3.821	1.291	0.537***	0.397***	2.042***	0.449**	2.445**	0.461*
	(2.25)	(2.27)	(1.33)	(1.02)	(3.19)	(2.86)	(2.78)	(2.01)	(2.57)	(1.70)
Qtr t+2	2.975**	0.468	4.147	1.305	0.479**	0.114	2.012***	0.554**	2.196**	0.456
	(2.05)	(1.25)	(1.46)	(1.14)	(2.47)	(0.79)	(2.78)	(2.24)	(2.29)	(1.39)
Qtr t+3	2.749*	0.333	4.801*	1.517	0.188	-0.127	1.790**	0.212	1.726*	-0.00681
	(1.91)	(0.87)	(1.67)	(1.58)	(1.07)	(-0.84)	(2.48)	(0.91)	(1.80)	(-0.02)
Qtr t+4	2.814**	0.596	5.561*	1.805	-0.0209	-0.158	1.714**	0.342	1.749*	0.417
	(1.98)	(1.62)	(1.91)	(1.53)	(-0.13)	(-1.09)	(2.35)	(1.33)	(1.78)	(1.19)
Qtr t+5	3.325**	1.091***	6.602**	2.236**	0.0864	0.0777	1.672**	0.326	1.669*	0.282
	(2.31)	(2.69)	(2.27)	(2.57)	(0.52)	(0.56)	(2.28)	(1.59)	(1.67)	(0.99)
Qtr t+6	3.251**	0.667*	7.653***	2.498***	-0.0519	-0.144	1.594**	0.283	1.436	0.130
	(2.26)	(1.75)	(2.61)	(2.95)	(-0.35)	(-1.13)	(2.11)	(1.29)	(1.42)	(0.42)
Qtr t+7	3.274**	0.727*	7.128**	1.165	0.0492	0.0806	1.356*	0.103	1.138	-0.000732
	(2.31)	(1.68)	(2.37)	(1.24)	(0.31)	(0.58)	(1.80)	(0.46)	(1.12)	(-0.00)
Qtr t+8	3.288**	0.727*	5.338*	-0.157	-0.0311	-0.0787	1.390*	0.357	1.158	0.295
	(2.30)	(1.77)	(1.74)	(-0.15)	(-0.19)	(-0.60)	(1.90)	(1.41)	(1.17)	(1.00)
Qtr t+9	3.339**	0.813*	4.302	0.151	0.0360	0.0850	1.130	0.0858	1.017	0.162
	(2.32)	(1.95)	(1.43)	(0.15)	(0.22)	(0.54)	(1.55)	(0.38)	(1.03)	(0.53)
Qtr t+10	3.357**	0.800*	4.830	1.491	0.144	0.121	1.005	0.235	0.888	0.227
	(2.36)	(1.83)	(1.60)	(1.20)	(0.85)	(0.85)	(1.35)	(0.92)	(0.89)	(0.71)
Qtr t+11	3.265**	0.621	6.207**	2.504**	-0.169	-0.249	1.198	0.419*	0.981	0.292
	(2.28)	(1.33)	(2.08)	(2.06)	(-0.90)	(-1.49)	(1.61)	(1.92)	(0.99)	(1.05)

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

Notes: Intent-to-treat (ITT) and treatment-on-treated (TT) elasticities—percentage change in the outcome due to a one percent change in fees. ITT includes the direct effect (TT) and the indirect effect through the impact on future assignments (Equation (7)). TT is recursively recovered via Equation (8). Leverage is the reciprocal of regulatory capital ratio: tier 1 capital over balance sheet assets (core) or over risk-based assets (risk-based). 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) $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$

	Core Leverage		Risk-Based Leverage		Loss Reserves	
	(1)	(2)	(3)	(4)	(5)	(6)
Fee Elasticity	-1.154	-0.802	-1.503	-0.636	-1.118	1.749
	(-1.64)	(-1.08)	(-1.58)	(-0.66)	(-0.85)	(1.34)
Effect at Mean	-0.134	-0.0933	-0.108	-0.0457	-0.000161	0.000253
Mean Dep. Var.	11.62	11.64	7.159	7.188	0.0144	0.0145
Mean Fee	187,197	186,221	187,173	186,204	184,937	187,435
Bandwidth	0.1	0.2	0.1	0.2	0.1	0.2
Poly. Degree	1	2	1	2	1	2
R-Sq	0.21	0.21	0.19	0.19	0.31	0.31
Obs	50,944	106,867	50,951	106,878	55,904	121,246

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 adding to each kink point in the fee function 0.1 log points. Fee elasticity is the percentage change in a dependent variable as a result of a one percent change in fees. 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: tier 1 capital over balance sheet assets (core) or over risk-based assets (tier 1 risk-based). Loss reserves are normalized by the total outstanding loans. All specifications are based on Equation (6) in Section 4.1, and control for a polynomial in size (distance from the kink) interacted with kink-date fixed effects. The choice of optimal badnwidths and polynomial degrees is described in Section 4.1. 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 TT 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 TT 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 $\log y_i = 8 + TT_0 \times \log Fees_i - 0.7 \times \log Assets_i + 0.1 \times (\log Assets_i)^2 + w_i$. 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 TT 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 TT 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 $\log y_i = 8 + TT_0 \times \log Fees_i - 0.7 \times \log Assets_i + 0.1 \times (\log Assets_i)^2 + w_i$. 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.

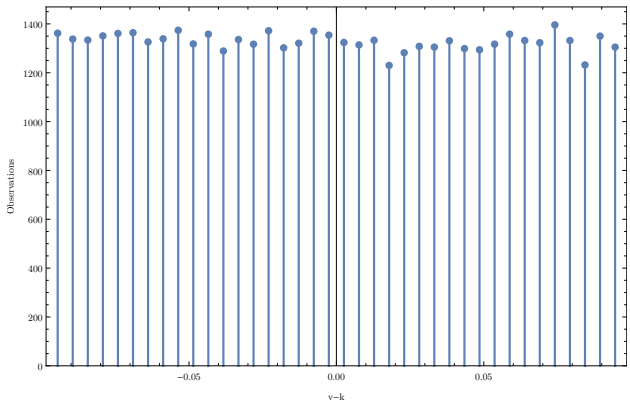


Figure A.1: **Histogram of Assignment Variable** ($\ln Assets$) **Around Kinks**

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. The regression results do not reject the null of a smooth density with t-statistic 0.92 for a polynomial of degree 1.