Deposit Insurance Premiums and Arbitrage

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Abstract

Deposit insurance premiums impose costs on interest on excess reserves arbitrage—borrowing federal funds and holding them as excess reserves. This paper estimates the effects of deposit insurance premiums on bank demand for reserves and interbank lending of federal funds using confidential data and a kink in the schedule of deposit insurance premiums. We show that deposit insurance premiums weaken bank demand for reserves and strengthen bank supply of federal funds. We discuss the implications of these findings for monetary policy implementation and optimal deposit insurance pricing.

JEL codes: E52, E58, G21, G28

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1 Introduction

In recent years, deposit insurance premiums have become critical for monetary policy implementation. Since 2015, the Federal Reserve has used the interest it pays on excess reserve balances (interest on excess reserves, or IOER) as its main tool to control the federal funds rate.[1] When the Fed raises the IOER rate, IOER arbitrage—buying federal funds and other short-term funds and holding those funds as excess reserves—becomes more profitable, strengthening bank demand for short-term funds and inducing upward pressure on short-term rates. In contrast, deposit insurance premiums reduce the profitability of IOER arbitrage. This is because purchasing short-term funds expands bank assets, which serves as the base on which the premiums are assessed. Consequently, the Federal Reserve must accommodate these effects of insurance premiums when using the IOER rate to control short-term interest rates. For this purpose, it is crucial to understand how insurance premiums affect the demand for reserves as well as the supply and demand for federal funds.

However, establishing a causal effect of deposit insurance premiums on bank demand for reserves and on interbank lending is difficult. The main challenge is that exogenous variation in insurance premiums, which is necessary to establish a causal effect, is scarce. Indeed, differences in insurance premiums over time and across banks are correlated with unobservable characteristics that affect banks' behavior in these markets. For example, domestic banks must pay deposit insurance premiums, while most foreign banks are exempt, and domestic and foreign banks are subject to distinct regulatory and supervisory frameworks that may determine demand for reserves and supply and demand for federal funds. Also, insurance premiums depend on measures of bank risk—such as capital ratios and supervisory ratings—that are correlated with unobservable shocks to banks' conditions that may affect their behavior in these markets. This correlation implies that estimates of the effects of deposit insurance premiums on bank demand for reserves and on interbank lending that rely on those differences will most likely be biased.

In this paper, we attempt to establish a causal effect of deposit insurance premiums on bank demand for reserves and on supply and demand for federal funds using a kink

[1] The Federal Open Market Committee Statement on Policy Normalization Principles and Plans from September 17, 2014, states that "the Federal Reserve intends to move the federal funds rate into the target range set by the FOMC primarily by adjusting the interest rate it pays on excess reserve balances" (Federal Open Market Committee, 2014).

in the schedule of deposit insurance premiums of small banks.[2] The Federal Deposit Insurance Corporation (FDIC) charges each bank a deposit insurance premium equal to the bank's assessment base multiplied by the bank's assessment rate. A small domestic bank's assessment base can be roughly defined as its total assets minus tangible equity and some adjustments, while its assessment rate is a linear function of measures of bank risk. The assessment rate, however, is subject to a minimum and a maximum, which generates two kinks in the assessment rate schedule. Many banks have unconstrained assessment rates close to the minimum, and we use this kink under a regression kink design (RKD) to estimate the effects of deposit insurance premiums on bank demand for reserves and on supply and demand for federal funds. Intuitively, we analyze changes in holdings of excess reserves and in amounts of federal funds purchased and sold in response to changes in the slope of the assessment rate schedule.

Our main results indicate that an increase in deposit insurance premiums weaken demand for reserves and strengthen the supply of federal funds. We estimate that a 1-basis point increase in the assessment rate decreases the amount of excess reserves that the average bank in the sample holds from \$6 million to \$1 million, and increases the amount of federal funds that the average bank sells to other banks from \$4 million to \$17 million. These results are economically meaningful, especially considering that small banks generally do not engage in IOER arbitrage and thus, in principle, might not respond to changes in assessment rates. Meanwhile, we find little evidence that assessment rates affect the amount of federal funds purchased by banks. To some extent, we can attribute this result to the fact that small domestic banks rarely purchase federal funds.

Our findings that assessment rates weaken demand for reserves and strengthen the supply of federal funds are robust to various validation and falsification tests. These tests include estimates of treatment effects on predetermined and placebo outcomes, tests of density of assessment rates, and estimates of treatment effects with false cutoffs, excluding observations near the true cutoff, and using different bandwidth choice procedures. We also provide graphical and statistical evidence that the assumptions of the RKD are valid.

This paper is related to the nascent literature on the effects of deposit insurance premiums on bank behavior. Kreicher et al. (2013) analyze the impact of a change in

[2] In this paper, we restrict our sample to banks with assets between \$100 million and \$5 billion.

the assessment base in 2011 on money markets and banks' balance sheets.[3] Keating and Macchiavelli (2017) study the effects of insurance premiums by comparing how often domestic and foreign banks borrow funds in federal funds and Eurodollar markets and how much of those funds they allocate into reserves. Banegas and Tase (2017) use a difference-in-differences strategy to examine how demand for reserves and trading in federal funds markets changed with the modification of the assessment base in 2011. Kandrac and Schlusche (2018) examine how reserve holdings affect bank lending using indicators of whether a bank is exempt of deposit insurance premiums and whether it is considered a custodial or a banker's bank as instrumental variables for reserve holdings. We differ from these papers by examining the effects of deposit insurance premiums with an identification strategy based on a kink in the assessment rate schedule faced by these banks. In addition, while these papers use indicator variables of time and bank characteristics to account for differences in deposit insurance premiums that banks pay, we are the first to use banks' assessment rates to quantify the effect of an increase in assessment rates on reserve demand and on supply and demand of federal funds.

Our research also contributes to the theoretical literature on monetary policy in an environment in which the central bank supplies a large amount of reserves and pays IOER, but banks incur in-balance sheet costs.[4] Martin et al. (2013), Afonso et al. (2018), Kim et al. (2018), and Schulhofer-Wohl and Clouse (2018) examine reserve demand and interbank lending with models in which banks are subject to exogenous costs that increase with balance sheet size. Duffie and Krishnamurthy (2016) and Armenter and Lester (2017) incorporate balance sheet costs into models of monetary policy implementation assuming that depository institutions incur a cost for taking deposits. All these papers use deposit insurance fees to motivate such costs in their models. Afonso et al. (2018) and Schulhofer-Wohl and Clouse (2018), in particular, calibrate their models of interbank lending with an estimate of assessment rates from Banegas and Tase (2017). In addition, Bianchi and Bigio (2018), Ennis (2018), and Williamson (2018) examine reserve demand and interbank

[3]The assessment base was changed from bank deposits to total assets minus tangible equity and some adjustments.

[4]Bech and Klee (2011), Afonso and Lagos (2015), and Bech and Keister (2017) also study monetary policy implementation in an environment with abundant reserves and with IOER, but do not assume that banks incur in-balance sheet costs. These papers assume that banks are subject to reserve requirements and Bech and Keister (2017) also assume that banks must satisfy a liquidity coverage ratio (LCR) requirement, but these two requirements generally do not constrain IOER arbitrage or increase its costs.

lending with models in which banks are subject to a capital requirement, a cost that also increases with balance sheet size. In all these papers, balance sheet costs influence monetary policy implementation by affecting demand for reserves and interbank lending. Our paper contributes to this literature with empirical evidence that deposit insurance premiums, which increase with balance sheet size, indeed affect demand for reserves and interbank lending. Moreover, we provide quantitative estimates of these effects.

This paper is also related to the literature on optimal deposit insurance pricing. In these papers, optimal deposit insurance premiums are mainly determined by individual bank failure risk and, more recently, also by systemic risks associated with the joint failure of large and systemically important banks (Buser et al., 1981; Kanatas, 1986; Ronn and Verma, 1986; Acharya and Dreyfus, 1989; Chan et al., 1992; Giammarino et al., 1993; Craine, 1995; John et al., 2000; Boyd et al., 2002; Pennacchi, 2006; Acharya et al., 2010; Allen et al., 2015; Dávila and Goldstein, 2016). To our best knowledge, optimal deposit insurance premiums in this literature do not depend on the aforementioned effects of premiums on bank demand for reserves and interbank lending. To the extent that bank demand for reserves and interbank lending affect monetary policy implementation and that monetary policy implementation may affect welfare, our evidence suggests that optimal deposit insurance premiums should depend on these effects as well.

The rest of this paper is organized as follows: Section 2 provides some background on deposit insurance premiums and IOER arbitrage, Section 3 summarizes our data, Section 4 describes our empirical strategy based on a RKD, Section 5 presents our results, and Section 6 concludes.

2 Institutional Background

2.1 Deposit Insurance Premiums

In the United States, the FDIC insures deposits at all domestic banks and at some branches and agencies of foreign banks.[5] To insure those deposits, the FDIC runs the Deposit Insurance Fund (DIF), which is primarily funded through quarterly assessments

[5] For customers of insured institutions, the FDIC protects all types of deposits, including checking accounts, saving accounts, money market deposit accounts (MMDAs), and time deposits such as certificates of deposit (CDs). If a bank fails, the FDIC provides up to $250,000 per depositor for each account and also helps resolve the failed bank.

on insured banks. Each bank's assessment, best understood as an insurance premium, is determined by multiplying its assessment base by its assessment rate. Since April 2011, the assessment base has been defined as the average consolidated total assets of the bank minus its average tangible equity and some adjustments for banker's banks and custodial banks during the assessment period.[6] The assessment rate of a bank with assets of less than $10 billion (small banks) is determined by the risk category of the bank, which is a function of three capital ratios—total risk-based capital ratio, tier 1 risk-based capital ratio, and leverage ratio—and its CAMELS composite rating, which summarizes the general condition of a bank.[7]

Risk categories range from 1 to 4, with risk category 1 generally containing well-capitalized banks with good CAMELS ratings and risk category 4 generally containing undercapitalized banks with poor ratings. Based on the risk category of the bank, the FDIC assigns it an initial base assessment rate. These rates increase with the risk category of the bank. During our sample period—from April 1, 2011, to June 30, 2016—the FDIC assigned to each risk category 1 bank an initial base assessment rate that ranged from 5 to 9 basis points to differentiate banks within this risk category, which accounts for 81 percent of small banks in our sample period. Risk category 2, 3, and 4 banks were assessed fixed initial base assessment rates of 14, 23, and 35 basis points, respectively, regardless of their other characteristics.

The FDIC computes an unconstrained initial base assessment rate for risk category 1 banks as a linear function of risk measures at the bank level. The constrained initial assessment base rate is equal to the minimum rate of 5 basis points if the unconstrained initial base assessment rate is below this minimum and it is equal to the maximum rate of 9 basis points if the unconstrained initial base assessment rate is above this maximum. As shown by the blue line in Figure 1, this rule creates a relationship between the constrained and the unconstrained base assessment rates that is flat on the left of 5 basis points,

[6]From the creation of the FDIC until March 2011, a bank's assessment base was about equal to its total domestic deposits. On April 1, 2011, the current definition of the assessment base was adopted, as required by the Dodd-Frank Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act).

[7]CAMELS ratings are assigned by bank supervisors based on off-site analysis and on-site bank safety and soundness examinations. Supervisors evaluate six main characteristics and assign a rating to each one. The characteristics are capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk, and the respective ratings are called component ratings. The six component ratings and the composite rating range from 1 to 5, where 1 is assigned to banks that raise no supervisory concern and 5 is assigned to institutions that warrant immediate attention from supervisors.

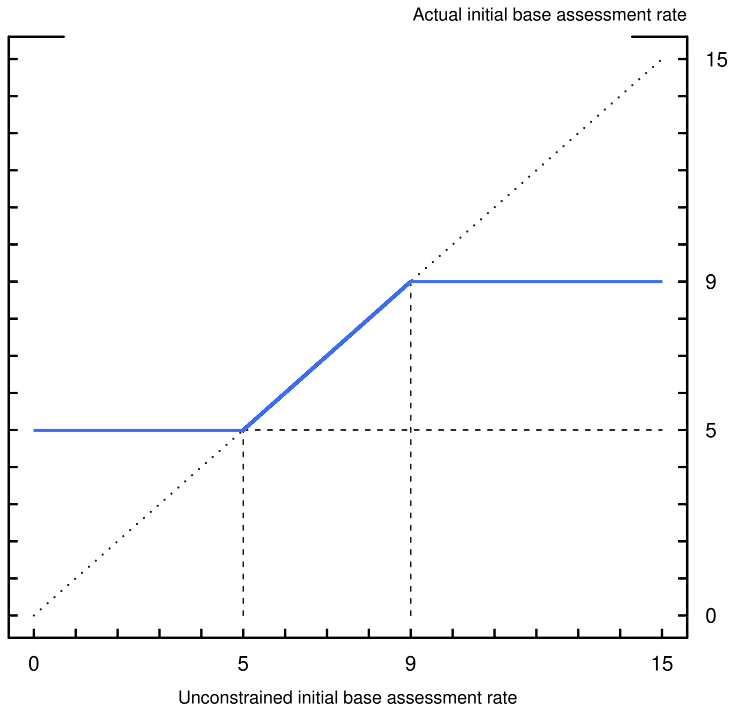

Figure 1: **Kinks in Initial Base Assessment Rate Schedule**

NOTE: The solid line shows the constrained initial base assessment rate as a function of the unconstrained initial base assessment rate for insured risk category 1 banks between April 1, 2011, and June 30, 2016, with total assets below $10 billion. Newly insured institutions (those that became insured within five years) are subject to different rates and are not included in analysis. Assessment rates are measured in basis points.

increasing with a slope equal to 1 between 5 and 9 basis points, and also flat on the right of 9 basis points. Our RKD exploits these kinks in the rate schedule to estimate the effects of assessment rates on bank behavior.

After the initial base assessment rate of a bank is calculated, this rate may be adjusted downward for unsecured debt and upward for brokered deposits and for debt issued by other institutions. The rate that results from these adjustments and is actually charged to banks is defined as the total base assessment rate. In this paper, we restrict our sample to banks that are not subject to any of these adjustments to ensure that their total base assessment rate is identical to their initial assessment base rate. In other words, the total assessment base rate as a function of the unconstrained rate for banks in our sample is identical to the function in Figure 1. In fact, most small banks are not subject to any of these adjustments, and our estimates of the effects of the assessment rates on bank behavior are similar when we use the full sample that includes banks subject to adjustments.[8] In Appendix A, we describe the calculation of assessment rates in more detail.

2.2 IOER Arbitrage

In this subsection, we discuss in more detail IOER arbitrage, which is broadly defined as borrowing federal funds and other short-term funds and holding those funds as excess reserves.[9] We first describe the revenues of IOER arbitrage, namely the IOER, and the costs, which include short-term funding costs and deposit insurance premiums. Next, we discuss the impact of these premiums on arbitrage over time and across banks.

In October 2008, the Federal Reserve started paying IOER to help implement monetary policy amid the Great Recession and a large expansion of its balance sheet. Paying IOER helps support the federal funds rate—the interest rate at which depository institutions lend reserve balances to one another overnight—because depository institutions would have no incentive to lend at rates below the IOER rate. However, the IOER rate does not serve as a hard minimum for the federal funds rate because certain types of financial institutions, such as government-sponsored enterprises (GSEs), cannot earn IOER but still trade federal funds. These institutions often find it profitable to sell federal funds at rates below the IOER rate because they would earn an even lower rate otherwise. Due to this segmentation, the federal funds rate is generally below the IOER rate (Bech and Klee, 2011). This motivates IOER arbitrage, through which banks borrow federal funds below the IOER rate and hold them in their reserve accounts to earn interest at the IOER rate.

There are several factors that can affect the profitability of IOER arbitrage. First, profitability can be affected by the cost of acquiring federal funds, which is determined by negotiations between the purchasing and selling entities. This cost can be proxied using the effective federal funds rate—a weighted median of rates on federal funds transactions.

[8] These results are available upon request from the authors. Of note, as discussed in Appendix A.2, the unsecured debt adjustment (UDA) is the only of these three adjustments that may affect our estimates of the effects of deposit insurance premiums on bank behavior, because the UDA attenuates the changes in slope of the initial base assessment rate as a function of the unconstrained initial base assessment rate. In contrast, the brokered deposit adjustment (BDA) only applies to banks in risk categories 2 to 4, and the depository institution debt adjustment (DIDA) does not depend on the initial base assessment rate.

[9] IOER arbitrage is very often referred to as borrowing federal funds to acquire excess reserves, which will be the promary focus of this paper.

As shown in Figure 2, the effective federal funds rate remained at historically low levels (below 50 basis points) during our sample period. Second, deposit insurance premiums also reduce the gains from IOER arbitrage. Throughout the sample period, the average unconstrained initial base assessment rate ranged between 6 and 7 basis points, which is a non-trivial cost for IOER arbitrage given the low IOER rate.

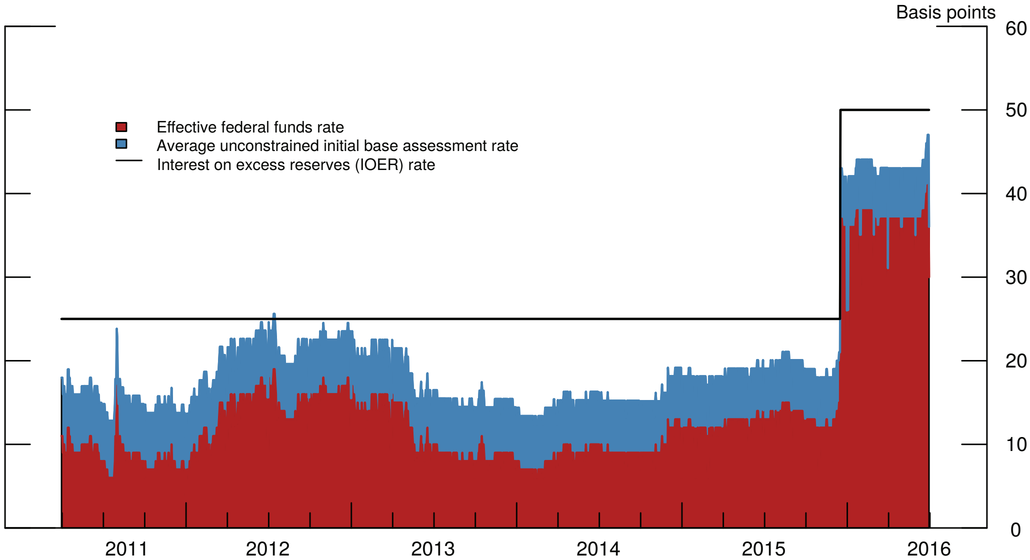

Figure 2: **IOER Arbitrage Profitability**

Figure 2 shows the evolution of the three important drivers that determine IOER arbitrage profitability: the IOER rate, the effective federal funds rate, and the average FDIC assessment rate. The solid black line shows the IOER rate, the red stacked bars indicate the level of the effective federal funds rate, and the blue stacked bars show the average unconstrained initial base assessment rate. Intuitively, the gap between the IOER rate line and the height of the combined blue and red shaded regions equals the profit rate from IOER arbitrage. The figure indicates that, apart from brief periods between the end of 2011 and mid-2012, the average profitability of IOER arbitrage activity was positive and fairly large, at between 5 and 10 basis points. This difference is evidence of strong incentives for banks to participate in such activity during our sample period. It is important to note, however, that banks incur other unobservable costs when engaging in IOER arbitrage, such as the costs of meeting minimum capital requirements. With this caveat in mind, we argue in our following analysis that, indeed, an increase in the FDIC assessment rate significantly reduces banks' holdings of excess reserves and induces banks to become suppliers in the federal funds market.

3 Data

The unit of observation in our panel data is a bank-quarter pair. We restrict the sample to the period between the second quarter of 2011 and the second quarter of 2016 because the method for calculating assessment rates that we use was introduced in April 1, 2011 and was revised again in July 1, 2016. This restriction ensures that all bank-quarter pairs in the sample are from a period in which the definitions of the assessment base and of assessment rates are constant. Therefore, our estimates are not driven by changes in such definitions, which may be correlated with changes in unobservable characteristics of banks or of the economy that might also affect reserve demand and interbank lending, thereby biasing our estimates.

We also limit our sample based on four bank characteristics. First, we restrict the sample to domestic commercial banks to ensure that all institutions in our sample are subject to a homogeneous regulatory framework and that detailed data on their relevant characteristics can be observed. Second, we limit our sample to risk category 1 banks because, as explained in Section 2, this is the only risk category for which assessment rates vary across banks. Third, we eliminate from the sample newly insured institutions, defined as banks that became insured within the past 5 years at the time of calculation, because all such banks are uniformly assigned an initial base assessment rate of 9 basis points if they are in risk category 1. We assume that commercial banks become insured when they open, and using attributes data from the National Information Center (NIC) database, we drop observations where the difference between the calculation date and the date the bank opened is less than or equal to 5 years.

Lastly, we limit the sample to banks with total assets between $100 million and $5 billion. We drop banks with less than $100 million in assets because a large majority of those banks do not have reserve accounts at Federal Reserve Banks and thus cannot hold reserves with the Federal Reserve.[10] We also eliminate banks with more than $5 billion

[10]Indeed, only 28 percent of the bank-quarter observations from banks with less than $100 million in total assets are from banks with reserve accounts, while 59 percent of the observations from banks with assets between $100 million and $5 billion are from banks with reserve accounts. Of note, our results are

in assets to ensure that all banks in the sample follow the same schedule of assessment rates. Indeed, banks with more than $10 billion in total assets, which the FDIC define as large and highly-complex institutions, must follow a different schedule, and banks with assets between $5 billion and $10 billion may choose between the schedule for small institutions—those with $10 billion in assets or less—and the schedule for large and highly-complex institutions under certain conditions. Including banks that follow the large and complex institutions schedule in the sample would impose two additional challenges to our empirical strategy. First, assessment rates of large and highly-complex institutions are a function of bank data that are not readily available from regulatory filings. Second, unconstrained initial assessment base rates for large and highly-complex institutions are a nonlinear function of those data, implying that the slope of the increasing part of the schedule of these banks is not constant and that the denominator of the RKD estimand would not be deterministic, thereby violating an assumption of the RKD. This restriction only causes a modest decrease in our final sample, because less than 4 percent of the commercial banks held more than $5 billion in total assets during our sample period.

For each bank-quarter pair, we calculate the assessment rate that applies to the respective bank in the given quarter using data that we describe in this section and details from the FDIC rule that determines how this rate is calculated.[11] Figure 3 shows the number of observations—bank-quarter pairs—around the thresholds for minimum (5 basis points) and maximum (9 basis points, not drawn) assessment rates for the banks included in our sample using 0.25-basis point bins, which have an average of 537 observations each. As discussed earlier, the number of observations around the 5-basis point threshold is much larger than the number around the 9-basis point threshold. Because the RKD methodology requires a large number of observations around treatment thresholds, we only conduct our analysis at the 5-basis point threshold.

As shown in Table A.3, the initial base assessment rate is calculated using six risk measures: tier 1 leverage ratio, ratio of loans past due 30-89 days to gross assets, ratio of nonperforming assets to gross assets, adjusted brokered deposits ratio, ratio of net loan charge-offs to gross assets, and ratio of net income before taxes to risk-weighted assets. The adjusted brokered deposits ratio is given by total brokered deposits divided by total

weaker when we include banks with less than $100 million of total assets in the sample. These results are not included in the paper, but can be made available from the authors upon request.

[11] We discuss these calculations in Appendix A.3.

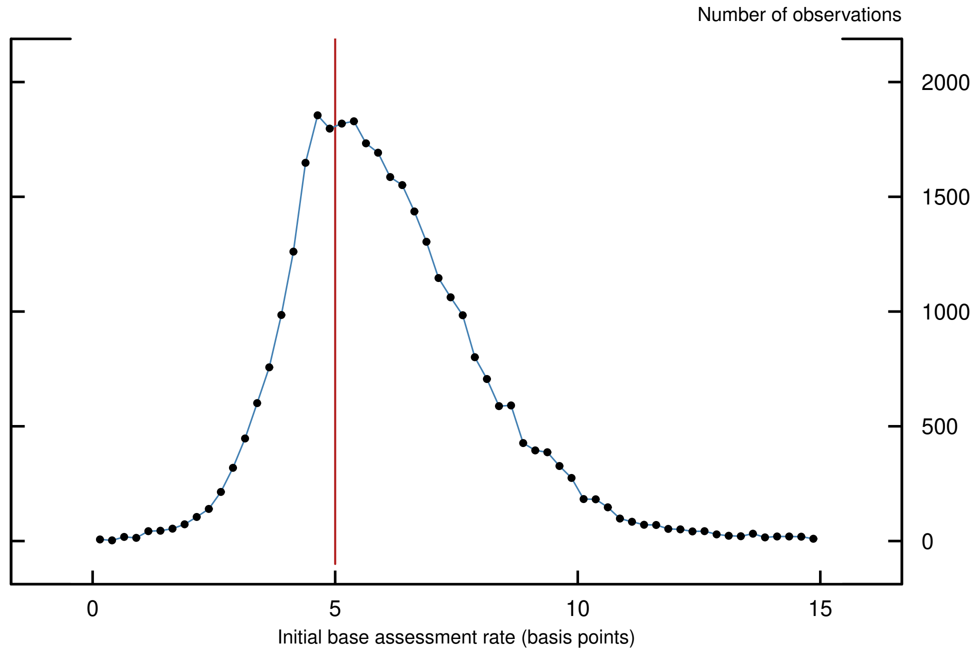

Figure 3: **Distribution of Unconstrained Initial Base Assessment Rates**

NOTE: This figure shows the number of observations—bank-quarter pairs—per bin of unconstrained initial base assessment rates in our sample. Bins are 0.25-basis point wide and contain 537 observations on average. The vertical solid line identifies the minimum initial base assessment rate of 5 basis points.

deposits and is adjusted for 4-year cumulative total gross asset growth. Also, the ratio of net loan charge-offs to gross assets and the ratio of net income before taxes to risk-weighted assets are adjusted for mergers that occurred during the measurement period and incorporate charge-off and income flows for the trailing 4 quarters. All financial ratios for the current quarter, except the 4-quarter trailing flows, are computed using balance sheet data from the end of the previous quarter contained in the Consolidated Reports of Condition and Income (FFIEC 031 and 041), also known as the Call Reports.

Following the FDIC's final rule for assessment rate calculation, we take the most recent CAMELS *composite* ratings from confidential Federal Reserve data to determine the risk category of banks. Then, for risk category 1 banks, we take the most recent CAMELS *component* ratings to compute assessment rates each quarter. The weighted average CAMELS component rating is calculated by taking the weighted sum of each of the component ratings, using the weights outlined in Table A.4 in Appendix A.1.

Our dependent variables measure reserve holdings and interbank lending activity in the federal funds market. We use confidential data on the dollar amounts of reserves and of excess reserves held by banks with the Federal Reserve in the last week of each quarter and the average amounts of reserves and excess reserves in each quarter.[12] We collect data on the amounts of federal funds sold and purchased from the Call Reports.

We also include additional bank characteristics to supplement our data. We use the total capital ratio and the tier 1 capital ratio to measure bank capitalization, and return on assets (ROA) and return on equity (ROE) to measure profitability. These characteristics measures are built using data from the Call Reports. We use these additional data to investigate whether variations in the average bank characteristics are smooth around the 5 basis-point cutoff in Subsection 4.2.

Table 1 summarizes the data. The mean unconstrained initial assessment rate, equal to 6.05 basis points, is close to the 5 basis points threshold, which is expected given the large number of observations with unconstrained initial assessment rates close to this threshold. The means of capital ratios and of profitability measures are high and the means of net charge-offs and of nonperforming loans ratios are low for post-crisis standards, which is consistent with the fact that risk category 1 banks—the banks in our sample—are the most capitalized, profitable, and safest banks, on balance. Of note, the number of observations for our various measures of reserves is less than 20,000, while the number of bank-quarter pairs in the sample exceeds 30,000, which is consistent with the fact that about 60 percent of the banks in our sample have reserve accounts at Federal Reserve Banks.

4 Regression Kink Design

4.1 RKD Estimator

We estimate the effects of deposit insurance premiums on our selection of dependent variables using a sharp RKD, as opposed to a fuzzy RKD, because the unconstrained and the constrained initial assessment rates are assigned deterministically based on the rule and the bank data described in Sections 2 and 3. We use the RKD estimator described by Calonico et al. (2014) and follow their description of the estimator as well. In particular,

[12] A bank's excess reserves is, for the most part, equal to its average end-of-day account balances due from Federal Reserve Banks less its reserve balance requirement (RBR). Balance data are from internal Federal Reserve accounting records whereas bank-level RBR is calculated based on confidential filings of the FR 2900 Report of Transaction Accounts, Vault Cash and Other Deposits.

Table 1: **Summary Statistics**

	Obs.	**Mean**	**Std. Dev.**
Outcome variables			
Reserves ($ million)	19,251	21.25	67.96
Excess reserves ($ million)	19,121	5.56	37.51
Average reserves ($ million)	19,251	21.75	65.25
Average excess reserves ($ million)	19,122	5.55	35.83
Federal funds sold ($ million)	32,568	3.71	18.04
Federal funds purchased ($ million)	32,568	0.39	1.85
Assignment variables			
Unconstrained initial base assessment rate (b.p.)	32,568	6.05	2.11
Tier 1 leverage ratio (pct.)	32,568	10.74	2.61
Loans past due 30-89 days/Gross assets (pct.)	32,568	0.52	0.55
Nonperforming Assets/Gross assets (pct.)	32,568	1.04	1.05
Net loan charge-offs/Gross assets (pct.)	32,568	0.14	0.23
Net income before taxes/Risk-weighted assets (pct.)	32,568	2.02	1.02
Adjusted brokered deposit ratio (pct.)	32,568	0.00	0.00
Weighted average CAMELS component rating	32,568	1.62	0.40
Other bank characteristics			
Total capital ratio (pct.)	32,568	19.09	6.84
Tier 1 capital ratio (pct.)	32,568	17.97	6.84
Return on assets (pct.)	32,568	1.06	0.60
Return on equity (pct.)	32,568	9.78	5.82

NOTE: Each observation is a bank-quarter pair and the sample period ranges from the second quarter of 2011 to the second quarter of 2016. The data are restricted to bank-pair observations from domestic commercial banks in FDIC's risk category 1 that were open 5 years before or more and with total assets between $100 million and $5 billion. b.p. and pct. are abbreviations for basis points and percent, respectively.

for each bank i and quarter t, with $i = 1, 2, ..., I$ and $t = 1, 2, ..., T$, X_{it} is the unconstrained initial base assessment rate—the score, forcing, assignment, or running variable in our setting—such that the bank-quarter pair $\{i, t\}$ is subject to the minimum rate of 5 basis points if $X_{it} < 5$ and to a rate of X_{it} basis points if $X_{it} \geq 5$. In simpler terms, the rate schedule implies that initial base assessment rates that are calculated to be lower than 5 basis points will be fixed at the floor rate of 5 basis points. We further define:

$$\mu(x) \equiv \mathbb{E}[Y_{it}|X_{it} = x] \tag{1}$$

$$\mu_+^{(\nu)} \equiv \lim_{x \to 5^+} d^\nu \mu(x)/dx^\nu \tag{2}$$

$$\mu_-^{(\nu)} \equiv \lim_{x \to 5^-} d^\nu \mu(x)/dx^\nu \tag{3}$$

As described in Card et al. (2015) and Landais (2015), the denominator of the RKD estimand is deterministic—it is the change in the slope of the schedule at the kink—and thus we only need to estimate the numerator of the estimand, namely the change in the slope of the conditional expectation function $\mu(x)$ at the kink, $\tau \equiv \mu_+ - \mu_-$. The bias-corrected local quadratic estimator is as follows:

$$\hat{\tau}(h_{IT}) \equiv \hat{\mu}_{+,2}^{(1)}(h_{IT}) - \hat{\mu}_{-,2}^{(1)}(h_{IT}) - h_n^2 \hat{B}(h_{IT}, b_{IT}), \tag{4}$$

where $\hat{\mu}_{+,2}^{(1)}(h_{IT})$ and $\hat{\mu}_{-,2}^{(1)}(h_{IT})$ are local-quadratic estimators of $\mu_+^{(1)}$ and $\mu_-^{(1)}$, respectively, and h_{IT} is a positive bandwidth. $h_{IT}^2 \hat{B}(h_{IT}, b_{IT})$ is a term intended to correct for the bias in the estimator caused by the mean-squared-error optimal choice of the bandwidth for $\hat{\mu}_{+,2}^{(1)}(h_{IT}) - \hat{\mu}_{-,2}^{(1)}(h_{IT})$. $\hat{B}(h_{IT}, b_{IT})$ is given by:

$$\hat{B}(h_{IT}, b_{IT}) \equiv \hat{\mu}_{+,3}^{(3)}(b_{IT})\mathcal{B}_+(h_{IT})/3! - \hat{\mu}_{-,3}^{(3)}(b_{IT})\mathcal{B}_-(h_{IT})/3! \tag{5}$$

where b_{IT} is a pilot bandwidth, $\hat{\mu}_{+,3}^{(3)}(b_{IT})$ and $\hat{\mu}_{-,3}^{(3)}(b_{IT})$ are the local-cubic estimators of $\mu_+^{(3)}$ and $\mu_-^{(3)}$, respectively, and $\mathcal{B}_+(h_{IT})$ and $\mathcal{B}_-(h_{IT})$ are asymptotically bounded observed quantities.[13]

Following Card et al. (2015), we estimate τ using local linear and quadratic estimators.[14] We estimate τ clustering standard errors at the bank level and using the software packages described in Calonico et al. (2017).

[13] These quantities are defined in Lemma A.1(B) of Calonico et al. (2014).

[14] The description of the local linear estimator is analogous to description of the local quadratic estimator and we omit it from the paper for the sake of brevity.

4.2 Smoothness Assumption of the RKD

The key identifying assumption of the SRKD is that the density of the running variable conditional on the unobservable determinants of the outcome variable is sufficiently smooth—that is, continuously differentiable—at the cutoff (Card et al., 2015). This smoothness condition is violated if the density of the running variable has a kink or a discontinuity at the cutoff. Such violation would suggest that individuals can manipulate precisely the running variable at the cutoff. In our context, this assumption requires that banks cannot lower their unconstrained initial base assessment rates in a neighborhood of the 5-basis point threshold.

Figure 3 shows that the distribution of the running variable is smooth around the 5-basis point threshold, indicating that banks do not manipulate their assessment rates within narrow neighborhoods around this threshold. This makes intuitive sense because the assessment rate is calculated based on several arguably orthogonal variables, making it difficult for banks to adjust with precision. We also test formally whether the density of unconstrained initial base assessment rates is continuous around this threshold. The results of these tests, which are presented in Table A.5 in Appendix B, do not reject the null hypothesis that the density of the running variable is continuous at the threshold of 5 basis points. This offers additional support to the validity of the RKD in our setting.

The smoothness assumption also implies that the expectation of any variable that should not be affected by treatment conditional on the running variable should be twice continuously differentiable at the cutoff. Figures 4 and 5 examine this hypothesis graphically showing the mean values of covariates as a function of the running variable. We analyze the following covariates: all risk measures listed in Table A.3 that determine the value of the running variable (except the adjusted brokered deposit rate, which is equal to 0 for all banks in our sample); and total capital ratio and tier 1 capital ratio, which, together with the tier 1 leverage ratio, determine each bank's capital group that in turn assigns the risk category. The figures show the mean values of these covariates in the year-quarter pair in which the running variable is measured.

Figure 5 also includes two measures of profitability, namely ROA and ROE, measured in the previous year-quarter pair. We use lagged values for ROA and ROE because, in principle, deposit insurance premiums could lower ROA and ROE, even though these effects should be modest because assessment rates are small compared to the means of

ROA and ROE. The figures show that the relationship between the running variable and the conditional expectations of those covariates is smooth around the cutoff, supporting the RKD smoothness assumption. In Appendix B, we also formally test whether these conditional expectations are twice continuously differentiable around the threshold of 5 basis points by estimating treatment effects on those covariates using the estimator $\hat{\tau}(h_{IT})$ and the cutoff of 5 basis points. As shown in Table A.6, the results from the test for all covariates do not reject the null hypothesis of no treatment effects, thereby providing further support to our RKD.

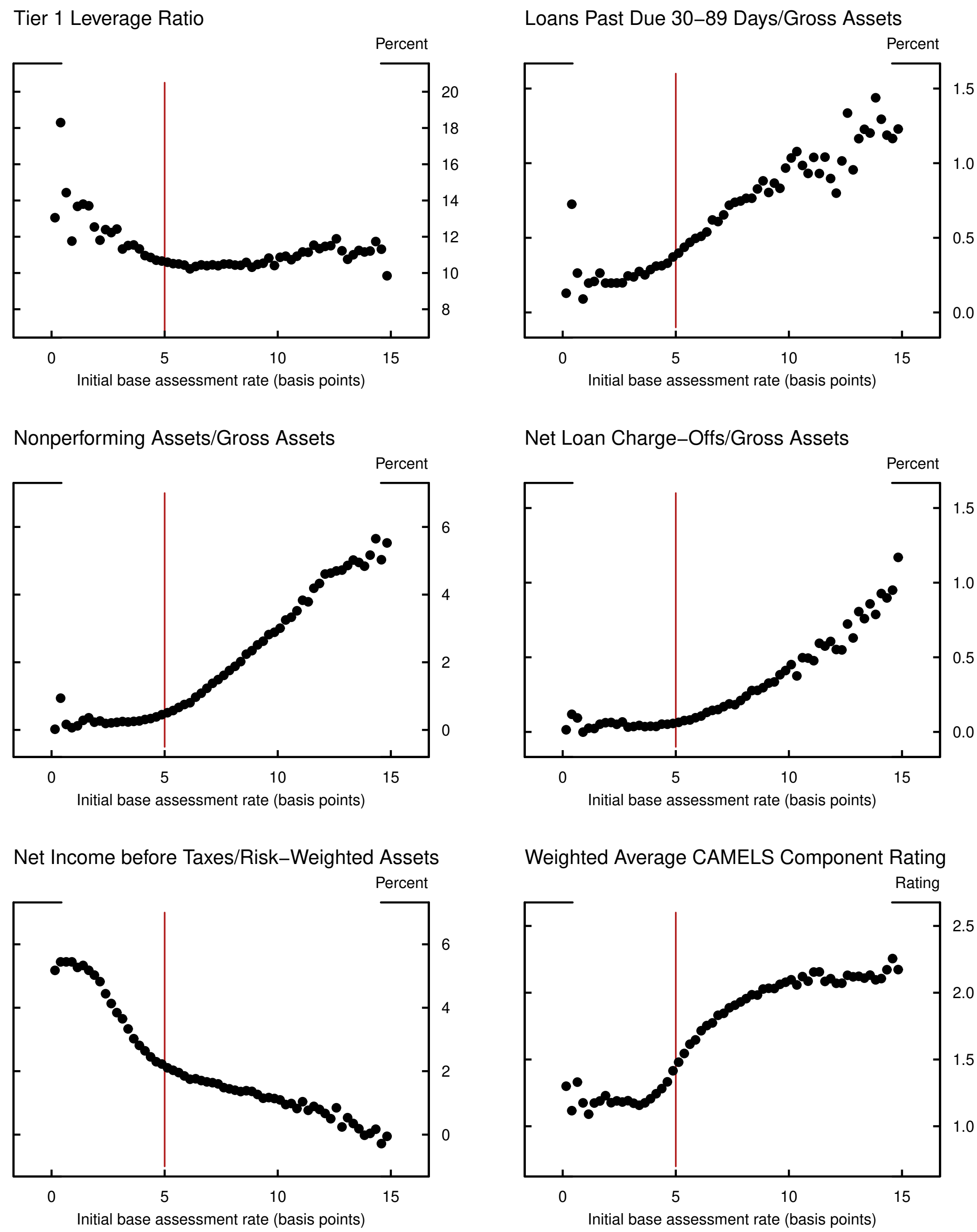

Figure 4: **Smoothness Assumption on Assessment Rate Components**

NOTE: This figure shows the mean values of covariates as a function of the running variable, namely the unconstrained initial base assessment rate. Mean values are measured in the same year-quarter pair as the running variable.

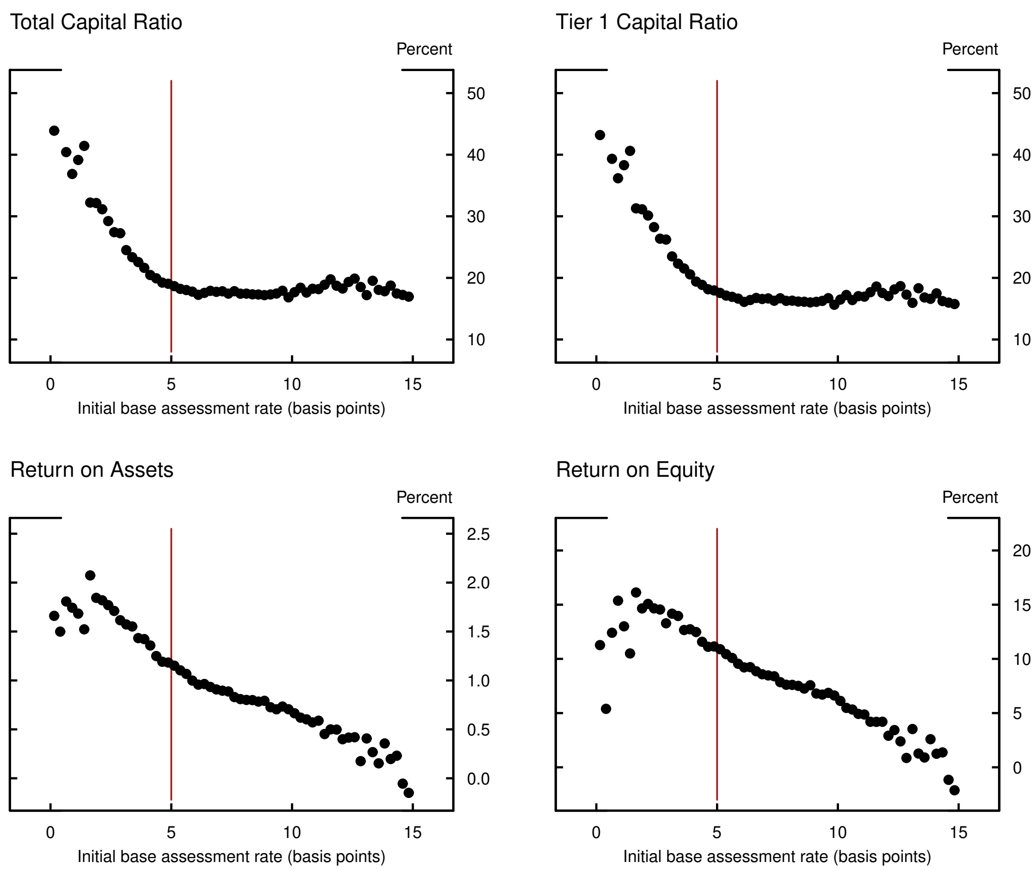

Figure 5: **Smoothness Assumption on Covariates**

NOTE: This figure shows the mean values of covariates as a function of the running variable, namely the unconstrained initial base assessment rate. Mean values are measured in the same year-quarter pair as the running variable, except ROA and ROE, which are measured in the previous year-quarter pair.

5 Results

5.1 Effects of Assessment Rates on Banks' Excess Reserves

In this subsection, we examine the effects of assessment rates on banks' excess reserves. We first provide graphical evidence to assist with intuition. Figure 6 shows the relationship between the unconstrained initial base assessment rate and the natural logarithm of quarter-end excess reserves of each bank. Assessment rates, shown in the horizontal axis, are divided into 60 33-basis point wide buckets. The mean value of the natural logarithm of excess reserves in each bucket is shown in the vertical axis. The figure shows a decrease in the slope of the relationship between the assessment rate and excess reserves at the 5-basis point threshold, which provides evidence that assessment rates weaken bank demand for reserves.

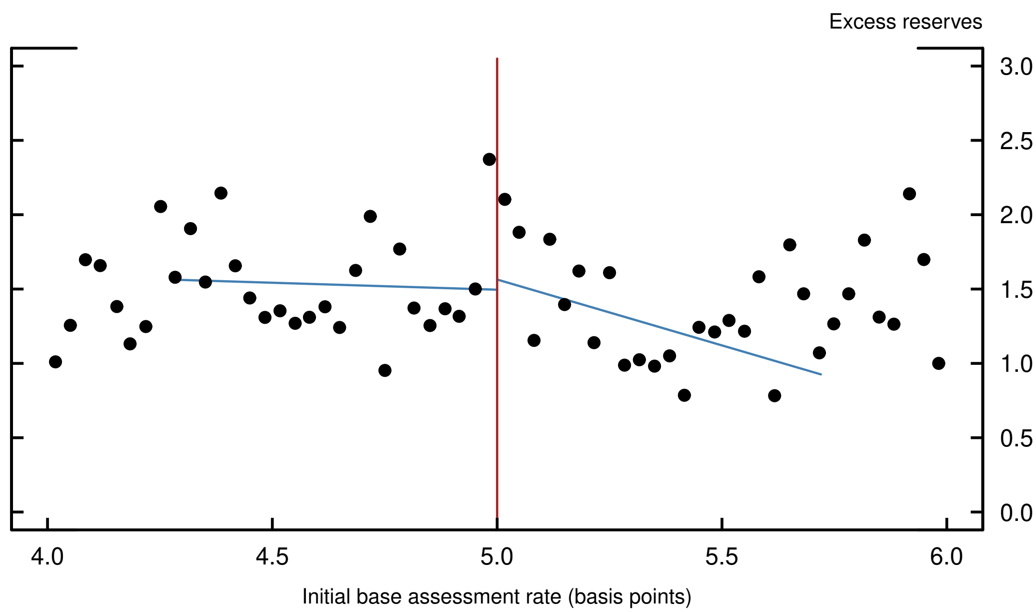

Figure 6: **Assessment Rates and Excess Reserves**

NOTE: This figure shows the relationship between unconstrained initial base assessment rates (in the horizontal axis) and the natural logarithm of millions of dollars of excess reserves (in the vertical axis). Assessment rates are divided into 60 33-basis point long buckets. The vertical solid line identifies the minimum initial base assessment rate of 5 basis points. The lines on the left and on the right of the 5-basis point cutoff are predicted values from local linear regressions estimated with a bandwidth equal to 0.720, the optimal bandwidth from column 1 of Table 2.

Table 2: **Effects of Assessment Rates on Bank Reserves**

	Local linear		Local quadratic	
	Quarter-end excess reserves (1)	Average excess reserves (2)	Quarter-end excess reserves (3)	Average excess reserves (4)
RKD treatment effect	-1.906	-1.952	-3.595	-3.249
Robust 95% CI	[-4.492, -0.595]	[-4.672, -0.603]	[-7.382, -1.054]	[-7.083, -0.649]
Robust p-value	0.011	0.011	0.009	0.019
N_-	3,003	2,895	4,202	4,179
N_+	3,125	3,003	4,996	4,955
h	0.720	0.695	1.190	1.186

NOTE: Point estimators are constructed using local polynomial estimators with triangular kernel. Robust p-values are constructed using bias-correction with robust standard errors as derived in Calonico et al. (2014). N_- and N_+ are the number of observations effectively used above and below the 5-basis point cutoff out of 18,282 (columns 1 and 3) and 18,184 (columns 2 and 4) observations. h is the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

Table 2 shows estimates of the effects of assessment rates on demand for reserves. Following Card et al. (2015) and Landais (2015) among others, we present results with linear and quadratic polynomials to evaluate whether the estimates depend on assumptions about the order of the polynomial. Columns 1 and 2 show estimates using local linear polynomials ($p = 1$) and columns 3 and 4 show estimates using local quadratic polynomials ($p = 2$), respectively. In columns 1 and 3, the dependent variable is the natural logarithm of quarter-end reserves, and in columns 3 and 4, the natural logarithm of quarter-average excess reserves.

Estimates of the effects of assessment rates on excess reserve amounts are large, statistically significant, and have the expected sign. The -1.906 estimate of τ in column 1 implies that a 1-basis point increase in the base assessment rate decreases the excess reserves of the average bank in the sample from about \$5.6 million to about \$0.8 million. The coefficient estimate in column 2, equal to -1.952, implies an effect of roughly the same size. The point estimate in column 3, equal to -3.595, is also very close to the -3.249 estimate in column 4 and both estimates imply that a 1-basis point increase in the base assessment rate drops the excess reserves of the average bank in the sample from about \$5.6 million to about \$0.2 million. Confidence intervals in columns 1 and 2 and in columns 3 and 4 are similar to each other as well.

While the magnitude of the decrease in excess reserves seem very large compared to the average excess reserve holdings of banks, they are more reasonable when accounting for the relative distributions of assessment rates and of excess reserves. A 1-basis point increase in the assessment rate roughly translates to 50 percent of a standard deviation increase of assessment rates, while the implied decreases in excess reserves (ranging between $4.8 million and $5.4 million) is less than 20 percent of the standard deviation of excess reserves at banks in our sample. In other words, we can roughly reformulate the results as a one standard deviation increase in assessment rates translating into a decrease in excess reserves holdings by about 40 percent of a standard deviation.

The estimates in columns 1 to 4 indicate that using quarter-end or quarter-average amounts yield similar results, which is consistent with the fact that quarter-end effects on reserve balances are generally modest at small domestic banks. Because the results with the two alternative measures of reserves are similar, for the sake of brevity we henceforth only present results using quarter-end measures.

In addition, the coefficient estimates in this table show that the conclusion that assessment rates lower excess reserve levels is robust to changes in the order of the polynomial employed. However, the effects implied by the estimates in columns 1 and 2 are smaller than the effects implied by the estimates in columns 3 and 4. Because the estimates with a local linear polynomial appear to be more conservative in our setting, in the remaining of the paper we will mostly focus on them.

5.2 Effects of Assessment Rates on Interbank Lending

We next examine the effects of assessment rates on the amounts of federal funds sold and purchased. Figures 7 and 8 show the relationship between the unconstrained initial base assessment rate and the natural logarithms of millions of dollars of federal funds sold and purchased, respectively. Federal funds sold rise with assessment rates, as shown by the increase in the slope of the line in Figure 7 at the 5-basis point cutoff. Meanwhile, federal funds purchased do not seem to respond to assessment rates, as shown in Figure 8.

Table 3 shows estimates of the effects of assessment rates on interbank lending. Columns 1 and 3 use the natural logarithm of federal funds sold and columns 2 and 4 use the natural logarithm of federal funds purchased as the dependent variable, respectively. Consistent

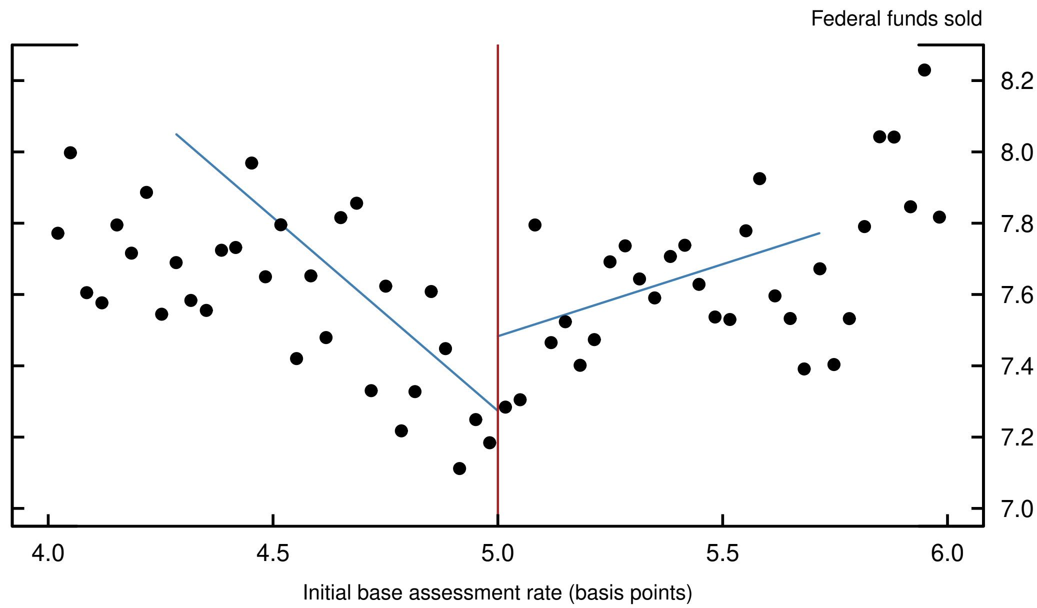

Figure 7: **Assessment Rates and Federal Funds Sold**

NOTE: This figure shows the relationship between unconstrained initial base assessment rates (in the horizontal axis) and the natural logarithm of millions of dollars of federal funds sold (in the vertical axis). Assessment rates are divided into 60 33-basis point long buckets. The vertical solid line identifies the minimum initial base assessment rate of 5 basis points. The lines on the left and on the right of the 5-basis point cutoff are predicted values from local linear regressions estimated with a bandwidth equal to 0.715, the optimal bandwidth from column 1 of Table 3.

with Figure 7, estimates of τ using the federal funds sold as the dependent variable are positive and statistically significant. The local linear estimate in column 1, equal to 1.507 indicates that the amount of federal funds sold at the average bank with a non-zero amount would jump from about \$3.7 million to around \$16.7 million after a 1-basis point increase in its assessment rate. The local quadratic estimate in column 3, equal to 1.723, implies the federal funds sold would jump to about \$20.8 million in response to such a change in assessment rates.

Analogous to our interpetation in the previous subsection, these increases in federal funds sold are large given the average amount of federal funds sold, but not much so relative to the distributions of assessment rates and of federal funds sold. Given that the size of a 1-basis point increase in assessment rates is about 50 percent of a standard deviation, the implied increase in federal funds sold of \$13.0 million to \$17.1 million translates into less than 50 percent of the standard deviation of federal funds sold by small banks that participate in any sale at all. To put simply, a one standard deviation

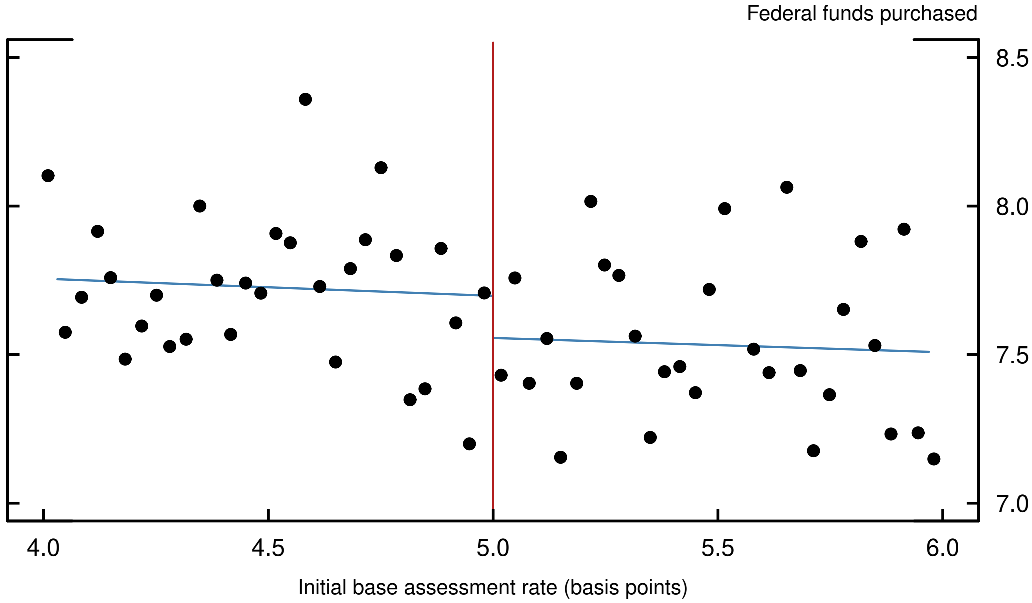

Figure 8: **Assessment Rates and Federal Funds Purchased**

NOTE: This figure shows the relationship between unconstrained initial base assessment rates (in the horizontal axis) and the natural logarithm of millions of dollars of federal funds sold (in the vertical axis). Assessment rates are divided into 60 33-basis point long buckets. The vertical solid line identifies the minimum initial base assessment rate of 5 basis points. The lines on the left and on the right of the 5-basis point cutoff are predicted values from local linear regressions estimated with a bandwidth equal to 0.969, the optimal bandwidth from column 2 of Table 3.

increase in assessment rates roughly leads to a one standard deviation decrease in federal funds sold.

Consistent with Figure 7, estimates of τ using the federal funds purchased as the dependent variable, in columns 2 and 4, are closer to zero and are not statistically significant, indicating that the amount of federal funds purchased by the banks in the sample does not respond to assessment rates. Overall, the findings in the subsection are consistent with the fact the banks in our sample—generally small, safe and sound banks—are much more likely to sell federal funds than to purchase them. In addition, the findings are consistent with the evidence that small banks typically do not engage in IOER arbitrage, as Keating and Macchiavelli (2017), for instance, discuss.

5.3 Additional Validation and Falsification Tests

In this subsection, we present three more tests to reinforce the validity of our RKD methodology: estimating treatment effects with false cutoffs, excluding observations near

Table 3: **Effects of Assessment Rates on Federal Funds Sold and Purchased**

	Local linear		Local quadratic	
	Federal funds sold (1)	Federal funds purchased (2)	Federal funds sold (3)	Federal funds purchased (4)
RKD treatment effect	1.507	0.264	1.723	0.606
Robust 95% CI	[0.708, 2.996]	[-0.797, 1.641]	[0.222, 3.369]	[-1.247, 2.845]
Robust p-value	0.002	0.497	0.025	0.444
N_-	2,351	722	3,650	902
N_+	2,543	682	4,700	957
h	0.715	0.969	1.380	1.451

NOTE: Point estimators are constructed using local polynomial estimators with triangular kernel. Robust p-values are constructed using bias-correction with robust standard errors as derived in Calonico et al. (2014). N_- and N_+ are the number of observations effectively used above and below the 5-basis point cutoff out of 15,521 (columns 1 and 3) and 3,078 (columns 2 and 4) observations. h is the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

the true cutoff, and using different bandwidth choice procedures.[15] Similar to the smoothness assumption tests presented in Section 4.2, the three tests in this subsection support the assumptions of our RKD research design.

5.3.1 Placebo Cutoffs

We first examine whether our estimates of treatment effects are significant at false (or "placebo") cutoff values. Estimates with placebo cutoffs help to evaluate whether the RKD assumption of continuity of the regression functions for treatment and control bank-year pairs at the cutoff would hold in the absence of treatment. Even though this assumption cannot be tested directly, evidence of discontinuities may indicate that it does not hold. Conversely, evidence of continuity away from the cutoff, while neither necessary nor sufficient for continuity at the cutoff, offers some support to that assumption.

We examine continuity away from the cutoff by estimating the effects of assessment rates replacing the true cutoff of 5 basis points with values at which no treatment should occur. For the sake of brevity, we present only results using excess reserve holdings and

[15] Together with the tests of continuity of the score variable and of null treatment effects on pre-treatment and placebo outcomes in Section 4.2 and Appendix B, these tests constitute the five validation and falsification tests that Cattaneo et al. (2018a) indicate for regression discontinuity and RKD designs.

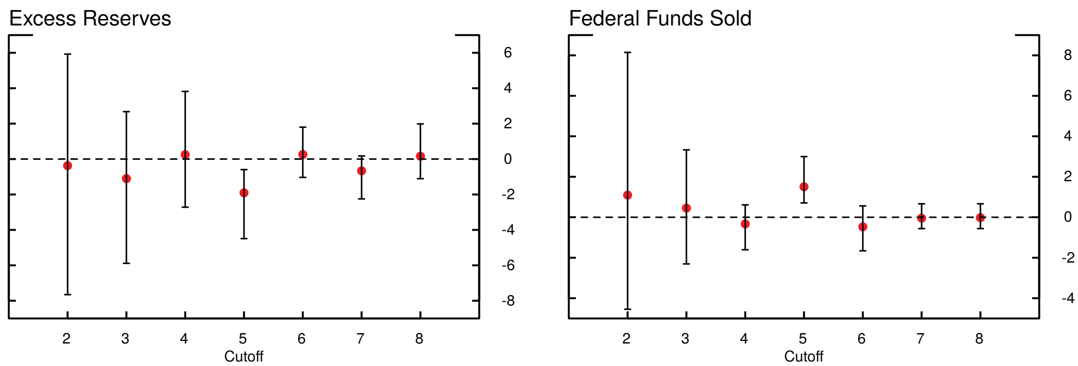

Figure 9: **RKD Estimates with True and Placebo Cutoffs**

NOTE: This figure shows RKD estimates using alternative cutoffs from 2 to 8. The true cutoff is at 5 basis points. The left and right panels use the natural logarithms of excess reserves and of federal funds sold as dependent variables. Red dots show our point estimates of treatment effects and the vertical lines show robust 95 percent confidence intervals. Table A.7 in Appendix B.2 shows the complete results.

the amounts of federal funds sold as dependent variables because the results in Tables 2 and 3 do not indicate that assessment rates affect the amounts of federal funds purchased. Also for conciseness, we only show estimates with a local linear polynomial because the conclusions using a local quadratic polynomial are basically the same.

Figure 9 shows our estimates using alternative cutoffs from 2 to 8. The left and right panels use the natural logarithms of excess reserves and of federal funds sold as dependent variables. Red dots show our point estimates of treatment effects and the vertical lines show robust 95 percent confidence intervals. For the sake of brevity and clarity, we report complete regression results in Table A.7 of Appendix B.2.

In both panels, the confidence intervals do not include zero only if we use the true cutoff of 5 basis points, which supports the assumption of continuity. Of note, the larger number of observations in our data closer to that cutoff, as shown in Figure 3, helps to narrow confidence intervals and reject the hypothesis of no treatment effect in that neighborhood. Still, the evidence from this figure favors the assumption of continuity.

5.3.2 Sensitivity to Observations near the Cutoff

We now examine whether the estimates of the effects of assessment rates on reserves and federal funds sold in Tables 2 and 3 change materially if we drop observations very close to the 5-basis point cutoff. This exercise, often known as the donut hole approach, attempts to assess whether systematic manipulation of assessment rates by banks drives our results. The test assumes that observations close to the cutoff are more likely to be of banks that manipulated their initial base assessment rates. Removing observations close to the cutoff would therefore drop the observations which are more likely subject to manipulation. Again, in our setting, manipulation should me a minor concern because assessment rates are determined by many variables that banks cannot control precisely, such as the fraction of loans past due and supervisory ratings. Still, as Cattaneo et al. (2018a) observe, even when manipulation is not a concern, such exercise helps assess the sensitivity of the results to the extrapolation inherent to local polynomial estimation, in which the observations close to the cutoff influence the results substantially.

Figure 10 shows how point estimates and confidence intervals change as we drop observations within a neighborhood of the cutoff ranging from 0 to 0.015 basis points to the left and to the right of the 5-basis point cutoff. The figure implies that the RKD estimates of the effects of assessment rates on excess reserves are somewhat sensitive to the removal of observations near the cutoff, while the estimates of the effects on federal funds sold are quite robust. In particular, the left panel shows that the point estimate and the confidence intervals of the effects of assessment rates on reserves get slightly closer to zero as we drop observations. Within a 0.015-basis point radius, in which case 119 observations drop from the sample, the point estimate is still negative and close to the estimate when using the full sample (a 0.000 exclusion radius), and the robust confidence interval still does not include 0. However, the confidence interval includes zero as we use a 0.020 or wider exclusion radius, implying that the estimates in Table 2 are somewhat sensitive to the observations near the cutoff.

The right panel in Figure 10 shows that, when we use the amount of federal funds sold as the dependent variable and drop observations within a 0.020-basis point radius (dropping 129 observations), the point estimate of the effects of assessment rates on federal funds sold remains positive and close to the estimate based on the full sample. The relevant confidence interval also does not include zero. In summary, the results

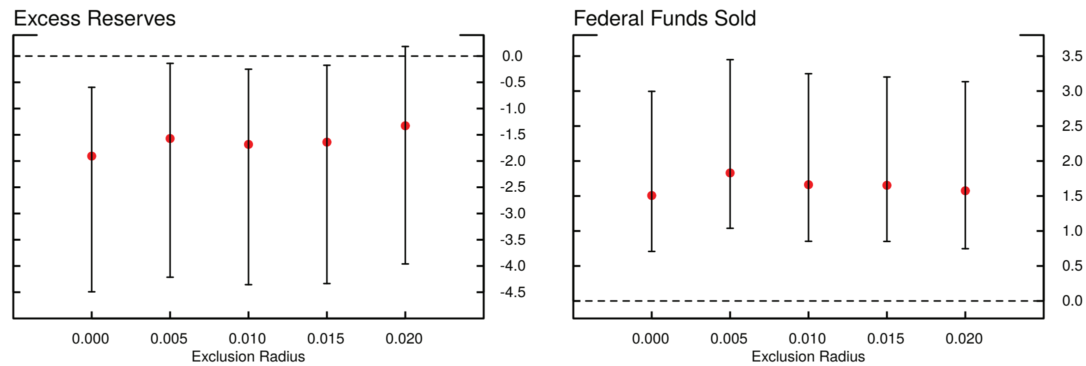

Figure 10: **RKD Estimates Excluding Observations near the Cutoff**

Note: This figure shows RKD estimates eliminating observations within a neighborhood of the cutoff ranging from 0 to 0.020 basis points to the left and to the right of the 5-basis point cutoff. The left and right panels use the natural logarithms of excess reserves and of federal funds sold as dependent variables. Red dots show our point estimates of treatment effects and the vertical lines show robust 95 percent confidence intervals. Table A.8 in Appendix B.3 shows the complete results.

from Table 3 remain about unchanged and thus can be considered quite robust to the elimination of observations near the cutoff.

5.3.3 Sensitivity to Bandwidth Choice

Our last robustness test examines whether our results are robust to changes in the procedure used to select bandwidths. Different procedures should generate bandwidths of different lengths, thereby affecting the results: a widening in bandwidths increases the bias of the local polynomial estimator and lowers the variance of the estimator. Accordingly, a widening in bandwidths generally narrows and displaces confidence intervals.

We compare the results with four alternative procedures: One common coverage error (1CCER)-optimal bandwidth selector, one common mean squared error (1CMSE)-optimal bandwidth selector (also used in Tables 2 and 3), two different coverage error (2DCER)-optimal bandwidth selectors, and two different mean squared error (2DMSE)-optimal bandwidth selectors. As discussed in Cattaneo et al. (2018a), mean squared error (MSE)-optimal bandwidth selectors have highly desirable properties for point estimation of treatment effects, but they also have serious disadvantages for building confidence intervals, while coverage error (CER)-optimal bandwidth selectors yield point estimators

Table 4: **Effects of Assessment Rates with Alternative Bandwidths**

Bandwidth selection procedure	RKD treatment effect	Robust 95% CI	Robust p-value	N_-	N_+	h_-	h_+
Panel A: Excess reserves as dependent variable							
Common CER-optimal	-3.783	[-6.618, -1.818]	0.001	2,118	2,153	0.489	0.489
Common MSE-optimal	-1.906	[-4.492, -0.595]	0.011	3,003	3,125	0.720	0.720
Different CER-optimal	-2.554	[-4.944, -0.673]	0.010	2,172	3,096	0.503	0.714
Different MSE-optimal	-0.925	[-3.199, 0.607]	0.182	3,079	4,484	0.739	1.050
Panel B: Federal funds sold as dependent variable							
Common CER-optimal	2.013	[0.744, 3.763]	0.003	1,674	1,734	0.490	0.490
Common MSE-optimal	1.507	[0.708, 2.996]	0.002	2,351	2,543	0.715	0.715
Different CER-optimal	1.835	[0.695, 3.514]	0.003	1,577	2,363	0.459	0.668
Different MSE-optimal	1.395	[0.703, 2.870]	0.001	2,234	3,429	0.671	0.975

Note: Point estimators are constructed using local polynomial estimators with triangular kernel. Robust p-values are constructed using bias-correction with robust standard errors as derived in Calonico et al. (2014). Panel A uses the natural logarithm of excess reserves measured in millions of dollars as the dependent variable, and Panel B uses the natural logarithm of federal funds sold measured in millions of dollars. N_- and N_+ are the number of observations effectively used above and below the 5-basis point cutoff out of 18,282 (Panel A) and 15,521 (Panel B) observations. h_- and h_+ are the second generation data-driven MSE-optimal bandwidth selectors proposed in Calonico et al. (2014) above and below the 5-basis point cutoff.

with too much variability relative to their biases, but also generate confidence intervals with better properties than the MSE-optimal bandwidth selectors. Meanwhile, results using one common bandwidth and two different bandwidths may vary meaningfully. For these reasons, we present results using the four possible combinations of MSE-optimal versus CER-optimal bandwidth and one common bandwidth versus two different bandwidth selectors.

Table 4 shows the results with the abovementioned alternative bandwidth selection procedures. Panel A and B present the estimates using the natural logarithms of excess reserves and of federal funds sold as the dependent variables, respectively. In both panels and when either one common or two different bandwidths are used, bandwidths are longer and the point estimate of the RKD effect is closer to 0 when we use an MSE-optimal procedure—the better procedure for point estimation—instead of a CER-optimal procedure. The point estimate in Panel A remains negative and large in absolute terms and the point estimate in Panel B remains positive and large in absolute terms across the four different procedures.

The confidence intervals in Table 4 indicate that our findings from Tables 2 and 3 are robust to changes in the bandwidth selection procedures. The confidence intervals exclude 0 in both panels and across all procedures, except when we estimate the RKD effect on excess reserves using two different MSE-optimal bandwidths. However, as Cattaneo et al. (2018a) discuss, the CER-optimal bandwidth is more appropriate than the MSE-optimal bandwidth for validation and falsification purposes because, in this case, our objective is to test the null hypothesis of no effect, and point estimates are less important. Thus, we conclude that our results from Tables 2 and 3 are also robust to changes in the bandwidth selection procedure.

6 Conclusion

This article explores the impact of deposit insurance premiums on banks' demand for reserves and on interbank lending in the federal funds market. Using a regression kink design that exploits a kink in the schedule of insurance assessment rates, we show that these premiums reduce demand for reserves and increase the supply of federal funds by banks. The magnitude and economic significance of our results are large, potentially indicating the extent of unobservable costs that limits the profitability of IOER arbitrage. Given that larger banks—those outside the scope of this paper—tend to have much higher reserve balances and participate more actively in the federal funds market, the true impact of deposit insurance premiums may be economically substantial.

Our findings have important policy implications. The results indicate that banks indeed respond to fluctuations in the FDIC insurance premiums they pay. In light of this, the Federal Reserve must take into account these counterbalancing effects on short term rates when conducting conventional monetary policy through IOER. Also, to the extent that monetary policy implementation may affect aggregate welfare, our results suggest that optimal deposit insurance pricing should depend on the effects of assessment rates on bank behavior examined in this paper.

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Appendix A Assessment Rates

This appendix provides more details on the assessment rates discussed in Section 2 and explains how we calculate them for this paper.

A.1 Initial Assessment Base Rate

Table A.1 describes how the capital ratios and the CAMELS composite rating of a bank determine its risk category. Risk categories range from category 1 to 4, with risk category 1 generally containing well-capitalized banks with good ratings (CAMELS of 1 or 2) and risk category 4 generally containing undercapitalized banks with bad ratings (CAMELS of 4 or 5).

Table A.1: **Risk Category Schedule**

	Supervisory group**		
Capital group*	A	B	C
1 (Well capitalized)	I	II	III
2 (Adequately capitalized)	II	II	III
3 (Undercapitalized)	III	III	IV

Note: * Well capitalized banks are defined as banks with total risk-based capital ratio equal to or greater than 10 percent, tier 1 risk-based capital ratio equal to or greater than 6 percent, and tier 1 leverage capital ratio equal to or greater than 5 percent; adequately capitalized banks are defined as banks that are not well capitalized and have total risk-based capital ratio equal to or greater than 8 percent, tier 1 risk-based capital ratio equal to or greater than 4 percent, and tier 1 leverage capital ratio equal to or greater than 4 percent; and undercapitalized banks are defined as banks that are neither well capitalized nor adequately capitalized.
** Supervisory group A generally include banks with CAMELS composite ratings of 1 or 2, supervisory group B generally includes banks with a CAMELS composite rating of 3, and supervisory group C generally includes banks with CAMELS composite ratings of 4 or 5.
Source: Federal Deposit Insurance Corporation (2011).

Based on the risk category of the bank, the FDIC assigns it an initial base assessment rate. Table A.2 shows the rates charged during our sample period, from April 1, 2011, to June 30, 2016. The FDIC assigns to each risk category 1 bank an initial base assessment rate that ranges from 5 to 9 basis points during this period. Risk category 2, 3, and 4 banks are assessed initial base assessment rates of 14, 23, and 35 basis points, respectively, regardless of their characteristics.

Table A.2: **Base Assessment Rate Schedule**

Risk category	I	II	III	IV
Initial base assessment rate	5 to 9	14	23	35
Unsecured debt adjustment	-4.5 to 0	-5 to 0	-5 to 0	-5 to 0
Brokered deposit adjustment	N/A	0 to 10	0 to 10	0 to 10
Total base assessment rate	2.5 to 9	9 to 24	18 to 33	30 to 45

NOTE: All amounts for all categories are in basis points annually. Total base assessment rates do not include the depository institution debt adjustment.
SOURCE: Federal Deposit Insurance Corporation (2011).

The FDIC computes the rate of risk category 1 banks by calculating the sum of risk measures at the bank level multiplied by coefficients derived from an econometric model of bank failures (Federal Deposit Insurance Corporation, 2011). These measures and their coefficients are outlined in Table A.3, while the weighted average CAMELS component rating is calculated by taking the weighted sum of each of the component ratings, using the weights outlined in Table A.4. The sum of the risk measures multiplied by the coefficients from Table A.3 is also added to a uniform amount, which is equal to 4.861 basis points for our sample period. We define the total as the unconstrained initial base assessment rate.

The initial base assessment rate that a risk category 1 bank is subject to is constrained by the minimum and maximum rates shown in the first column of Table A.2. The constrained initial assessment base rate is equal to the minimum rate of 5 basis points if the unconstrained initial base assessment rate is below this minimum and it is equal to the maximum rate of 9 basis points if the unconstrained initial base assessment rate is above this maximum. As shown by the blue line in Figure 1, this rule creates a relationship between the constrained and the unconstrained base assessment rates that is flat on the left of 5 basis points, increasing with a slope equal to 1 between 5 and 9 basis points, and also flat on the right of 9 basis points.

Table A.3: **Risk Measures and Coefficients**

Risk measures	Coefficients
Tier 1 leverage ratio	-0.056
Loans past due 30-89 days / gross assets	0.575
Nonperforming assets / gross assets	1.074
Net loan charge-offs / gross assets	1.210
Net income before taxes / risk-weighted assets	-0.764
Adjusted brokered deposit ratio	0.065
Weighted average CAMELS component rating	1.095

NOTE: Ratios are expressed as percentages and pricing multipliers are rounded to three decimal places.

Table A.4: **Weighted Average CAMELS Component Rating**

Component	Weight (percent)
Capital adequacy	25
Asset quality	20
Management administration	25
Earnings	10
Liquidity	10
Sensitivity to market risk	10

NOTE: Each numerical rating is a round number between 1 and 5. The weighted average component rating is computed by multiplying the rating by the weight, and summing across the six categories. The results are rounded to three decimal points for initial base assessment rate calculation.

A.2 Adjustments to the Initial Assessment Base Rate

After the initial base assessment rate of a bank is calculated, this rate may be adjusted downward for unsecured debt and upward for brokered deposits and for debt issued by other institutions. The UDA of a bank is calculated by adding the initial base assessment rate to 40 basis points and multiplying this sum by the ratio of the bank's long-term unsecured debt to its assessment base. This amount, limited to a maximum equal to the lesser of 5 basis points or 50 percent of the bank's initial base assessment rate, is subtracted from the initial base assessment rate. The BDA applies only to banks in risk categories 2 to 4 and whose ratio of brokered deposits to domestic deposits is greater than 10 percent. This adjustment is calculated by multiplying 25 basis points by the ratio of the difference between an insured depository institution's brokered deposits and 10 percent of its domestic deposits to its assessment base. This amount, limited to a minimum of zero and a maximum of 10 basis points, is added the initial base assessment rate. The DIDA is a 50 basis point charge on the amount of long-term unsecured debt the bank holds holds that was issued by another insured depository institution and that exceeds 3 percent of the bank's tier 1 capital. The rate that results from these adjustments, and which is actually charged from banks, is defined as the total base assessment rate.

Among these three adjustments, the UDA is the only one that affects our estimates of the effects of deposit insurance premiums on bank behavior. In this paper, we use the change in the slope of the total base assessment rate of risk category 1 banks as a function of the unconstrained initial base assessment rate to identify these effects. Thus, the BDA does not affect these estimates because this adjustment only applies to banks in risk categories 2 to 4. Also, the DIDA does not affect the estimates either because the DIDA does not depend on the initial base assessment rate. Therefore, we next discuss only the impact of the unsecured debt adjustment on our estimates.

The unsecured debt adjustment attenuates the changes in slope of the initial base assessment rate as a function of the unconstrained initial base assessment rate, thereby affecting the economic interpretation of our coefficient estimates. The unsecured debt adjustment attenuates the changes at 5 and 9 basis points, shown in Figure A.1, because it is, in absolute terms, an increasing function of the initial base assessment rate that is smaller than this rate and that is subtracted from this rate. Indeed, the change in slope at 5 basis points is largest, going from 1 to zero, when the unsecured debt adjustment is equal to zero, as shown by the blue solid line, and is smallest, going from 0.5 to zero, when the unsecured debt adjustment reaches its cap of 50 percent of the initial base assessment rate, as shown by the red dashed line. For this reason, the economic effect implied by coefficient estimates under the assumption that the unsecured debt adjustment is equal to zero–and that the slope of the total base assessment rate as a function of the unconstrained initial base assessment rate really changes from 1 to zero–is a lower bound for the effect implied by those estimates without this assumption. Similarly, the economic effect implied by coefficient estimates under the assumption that the unsecured debt adjustment is the highest possible—and that the slope of the total base assessment rate as a function of the unconstrained initial base assessment rate really changes from 0.5 to zero–is a higher bound for the effect implied by those estimates without this assumption and is twice as large as the lower bound.

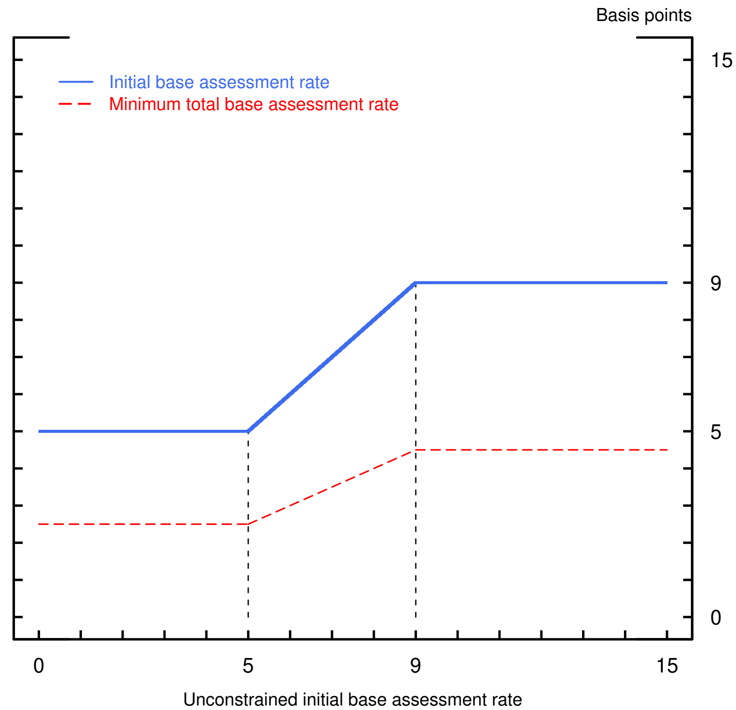

Figure A.1: **Kinks at Assessment Rate with Unsecured Debt Adjustment**

NOTE: The blue line plots assessment rates for all insured risk category 1 banks between 2012:Q1 and 2015:Q4 with total assets below \$10 billion. Newly insured institutions (those that became insured within five years) are excluded. All assessment rates are expressed in basis points.

A.3 Calculation of Assessment Rates

The rule that determines the method for calculating assessment rates is described by Federal Deposit Insurance Corporation (2011). The FDIC also publishes on their website a calculator that illustrates how a bank's assessment rate is determined. The calculator, maintained in the form of a spreadsheet, is designed to help banks understand how their assessment rates are calculated and to help banks simulate the impact of changes in their characteristics on their rates. Thus, we use the inputs of the calculator that we construct or obtain from our data and we compare the initial base assessment rate for small banks during our sample period that results from our own calculations and from the FDIC calculator. We find that the numbers are the same.

Of note, the Call Reports include data on dollar amounts of assessment fees that banks pay to the FDIC, which we also compare to our calculations. We divide the dollar amounts of assessment fees reported in the Call Reports by the assessment bases that we calculate and compare those with the assessment rates that we also calculate. The results are similar, on balance, but are not always the same. In fact, for various reasons the value that the FDIC charges banks may differ from the amounts that banks report in the Call Reports. For instance, payments might be delayed to the FDIC or banks and the FDIC may disagree on the amount charged.

Appendix B Additional Validation and Falsification Results

B.1 Additional Evidence on Smoothness Assumption

In this appendix, we present additional evidence that the assumptions of the RKD are satisfied in our setting. Table A.5 presents the results of tests of the null hypothesis that the density of the running variable is continuous at the cutoff of 5 basis points. The three columns show the results of tests proposed by Cattaneo et al. (2018b,c) under different specifications. In all three columns, the p-values are large and thus the null hypothesis is never rejected by these tests. Thus, these results support the validity of the RKD in our setting.

Table A.5: **Density Tests of Assessment Fees**

	Unrestricted inference with distinct bandwidths	Unrestricted inference with identical bandwidths	Restricted inference with identical bandwidths
	(1)	(2)	(3)
h_-	0.821	1.424	0.617
h_+	0.976	1.424	0.617
N_-	5,733	8,091	4,497
N_+	6,963	9,810	4,463
p-value	0.434	0.523	0.819

Note: This table shows tests of the null hypothesis that the density of the running variable is continuous at the cutoff of 5 basis points. h_- and h_+ denote the estimator bandwidth on the left and on the right of the cutoff, respectively. N_- and N_+ denote the effective number of observations on the left and on the right of the cutoff, respectively. Density test p-values are computed using Gaussian distributional approximation to bias-corrected local-linear polynomial estimator with triangular kernel and robust standard errors. Column 1 shows results of unrestricted inference with two distinct bandwidths, column 2 shows results of unrestricted inference with one common bandwidth, and column 3 shows results of restricted inference with one common bandwidth. See Cattaneo et al. (2018b,c) for methodological and implementation details.

We now test formally whether the conditional expectations of the 10 covariates shown in Figures 4 and 5 are twice continuously differentiable around the threshold of 5 basis points by estimating treatment effects on those covariates using the estimator $\hat{\tau}(h_{IT})$ and the cutoff of 5 basis points. We show the results of these tests using our preferred specification for the estimator, that is, using a local-quadratic estimator. As shown in

Table A.6: **Treatment Effects on Covariates**

	Tier 1 leverage ratio (1)	Loans past due to gross assets ratio (2)	Nonperf. assets to gross assets ratio (3)	Net loan chg-offs to gross assets ratio (4)
RKD treatment effect	-0.249	0.016	-0.076	-0.000
Robust 95% CI	[-1.884, 1.115]	[-0.182, 0.181]	[-0.333, 0.139]	[-0.064, 0.056]
Robust p-value	0.615	0.996	0.422	0.907
N_-	7,990	8,813	8,098	8,169
N_+	9,606	11,509	9,830	9,992
h	1.388	1.710	1.426	1.454

	NIBT to R-W assets ratio (5)	Weighted average CAMELS (6)	Total capital ratio (7)	Tier 1 capital ratio (8)
RKD treatment effect	-0.156	-0.064	-1.421	-1.356
Robust 95% CI	[-0.604, 0.256]	[-0.234, 0.103]	[-5.871, 2.467]	[-5.761, 2.564]
Robust p-value	0.428	0.444	0.424	0.452
N_-	7,796	8,446	7,366	7,376
N_+	9,203	10,700	8,396	8,426
h	1.323	1.566	1.198	1.202

	Return on assets (9)	Return on equity (10)
RKD treatment effect	-0.142	-1.566
Robust 95% CI	[-0.485, 0.018]	[-4.99, 0.274]
Robust p-value	0.068	0.079
N_-	4,252	4,436
N_+	4,220	4,383
h	0.582	0.607

NOTE: This table shows estimates of treatment effects on covariates using a cutoff of 5 basis points. Point estimators are constructed using local-quadratic polynomial estimators with triangular kernel. Robust p-values are constructed using bias-correction with robust standard errors as derived in Calonico et al. (2014). h is the second generation data-driven MSE-optimal bandwidth selector from Calonico et al. (2014). N_- and N_+ denote the effective number of observations on the left and on the right of the cutoff, respectively. All variables are measured in the same year-quarter pair as the running variable, except ROA and ROE, which are measured in the previous year-quarter pair.

Table A.6, for all the covariates the estimate of the robust 95-percent confidence interval includes 0 and the robust p-value does not allow us to reject the null hypothesis that $\tau = 0$, which supports the smoothness assumption of our RKD.

B.2 Placebo Cutoffs

We next present estimates of the effects of assessment rates on excess reserve balances and amounts of federal funds sold using alternative cutoff points. Table A.7 shows the complete results summarized in Figure 9.

Table A.7: **Effects of Assessment Rates using Alternative Cutoffs**

Alternative cutoff	RKD treatment effect	Robust 95% CI	Robust p-value	N_-	N_+	h
Panel A: Excess reserves as dependent variable						
2	-0.373	[-7.655, 5.928]	0.803	93	567	1.176
3	-1.102	[-5.886, 2.677]	0.463	374	1,438	0.976
4	0.249	[-2.717, 3.820]	0.741	1,263	2,864	0.771
5	-1.906	[-4.492, -0.595]	0.011	3,003	3,125	0.720
6	0.256	[-1.034, 1.801]	0.596	4,254	3,390	0.994
7	-0.663	[-2.249, 0.176]	0.094	3,736	2,369	1.077
8	0.160	[-1.107, 1.985]	0.578	2,516	1,314	1.096
Panel B: Federal funds sold as dependent variable						
2	1.095	[-4.545, 8.144]	0.578	63	167	0.735
3	0.453	[-2.306, 3.330]	0.722	297	1,023	0.899
4	-0.331	[-1.605, 0.611]	0.379	1,122	2,672	0.894
5	1.507	[0.708, 2.996]	0.002	2,351	2,543	0.715
6	-0.472	[-1.658, 0.561]	0.333	2,614	2,290	0.745
7	-0.044	[-0.560, 0.665]	0.867	3,544	2,282	1.170
8	-0.021	[-1.153, 0.713]	0.644	2,012	1,192	1.004

NOTE: This table shows estimates of treatment effects on covariates using a cutoff of 5 basis points. Panel A uses the natural logarithm of excess reserves measured in millions of dollars as the dependent variable, and Panel B uses the natural logarithm of federal funds sold measured in millions of dollars. Point estimators are constructed using local-quadratic polynomial estimators with triangular kernel. Robust p-values are constructed using bias-correction with robust standard errors as derived in Calonico et al. (2014). h is the second generation data-driven MSE-optimal bandwidth selector from Calonico et al. (2014). N_- and N_+ denote the effective number of observations on the left and on the right of the cutoff, respectively.

B.3 Sensitivity to Observations Near the Cutoff

We now examine whether the estimates of the effects of assessment rates on reserves and federal funds sold in Tables 2 and 3 change materially if we drop observations very close to the 5-basis point cutoff. Table A.8 shows the complete results summarized in Figure 10.

Table A.8: **Effects of Assessment Rates Excluding Observations Near the Cutoff**

Exclusion radius	RKD treatment effect	Robust 95% CI	Robust p-value	N_-	N_+	h	Observ. excluded on left	Observ. excluded on right
			Panel A: Excess reserves as dependent variable					
0.000	-1.906	[-4.492, -0.595]	0.011	3,003	3,125	0.720	0	0
0.005	-1.571	[-4.214, -0.139]	0.036	2,927	3,049	0.707	23	25
0.010	-1.683	[-4.356, -0.250]	0.028	2,886	3,009	0.701	40	40
0.015	-1.640	[-4.335, -0.175]	0.034	2,884	3,005	0.704	60	59
0.020	-1.328	[-3.961, 0.183]	0.074	2,912	3,302	0.716	77	77
			Panel B: Federal funds sold as dependent variable					
0.000	1.507	[0.708, 2.996]	0.002	2,351	2,543	0.715	0	0
0.005	1.830	[1.039, 3.449]	0.000	2,238	2,377	0.679	14	24
0.010	1.662	[0.853, 3.248]	0.001	2,287	2,448	0.702	26	43
0.015	1.653	[0.851, 3.201]	0.001	2,240	2,393	0.690	40	58
0.020	1.575	[0.747, 3.134]	0.001	2,256	2,419	0.702	57	72

Note: This table shows estimates of treatment effects on covariates using a cutoff of 5 basis points. Panel A uses the natural logarithm of excess reserves measured in millions of dollars as the dependent variable, and Panel B uses the natural logarithm of federal funds sold measured in millions of dollars. Point estimators are constructed using local-quadratic polynomial estimators with triangular kernel. Robust p-values are constructed using bias-correction with robust standard errors as derived in Calonico et al. (2014). h is the second generation data-driven MSE-optimal bandwidth selector from Calonico et al. (2014). N_- and N_+ denote the effective number of observations on the left and on the right of the cutoff, respectively.