Deposit Insurance Premiums and Bank Risk

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Abstract

Deposit insurance premiums impose costs on banks' balance sheets, narrowing profit margins and inducing banks to "search for yield." This paper estimates the effects of deposit insurance premiums on bank portfolio rebalancing using supervisory data and a kink in the insurance premium schedule. We show that deposit insurance premiums weaken banks' demand for reserves (a liquid asset with no credit risk) and strengthen the supply of short-term interbank loans (a less liquid asset with credit risk). We discuss the implications of these findings for optimal deposit insurance pricing.

Keywords: Deposit Insurance, Reserves, Federal Funds, Regression Kink Design
JEL Codes: G21, G28

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1 Introduction

In the decade following the Great Recession, banking regulation was drastically reformed. Policymakers tightened capital requirements and changed deposit insurance pricing, which led to notable increases in banks' balance sheet costs. These costs narrowed profit margins and may have induced banks to "search for yield" by rebalancing their asset portfolios (Stein, 2013). Whether balance sheet costs affect bank risk has become an important consideration for banking regulation.

However, establishing the causal effect of balance sheet costs on banks' portfolios is difficult because exogenous variation in these costs is scarce. Differences in these costs over time and across banks are correlated with unobservable characteristics that influence banks' behavior. Moreover, measures of balance sheet costs generally depend on bank risk indicators (such as capital and liquidity ratios) that are also correlated with unobservable shocks that affect banks' activities. Estimates of the effects of balance sheet costs that do not account for these correlations, therefore, will most likely be biased.

In this paper, we analyze the impact of one important type of balance sheet cost—deposit insurance premiums charged by the Federal Deposit Insurance Corporation (FDIC)—on banks' portfolio rebalancing behavior. Deposit insurance premiums for banks with total assets less than $10 billion are a linear function of risk measures, and we exploit a kink in this function to estimate the effects of premiums on the composition of banks' liquid assets. Specifically, we use a regression kink design (RKD) to test whether banks subject to higher premiums attempt to raise their yields by shifting away from highly liquid assets with no risk (reserves) and towards less liquid assets with low risk (interbank loans).

Our results confirm the hypothesis that deposit insurance premiums weaken the demand for reserves and strengthen the supply of interbank loans. We estimate that a 1-basis point increase in the assessment rate charged annually on each dollar of total assets decreases a bank's holdings of excess reserves by about 80 percent (from $5.5 million to $1.1 million), and more than doubles the amount loaned to other banks (from $3.5 million to $8.9 million). These results are economically meaningful and robust to various validation and falsification tests. Taken together, our findings suggest that deposit insurance premiums induce banks to search for yield.

Our paper is related to the growing interest in banks' demand for liquid assets, which is largely motivated by recent episodes of stress in financial markets (Correa et al., 2020; Quarles, 2020; d'Avernas and Vandeweyer, 2021; Copeland et al., 2021). When market dislocations occur, reserves are readily available to meet cash outflows, whereas Treasury securities must be monetized and interbank loans must be repaid before they can be used to settle cash transactions. As a result, banks' demand for reserves increases and their willingness to exchange reserves for other liquid assets such as Treasury securities and interbank loans falls. The recent stress events highlight the importance of understanding what drives banks' allocation of liquid assets, and we provide evidence that balance sheet costs induce substitution between reserves and interbank loans.

This paper also contributes to the literature on the effects of balance sheet costs on bank lending. Heider et al. (2019), Basten and Mariathasan (2020) and Duquerroy et al. (2020) study the behavior of European banks when monetary policy rates dropped below zero, and document that lower monetary policy rates affect bank lending through funding costs. We contribute to this literature with evidence that, under low interest rates, an increase in balance sheet costs unrelated to interest rate changes can also motivate banks to rebalance their asset portfolios. In addition, whereas the existing literature has mainly examined effects on loans to households and businesses, we study effects on banks' composition of liquid assets.[1]

Moreover, our paper is related to the nascent literature on the impact of deposit insurance premiums on bank behavior. Kreicher et al. (2013), Keating and Macchiavelli (2017), Klee et al. (2019), Banegas and Tase (2020), and Kandrac and Schlusche (2021) show evidence that deposit insurance premiums and the characteristics that determine those premiums (such as domestic or foreign ownership) affect banks' demand for liquid assets. Our approach differs because we exploit a kink in the assessment rate schedule to estimate the effects of deposit insurance premiums. This strategy enables us to compare the behavior of similar banks subject to different assessment rates.

Lastly, our paper contributes to the literature on optimal deposit insurance pricing. Optimal deposit insurance premiums are determined by individual bank failure risk (Buser et al., 1981; Kanatas, 1986; Ronn and Verma, 1986; Acharya and Dreyfus, 1989; Chan

[1]Recent theoretical articles on post-crisis monetary policy refer to deposit insurance premiums as important examples of balance sheet costs in their models. See Martin et al. (2013), Duffie and Krishnamurthy (2016), Armenter and Lester (2017), Schulhofer-Wohl and Clouse (2018), Afonso et al. (2019), Afonso et al. (2020), and Kim et al. (2020).

et al., 1992; Giammarino et al., 1993; Craine, 1995; John et al., 2000; Boyd et al., 2002; Duffie et al., 2003) as well as systemic risks associated with the joint failure of large and systemically important banks (Pennacchi, 2006; Acharya et al., 2010; Allen et al., 2015; Dávila and Goldstein, 2020). To our best knowledge, the literature does not consider the feedback effects of premiums on bank behavior. As bank behavior may affect welfare, our evidence suggests that optimal deposit insurance premiums should also incorporate these effects.

The rest of this paper is organized as follows: Section 2 provides an overview of deposit insurance premiums, describes how assessment rates are calculated, and discusses how these rates affect the allocation of liquid assets in banks' balance sheets. Section 3 summarizes our data and presents summary statistics. Section 4 describes our empirical strategy based on the RKD, and Section 5 presents our main results as well as robustness tests. Section 6 concludes.

2 Institutional Background

2.1 Deposit Insurance Premiums

Deposit insurance protects depositors from bank runs and failures. In the United States, the FDIC insures deposits at all domestic banks and at some branches and agencies of foreign banks through the Deposit Insurance Fund (DIF), which is maintained by quarterly premiums (called assessments) that insured banks pay. Each bank's assessment is calculated as its assessment base multiplied by an assessment rate. Following the Dodd-Frank Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act), the assessment base of a bank has been defined as the average consolidated total assets minus average tangible equity and some adjustments for banker's banks and custodial banks.[2] Assessment rates are a function of indicators of bank risk, as we describe next.

[2]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 Act.

2.2 Assessment Rate Calculation

The assessment rate of a bank with less than $10 billion in total assets is determined by its risk category, which is a function of three capital ratios (total risk-based capital ratio, tier 1 risk-based capital ratio, and leverage ratio) and the CAMELS composite rating, which summarizes the general condition of a bank.[3] 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 CAMELS ratings. The FDIC then assigns each bank an initial base assessment rate, which increases with the risk category of the bank. During our sample period from April 1, 2011, to June 30, 2016, risk category 2, 3, and 4 banks were assessed fixed initial base assessment rates of 14, 23, and 35 basis points per annum, respectively.

For risk category 1 banks, which comprise 81 percent of the banks in our sample, the FDIC first computes an unconstrained initial base assessment rate as a linear function of six risk measures at the bank level.[4] Next, the constrained initial base assessment rate is set at the minimum rate of 5 basis points if the unconstrained initial base assessment rate is below this minimum and at the maximum rate of 9 basis points if the unconstrained initial base assessment rate is above this maximum. As shown by the solid line in Figure 1, this rule creates a relationship between the constrained and unconstrained initial base assessment rates that is flat to the left of 5 basis points, increasing with a slope equal to 1 between 5 and 9 basis points, and flat to the right of 9 basis points. Due to the smaller number of observations around the higher kink, we focus our analysis on the lower kink throughout this paper.

After the constrained initial base assessment rate of a bank is calculated, this rate may be adjusted downward for unsecured debt and upward for brokered deposits and debt issued by other institutions. The rate that results from these adjustments is defined as the total base assessment rate. We restrict our sample to banks that are not subject to any of these adjustments to ensure that the total base assessment rate matches the constrained assessment rate. In other words, the total base assessment rate as a function

[3]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.

[4]The six measures are different from the ones used to determine the risk category. Further details can be found in Section 3.

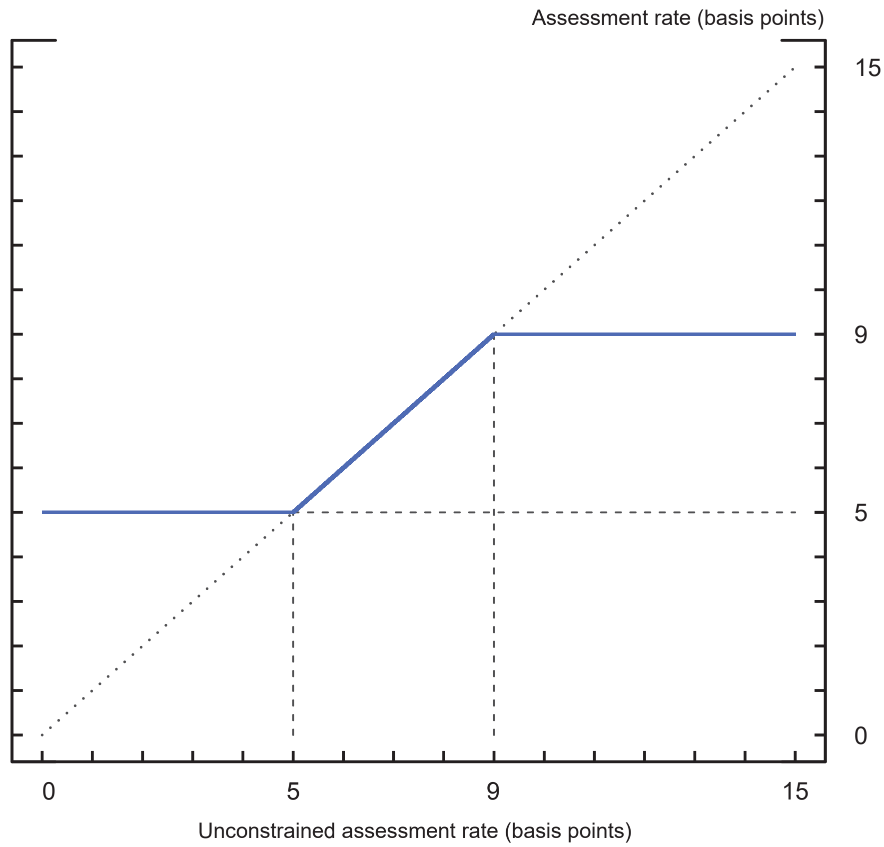

Figure 1: **Kinks in Deposit Insurance Assessment Rate Schedule**

NOTE: The solid line shows the assessment rate as a function of the unconstrained 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 the analysis.
SOURCE: Federal Deposit Insurance Corporation (2011).

of the unconstrained initial base assessment rate for banks in our sample is identical to the function in Figure 1. Most banks are not subject to any of these adjustments, and our main results hold when we include banks subject to adjustments.[5] In the remaining sections, we refer to the total base assessment rate as the assessment rate and refer to the

[5]The unsecured debt adjustment (UDA) is the only one of these three adjustments that may affect our estimates, 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. Appendix B describes the calculation of assessment rates in more detail.

unconstrained initial base assessment rate as the unconstrained assessment rate.

2.3 Assessment Rates, Excess Reserves, and Interbank Lending

Assessment rates raise the cost of assets and narrow profitability, which may affect banks' allocation of liquid assets. Banks can respond to narrower margins by shifting away from safer and more liquid assets with lower returns and towards riskier and less liquid assets with higher returns. We study how assessment rates affect the substitution between excess reserves and loans to other financial institutions in the federal funds market.

A bank with a reserve account at a Federal Reserve Bank can deposit funds and earn interest on excess reserves (IOER). A bank without a reserve account can only receive IOER via accounts managed by a correspondent bank, which charges a fee for this service. Alternatively, a bank can lend funds overnight to another financial institution in the federal funds market and earn the interest negotiated between the two parties. Banks may earn a higher rate lending to other banks than they would earn holding reserves in their own accounts or through correspondent banks.[6] More generally, banks demand a premium when lending funds to other financial institutions because those borrowers might default on their loans, whereas reserves held at Federal Reserve Banks are considered free of credit risk. Reserves can also be used immediately to meet cash outflows, whereas interbank loans must be repaid before they can be used to settle transactions.

Due to these institutional differences, the choice between excess reserves and interbank loans can be interpreted as a trade-off between the lower risk and higher liquidity of the former and the larger return of the latter. Deposit insurance premiums affect this trade-off because the assessment base of a bank increases with its total assets: when the assessment rate of a bank rises, the average cost of each dollar of assets also increases.

3 Data

The unit of observation in our panel data is a bank-quarter pair. We study the period between the second quarter of 2011 and the second quarter of 2016, because the relevant rule for calculating assessment rates was introduced on April 1, 2011, and revised again

[6] See Appendix A for a discussion of the relationship between IOER rate and the effective federal funds rate (EFFR), a measure of interest rates for interbank loans.

on July 1, 2016. Therefore, our estimates are not driven by changes in regulation, which may be correlated with unobservable characteristics of banks or the economy that might also affect banks' behavior.

We additionally restrict our sample based on four bank characteristics. First, we limit the sample to domestic commercial banks to ensure that all institutions in our sample are subject to a homogeneous regulatory framework and that we can observe data on their relevant characteristics. Second, we limit our sample to risk category 1 banks because, as explained in Section 2.2, this is the only risk category for which assessment rates vary across banks. Third, we eliminate newly insured institutions from the sample, which are defined as banks that became insured within the past five years at the time of calculation. Newly insured banks are uniformly assigned an assessment rate of 9 basis points if they are in risk category 1.

Fourth, 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.[7] We eliminate banks with more than \$5 billion in assets to ensure that all banks in the sample follow the same schedule of assessment rates. As discussed in Section 2.2, banks with more than \$10 billion in total assets, which the FDIC defines as large and highly complex institutions, must follow a schedule that uses bank data that are not readily available from regulatory filings. We drop banks with assets between \$5 billion and \$10 billion because they may choose the schedule for large and highly complex institutions under certain conditions. This restriction only causes a modest decrease in our final sample, because less than 4 percent of commercial banks held more than \$5 billion in total assets during our sample period.

For each bank-quarter observation, we calculate the corresponding unconstrained assessment rate following the FDIC's rule.[8] Figure 2 plots the number of bank-quarter observations around thresholds for the minimum and maximum assessment rates (5 and 9 basis points, respectively), using 0.33-basis point bins with an average size of 716 observations. Importantly, the distribution is heavily skewed and the number of observations

[7] Only 28 percent of observations from banks with less than \$100 million in total assets are from banks with reserve accounts, whereas 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 weaker when we include banks with less than \$100 million of total assets in the sample.

[8] We discuss these calculations in Appendix B.3.

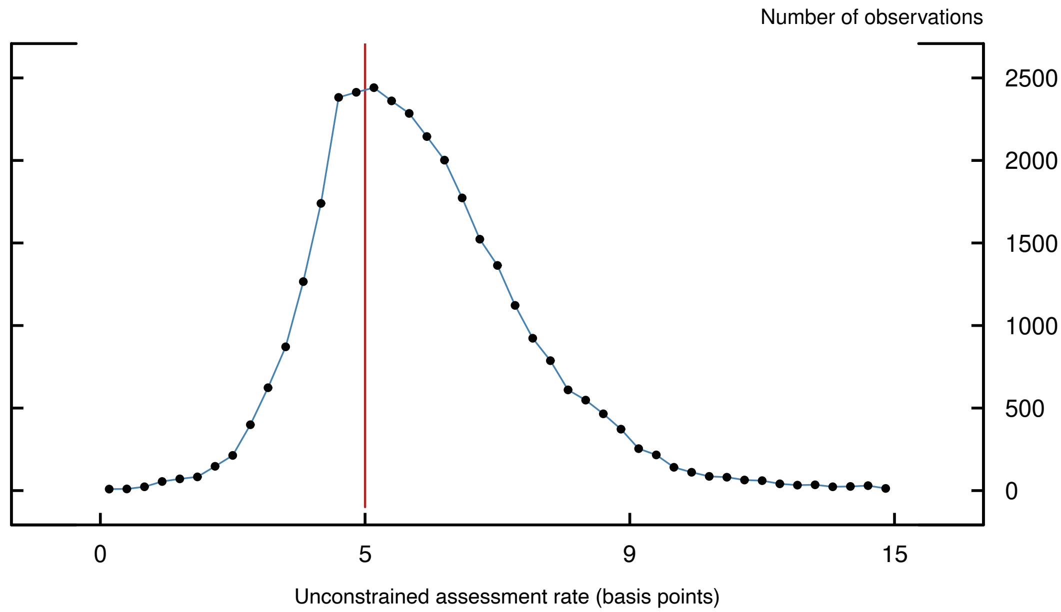

Figure 2: **Distribution of Unconstrained Assessment Rates**

Note: This figure shows the number of bank-quarter observations per bin of unconstrained assessment rates in our sample. Bins are 0.33 basis points wide and contain 716 observations on average. The vertical solid line identifies the minimum assessment rate of 5 basis points. The density of the running variable is continuous at the threshold of 5 basis points (Table C.1).
Source: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

around the 5-basis point threshold is much higher than the number around the 9-basis point threshold. Because the RKD estimation strategy requires a large number of observations around treatment thresholds, we restrict our analysis to the 5-basis point threshold.

As shown in Table B.3, the unconstrained 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 deposits and is adjusted for four-year cumulative total gross asset growth. Additionally, 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 four quarters. All financial ratios for the current quarter, except the four-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 rule, we take each bank's most recent CAMELS composite rating from confidential Federal Reserve data to determine its risk category. Then, for each risk category 1 bank, we take the most recent weighted average CAMELS component rating to compute the unconstrained assessment rate for a given quarter. The weighted average CAMELS component rating is calculated using weights outlined in Table B.4.

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 excess reserves held by banks with the Federal Reserve in the last week of each quarter, as well as the average amounts of reserves and excess reserves each quarter.[9] We collect quarterly data on the amounts of federal funds sold and purchased, of securities purchased under agreements to resell (repo), and of securities sold under agreements to repurchase (reverse repo) from the Call Reports.

We also 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. We build these measures with Call Report data to investigate whether variations in the average bank characteristics are smooth around the 5-basis point cutoff in Section 4.2.

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

[9] 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 ($ millions)	19,124	21.09	67.51
Excess reserves ($ millions)	19,124	5.46	37.30
Average reserves ($ millions)	19,124	21.58	64.73
Average excess reserves ($ millions)	18,995	5.42	35.55
Federal funds sold ($ millions)	32,384	3.56	16.20
Federal funds purchased ($ millions)	32,384	1.60	50.18
Repo ($ millions)	32,384	0.10	2.10
Reverse repo ($ millions)	32,384	4.72	22.72
Assignment variables			
Unconstrained assessment rate (b.p.)	32,384	6.06	2.08
Tier 1 leverage ratio (pct.)	32,384	10.77	3.30
Loans past due 30-89 days/Gross assets (pct.)	32,384	0.53	0.58
Nonperforming Assets/Gross assets (pct.)	32,384	1.04	1.05
Net loan charge-offs/Gross assets (pct.)	32,384	0.14	0.24
Net income before taxes/Risk-weighted assets (pct.)	32,384	2.04	1.14
Adjusted brokered deposit ratio (pct.)	32,384	0.00	0.00
Weighted average CAMELS component rating	32,384	1.62	0.40
Other bank characteristics			
Total capital ratio (pct.)	32,384	19.16	7.65
Tier 1 capital ratio (pct.)	32,384	18.04	7.67
Return on assets (pct.)	32,384	1.07	0.72
Return on equity (pct.)	32,384	9.86	6.66

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 domestic commercial banks in FDIC's risk category 1 that have been open for more than five years, have total assets between $100 million and $5 billion, and are not subject to the unsecured debt adjustment, brokered deposit adjustment, and depository institution debt adjustment. B.p. and pct. are abbreviations for basis points and percent, respectively.
SOURCE: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

4 Regression Kink Design

4.1 RKD Estimator

We estimate the effects of deposit insurance premiums using a sharp RKD, as opposed to a fuzzy RKD, because assessment rates are assigned deterministically based on the method described in Sections 2 and 3. In particular, we use the RKD estimator described by Calonico et al. (2014). For each bank i and quarter t, with $i = 1, 2, ..., I$ and $t = 1, 2, ..., T$, X_{it} is the unconstrained 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 X_{it} basis points if $X_{it} \geq 5$. In simpler terms, the rate schedule implies that unconstrained assessment rates 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, which is equal to 1 at the 5-basis point threshold. 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:

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

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 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.[10] We estimate τ using local linear and quadratic estimators, clustering standard errors at the bank level, and using the software packages described in Calonico et al. (2017).[11]

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

[11]The description of the local linear estimator is analogous to description of the local quadratic esti-

4.2 Smoothness Assumption of the RKD

The key identifying assumption of the sharp RKD 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 precisely manipulate the running variable at the cutoff. In our context, this assumption requires that banks cannot lower their unconstrained assessment rates in a neighborhood of the 5-basis point threshold.

Figure 2 shows that the distribution of the running variable is smooth around 5 basis points, indicating that banks do not manipulate their unconstrained assessment rates within a narrow neighborhood of this threshold. This finding is expected because the unconstrained assessment rate is determined by variables that depend on market prices and decisions of bank supervisors and borrowers, making it difficult for banks to adjust these variables with precision. We also formally test whether the density of unconstrained assessment rates is continuous around this threshold. These tests, which we present in Table C.1 in Appendix C, do not reject the null hypothesis that the density of the running variable is continuous at the threshold of 5 basis points, offering additional support to our RKD.

The smoothness assumption also implies that the expectation of any variable that should not be affected by treatment conditional on the running variable must be twice continuously differentiable at the cutoff. Figures 3 and 4 examine this hypothesis graphically showing the mean values of covariates as a function of the running variable. In Figure 3, we analyze the risk measures 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. In Figure 4, we examine the total capital ratio and the tier 1 capital ratio, which, together with the tier 1 leverage ratio, determine each bank's capital group and risk category. The figures show the mean values of these covariates in the year-quarter that the running variable is measured. Figure 4 also includes two measures of profitability, namely ROA and ROE, measured in the previous year-quarter. We use lagged values for ROA and ROE because, in principle, deposit insurance premiums could lower ROA and ROE,

mator, and we omit it from the paper for the sake of brevity.

even though these effects should be modest as assessment rates are small compared to the means of ROA and ROE.

The two figures show that the relationship between the running variable and the conditional expectations of those covariates is smooth around the cutoff. In Appendix C, we 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 C.2, the tests for all covariates do not reject the null hypothesis of no treatment effects, thereby providing further support to our RKD.

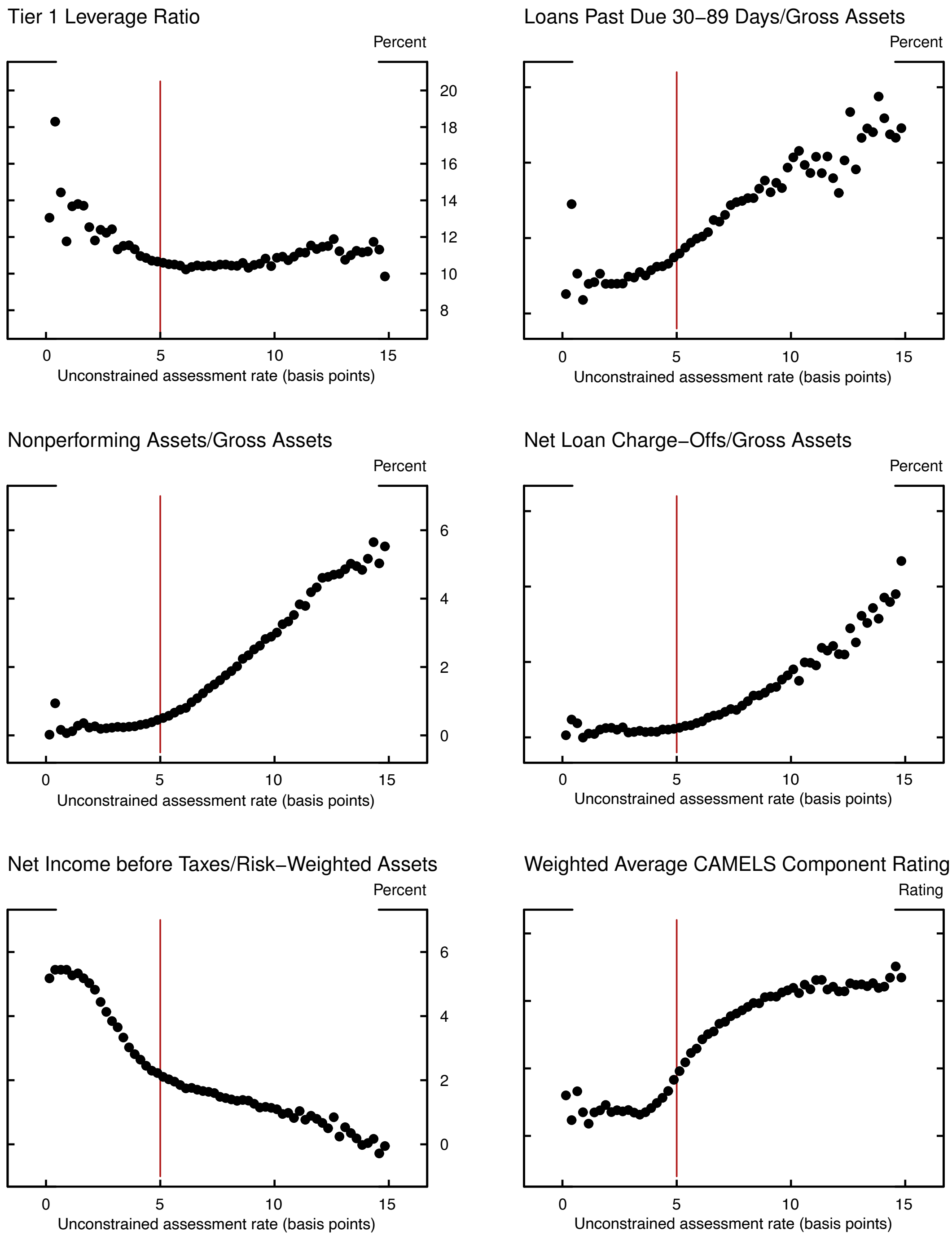

Figure 3: **Smoothness Assumption on Assessment Rate Components**

NOTE: This figure shows the mean values of covariates as a function of the running variable (unconstrained assessment rate). Mean values are measured in the same year-quarter as the running variable.
SOURCE: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

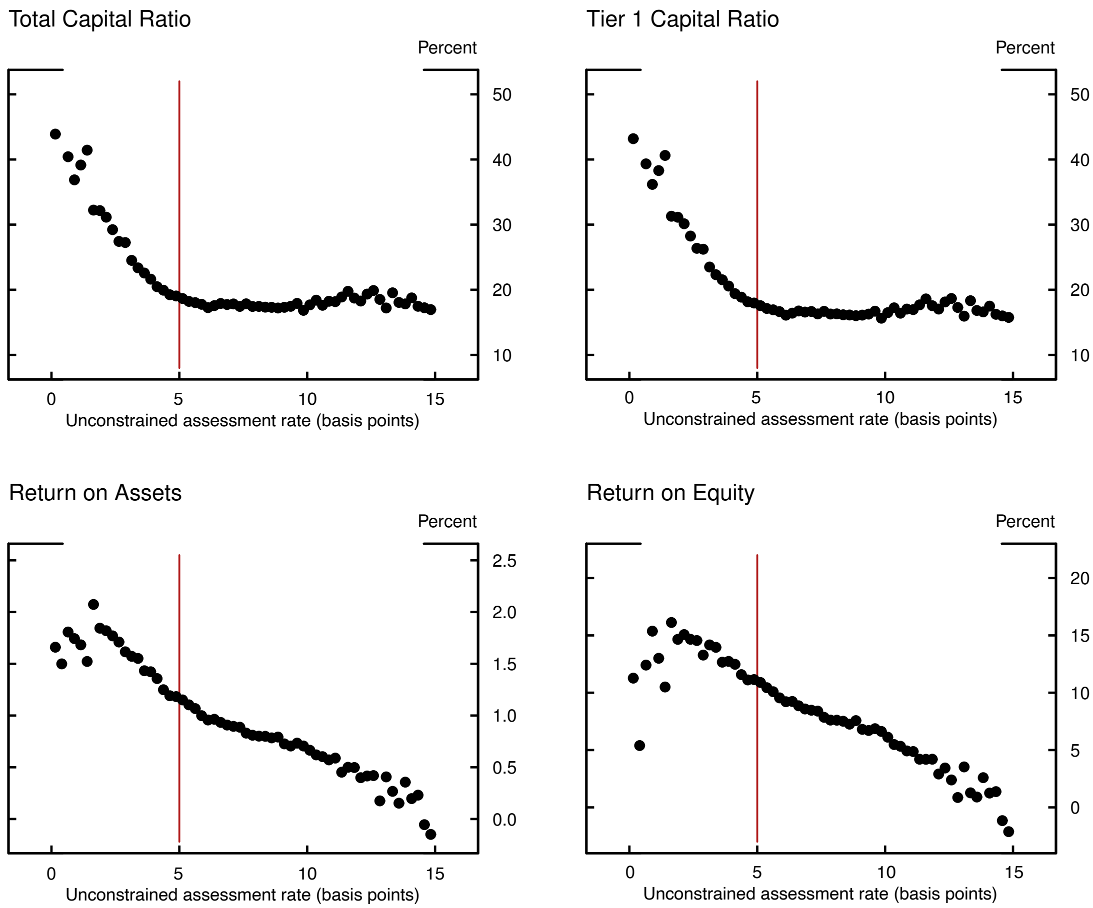

Figure 4: **Smoothness Assumption on Covariates**

Note: This figure shows the mean values of covariates as a function of the running variable (unconstrained assessment rate). Mean values are measured in the same year-quarter as the running variable, except ROA and ROE, which are measured in the previous year-quarter.
Source: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

5 Results

In this section, we examine the effects of assessment rates on banks' excess reserves and interbank lending. We measure the running variable (unconstrained assessment rate) in quarter t and the outcome variables (excess reserves and federal funds sold and purchased) in quarter $t+1$. Our empirical strategy assumes that banks consider their assessment rates in quarter t to be reliable approximations of their rates in $t+1$, which in turn apply to their assessment bases in $t+1$ and affect their decisions about reserve amounts and interbank lending in $t+1$. This assumption is adequate as unconstrained assessment rates are highly correlated over time at the bank level (see Appendix D).

5.1 Effects of Assessment Rates on Banks' Excess Reserves

We first provide graphical evidence that assessment rates affect banks' excess reserves. Figure 5 shows the relationship between the unconstrained assessment rate in t and the natural logarithm of quarter-end excess reserves in $t+1$. Unconstrained assessment rates, shown in the horizontal axis, are divided into 30 0.67-basis point wide buckets. The mean value of the natural logarithm of excess reserves in each bucket, as well as 95-percent confidence intervals, are shown in the vertical axis.

The figure shows that excess reserves increase with unconstrained assessment rates when the constrained rates are constant (left of the 5-basis point cutoff), consistent with riskier banks holding more reserves for precautionary reasons. Additionally, excess reserves decrease with the unconstrained assessment rates when assessment rates are not constrained by the 5-basis point minimum (right of the 5-basis point cutoff). The decrease in the slope of the relationship between assessment rates and excess reserves at the 5-basis point threshold indicates that assessment rates weaken banks' demand for reserves. This supports the hypothesis that balance sheet costs induce banks to search for yield. Still, the figure shows large dispersion in excess reserve amounts relative to the change in slope, and we leave a more definitive conclusion to the regression analysis.

Table 2 shows estimates of the effects of assessment rates on banks' 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

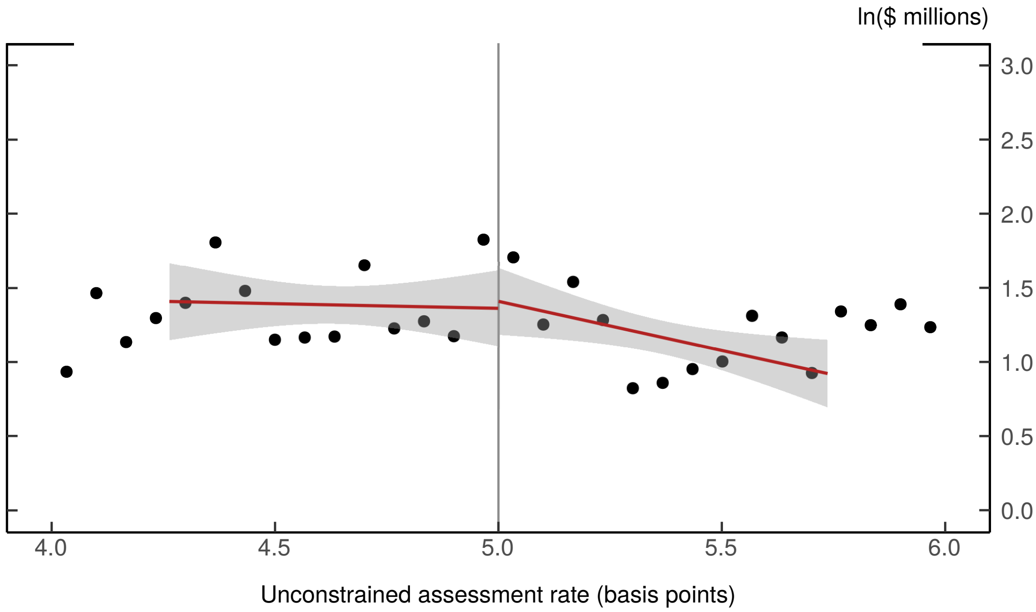

Figure 5: **Assessment Rates and Excess Reserves**

Note: This figure shows the relationship between unconstrained assessment rates (in the horizontal axis) and the natural logarithm of excess reserves (in the vertical axis). Unconstrained assessment rates are divided into 30 0.67-basis point wide buckets. For each bucket, we plot the mean dependent variable and 95 percent confidence intervals. The vertical solid line identifies the minimum assessment rate of 5 basis points. The red 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 0.736, the optimal bandwidth from column 1 of Table 2.
Source: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

linear polynomials ($p = 1$) and columns 3 and 4 show estimates using local quadratic polynomials ($p = 2$). In columns 1 and 3, the dependent variable is the natural logarithm of quarter-end excess reserves, and in columns 3 and 4, the dependent variable is the natural logarithm of quarterly average excess reserves.

Estimates of the effects of assessment rates on excess reserve amounts are large, statistically significant, and have the expected sign. The -1.579 estimate of τ in column 1 implies that a 1-basis point increase in the assessment rate decreases the excess reserves of the average bank in the sample from \$5.5 million to \$1.1 million. The coefficient estimate in column 2, equal to -1.694, implies an effect of roughly the same size. The point estimate in column 3, equal to -2.680, implies that a 1-basis point increase in the

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	-1.579	-1.694	-2.680	-2.814
Robust 95% CI	[-4.084, -0.296]	[-4.182, -0.452]	[-6.094, -0.301]	[-6.231, -0.488]
Robust p-value	0.023	0.015	0.030	0.022
N_-	3,131	3,082	4,523	4,456
N_+	3,300	3,244	5,607	5,483
h	0.736	0.727	1.307	1.281

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 18,907 (columns 1 and 3) and 18,805 (columns 2 and 4) observations. h is the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

assessment rate drops the excess reserves of the average bank in our sample from $5.5 million to $0.4 million. The coefficient when using average excess reserves is similar at −2.814. Moreover, we observe similar confidence intervals between columns 1 and 2 and between columns 3 and 4.

Although these changes seem large given the level of banks' excess reserve holdings, they are reasonable considering the distributions of assessment rates and excess reserves. A 1-basis point increase in the assessment rate is roughly one-half of a standard deviation of unconstrained assessment rates in our sample, and the implied decrease in excess reserves (ranging from $4.4 million to $5.1 million) is less than 15 percent of a standard deviation of excess reserves. In other words, we can interpret the results as a standard deviation increase in assessment rates lowering excess reserves by one-third of a standard deviation.

The estimates in Table 2 indicate that using quarter-end or quarterly average amounts yield similar results, consistent with the fact that quarter-end effects on reserve balances are generally modest at small banks. Because the results using the two alternative measures of reserves are similar, we henceforth only present results using quarter-end measures.

The coefficient estimates in Table 2 also show that our results are 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 under our setting, we mostly focus on this specification in the remainder of the paper.

5.2 Effects of Assessment Rates on Interbank Lending

We next examine whether assessment rates affect short-term lending in the federal funds market. Figures 6 and 7 present the relationship between the unconstrained assessment rate and the natural logarithms of federal funds sold and purchased, respectively. Figure 6 shows that federal funds sold decrease with the unconstrained assessment rate when the constrained rates are constant (left of the 5-basis point cutoff), suggesting that bank risk weakens interbank loan supply when assessment rates do not vary with bank risk. This negative relationship is consistent with the evidence from Figure 5 that excess reserves increase with unconstrained rates on the left of the cutoff, and implies that riskier banks reduce their supply of interbank loans to hold more excess reserves for precautionary reasons.

Figure 6 also shows that federal funds sold rise with the unconstrained assessment rate when assessment rates are not constrained by the 5-basis point minimum (right of the 5-basis point cutoff). Once again, this positive relationship is consistent with the negative relationship between excess reserves and assessment rates on the right of the cutoff shown in Figure 5, and indicates that deposit insurance premiums motivate banks to take on more risk by shifting their allocations of liquid assets from excess reserves to interbank loans.

Meanwhile, federal funds purchased do not seem to respond to assessment rates, as shown in Figure 7. Although the weak relationship between interbank borrowing and assessment rates contrasts with the strong relationship between interbank lending and rates seen in Figure 5, the result can be explained by the fact that, on average, small banks sell more funds than they buy.

Table 3 shows estimates of the effects of assessment rates on interbank lending. In Panel A, 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.

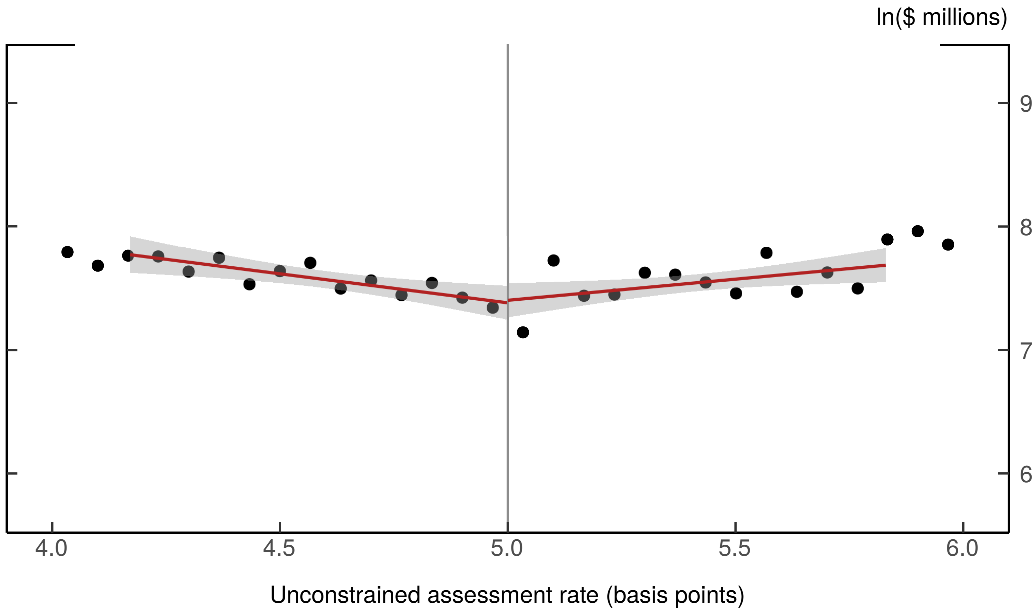

Figure 6: **Assessment Rates and Federal Funds Sold**

NOTE: This figure shows the relationship between unconstrained assessment rates (in the horizontal axis) and the natural logarithm of federal funds sold (in the vertical axis). Unconstrained assessment rates are divided into 30 0.67-basis point wide buckets. For each bucket, we plot the mean dependent variable and 95 percent confidence intervals. The vertical solid line identifies the minimum assessment rate of 5 basis points. The red 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 0.829, the optimal bandwidth from column 1 of Table 3.
SOURCE: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

Consistent with Figure 6, estimates of τ using federal funds sold as the dependent variable are positive and statistically significant. The local linear estimate in column 1, equal to 0.949, indicates that the amount of federal funds sold at the average bank would jump from $3.5 million to $8.9 million following a 1-basis point increase in its assessment rate. The local quadratic estimate in column 3, equal to 1.212, implies that the federal funds sold would jump to $11.6 million in response to a 1-basis point increase in assessment rates.

Analogous to our interpretation in Section 5.1, these increases in federal funds sold are large given the average amount of federal funds sold, but not relative to the distributions of those two variables. A 1-basis point change in the assessment rate is about one-half of a standard deviation of the unconstrained assessment rates in our sample. The increase

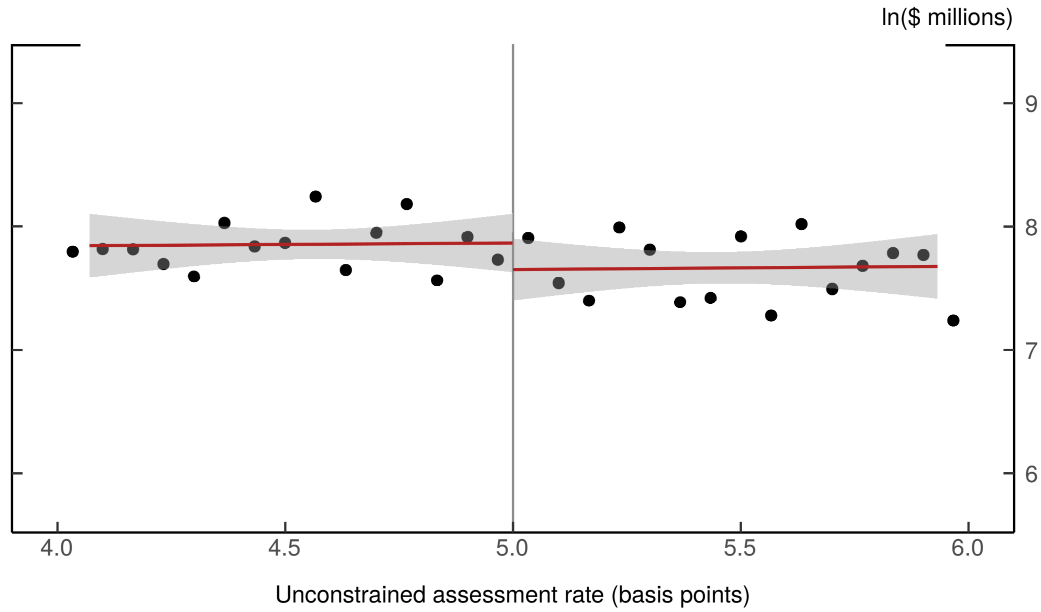

Figure 7: **Assessment Rates and Federal Funds Purchased**

Note: This figure shows the relationship between unconstrained assessment rates (in the horizontal axis) and the natural logarithm of federal funds purchased (in the vertical axis). Unconstrained assessment rates are divided into 30 0.67-basis point wide buckets. For each bucket, we plot the mean dependent variable and 95 percent confidence intervals. The vertical solid line identifies the minimum 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 0.932, the optimal bandwidth from column 2 of Table 3.
Source: Consolidated Reports of Condition and Income (FFIEC 031 and 041) and Federal Reserve supervisory data.

in federal funds sold caused by this change in assessment rates (ranging from $5.4 million to $8.1 million) is roughly equal to one-third or one-half of a standard deviation of federal funds sold by small banks. Thus, these results imply that a standard deviation increment in assessment rates raises the amount of federal funds sold by one-third to one-half of a standard deviation.

Consistent with Figure 7, estimates of τ using the federal funds purchased as the dependent variable, in columns 2 and 4 of Panel A, are closer to zero and not statistically significant. These estimates indicate that the amount of federal funds purchased by the banks in our sample does not respond to assessment rates. In Panel B, we repeat the regressions from Panel A adding reverse repo and repo amounts to federal funds sold and purchased, respectively. Reverse repos and repos are alternative operations that banks

Table 3: **Effects of Assessment Rates on Interbank Lending**

Panel A: Federal funds

	Local linear		Local quadratic	
	Federal funds sold (1)	Federal funds purchased (2)	Federal funds sold (3)	Federal funds purchased (4)
RKD treatment effect	0.949	-0.093	1.212	0.079
Robust 95% CI	[0.260, 1.638]	[-1.554, 1.652]	[0.170, 2.413]	[-2.261, 3.126]
Robust p-value	0.007	0.932	0.024	0.753
N_{-}	2,606	724	4,057	887
N_{+}	2,862	652	6,096	860
h	0.829	0.932	1.903	1.304

Panel B: Federal funds and securities repurchase agreements

	Local linear		Local quadratic	
	Federal funds sold + reverse repo (1)	Federal funds purchased + repo (2)	Federal funds sold + reverse repo (3)	Federal funds purchased + repo (4)
RKD treatment effect	0.961	-0.023	1.196	-0.127
Robust 95% CI	[0.077, 2.201]	[-1.680, 1.718]	[0.164, 2.384]	[-3.194, 2.868]
Robust p-value	0.036	0.983	0.047	0.916
N_{-}	2,612	728	4,003	890
N_{+}	2,867	660	5,884	863
h	0.830	0.944	1.826	1.315

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 15,272 (columns 1 and 3) and 3,098 (columns 2 and 4) observations. h is the second generation data-driven MSE-optimal bandwidth selector proposed in Calonico et al. (2014).

conduct to lend and borrow short-term funds. We include reverse repos and repos in the dependent variables to examine whether the estimates in Panel A change if we consider a broader set of short-term borrowing and lending operations. The coefficient estimates in Panel A and B are very close, which can be attributed to the fact that small banks rarely engage in repo operations. Overall, the findings in this section 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 purchase federal funds, as discussed in Keating and Macchiavelli (2017) and others.

5.3 Validation and Falsification Tests

In this section, we present three additional validity tests for our RKD methodology: estimating treatment effects with placebo cutoffs, using different bandwidth choice procedures, and excluding observations near the cutoff.[12] Similar to the smoothness assumption tests from Section 4.2, these three tests support the assumptions of our RKD.

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 evaluate whether the RKD assumption of continuity of regression functions for treatment and control observations at the cutoff in the absence of treatment hold. Even though this assumption cannot be tested directly, evidence of discontinuities would indicate that it does not hold. Conversely, evidence of continuity away from the cutoff, which is neither necessary nor sufficient for continuity at the cutoff, would offer some support to that assumption.

We examine continuity away from the cutoff by estimating the effects of assessment rates after replacing the true cutoff of 5 basis points with values at which no treatment occurs. We present results using excess reserve holdings and the amounts of federal funds sold as dependent variables because the results in Table 3 do not indicate that assessment rates affect the amounts of federal funds purchased. Additionally, we only show estimates with a local linear polynomial because the conclusions using a local quadratic polynomial are about the same.

Figure 8 shows our estimates using alternative cutoffs from 2 basis points to 8 basis points. The left and right panels use the natural logarithms of excess reserves and federal funds sold as dependent variables, respectively. Red dots show our point estimates of treatment effects and the vertical lines show robust 95 percent confidence intervals. We report complete regression results in Table C.3 of Appendix C.2.

[12]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 C, these tests constitute the five validation and falsification tests that Cattaneo et al. (2018a) introduce for regression discontinuity and RKD designs.

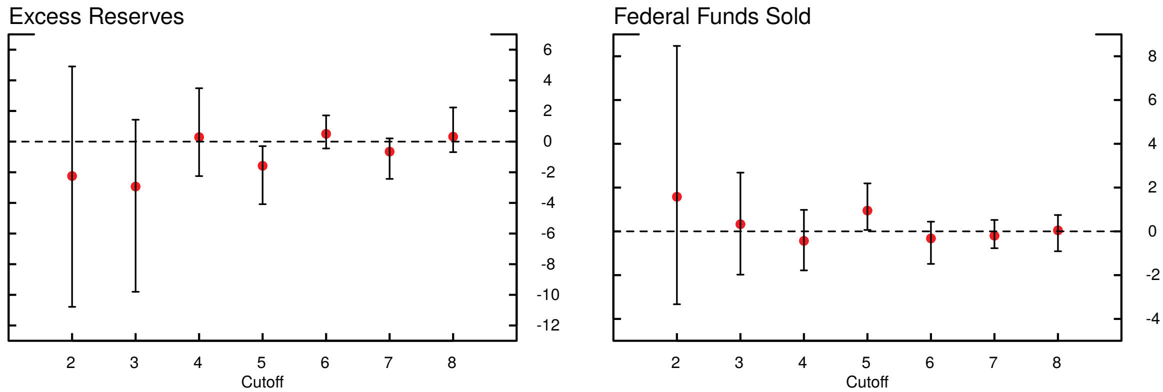

Figure 8: **RKD Estimates with True and Placebo Cutoffs**

Note: This figure shows RKD estimates using alternative cutoffs from 2 basis points to 8 basis points. The true cutoff is at 5 basis points. The left and right panels use the natural logarithms of excess reserves and federal funds sold as dependent variables, respectively. Red dots show our point estimates of treatment effects and the vertical lines show robust 95 percent confidence intervals. Table C.3 in Appendix C.2 shows the complete results.

In both panels, the confidence intervals do not include zero only when 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 2, 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 Bandwidth Choice

We next examine whether our results are robust to changes in the procedure used to select bandwidths. Different procedures can affect results by generating bandwidths of different lengths: 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 using 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

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	-3.103	[-5.869, -1.170]	0.003	2,198	2,284	0.500	0.500
Common MSE-optimal	-1.579	[-4.084, -0.296]	0.023	3,131	3,300	0.736	0.736
Different CER-optimal	-2.559	[-4.875, -0.931]	0.004	2,551	2,754	0.583	0.611
Different MSE-optimal	-0.980	[-3.143, 0.181]	0.081	3,536	3,979	0.858	0.899
Panel B: Federal funds sold as dependent variable							
Common CER-optimal	1.351	[0.169, 2.779]	0.027	1,892	1,951	0.568	0.568
Common MSE-optimal	0.949	[0.064, 2.191]	0.038	2,606	2,862	0.829	0.829
Different CER-optimal	1.271	[0.115, 2.625]	0.032	1,797	2,339	0.540	0.676
Different MSE-optimal	0.966	[0.085, 2.138]	0.034	2,515	3,383	0.788	0.986

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). Panels A and B use, respectively, the natural logarithms of excess reserves and federal funds sold measured in millions of dollars as the dependent variable. N_- and N_+ are the number of observations effectively used above and below the 5-basis point cutoff out of 18,907 (Panel A) and 15,272 (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.

(MSE)-optimal bandwidth selectors have highly desirable properties for point estimation of treatment effects, but they also have serious disadvantages for building confidence intervals, whereas coverage error (CER)-optimal bandwidth selectors yield point estimators 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 using the alternative bandwidth selection procedures. Panels A and B present estimates using the natural logarithms of excess reserves and federal funds sold as the dependent variables, respectively. In both panels, the bandwidths are longer and the point estimates of the RKD effect are closer to 0 when we use an MSE-optimal procedure—the better procedure for point estimation—instead of a CER-optimal procedure. Importantly, the point estimates in Panel A remain negative and large in absolute terms and the point estimates in Panel B remain 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 zero in 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 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.

5.3.3 Sensitivity to Observations near the Cutoff

Our last robustness test investigates whether the estimates of the effects of assessment rates on reserves and federal funds sold change materially if we drop observations very close to the 5-basis point cutoff. This exercise, often known as the donut hole approach, tests 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 unconstrained assessment rates. Removing observations close to the cutoff would therefore drop observations that are more likely subject to manipulation. Again, manipulation should be a minor concern in our setting because assessment rates are determined by many variables that banks cannot control precisely (e.g. fraction of loans past due and supervisory ratings). However, 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 9 shows how point estimates and confidence intervals change as we drop observations up to 0.020 basis points on either side of the 5-basis point cutoff. The top and bottom rows show results using MSE-optimal and CER-optimal bandwidths, respectively. The RKD estimate using MSE-optimal bandwidths and excess reserves as the dependent variable is somewhat sensitive to the removal of observations near the cutoff, as the confidence intervals include zero even when we drop observations within a 0.005-basis point

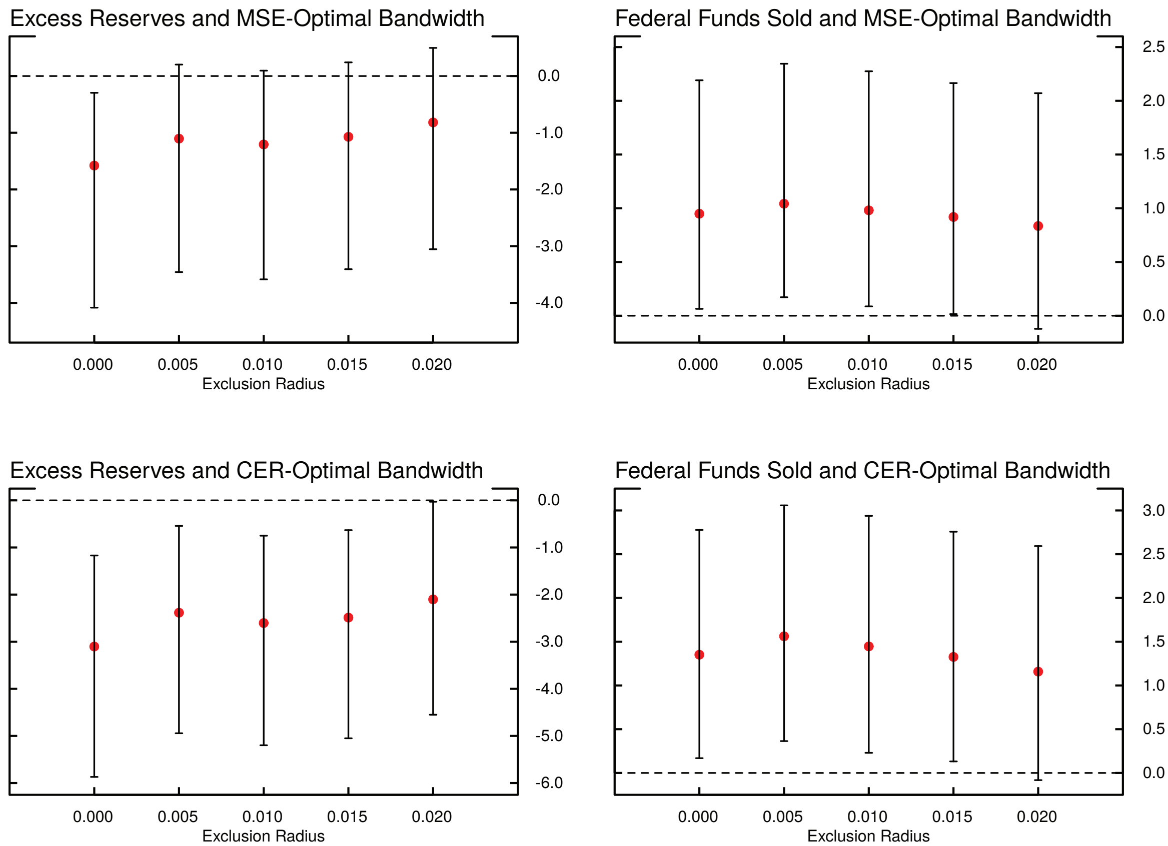

Figure 9: **RKD Estimates Excluding Observations near the Cutoff**

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 C.4 in Appendix C.3 shows the complete results.

radius around the cutoff (top-left panel).

As discussed in Section 5.3.2, confidence intervals constructed with CER-optimal bandwidths have better properties than MSE-optimal intervals. The bottom row panels provide evidence that our estimates remain statistically significant even if drop observations from a wider interval around the 5-basis point cutoff. We find that dropping observations up to a 0.015-basis point radius does not change the signs of the estimates on excess reserves and federal funds sold or induce the robust confidence intervals to include zero. In summary, the results from Table 3 are mostly unchanged when we remove observations close to the 5-basis point cutoff.

5.4 Discussion

In this section, we discuss how our findings relate to optimal deposit insurance systems and pricing. Our results shed some light on this topic, but a comprehensive framework that accounts for the benefits of deposit insurance premiums would be more appropriate to determine what assessment rates and systems would maximize social welfare.

Optimal deposit insurance premiums should depend on the effects of bank behavior on welfare, which we don't consider in this paper. For example, optimal premiums should also account for the potential benefits of interbank loans. In fact, a higher supply of interbank loans helps keep the federal funds market liquid, allowing banks to meet reserve requirements and avoid costly government interventions.

Of note, our estimates on the effects of deposit insurance premiums on bank behavior likely depend on the characteristics of banks around the 5-basis point threshold. The FDIC sets its assessment rate schedule—including the threshold—to make premiums actuarially fair, that is, to make the DIF break even in expectation.[13] However, an assessment rate schedule that is actuarially fair potentially differs from a schedule that maximizes welfare. This difference implies that our estimates might not hold in an environment in which assessment rates are set to maximize welfare.[14]

In addition, a more comprehensive framework is necessary to design an optimal deposit insurance system. We do not consider several benefits of deposit insurance in this paper. For example, deposit insurance helps prevent bank runs by enabling banks to liquidate assets in an orderly manner. As such, the effect of premiums on bank behavior that we examine constitute only one component of a cost and benefit analysis of deposit insurance. In fact, several prominent models that study these costs and benefits abstract from premiums and assume that the government provides deposit insurance for free (Keeley, 1990) or funds it through taxes levied on depositors (Diamond and Dybvig, 1983).

[13]The schedule of assessment rates over the sample period was largely affected by the Dodd-Frank Act, which required the FDIC to increase rates in order to restore the DIF and to have the cost of this transition be borne by large banks. More generally, the DIF has historically been funded only by assessment fees from banks.

[14]Chan et al. (1992), Craine (1995), and Dávila and Goldstein (2020) discuss differences between optimal deposit insurance premiums and actuarially fair premiums.

6 Conclusion

This paper examines the impact of deposit insurance premiums on banks' demand for reserves and interbank lending in the federal funds market. By exploiting a kink in the schedule of deposit insurance assessment rates, we show that these premiums reduce the demand for reserves and increase the supply of federal funds. The economic significance of our results are large, indicating that balance sheet costs can induce banks to search for yield. Given that larger banks—those outside the scope of this paper—generally have much higher reserve balances and participate more actively in the federal funds market, the impact of deposit insurance premiums may be economically substantial.

Meanwhile, the effects of deposit insurance premiums on bank behavior are likely stronger in a low-interest rate environment. Over the period we study, low interest rates kept banks' net interest margins narrow, implying that changes in assessment rates of a few basis points could drive material changes in bank behavior. It is plausible that these effects would be weaker under higher interest rates.

Our findings have an important policy implication. We show that small changes in deposit insurance premiums can meaningfully reduce banks' demand for reserves, a highly liquid asset with negligible credit risk, and raise demand for interbank loans, a less liquid asset with credit risk. Because balance sheet costs imposed by deposit insurance premiums can induce banks to search for yield, optimal deposit insurance pricing should account for the feedback effects of deposit insurance premiums on bank risk.

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Appendix A IOER Rate and Federal Funds Rates

In this appendix, we discuss the relationship between the IOER rate and the rates on overnight federal funds transactions. In principle, the IOER rate should serve as a floor for interbank loans. However, throughout our sample period, the IOER rate stayed above the EFFR, which is a volume-weighted median of the rate on overnight federal funds transactions. The EFFR is often below the IOER rate primarily due to loan supply from other financial institutions that cannot hold reserves at the Federal Reserve. These institutions, which include government-sponsored enterprises (for example, Fannie Mae, Freddie Mac, and Federal Home Loan Banks), collectively account for about three- quarters of total interbank lending in the federal funds market since the Global Financial Crisis. Banks that do not have reserve accounts and can only earn IOER at a discount also contribute to the downward pressure on the EFFR, but most likely have a weaker effect than GSEs and other financial institutions because of their smaller size. See Bech and Klee (2011) for a discussion on the topic.

Even though the IOER may exceed the EFFR, banks may find it profitable to supply interbank loans for various reasons. First, many small banks without reserve accounts at a Federal Reserve Bank can only receive IOER via accounts managed by correspondent banks that charge a fee for this service. Accounting for those fees, holding excess reserves becomes less profitable as these banks cannot earn the full IOER rate. Second, these banks can more easily lend to correspondent banks without transferring funds (Afonso et al., 2011). Thus, small banks with no reserve accounts—about two-fifths of the banks in our sample—may find interbank loans to correspondent banks less costly or more convenient than holding excess reserves.

Third, in the case of banks with reserve accounts, we argue that they likely extend interbank loans at rates above the IOER rate. The EFFR is calculated based on transactions that include banks that can earn IOER and other financial institutions that cannot earn IOER. Because the EFFR is pressured downwards by institutions that cannot earn IOER, banks that supply interbank loans in lieu of earning IOER likely do so at a rate higher than the IOER rate. Indeed, interbank rates can be above the IOER rate due to search costs incurred by borrowing entities or increased demand for funds late in the trading day (Afonso and Lagos, 2015; Kim et al., 2020).

Appendix B Assessment Rates

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

B.1 Initial Base Assessment Rate

Table B.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 B.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 includes 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 B.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 B.2: **Initial 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).

Table B.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.
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 B.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 B.4. The sum of the risk measures multiplied by the coefficients from Table B.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, and simply refer to it as the unconstrained assessment rate.

The unconstrained assessment rate of a risk category 1 bank is constrained by the minimum and maximum rates shown in the first column of Table B.2. The constrained assessment rate is equal to the minimum rate of 5 basis points if the unconstrained

Table B.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 places for unconstrained assessment rate calculation.
SOURCE: Federal Deposit Insurance Corporation (2011).

assessment rate is below this minimum and it is equal to the maximum rate of 9 basis points if the unconstrained assessment rate is above this maximum. As shown by the solid line in Figure 1, this rule creates a relationship between the constrained and the unconstrained assessment rates that is flat to the left of 5 basis points, increasing with a slope equal to 1 between 5 and 9 basis points, and also flat to the right of 9 basis points.

B.2 Adjustments to the Unconstrained Assessment Rate

After a bank's unconstrained assessment rate is calculated, this rate may be adjusted downward for unsecured debt (UDA) and upward for brokered deposits (BDA) and for debt issued by other institutions (DIDA). The UDA of a bank is calculated by adding 40 basis points to the unconstrained assessment rate 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 and 50 percent of the bank's unconstrained assessment rate, is subtracted from the unconstrained assessment rate. Conversely, the BDA only applies 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 as 25 basis points times the ratio of the difference between 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 to the unconstrained assessment rate. Lastly, the DIDA is a 50 basis point charge on the amount of long-term unsecured debt 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 three adjustments, and which is actually charged to banks, is defined as the total base assessment rate. We also refer to this rate as the assessment rate throughout the paper.

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 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. Moreover, the DIDA does not affect the estimates because it does not depend on the unconstrained assessment rate.

The UDA attenuates the changes in slope of the constrained assessment rate as a function of the unconstrained assessment rate, thereby affecting the economic interpretation of our coefficient estimates. The UDA attenuates the changes at 5 basis points, shown in Figure B.1, because it is in absolute terms an increasing function of the constrained assessment rate. Indeed, the change in slope at 5 basis points is largest when the UDA is equal to zero (solid line) and is smallest when the UDA reaches its cap of 50 percent of the unconstrained assessment rate (dashed line). For this reason, the economic effect implied by coefficient estimates under the assumption that the UDA is equal to zero (i.e. the slope of the total base assessment rate as a function of the unconstrained assessment rate 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 UDA is the highest possible (i.e. the slope of the total base assessment rate as a function of the unconstrained assessment rate 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.

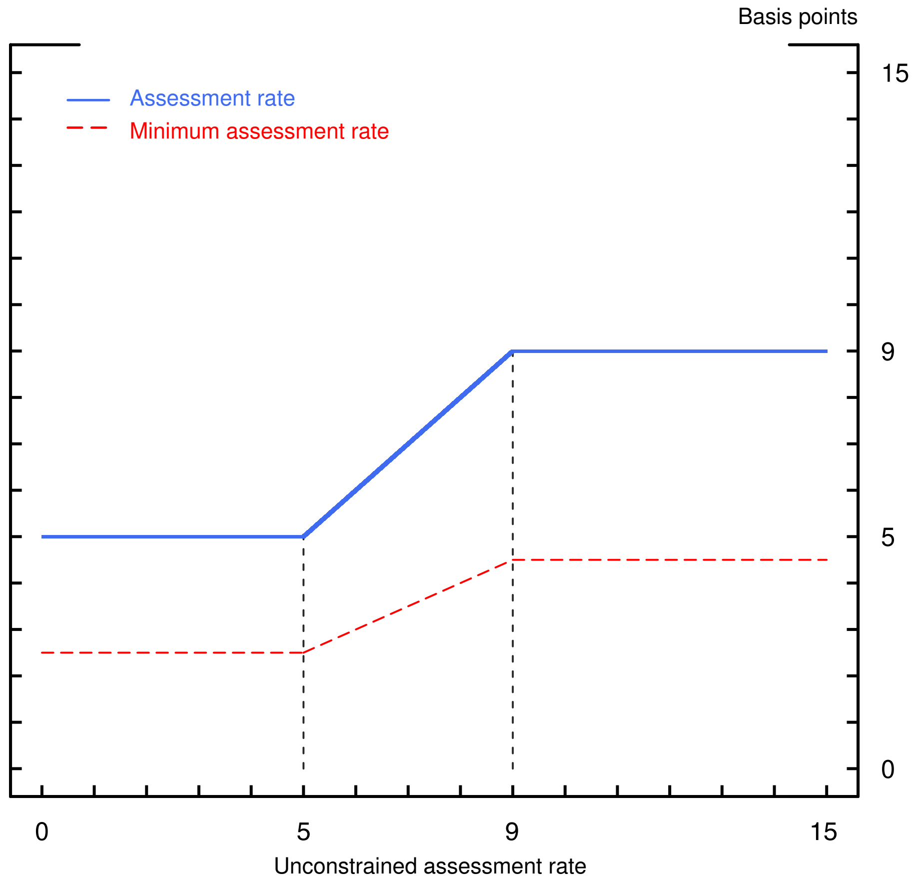

Figure B.1: **Kinks at Assessment Rate with Unsecured Debt Adjustment**

NOTE: The solid line shows the constrained assessment rate as a function of the unconstrained 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 the analysis. Assessment rates are measured in basis points.
SOURCE: Federal Deposit Insurance Corporation (2011).

B.3 Calculation of Assessment Rates

The rule that determines the method for calculating assessment rates is described in 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. Its downside, however, is that it is designed to show rates for a single bank at a time. To overcome this challenge, we first use the FDIC's documentation and our own data set to compute the unconstrained assessment rate for all small banks during our sample period. We then compare our data-driven rate to the calculator's rate for a random selection of banks and verify that the numbers are exactly the same.

We also compare our assessment rate calculations to Call Report data on dollar amounts of FDIC fees. Specifically, we analyze whether the reported assessment fees divided by the assessment base is consistent with our calculated assessment rates. The results are similar on balance but not always the same, indicating that actual FDIC charges may differ from the amounts that banks report in the Call Reports for various reasons. For instance, payments might be delayed or banks and the FDIC may disagree on the amount charged.

Appendix C Additional Validation and Falsification Results

C.1 Evidence on the Smoothness Assumption

In this appendix, we present additional evidence that the assumptions of the RKD are satisfied in our setting. Table C.1 presents 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, 2020) under different specifications. The p-values are large in all three columns, indicating that the null hypothesis is never rejected by these tests. Thus, these results support the validity of the RKD in our setting.

We now test formally whether the conditional expectations of the ten covariates shown in Figures 3 and 4 are twice continuously differentiable around the threshold of 5 basis points. We estimate treatment effects on those covariates using the estimator $\hat{\tau}(h_{IT})$ and the cutoff of 5 basis points. Table C.2 shows the results of these tests using our preferred specification for the estimator (local-linear). We find that the estimate of the robust 95-percent confidence interval for all covariates includes zero and the robust p-value does not allow us to reject the null hypothesis that $\tau = 0$. This finding supports the smoothness assumption of our RKD.

C.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 C.3 shows the complete results summarized in Figure 8.

C.3 Sensitivity to Observations Near the Cutoff

We examine whether the estimates in Tables 2 and 3 change materially if we drop observations close to the 5-basis point cutoff. Table C.4 shows the complete results summarized in Figure 9.

Table C.1: **Density Tests of Assessment Fees**

	Unrestricted inference with distinct bandwidths	Unrestricted inference with identical bandwidths	Restricted inference with identical bandwidths
	(1)	(2)	(3)
h_-	0.823	1.427	0.617
h_+	0.978	1.427	0.617
N_-	5,712	8,062	4,477
N_+	6,940	9,790	4,448
p-value	0.511	0.587	0.907

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 used above and below the 5-basis point cutoff out of 32,384 observations. 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, 2020) for methodological and implementation details.

Table C.2: **Treatment Effects on Covariates**

	Tier 1 leverage ratio	Loans past due to gross assets ratio	Nonperf. assets to gross assets ratio	Net loan chg-offs to gross assets ratio
	(1)	(2)	(3)	(4)
RKD treat. eff.	-0.136	0.032	-0.049	0.015
Robust 95% CI	[-1.788, 0.952]	[-0.098, 0.120]	[-0.334, 0.046]	[-0.037, 0.039]
Robust p-value	0.550	0.838	0.137	0.950
N_-	4,569	6,883	4,209	6,087
N_+	4,553	7,655	4,159	6,404
h	0.630	1.083	0.575	0.902

	NIBT to R-W assets ratio	Weighted average CAMELS	Total capital ratio	Tier 1 capital ratio
	(5)	(6)	(7)	(8)
RKD treat. eff.	-0.067	-0.034	-0.589	-0.526
Robust 95% CI	[-0.583, 0.139]	[-0.229, 0.082]	[-4.806, 1.245]	[-4.720, 1.332]
Robust p-value	0.229	0.354	0.249	0.272
N_-	4,053	4,805	4,320	4,338
N_+	4,001	4,824	4,287	4,306
h	0.554	0.669	0.592	0.595

	Return on assets	Return on equity
	(9)	(10)
RKD treat. eff.	-0.155	-1.498
Robust 95% CI	[-0.511, 0.006]	[-4.804, 0.360]
Robust p-value	0.056	0.092
N_-	4,665	4,891
N_+	4,643	4,950
h	0.646	0.687

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 as the running variable, except ROA and ROE, which are measured in the previous year-quarter.

Table C.3: **Effects of Assessment Rates Using Alternative Cutoffs**

Alternative cutoff (b.p.)	RKD treatment effect	Robust 95% CI	Robust p-value	N_-	N_+	h
Panel A: Excess reserves as dependent variable						
2	-2.247	[-10.784, 4.904]	0.463	87	337	0.929
3	-2.934	[-9.802, 1.428]	0.144	359	1,046	0.754
4	0.292	[-2.250, 3.484]	0.673	1,361	3,073	0.806
5	-1.579	[-4.084, -0.296]	0.023	3,131	3,300	0.736
6	0.506	[-0.448, 1.710]	0.252	5,244	4,048	1.197
7	-0.652	[-2.433, 0.209]	0.099	3,271	2,199	0.942
8	0.323	[-0.687, 2.227]	0.301	2,314	1,297	1.002
Panel B: Federal funds sold as dependent variable						
2	1.579	[-3.330, 8.471]	0.393	68	210	0.853
3	0.327	[-1.978, 2.683]	0.767	302	1,206	1.028
4	-0.434	[-1.783, 0.981]	0.570	1,044	2,388	0.827
5	0.949	[0.064, 2.191]	0.038	2,606	2,862	0.829
6	-0.322	[-1.487, 0.442]	0.288	2,807	2,426	0.812
7	-0.199	[-0.770, 0.521]	0.706	3,442	2,200	1.154
8	0.046	[-0.909, 0.746]	0.846	2,354	1,299	1.148

NOTE: This table shows estimates of treatment effects on covariates using alternative cutoff 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.

Table C.4: **Effects of Assessment Rates Excluding Observations Near the Cutoff**

Exclusion radius (b.p.)	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 and MSE-optimal bandwidth								
0.000	-1.579	[-4.084, -0.296]	0.023	3,313	3,300	0.736	0	0
0.005	-1.104	[-3.457, 0.202]	0.081	3,216	3,406	0.766	21	29
0.010	-1.206	[-3.585, 0.095]	0.063	3,178	3,367	0.761	38	45
0.015	-1.072	[-3.406, 0.241]	0.089	3,222	3,418	0.777	60	64
0.020	-0.818	[-3.054, 0.496]	0.158	3,278	3,489	0.800	78	84
Panel B: Federal funds sold as dependent variable and MSE-optimal bandwidth								
0.000	0.949	[0.064, 2.191]	0.038	2,606	2,862	0.829	0	0
0.005	1.042	[0.172, 2.345]	0.023	2,552	2,782	0.810	13	22
0.010	0.981	[0.087, 2.275]	0.034	2,570	2,808	0.824	27	38
0.015	0.919	[0.015, 2.165]	0.047	2,550	2,793	0.823	44	50
0.020	0.835	[-0.122, 2.071]	0.081	2,551	2,802	0.832	63	68
Panel C: Excess reserves as dependent variable and CER-optimal bandwidth								
0.000	-3.103	[-5.870, -1.170]	0.003	2,198	2,284	0.500	0	0
0.005	-2.385	[-4.943, -0.543]	0.015	2,256	2,337	0.520	21	29
0.010	-2.604	[-5.198, -0.750]	0.009	2,227	2,311	0.517	38	45
0.015	-2.489	[-5.050, -0.632]	0.012	2,252	2,339	0.528	60	64
0.020	-2.102	[-4.550, -.0292]	0.026	2,302	2,384	0.544	78	84
Panel D: Federal funds sold as dependent variable and CER-optimal bandwidth								
0.000	1.351	[0.169, 2.777]	0.027	1,892	1,951	0.568	0	0
0.005	1.562	[0.364, 3.058]	0.013	1,838	1,882	0.556	13	22
0.010	1.446	[0.230, 2.938]	0.022	1,853	1,896	0.565	27	38
0.015	1.326	[0.132, 2.757]	0.031	1,829	1,880	0.564	44	50
0.020	1.158	[-0.082, 2.593]	0.066	1,835	1,889	0.570	63	68

NOTE: This table shows estimates of treatment effects on covariates when dropping observations near the 5 basis point cutoff. Panels A and C use the natural logarithm of excess reserves measured in millions of dollars as the dependent variable, and Panel B and D use the natural logarithm of federal funds sold measured in millions of dollars. Panels A and B use MSE-optimal bandwidths, and Panels C and D use CER-optimal bandwidths. 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 used above and below the 5-basis point cutoff out of 18,907 (Panels A and C) and 15,272 (Panels B and D) observations.

Appendix D   Additional Results

In this appendix, we provide evidence that banks' unconstrained assessment rates are correlated over time. This evidence supports an assumption that we introduce in Section 5, namely that banks consider the rates in t reliable approximations of their rates in $t+1$. To evaluate this assumption, we use ordinary least squares (OLS) to estimate the following equation:

$$UAR_{i,t+1} = \alpha \times UAR_{i,t} + \nu_i + \varphi_t + \varepsilon_{it}, \tag{D.1}$$

where $UAR_{i,t}$ is the unconstrained assessment rate of bank i in period t measured in basis points, ν_i and φ_t are bank and time fixed effects, and ε_{it} an idiosyncratic shock. Standard errors are clustered at the bank level. α is the coefficient of interest, and we test the null hypothesis that $\alpha = 0$. A rejection of the null hypothesis with an estimate of α close to 1 indicates that unconstrained assessment rates are correlated over time within banks, and we interpret these findings as evidence in favor of our assumption.

Table D.1 presents estimates of equation (D.1). In column 1, we use the same sample from Section 5. In columns 2 to 4, we restrict the sample to bank-quarter observations such that $UAR_{i,t}$ belongs to the interval $(5-h, 5+h)$, where h ranges between 2 basis points (column 2) and 0.5 basis points (column 4). We estimate equation (D.1) with different bandwidths to examine whether evidence that assessment rates are correlated over time depends on the distance between rates and the 5-basis point cutoff.

The estimates of α in the four columns are positive and statistically significant, rejecting the hypothesis of no correlation over time in assessment rates and, therefore, supporting our assumption. Although the estimate decreases as we narrow the bandwidth (going from column 1 to 4), the results show that rates remain correlated over time within banks even when we employ a bandwidth of $h = 0.5$—the narrowest used in Section 5. These results support our assumption that banks consider the rates in t to be reliable approximations of their rates in $t+1$.

Table D.1: **Correlation of Assessment Rates over Time**

	$h = 20$	$h = 2$	$h = 1$	$h = 0.5$
	(1)	(2)	(3)	(4)
$UAR_{i,t}$	0.800**	0.722**	0.705**	0.611**
	(0.018)	(0.017)	(0.028)	(0.054)
Observations	32,075	22,080	13,466	7,233
Banks	2,410	1,996	1,553	1,180
R-squared	0.78	0.68	0.65	0.61

NOTE: This table shows OLS estimates of equation (D.1). The dependent variable is the unconstrained assessment rate of bank i in quarter $t + 1$ measured in basis points. h is the bandwidth that defines which observations on the left and on the right of the 5-basis point cutoff are used in the regression. All columns include bank and time fixed effects.