Benchmark Rate Mismatch

Job Market Paper

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Abstract

Establishing and maintaining financial benchmarks can reduce information asymmetry and other contracting costs but can also generate large distributional consequences. This study examines the replacement of an existing financial benchmark (LIBOR) with a new one (SOFR) as a lobbying outcome of banks with divergent capital structures. Large banks' efforts to steer the market standard towards SOFR were driven by their reliance on correlated secured repo funding, in contrast with smaller banks that rely primarily on unsecured overnight bank funding. I document large adverse competitive effects on smaller banks following the transition, including reduced equity returns, higher interest spreads, and loss of market share on loans, due to their increased exposure to interest rate mismatch risks. Model-based estimates indicate that the optimal benchmark reference rate would have assigned only 33% to 57% of its weight to SOFR, depending on whether the objective is to maximize banks' shareholder wealth or borrowers' liquidity.

JEL Codes: G18, G21, G32, D72

Key Words: bank funding structure, interest rate mismatch, lobbying, LIBOR, SOFR, OBFR

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1 Introduction

Financial benchmarks play a crucial role in enhancing market efficiency. Benchmarks reduce information asymmetry, simplify contract settlement, and decrease shopping costs in over-the-counter markets. They can also speed up trade execution, and lower negotiation costs (Duffie and Stein (2015)). Once established, a benchmark may generate agglomerative effects by channeling capital flows into standardized products.

How are benchmarks chosen, and what are the features of benchmarks that lead to the adoption of one versus another? The recent replacement of the London Interbank Offered Rate (LIBOR) as the base rate of interest rate in corporate and consumer credit markets has spurred an important discussion about the desirable features of a benchmark that best serves the public good (Cooperman et al. (2023), Duffie and Stein (2015), Jarrow and Li (2022, 2023), Jermann (2019, 2024), Kirti (2022)). For example, from a social planner's perspective, benchmarks should be free from manipulation, easily verifiable, reflect underlying market conditions, and perhaps be transaction-based. However, institutions may also have individual preferences for one potential benchmark over another based on their specific business models. Practically speaking then, benchmark choice may be less about finding a social optimum and more like the outcome of a lobbying contest among competing interest groups, with potentially significant distributional consequences.

In this paper, I use the transition away from LIBOR to a replacement benchmark rate as an experiment to better understand the political economy behind benchmark choice and the economic consequences thereof. I conjecture, and show, that institutions have strong and divergent economic preferences for different benchmarks based on their funding structure—a "natural habitat" view of benchmark choice. For example, smaller banks dependent on unsecured overnight borrowing would benefit more from an unsecured reference rate, naturally immunizing them against interest rate mismatch by aligning interest income and funding cost. Conversely, large banks heavily reliant on collateral-backed funding had incentives to advocate for a benchmark based on secured funding markets. After demonstrating the substantive economic incentives to implement different replacement rates, I show that large banks' exclusive representation inside the decision-making committee led to a benchmark choice benefiting repo-funded institutions like themselves.

The resulting change in the benchmark rate had significant economic consequences. Post-transition, bigger banks, benefiting from the aligned benchmark rate, offered more competitive loan terms, disadvantaging smaller lenders. This dynamic concentrated market power among the large banks, as reflected by an immediate increase in their equity value post-transition. Smaller businesses, which typically borrow from small and mid-sized lenders, faced reduced access to affordable credit as a result, demonstrating that benchmark choice influenced a wide range of outcomes, from market structure, to bank valuation, to borrower growth.

What drives banks with different funding structures to prefer distinct benchmarks? I propose that this preference arises from their incentive to align the reference rate with their funding costs, thereby mitigating interest rate mismatch risk. Mismatch risk—the risk of fluctuations in net interest income due to unmatched interest rate exposures on assets and liabilities—is central to a bank's profitability and stability (see Acharya and Mora (2015), Angbazo (1997), Bai et al. (2018), Diamond and Dybvig (1983), McPhail et al. (2023), Purnanandam (2007), among others). But I also show in this paper that benchmarks can exacerbate or mitigate baseline interest rate mismatch, depending on a bank's funding structure and the benchmark choice. LIBOR for example, was invented precisely to match actual banks' short-term funding costs, and as a result, was a natural reference rate, historically serving 97% of syndicated loans, as well as mortgages and student loans (Market Participants Group (2014))[1]. When banking entities with "LIBOR-like" funding costs lent at "LIBOR + spread," the banks' interest income closely matched their funding costs, reducing the impact of varying short-term rates on the net interest margins and minimizing interest rate mismatch risk.

Following the 2008 Financial Crisis, however, it was discovered that several major banking entities colluded to manipulate LIBOR by reporting rates different from what they

[1] LIBOR was calculated by averaging the borrowing rates self-reported by 18 major global banks, using the middle ten responses. According to the Intercontinental Exchange (ICE), it served as the benchmark rate for pricing approximately $350 trillion worth of financial products, including loans, mortgages, bonds, and derivatives. These products were traded widely by financial intermediaries, including banks, mutual funds, insurance companies, and private equity firms.

actually charged[2]. This scandal eroded trust in the benchmark, leading to an urgent need for reform in the rate-setting process. Given the evolution of the banking market to include institutions with more diverse financing structures and costs, selecting a replacement for LIBOR became less straightforward. Banks raise capital through various channels, including deposits, overnight borrowings, and securities sold under agreements to repurchase (repo), with costs influenced by prevailing market rates. Ideally, by lending at a floating reference rate that mirrors their borrowing expenses, lenders could align their long-term lending income with their short-term borrowing costs, protecting against rate variability. Therefore, in theory, banks would naturally desire the floating reference rate to synchronize with their funding costs according to their capital structure. Driven by these divergent preferences, this paper examines how competing incentives of market participants, as opposed to welfare maximization, shaped the new benchmark choice.

In response to the LIBOR scandal, the Federal Reserve convened the Alternative Reference Rates Committee (ARRC) in 2014 to find a reliable alternative to the USD LIBOR. Comprised of major banks and financial organizations, the ARRC aimed was to identify a transparent, manipulation-free rate that accurately reflected market conditions. The committee considered mainly two candidates: the Secured Overnight Funding Rate (SOFR) and the Overnight Bank Funding Rate (OBFR). SOFR, a secured rate, is based on repo market transactions where banks borrow funds by selling U.S. Treasury bonds with an agreement to repurchase them. This makes it more suitable for large dealer banks that engage in collateralized lending. Meanwhile, OBFR, an unsecured rate, is based on overnight borrowing between banks through federal funds, Eurodollar, and certain domestic deposit transactions. It captures a broader range of non-collateralized bank financing, which smaller lenders rely on more heavily. Although both benchmarks are risk-free and transaction-based, on June 22, 2017, the ARRC selected SOFR as the preferred standard over OBFR. This decision marked a fundamental shift in financial benchmarking, aiming to provide a more stable and transparent framework for global markets.

To understand why the group chose SOFR over OBFR, this paper begins by calibrating

[2] For details on the investigation by the U.S. Commodity Futures Trading Commission, see http://www.cftc.gov/ucm/groups/public/@lrenforcementactions/documents/legalpleading/ enfbarclaysorder062712.pdf.

a toy model to capture banks' predicted choices based solely on their funding structures. I then show that the selection of SOFR can be easily explained, not necessarily as the first-best choice among all banks, but rather as the preferred option among banks represented on the ARRC that were granted voting rights[3]. Although among the top 5% of the largest U.S. bank holding companies, there were significant differences in preferences toward each candidate benchmark rate, the makeup of banks on the ARRC significantly favored banks with predictable inclinations for SOFR as opposed to OBFR. This highlights how a committee's composition and governance are crucial, as they determine how well diverse interests can be balanced and represented. This finding contributes to the literature on how financial regulation and its enforcement reflect the balance of power between social and economic groups, including Borisov et al. (2016), Lancieri et al. (2022), Pagano and Volpin (2001), Perotti and Spier (1993), and Rajan and Zingales (2003).

Analogous findings show up globally. In the international setting, LIBOR rates were historically calculated for five major currencies, resulting in the need for five replacement rates. Consistent with the US dollar experience, I show that the choice between secured (such as SOFR) and unsecured (such as OBFR) alternative rates in different currency zones is closely related to the financing models of the largest banks in those regions

In the equity market, I observe strong announcement effects impacting lenders' stock performance. Large banks, particularly those with substantial exposure to the repo market volatility, experienced a notable boost in their cumulative abnormal returns following the announcement. This surge could be attributed to reduced risks from benchmark rate mismatch, which I refer to as the discrepancy between the market-wide reference rate and a bank's short-term funding costs due to its specific capital structure. In contrast, smaller banks, lacking sophisticated risk management programs, especially further exposure due to the mismatch, encountered challenges during the transition, negatively affecting their stock performance. This evidence also indicates that the market did not fully anticipate SOFR's selection, highlighting the significant impact of this announcement on the banking sector.

I then use data from the syndicated loan market to explore how the benchmark replace-

[3] I examine the LIBOR-SOFR transition through ARRC open letters, Q&As, agendas, and minutes, presenting evidence of possible lobbying and misalignment between the interests of Wall Street and Main Street in Appendix B.

ment affected interest spreads, market segregation, and competition during the LIBOR-to-SOFR transition. Because of SOFR's risk-free nature, the interest margins were expected to widen to compensate for the absence of a credit risk premium. However, empirical evidence reveals a more nuanced situation. Banks with different capital structures reacted distinctively to the SOFR transition. Those heavily dependent on the repo market strategically lowered their fixed interest spreads on loans after SOFR was announced as the successor. My interpretation is that these financial intermediaries took advantage of the hedged risk premium under the new benchmark rate to offer more competitive loan prices, thereby attracting more borrowers and expanding their market share.

Beyond affecting interest margins and market distribution, this shift has changed how banks with different funding structures participate in syndicated loans. Following the designation of SOFR as the new benchmark, there was a notable decline in the diversity of lenders' funding structures within individual loan tranches. That is, financial intermediaries are now more likely to syndicate with others that have similar funding structures, particularly regarding their exposure to the repo market, which SOFR reflects. In the syndicated loan market, multiple lenders typically share common contract terms and pricing structures within a tranche. The shift to SOFR has led banks to partner with others sharing similar capital structures and repo market exposure, rather than diversifying the capital portfolio within a tranche. Banks relying on the repo market for funding can jointly offer lower interest spreads due to better-hedged benchmark rate mismatch risks, making their loans more attractive to borrowers. Conversely, smaller banks that depend on other funding channels become marginalized, as they cannot match these lower spreads.

The LIBOR-SOFR transition appears to have favored large banks while disadvantaging smaller ones. Given that small banks play a crucial role in financing small businesses (Berger et al. (2005)), benchmark replacement had a significant economic impact through the lending channel, affecting borrowers' investment, value, and employment. To precisely evaluate these impacts, I employ their relationship lenders' funding structures as instrumental variables for interest spread. The analysis shows that higher interest spreads-primarily charged by smaller banks-are associated with smaller borrower sizes, undervalued borrowers (measured by Tobin's Q), and borrowers with fewer employees. These effects suggest that smaller businesses faced higher borrowing costs post-transition, leading to reduced access to affordable capital and employment opportunities.

What would have been the optimal benchmark rate? From the perspective of a social planner, the 'optimal' depends on the objective function. For instance, whether it is to maximize financial institutions' shareholder wealth or to ensure ample liquidity for borrowers. Previously, we discussed the transition of major currencies' LIBORs into risk-free, transaction-based successors, but distinguishing between secured and unsecured markets. Conditional on accepting these two features, I explore various optimal benchmark rate choices by numerically balancing benchmark mismatch risks from both secured and unsecured markets.

To do so, I construct a hypothetical benchmark rate by assigning weights, γ to SOFR and $1 - \gamma$ to OBFR. I show that, at $\gamma = 0.57$, banks' overall expected shareholder wealth is maximized as the benchmark rate mismatch risks are minimized. This result is derived from calibrating daily data to determine the variance and covariance between the hypothetical indices and overnight funding costs, factoring in banks' quarterly funding structures. When γ is set to 0.49, the aggregated adverse effects of benchmark mismatch risks on borrowers' size, market value, and employment are diminished. I interpret this result as mainly driven by the smaller banks, which tend to favor OBFR. Their clients—typically small and local businesses—benefit more substantially from reduced interest spreads once unsecured market volatility is hedged.

The remainder of this paper is organized as follows: Section 2 outlines the institutional background of the transition process. Section 3 presents data and measurement construction. Section 4 outlines the model of benchmark rate mismatch and banks' divergent preferences on the alternative reference rate. Section 5 discusses the choices of LIBOR successor rates in five major currencies. Section 6 presents the empirical strategy and estimated results of loan market consequences. Section 7 discusses the benchmark replacement effects on smaller banks and the borrower's size, value, and employment. Section 8 discusses the optimal benchmark rate. Section 9 presents the equity market evidence. Section 10 concludes.

2 Institutional Background: the ARRC

The following section provides an institutional overview of the key milestones in the transition from USD LIBOR to SOFR, as shown in Figure 4, alongside the role of the Alternative Reference Rates Committee (ARRC), which guided this process[4].

Tasked with finding a new reference rate following the LIBOR scandal, the ARRC was convened in 2014 by the Federal Reserve Board and the Federal Reserve Bank of New York (FRBNY). The committee comprises a group of major private-sector banks, insurers, and financial trade organizations. Its mission was to identify and recommend a reliable and transparent alternative to the traditional USD LIBOR. Its mission was to either reform LIBOR to prevent manipulation or replace it with a new rate that better reflected market conditions.

The ARRC mainly considered two candidate rates. The first one (ultimately chosen by the ARRC) was SOFR, Secured Overnight Funding Rate, a secured risk-free rate calculated based on repo market transactions. The primary alternative considered was OBFR, Overnight Bank Funding Rate, an unsecured risk-free rate calculated based on overnight bank borrowing market transactions. SOFR and OBFR are both risk-free rates based on daily transactions, arguably offering robust and manipulation-free reference. However, they reflect the overnight borrowing costs in two distinct money market segments. SOFR derives from transactions in the U.S. Treasury repurchase agreement (repo) market, where investors offer banks overnight loans backed by bonds, thereby tracking the secured lending environment. In contrast, OBFR captures the cost of overnight borrowing across depository institutions through federal funds, Eurodollar, and certain domestic deposit transactions, offering a broader perspective of unsecured bank funding costs. Another key distinction between these two rates lies in the banking sectors they serve: large banks predominantly operate in the repo market due to their substantial transaction volumes and available collateral, making SOFR more suitable for their funding strategies. Conversely, smaller retail banks, with less access to the repo market, often depend on unsecured overnight bank borrowing, which aligns more closely with OBFR.

[4]For more institutional details, see the official website of ARRC at https://www.newyorkfed.org/arrc.

On June 22, 2017, the ARRC endorsed SOFR as the preferred alternative to OBFR. A month later, the Financial Conduct Authority negotiated with banks to continue providing LIBOR data until December 2021, with its future uncertain beyond that point. By November 2020, U.S. financial regulators, including the Federal Reserve Board, the Office of the Comptroller of the Currency, and the Federal Deposit Insurance Corporation (FDIC), issued a statement advising against entering new contracts referencing LIBOR after December 31, 2021. Despite the initial timeline, LIBOR's complete phase-out was delayed. The 12-Month USD LIBOR officially ended on June 30, 2023, while the 1-, 3-, and 6-Month LIBOR rates continued on a temporary, synthetic basis until September 2024. This transition marked a significant shift in financial benchmarking, aiming to restore confidence and ensure the stability of global financial markets by establishing a more transparent and resilient framework for interest rate referencing.

3 Data and Measurement

This study focuses on the event window from the first quarter of 2013, one year before the ARRC formed, to the last quarter of 2019, before the COVID-19 pandemic. I use four datasets. First, I collect the daily published OBFR and SOFR data from the FRBNY's website. OBFR is a measure of wholesale, unsecured, overnight bank funding costs. It is calculated using federal funds transactions, certain Eurodollar transactions, and certain domestic deposit transactions, all as reported in the FR 2420 Report of Selected Money Market Rates.

SOFR is a broad measure of the cost of borrowing cash overnight collateralized by Treasury securities. SOFR includes all trades in the Broad General Collateral Rate plus bilateral Treasury repurchase agreement (repo) transactions cleared through the Delivery-versus-Payment service offered by the Fixed Income Clearing Corporation, which is filtered to remove a portion of transactions considered "specials." The FRBNY officially released OBFR data since March 1st, 2016, and SOFR since April 2nd, 2018. To best cover the sample period with public data, I use the "brokered OBFR" and the "indicative SOFR" data as the historical OBFR and SOFR during the ARRC's decision period[5]. These recent and historical data cover OBFR for the entire research window and extend the availability of SOFR back to August 22nd, 2014. For the remaining unreported period from January 2nd, 2013, to August 21st, 2014, I use the cross-validation LASSO estimation to predict SOFR based on the time series of daily LIBOR, OBFR, and EFFR. I further calculate the 1-month moving average of OBFR (SOFR) based on the daily rate as the 1-month OBFR (SOFR), which is a most common tenor used in syndicated loans (Market Participants Group (2014))[6]. Figure 1 and 2 show the time series of the overnight and 1-month SOFR and OBFR with the gap of SOFR surpass OBFR, respectively. Compared to the unsecured rate, the SOFR is more volatile with pikes and a higher underlying trading volume.

I analyze balance sheet details from Bank Holding Companies (BHCs) and their domestic subsidiaries, including banks and branches, to evaluate the levels of BHCs' funding costs exposed to OBFR and SOFR. Banks overseen by the FDIC, the Federal Reserve, and the Office of the Comptroller of the Currency must submit Call Reports, which provide detailed balance sheet and income information. The Federal Reserve gathers and releases this data quarterly in the FR Y-9C Consolidated Financial Statements for Holding Companies. The unique identifier assigned to financial institutions by the Federal Reserve is RSSD9001, which umbrellas its associated balance sheets.

Mapping the transaction channels that the Fed collects to calculate OBFR and SOFR, I approximated BHCs' funding costs exposed to the two market rates. I use the sum of Federal funds purchased interest expenses (a proportion of BHCK4180), foreign offices deposit interest expenses, and over $250k deposits interest expenses as a share of total interest expense

[5]The "brokered OBFR" data is available at https://www.newyorkfed.org/newsevents/speeches/2017/fro171108, and the "indicative SOFR" is provided at https://www.newyorkfed.org/arrc/faq. Although the FRBNY promised to continue to investigate the possibility of publishing a more extended history of indicative historical rates for SOFR, any such extension of the series is unlikely to include more than a few years of additional data.

[6]The FRBNY calculation methodology for the 1-month SOFR Averages is slightly more sophisticated than a traditional moving average, including the way to handle weekends and public holidays. However, the methodology is not implied for OBFR. To make the calculation methodology consistent across the two rates, I chose the moving average approach. The correlation between the moving average calculated SOFR and the Fed's published SOFR Averages is 0.99 for the 1-month tenors, respectively. For the Fed's detailed Calculation Methodology for the SOFR Averages and Index, see https://www.newyorkfed.org/markets/reference-rates/additional-information-about-reference-rates#sofr_ai_calculation_methodology.

to represent the percentage of BHCs' funding costs exposed to OBFR. I use the interest expense on securities sold under agreements to repurchase (a proportion of BHCK4180) as a share of total interest expense to measure the percentage of BHCs' funding costs exposed to SOFR.

Given that the FR Y-9C form combines the interest expense on federal funds purchased and securities sold under agreements to repurchase as BHCK4180, I use the BHCs' liabilities structure as the approximation to separate the two. That is, I use the ratio of the liability of the Federal funds purchased to the securities sold under agreements to repurchase to determine the two interest expenses' proportional share of the BHCK4180. I also use the percentage of BHCs' liabilities related to SOFR and the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds as two alternative measures for how much a bank's funding costs are exposed to SOFR. I adjust the chosen accounting cell following the updates of the FR Y-9C. I present the detailed variable definitions, construction methods, and sources in Appendix Section A.

The Center for Research in Security Prices (CRSP) supplies individual daily stock prices, recorded by the unique stock (share class) level identifier PERMNO, for publicly traded companies, including BHCs. I use this information to calculate BHCs' equity market abnormal returns as an announcement effect when the ARRC voted and declared SOFR as the successor rate for USD LIBOR on June 22, 2017. The abnormal returns are calculated based on the classical CAPM model and the Fama-French Three Factor model using the daily event study method suggested by the Wharton Research Data Services (WRDS). I present the detailed event study methodology in Appendix Section C. The linkage between the BHCs, identified by RSSD9001, and the unique company-level identifier at CRSP, PERMCO, is facilitated through the CRSP–FRB connection available on the FRBNY's website (http://https://www.newyorkfed.org/research/banking_research/crsp-frb). I further use the WRDS offered CRSP/Compustat Merged Database to match BHCs (PERMCO) and their associated stock (PERMNO) abnormal returns. I utilize these links to identify the relationship between BHCs' capital structure and equity market returns.

The primary goal is to investigate the loan market consequences of replacing the benchmark reference rate. I obtain the sample of loans from the Reuters Loan Pricing Corporation's DealScan database for the 2013-2019 period. DealScan is a global commercial loan market database that tracks detailed terms and conditions on loan transactions, including tranche-level fixed interest spread margin, amount, active date, maturity date, and their associated basic borrowers' and lenders' identification information. To link the DealScan tranche level records to BHCs' capital structure, I first follow Schwert's (2018) method to match the lender company ID from DealScan (LPC Legacy ID) to the Compustat unique company identifier, the lender's gvkey. Then, I merge DealScan with CRSP by lender's gvkey through the CRSP/Compustat Merged Database. The remaining procedures follow the matching strategy described previously. I select only the tranches that contracted at LIBOR as the base reference rate and the matched lender who worked as an administrative agent or arranger[7]. Overall, I obtained 49,431 unique tranche-leader-level pairs of observations within the sample period.

To further control for the borrower side characteristics and investigate the effects on the borrower, I collect data from Standard & Poor's Compustat database. Compustat is a comprehensive database of the annual fundamental financial and market information on active and inactive global companies, indices, and industries. I obtained standard borrower controls, including size, cash flow, Tobin's Q, tangibility, leverage, investment, employment, and Z-score. I merged Compustat with DealScan using the latest updated file provided by Chava and Roberts (2008). This refines the data to 25,258 unique tranche-lender-borrower level observations.

3.1 Divergent Capital Structure and Sticky Business Model

Table 1 presents the summary statistics for the key contract-level variables, categorized by their role in the ARRC. After categorizing the detailed BHCs' funding costs into OBFR and SOFR in Table 2, a clear division emerges in the banks' funding structure, role in the ARRC, asset size, and other characteristics. For instance, ARRC banks have funding costs exposed to SOFR that are almost four times higher than those exposed to OBFR. Conversely, the

[7] I consider a lender to be an arranger if the DealScan tracks the lenders' role as "(co-)arranger," "(co-)lead-arranger," "(co-)senior-arranger," or "mandated (lead) arranger." These lenders may or may not win the mandate but typically contributed large amounts to the loan.

scale is flipped for non-ARRC banks. Intuitively, if a bank's short-term funding costs are more closely related to SOFR, it would be naturally incentivized to sign a contracted floating reference rate at SOFR, and analogous to OBFR, to hedge its interest rate mismatch risk. I acknowledge the data limitation for not having the money market transaction-level records, which could be a direct measure of the extent to which a bank is exposed to certain rate risks.

Institutions may prefer certain benchmarks based on their business models. Kashyap et al. (2021, 2023) highlight the agglomerative effects of benchmarking, as it encourages portfolio managers to hold more assets tied to it, which inflates prices and leads to crowded trades. One consequence is that, when a benchmark is newly established, such replacement may cause backfire for banks to switch their business model and funding structure to adapt to the new alternative benchmark. However, Table 2 does not support this concern, especially for small and mid-sized lenders. After SOFR replaced LIBOR, large ARRC-member institutions relied more on the repo market, shown by their rising expenses and liabilities tied to SOFR. In contrast, small and mid-sized lenders have been more resistant to this shift, opting to keep their traditional funding channels. Their interest expenses and liabilities linked to SOFR have remained relatively stable, averaging 1.6% and 2.4%, respectively, while OBFR-related liabilities only saw a slight decrease from 11.6% to 11.5%. These banks were likely constrained by limited resources and operational strategies and struggled to make the necessary technological upgrades.

Table 3 presents the correlation among key characteristics of banks from the DealScan matched sample. The findings indicate that large banks tend to be more exposed to SOFR-related funding risks. This is measured by the correlation between bank size and three indicators: SOFR-related interest expenses, SOFR-related liabilities, and the proportion of Available-for-Sale U.S. Treasury Securities in total securities held by the bank. Conversely, OBFR-related interest expenses are negatively correlated with these three measures, indicating that banks typically treat repo and overnight bank funding channels as substitutes rather than complements. Economically, these findings indicate that large banks, which are more integrated into the secured overnight funding market, benefit from lower benchmark rate mismatch risks as the market increasingly adopts SOFR. Furthermore, banks that rely heavily on the secured overnight funding market tend to have higher Tier 1 capital ratios but lower proportions of loans to assets, equity to assets, and deposits to liabilities[8]. They also have fewer risk-weighted assets. This conservative asset structure, typical of large dealer banks, suggests that these banks are better positioned to manage funding risks, consistent with the findings of Berger and Bouwman (2009).

Smaller banks are disadvantaged when the market implements SOFR as a benchmark reference rate. They typically do not have the same level of access to the secured overnight funding market and are, therefore, more reliant on unsecured funding channels. Consequently, they face higher benchmark rate mismatch risks without the mitigating benefits of large holdings in liquid securities or high Tier 1 capital ratios. This disparity generates the challenges smaller banks face in a SOFR-dominated market, leading to potential declines in market share and expected profits. This is particularly concerning given the crucial role small banks play in utilizing soft information and financing small businesses, as highlighted by Berger et al. (2005), Rajan (1992), and Stein (2002). The disadvantage faced by smaller banks could infect the borrower side, potentially harming local and small businesses that rely heavily on these lenders for financing. I address this in Section 8 with a more detailed causal inference.

4 Lobbying Incentive

4.1 Quantitative Exercise on Optimal Floating Reference Rate

I set up a toy model to frame the interest rate mismatch risk hedging strategy incentivized by banks under a heterogeneous funding structure. I assume bank j has one loan to finance. The bank receives a fixed interest spread r_j and a floating reference rate R_j as interest income from such loan. The bank finances this loan through multiple fungible liabilities. The bank pays interest expenses c_{ij} on each liability i, such as interest on domestic and foreign deposits, expenses on federal funds purchased, and expenses on securities sold under agreements to

[8] Drechsler et al. (2021) argues that, although deposits comprise a significant portion of banks' liabilities, they are less insensitive to interest rate matching risks and the costs are low. In my sample matched with DealScan, deposits represent 60% of banks' liabilities but account for only 27% of interest expenses.

repurchase. Each interest expense i shares w_{ij} proportion of the bank's overall interest expenses. Therefore, bank j's funding structure has the feature $C_j = \sum_i w_{ij} c_{ij}$. Following the data pattern described in Section 3.1, I assume banks' business models are sticky and the funding structures w_{ij}s are therefore exogenously given. The floating reference rate R_j and interest expenses on these liabilities c_{ij}s are uncertain ex-ante. I use the incomplete contract framework by assuming that the bank funding costs c_{ij}s are not contractible ex-ante.

Before proceeding to the main analysis, it is useful to capture the standard belief about what banks can optimally do. I first allow banks to choose their individual floating reference rate R_j. I model banks' interest rate mismatch hedging incentive by assuming that the banks' profits have the shape of constant absolute risk aversion (CARA) utility functions with a coefficient of absolute risk aversion $A > 0$. Therefore, the bank j's expected utility of profits for each dollar lending out at the time of loan contracting is the following:

$$EU(r_j + R_j - \sum_i w_{ij} c_{ij}) = \sum_t p_t (1 - e^{-A(r_j + R_{jt} - \sum_i w_{ij} c_{ijt})})/A \tag{1}$$

where I denote p_t as the density for daily rates at date t.

To illustrate the main intuition, I assume the uncertain floating reference rate R_j and the interest expenses on these liabilities c_{ij}s are normally distributed for now. The expected reference rate is μ_{R_j}, and the variance is $\sigma^2_{R_j}$. The expected interest expenses on these liabilities, mostly transactions on the overnight money market such as the overnight SOFR and overnight OBFR, are $\mu_{c_{ij}}$s, and the variances are $\sigma^2_{c_{ij}}$s. I denote the covariance between the floating reference rate R_j and the overnight funding transaction rate c_{ij} as $\sigma_{R_j, c_{ij}}$. For simplicity, I assume the liabilities are independently distributed with $cov(c_{ij}, c_{lj}) = 0$ for $\forall i \neq l$[9].

To characterize the optimal floating reference rate, I first allow banks to design their own base rate. I further assume the loan market pricing equilibrium is characterized by lenders' cooperative pricing strategies. In this scenario, conditional on settling down a contract, a borrower expects to pay a fixed overall interest rate at $I = \mu_{R_j} + r_j$ independent of the lenders.

[9]Given the covariance between short-term funding costs c_{ij}s are independent with the reference rate R_j, Lemmas 1 and 2 still hold even without this assumption.

Thanks to the distributional assumption on the uncertain long-term floating reference R_j and short-term funding costs c_{ij}, I can rewrite the bank's ex-ante expected profits using a certain-equivalent approach. Therefore, banks design their optimal base rate by solving the maximization problem:

$$\max_{R_j} r_j + \mu_{R_j} - \sum_i w_i \mu_{c_{ij}} - \frac{A}{2}\left[\sigma^2_{R_j} + \sum_i {w_i}^2 \sigma^2_{c_{ij}} - 2\sum_i w_i \sigma_{R_j,c_{ij}}\right] \tag{2}$$

To hedge the interest rate mismatch risk, I now show that the variance term is minimized at $\sigma^*_{R_j} = \sum_i w_i \sigma_{c_{ij}}$. In this way, the banks' long-run floating reference rates perfectly synchronize with their short-term borrowing rate. The banks' interest rate risks are fully hedged. For the mean term, one solution jumps out ahead: $\mu^*_{R_j} = \sum_i w_i \mu_{c_{ij}}$. This satisfies both the competitive loan market condition and banks' individual rationality constraint[10].

Lemma 1: Bank j's optimal floating reference rate R^*_j satisfies the distributional condition at $\sigma^*_{R_j} = \sum_i w_i \sigma_{c_{ij}}$, where the reference rate fully synchronizes with bank's funding costs.

Proof: Given the assumption that the loan market pricing equilibrium is characterized by lenders' cooperative pricing strategies, the bank's optimal floating reference rate minimizes the non-negative variance term. Following Cauchy-Schwarz inequality, the variance is bounded below at $\left[\sigma^2_{R_j} + \sum_i {w_i}^2 \sigma^2_{c_{ij}} - 2\sum_i w_i \sigma_{R_j,c_{ij}}\right] \geq \left[\sigma^2_{R_j} + \sum_i {w_i}^2 \sigma^2_{c_{ij}} - 2\sum_i w_i \sigma_{R_j} \sigma_{c_{ij}}\right]$. When $\sigma^*_{R_j} = \sum_i w_i \sigma_{c_{ij}}$, since the short-term funding costs are independent and identically distributed, the variance term is minimized at 0. ■

One example of a floating reference commonly used by banks is the prime rate; independently determined by each bank. It is the interest rate that each commercial bank charges to its most creditworthy customers and is based on the bank's individual overnight funding costs. In this exercise, the overnight funding costs are abstracted as $\sum_i w_i \mu_{c_{ij}}$.

[10] As lenders, banks typically benefit from a high floating reference rate and fixed interest spread. I rule out this unrealistic partial equilibrium result by assuming a competitive loan market such that borrowers pay $I = \mu_{R_j} + r_j$ independent of banks. Since banks are sometimes on the other side of the transaction, such as buyers in the secondary loan market who wish to purchase a loan by paying $\mu_{R_j} + r_j$, they would want accurate pricing rather than a high rate.

4.2 Divergent Preferences and Lobbying Incentive

Rather than observing the transactions placed under each bank's individually chosen prime rate, what makes this floating reference rate setting intriguing is that the market participants typically rely on just one benchmark rate. Second by second, decades over decades, we see trillions of financial products used to be traded under LIBOR, now SOFR, by thousands of independent establishments, including banks, mutual funds, insurance companies, private equities, etc. But why use a benchmark at all? Duffie and Stein (2015) share their broad insights on the benefits of introducing a benchmark, which includes reducing contract settlement efforts, lowering shopping costs in bilateral over-the-counter markets, accelerating trade executions, and cutting down negotiation costs on private information.

In the previous section, I demonstrated that the interest rate mismatch hedging incentive in a bilateral lending relationship leads banks to tailor their optimal floating reference rate to fit individual funding structures. I now show how, in a more complex multilateral lending market, a financial benchmark could hedge the common components of banks' interest rate mismatch risks. Moreover, it can accurately price syndicated loan contracts and reduce the secondary loan market transaction costs. However, establishing a financial benchmark simultaneously causes distributional consequences for banks' long-run profitability and shareholder wealth, creating winners and losers on benchmark rate mismatch risks.

Lemma 2: For any given benchmark rate $\bar{R}$, such that $var(\bar{R} - R_j^*) \neq 0$, the benchmark rate mismatch risk occurs as $\tau_j = U(R_j^*, \mathbf{w}_j) - U(\bar{R}, \mathbf{w}_j) > 0$.

Proof: Since function $U(R_j, \mathbf{w}_j)$ is concave and maximized at $R_j = R_j^*$, the variance term under the certainty-equivalent approach is minimized at zero if and only if $\bar{R} - R_j^* = \lambda$, where λ is a constant. ■

The idea should be straightforward. When a unique benchmark rate is implemented in the market, banks pay a deadweight loss compared to the floating reference rate that banks would like to optimally set to hedge their *individual* interest rate mismatch risks. The interest rate mismatch risk transforms into the benchmark rate mismatch risk. The further a bank's funding costs diverge from the contracted benchmark rate, the more the banks are exposed to the benchmark rate mismatch risk. When the market considers candidate rates for the benchmark rate, banks have different inclinations towards each rate depending on which candidate is closer to reconciling with its funding structure. One example is the choice between SOFR and OBFR as the successor rate for USD LIBOR. Dealer banks would naturally wish to introduce the secured rate, rather than the unsecured one, as the successor rate. The unsecured overnight bank funding rate would be a better fit from the perspective of traditional small and mid-sized commercial banks.

Banks could theoretically use derivatives, such as basis swaps, to hedge benchmark rate mismatch risks. For instance, a lender funded by the overnight bank borrowing market might swap a SOFR-based loan for an OBFR-based cash flow. However, the model suggests that finding a suitable counterparty is difficult, particularly because few are willing to take on the associated systemic risks. Dealer banks that prefer the SOFR rate would ask higher fees to compensate for the benchmark risk exposure and related transaction costs. Conversely, non-dealer banks would only bid a lower price reflecting their exposure, leading to a discrepancy between the pricing expectations of both sides. This analysis builds on McPhail et al. (2023). Examining non-public data on bank-level swap positions, the authors conclude that although interest rate swaps are frequently used in the banking sector, their effectiveness in hedging overall interest rate risk remains limited[11]. Based on my knowledge, no swap instruments currently exist to convert SOFR to OBFR, or if they do, the market is likely small and lacks visibility. As of the third quarter of 2023, syndicated tranches recorded in DealScan indicate no contracts using an OBFR basis, which suggests no opposite party exists within the global commercial loan market.

In the political economy literature (see Grossman and Helpman (2002)), the gap between an interest group's utility under multiple distinct policies is usually considered as the lobbying incentive of such an agent for one policy over another. I gather data on bank holding companies' funding structure and the daily and monthly rates of the two candidate successors. One counterfactual calibration I can directly measure is the banks' lobbying incentive

[11] Rather than relying on swaps, McPhail et al. (2023) argue that banks predominantly hedge interest rate risk through their deposit franchise. Deposits possess negative duration, which counterbalances the positive duration of the bank's assets. This approach to hedging with deposits is more economically impactful than using swaps. In Section 6, I find that banks also price the mismatch risk premium into their issued loans.

for choosing SOFR over OBFR based on the equation 2 outlined in the previous section.

$$EU(r + R_S - \sum_i w_i c_i) - EU(r + R_O - \sum_i w_i c_i) \tag{3}$$

$$= \mu_{R_S} - \mu_{R_O} - \frac{A}{2}\left[\sigma^2_{R_S} - \sigma^2_{R_O} - 2(\sum_i w_i \sigma_{R_S,c_i} - \sum_i w_i \sigma_{R_O,c_i})\right] \tag{4}$$

Specifically, I use rolling 1-month average SOFR, 1-month average OBFR, overnight SOFR, and overnight OBFR as the R_S, R_O, c_S and c_O respectively[12]. Constrained by the data limitation at the BHCs' quarterly balance sheet level, I assume banks' funding structures remain stable in each given quarter and denote the normalized portion of BHCs' funding costs exposed to SOFR and OBFR as the weights in two funding channels, w_S and w_O.

Due to SOFR's risk-free nature, the interest spreads were expected to widen to compensate for the absence of a credit risk premium. The ARRC recommended a positive credit spread adjustment for newly issued LIBOR loans when switching to SOFR, based on the historical median difference between the two rates[13]. Therefore, I assume the first two terms $\mu_{R_S} - \mu_{R_O}$ cancel out after the credit spread adjustment; parties would not prefer one rate over the other solely because one rate is higher on average mechanically. I calculate the variance of reference rates and the covariance between the reference rate and overnight funding costs at the quarter level. In this setting, the bank's lobby incentive considers the variance of reference rates rather than the mean term. Moreover, the covariance term further depends on the bank's funding structure. Overall, these gaps in the variance and covariance term are specific to each bank and difficult for policymakers to adjust, which drives banks' divergent

[12] I choose the 1-month average benchmark rate here for two main reasons. First, as reported by the Market Participants Group (2014), the 1-month tenor benchmark rate is most commonly used in the loans and securitizations market. Second, SOFR was initially introduced only as an overnight rate, lacking the forward-looking term structure that LIBOR offered. The Chicago Mercantile Exchange (CME) developed the 1-month Term SOFR not being published until 2019 – over one and a half years after the vote. Therefore, I assume that institutions mainly considered the available 1-month average alternatives when they voted.

[13] The adjustment settled on the five-year historical median difference between LIBOR and SOFR at fixed increases of 11.45 bp for 1-month, 26.16 bp for 3-month and 42.83 bp for 6-month tenors. Detailed methodology and fallback language recommendations can be found in the ARRC minutes from June 24, 2020 https://www.newyorkfed.org/medialibrary/microsites/arrc/files/2020/ARRC-Minutes-june24-2020.pdf. For instance, if a credit agreement was contracted at an interest rate "1-month LIBOR + 100 bp" in the old episode, the spread is recommended to be adjusted to "1-month SOFR + 100bp + 11.45 bp" under the new benchmark rate.

inclinations for each candidate benchmark rate.

Figure 3 shows the counterfactual calibration results of the lobby incentive of the largest 5% of bank holding companies by the asset size when implementing SOFR versus OBFR as the LIBOR substitute rate. The incentives, calibrated based on the model described above, represent the expected surplus for each bank holding company when selecting SOFR over OBFR, averaged from the formation of the ARRC in the first quarter of 2013 until the committee's vote at the end of the second quarter of 2017. For this analysis, I assume the bank's coefficient of absolute risk-aversion is one and focus on U.S. corporation banks with positive capital structure w_i records on their balance sheets. The further a bank's hedged benchmark rate mismatch risk is stretched to the right (left), the more the bank prefers to execute SOFR (OBFR) as the new reference rate. Being positive on the right side of the panel indicates that the bank will favor SOFR over OBFR, and vice versa.

The graph reveals divergent preferences towards the two candidate base rates of interest, even among the largest 5% of bank holding companies. The banks highlighted in red had voting rights and attended the ARRC meeting to decide between SOFR and OBFR on June 22, 2017. Our calibration shows that the ARRC banks supporting SOFR reached a super-majority. Additionally, the ARRC welcomed a small number of new banks to join the committee immediately after the decision and assigned them to subgroups to facilitate a smooth transition from LIBOR to SOFR. These banks are shown in blue in Figure 3[14]. Overall, the counterfactual calibration results are consistent with the committee's decision regarding the LIBOR replacement rate. This exercise echoes the conjecture that the diverse incentives driving the lobbying behavior of large financial institutions result in banks' heterogeneous funding structure. This exercise supports the conjecture that the diverse incentives driving the lobbying behavior of large financial institutions are a result of their heterogeneous funding structures.

[14] Figure 8 presents the full list of attendees with voting rights on the ARRC June 22, 2017 meeting.

5 LIBOR Successor Rates in Other Currencies

LIBOR rates are calculated for five major currencies and seven borrowing periods. While some currencies, like the Canadian dollar, were not directly linked to LIBOR, their benchmark rates—known as IBORs—shared similar calculation methods and technical features. These survey-based unsecured IBORs capture credit risks, but most of these major currencies' IBORs have transitioned into risk-free and transaction-based overnight rates, which the authorities consider more robust and manipulation-free.

This transition has led to diverging approaches among these five major currencies plus the CAD. While the USD, CHF, and CAD have adopted secured benchmark rates, the GBP, EUR, and JPY have opted for unsecured rates[15]. The divergence between secured and unsecured benchmark rates across major currencies can be attributed to each country's institutional and financial system. The policymakers' concerns could include factors such as major banks' risk management preferences, asset and liability portfolios, lending and borrowing channels, central bank operations, market interventions, market depth, and liquidity conditions. I conjecture, and show that the divergence in reference rate choice is rooted in the capital structures of the largest banks in most of these currency zones.

This section tests a model in which a bank's benchmark rate preference is based on its primary funding channel in an international setting. The FR Y-9C data collects quarterly financial data from U.S. bank holding companies (BHCs) and intermediate holding companies (IHCs). I investigate the financial records of the three largest banks in the UK, Europe, Switzerland, Japan, and Canada that report sufficient interest expense details to construct the key measures. I successfully identified ten out of fifteen which are mostly labeled as IHC in the data. The benefit of FR Y-9C data is its quarterly consistency in measuring banks' capital structures. I acknowledge that the discrepancies in funding structures between these banks' U.S. IHCs and homeland holding companies limit our data.

I calibrate these banks' risk premium surplus by implementing the secured over unsecured

[15]The LIBOR successor rates are named differently across currencies. The successor benchmark rates for USD, CHF, GBP, EUR, and JPY LIBOR, as well as CAD CDOR, are called SOFR, SARON, SONIA, ESTR, TONA and CORRA, respectively.

benchmark rate using Equation (4). A positive value indicates the bank favors a secured rate, whereas a negative sign means a preference for an unsecured rate. Figure 6 shows the calibration results on choosing secured over unsecured rates for the major USD, CHF, and CAD banks. Eight out of nine largest banks in these currency zones would gain surplus from implementing a secured benchmark rate. Figure 7 shows the calibration results on selecting secured over unsecured rates for the largest GBP, EUR and JPY banks. Five out of seven banks in these monetary areas would gain surplus from choosing an unsecured benchmark rate. Overall, with tolerance for a few outliers, the divergence between secured and unsecured benchmark rates across major currencies could be attributed to the funding structures of the largest banks in each region.

6 Loan Market Consequences

A benchmark reference rate plays a crucial role in the loan market by providing standardized references for pricing loans, setting terms, and ensuring consistency and transparency across the financial market. Many loans, especially floating-rate loans, adjust interest rates based on a benchmark rate, helping borrowers and lenders manage changing market conditions. Most of the interest margins of syndicated loans are contracted at the floating benchmark rate plus a fixed interest spread, for instance, "LIBOR + spread." Financial institutions also use benchmark rates to hedge interest rate risks through derivatives like interest rate swaps. Benchmark rates provide a stable foundation for setting loan terms, contributing to overall financial market stability. What are the loan market consequences as the benchmark rate transitions from LIBOR to SOFR? I explore the effects on interest spread, market segregation, and competition by collecting empirical evidence from syndicated loan markets.

6.1 Empirical Strategy

I employ the Difference-in-Differences (DID) approach with a continuous treatment effect to evaluate the causal impact of the benchmark replacement of LIBOR by SOFR on the relationship between bank funding structure and certain loan market indicators. My empirical specification is designed to test whether the relationship between the SOFR and OBFR-related funding weights and several measures at the syndication tranche level changes after announcing SOFR, rather than OBFR, as the successor rate for USD LIBOR on June 22 (second quarter), 2017. This approach leverages the quasi-experimental nature of the announcement to isolate its causal effect on the loan spreads, syndication participants, and market shares. The primary regression model is specified as follows:

$$\texttt{Y}_{it} = \alpha + \beta_1 \texttt{Capital}_{it} + \beta_2 \texttt{post-SOFR}_t + \beta_3 \texttt{Capital}_{it} \times \texttt{post-SOFR}_t + \mathbf{X}'_{it}\delta + \mathbf{D}'_t\lambda + \epsilon_{it} \quad (5)$$

where $\texttt{Y}_{it}$ is the dependent variable representing the spread, loan portfolio, and market share for bank i at tranche t. The $\texttt{Capital}_{it}$ is the continuous independent variable that measures bank i's SOFR and OBFR market-related funding structure at the tranche t's activation quarter. The event variable, $\texttt{post-SOFR}_t$, takes the value of one if the observation is post-announcement and zero otherwise. The interaction term, $\texttt{Capital}_{it} \times \texttt{post-SOFR}_t$, is crucial for testing whether the slope of $\texttt{Capital}_{it}$ on the outcome variable changes after the announcement. In this specification, the control group is the set of banks' capital structures with zero expenses in the repo market. The treatment group contains banks with various positive expenses in the repo market, which measures the intensity of the treatment. I include a vector of control variables $\mathbf{X}_{it}$ and fixed effects $\mathbf{D}_t$ to account for potential confounders and unobserved heterogeneity. $\mathbf{X}_{it}$ includes tranche-level controls such as log tranche amount, log maturity length (measured in months), number of lenders, and deal purpose. Additionally, borrower-side controls from Compustat are included, such as firm size, leverage, cash flow, asset tangibility, Q, and Altman (unleveraged) Z-Score. The fixed effects $\mathbf{D}_t$ represent year-quarter fixed effects at tranche activation. The error term is ϵ_{it}. By clustering the standard errors at the bank holding company level, I account for potential correlation in the error terms within banks over time, providing a more robust inference.

The identification strategy relies on the assumption that, in the absence of benchmark rate replacement, the expected change in the dependent variable $\texttt{Y}_{it}$ would have been the same across different levels of $\texttt{Capital}_{it}$. This assumption ensures that any differential change in the outcome variable $\texttt{Y}_{it}$ across different levels of $\texttt{Capital}_{it}$ after the SOFR announcement can be attributed to the treatment effect rather than pre-existing trends. This assumption holds because banks uniformly contracted on LIBOR before the announcement of SOFR as the new benchmark reference rate. The interest rate spreads were determined by "LIBOR + spread," independent of SOFR and unrelated to differences in banks' funding structures. Empirical evidence in Tables 4 and 5 supports this, showing insignificant coefficients for funding structure variables on interest spread and market share before the SOFR announcement.

6.2 Effects on Interest Spread

The transition from LIBOR to SOFR marks a significant shift in the financial benchmark landscape. This change can have substantial effects on the interest spread for loans. LIBOR and SOFR are embedded in different underlying markets. LIBOR is based on unsecured interbank lending rates, which include a credit risk premium, whereas SOFR is based on secured transactions in the U.S. Treasury repurchase market, reflecting a nearly risk-free rate.

The absence of a built-in credit risk component in SOFR could lead to wider interest margins than those under LIBOR, as lenders must increase the spreads to appropriately price in credit risk. This gap is captured by the model equation $\mu_{R_S} - \mu_{R_{LIBOR}} < 0$. Conversely, SOFR generally exhibits lower day-to-day volatility than LIBOR due to its foundation on the deep and liquid Treasury repurchase market. Holding lenders' overall expected profits equal, this reduced volatility might result in more stable and potentially lower spreads as lenders face less uncertainty in the underlying benchmark rate. This channel can be captured by the model equation $\sigma^2_{R_S} - \sigma^2_{R_{LIBOR}} < 0$. Initially, SOFR was introduced only as an overnight rate, lacking the forward-looking term structure that LIBOR offered. Although efforts are being made to develop a term SOFR, the uncertainty and complexity in transitioning to a new term structure could affect how spreads are set, particularly for longer-duration loans. Many existing financial instruments and credit agreements were pegged to LIBOR, and their transition to SOFR may require spread adjustments to maintain the terms' economic equivalency. For these general reasons, the ARRC recommended several examples of fallback language, including adding credit spread adjustments, to compensate lenders for the differences in quantity gap between LIBOR and SOFR for newly issued loans during the transition period.

In addition to these mechanical differences between the LIBOR and SOFR rates, which generally have the same economic impact on market participants, I explore the potential heterogeneous effects on loans issued by banks with divergent capital structures. As SOFR best hedges the repo market interest risk, banks primarily relying on the repo market as their overnight funding channel would expect to be more profitable with SOFR as the alternative rate. Would those banks take the entire surplus from hedged benchmark rate mismatch risk, or would they give up a part of the premium to reduce the interest spread, making their offered loans more attractive to borrowers? My initial hypothesis is the latter: banks facing elevated borrowing costs in the repo market would narrow their interest spreads after selecting SOFR as the replacement.

Table 4 shows that, after SOFR was announced as the substitute rate to LIBOR, banks with a heavier reliance on the repo market for funding requested lower loan margins. The dependent variable is the log of interest spread. In columns (1)-(6), I use three measures to assess a bank's involvement in the repo market: SOFR-related interest expense shares (*SOFR IntExp.*), SOFR-related liability shares (*SOFR Liability.*), and U.S. Treasury Securities available for sale under repurchase agreements as a share of total securities (*UST. AFS. Sec.*) on a quarterly basis. In columns (7) and (8), I use OBFR-related interest expense shares (*OBFR IntExp.*) to measure how heavily a bank relied on the overnight bank funding market as a financing channel. I use the DID identification strategy by interacting the key variables with a dummy variable that equals one if the tranche active date is after June 2017. I control for year-quarter fixed effects and cluster the standard errors at the bank holding company level. In columns (2), (4), (6), and (8), I further add borrower-side control variables, including firm size, leverage, cash flow, asset tangibility, Tobin's Q, and Altman (unleveraged) Z-Score, as well as tranche-level controls, including log tranche amount, log maturity length (measured in months), number of lenders, and deal purpose.

Columns (1), (3), and (5) indicate that, following the announcement of SOFR as LIBOR's successor, banks heavily dependent on the repo market for funding tended to ask for a lower interest spread. The results remain significant after adding borrower side and tranche level controls in Columns (2), (4), and (6). Specifically, Column (2) indicates that one standard deviation move in SOFR-related Interest Expense equates 0.06% reduction in loan margins post-announcement, which is approximately 17bp based on the mean spread.

Note, I estimated these effects by limiting the sample to LIBOR-referenced tranches. Despite adding credit spread adjustments to maintain economic equivalency in the transition from LIBOR to SOFR, evidence suggests that banks have already begun factoring the interest rate mismatch risk premium under SOFR into the interest spreads when contracting at LIBOR. Roberts (2015) finds that a typical bank loan is renegotiated five times, approximately every nine months, with significant modifications to pricing, maturity, amount, and covenants during each renegotiation. However, rather than amending the spread when formally switching to SOFR, the evidence suggests that banks have already started pricing the interest rate mismatch risk premium under SOFR into the spread margin when contracting at LIBOR. These results are institutionally feasible and economically plausible[16]. When the ARRC announced SOFR as the successor rate in June 2017, the initial target was to complete the entire LIBOR-SOFR transition by the end of 2021 (the "2021 objective"). Given that the average maturity length of the sample syndication contracts is 51.4 months, contracting parties would reasonably anticipate the benchmark rate to switch from LIBOR to SOFR before the loans mature.

6.3 Increased Market Segregation

Benchmark rate mismatch often creates different risk premiums, which can affect how loans are structured based on the capital structure of the lenders.

[16]Here I justify the economic causal and scale using the model in Section 4. I assume banks' overall expected net profits remain stable from a given loan, either contracted at LIBOR or SOFR. The capital structure affects the bank's profits, thus shareholder wealth, only through the expected costs, variance, and covariance with the reference rate. Write this formally, $r_{LIBOR} + \mu_{R_{LIBOR}} - \sum_i w_i \mu_{c_i}) - \frac{A}{2}[\sigma^2_{R_{LIBOR}} + \sum_i {w_i}^2 \sigma^2_{c_i}) - \sum_i w_i \sigma_{R_{LIBOR},c_i})] = R_S + \mu_{R_S} - \sum_i w_i \mu_{c_i}) - \frac{A}{2}[\sigma^2_{R_S} + \sum_i {w_i}^2 \sigma^2_{c_i}) - \sum_i w_i \sigma_{R_S,c_i})] + \xi$, where ξ is independent with w_is. Rearrange and check the effect of repo-related interest expense on interest spread gap by taking the partial derivative with respect to w_{repo}, it gives $\partial(r_{LIBOR} - R_S)/\partial w_{repo} = A[\sigma_{R_S,c_{repo}}) - \sigma_{R_{LIBOR},c_{repo}}]$. Taking off the log from the dependent variable, the linear estimated coefficient of column (1) in Table , which can be interpreted as the partial derivative term, is -207 bps. Together with the calibrated gap between the two covariance terms at -693.46 bps, it implies the coefficient of absolute risk aversion A is around 3.35, which is close to the literature estimation.

SOFR is a risk-free rate based on secured overnight transactions in the repo market, while LIBOR includes a credit risk component. The transition to SOFR creates mismatches in existing hedging strategies, leading to increased costs and complexity for banks. As previously noted, with SOFR stepping in as the new benchmark post-LIBOR, banks that draw more on the repo market for their funding needs are offering significantly narrower fixed interest spreads, reflecting their altered market strategies. In the syndicated loan market, each tranche typically involves multiple lenders under one contract, sharing common pricing terms, covenants, maturity, and interest margins, etc. Banks have different capital structures and are exposed to various interest risks in each funding market. How do they approach syndication with other banks? Cai et al. (2018) examine common exposures among financial institutions and document a high propensity of bank lenders to consolidate on syndicate partners rather than diversify. After the ARRC ruled out OBFR as the successor rate, I found a similar result: lenders vary in the profitability of pricing syndicated loans because they are heterogeneously exposed to repo market overnight risks. A benchmark drives banks to partner with others having similar capital structures to ensure a consistent pricing regime and profitability when engaging in syndication.

My second hypothesis posits that the shift from LIBOR to SOFR segregated the syndicated loan market. Banks, now differentiated by their risk premiums relative to SOFR, gravitated towards contract partners who shared their funding structure. To test this hypothesis, I use the tranche level standard deviation of SOFR-related interest expenses (*sd(SOFR IntExp.)*) and OBFR-related interest expenses (*sd(OBFR IntExp.)*) as measures for the variation of syndicators' funding structure. I control for the overall dynamics by adding the market average SOFR- and OBFR-related interest expenses as market controls. At the tranche level, I add the average SOFR and OBFR-related interest expense within the given tranche, in addition to the standard control variables such as amount, maturity length, and spread. Table 6 shows that establishing SOFR as the new financial benchmark caused syndication market segregation. Columns (1) and (2) show that as more lenders joined syndication after the ARRC chose SOFR, lenders' reliance on the repo market within a given tranche became significantly less diversified by around 30%. Column (3) reports a similar effect when using OBFR-related interest expenses. However, Column (4) erases such an effect when I control for borrower-side characteristics.

These results are consistent with the empirical findings on the interest spread in Section 6.2 and fit the quantitative exercise in Section 4.2. Before the announcement, banks would diversify the capital structure within syndication to hedge the uncertainty in the benchmark rate mismatch risk with other institutions that fund through different channels. Given that all the lenders within syndication typically face the same contract, the agreed pricing, terms, conditions, covenants, and other critical features should generate a similar economic value for each participant. As SOFR replaced LIBOR, the findings indicate that banks exposed to similar benchmark rate mismatch risk would group together. In these newly shuffled matches, large banks that mainly rely on repo overnight funding would better hedge their interest risk and, thus, could jointly charge a relatively lower fixed spread. However, small and mid-sized banks that mainly fund through other money markets could not implement their favored benchmark rate to reduce long-run uncertainty on their balance sheet. As a result, these banks needed to charge a higher risk premium collectively. Overall, the syndication market is further segregated, measured by lenders' funding structure.

6.4 Reduced Market Competition

My third hypothesis is that small and mid-sized banks lose market share when the reference rate favored by large banks is selected as the benchmark. I arrived at this hypothesis for two reasons. First, the previous empirical evidence suggests that banks prefer collaborating with institutions that have similar exposure to SOFR-related interest rate mismatches. Large banks offer lower interest spreads due to their better-hedged rate risk premiums, making their loan packages more attractive. Small and mid-sized banks face a significant competitive disadvantage as large banks leverage SOFR to reduce the spread margin on loans. This dynamic entices borrowers to choose large banks over smaller, Main Street banks.

Second, the transition to SOFR and the subsequent changes in loan structuring necessitate significant technological investments. Large banks with robust capital reserves can swiftly adapt their systems to accommodate the new benchmark, offering seamless and efficient loan processing. In contrast, small and mid-sized banks, constrained by limited resources and operational strategies, struggle to make the necessary technological upgrades.

This leads to operational inefficiencies and reduced market competition[17]. Smaller-sized banks thereby reduce their participation in syndicated loans and lose out on lucrative lending opportunities. These two factors collectively erode market share for small and mid-sized banks as they grapple with the challenges posed by the transition to SOFR and competing with larger, more resourceful banks

Table 5 shows the relationship between banks' capital structure and syndicated loan competitive position before and after selecting SOFR as the replacement rate. *Market Share* is measured by aggregating the deal amount activated under each lender's parent ID as a quarterly share of the overall market deal amount. I calculate the market share using DealScan before merging with other datasets. I include only the origination tranches contracted under U.S. dollar LIBOR in the given quarter. I control for bank holding company and year-quarter fixed effects and cluster standard error at the bank holding company level. Column (1) shows that, ARRC banks' market share increased 0.37% on average after announcing their favored rate as the successor. Based on the descriptive sum, the overall market share taken by ARRC banks increased 7.64% (or 1.6 pp). Columns (2)-(4) outline three continuous measures for how heavily a bank relies on the SOFR-related money market as the funding source. These three estimated coefficients indicate that greater exposure to SOFR-related interest rate mismatch risk results in higher market gain after the announcement. Note that these relationships are statistically insignificant before the announcement. On the contrary, Column (5) shows no significant correlation between the banks' interest expenses on the overnight bank funding market.

Large banks, which primarily rely on the SOFR-embedded repo market, play a dominant role in the syndicated loan markets, and their role is further powered after transitioning from LIBOR to SOFR. Their ability to offer competitive loan pricing under the new rate regime and superior risk management allowed them to capture a larger competitive position. This competitive edge was less accessible to smaller banks. The increased market share and profitability in syndicated loans translated into higher abnormal returns for large banks in the stock market. I explore the immediate announcement effect in Section 9.

[17] Jarrow and Li (2022) provide a more detailed discussion of the smaller institution's disadvantage in trading strategies and associated profit losses during the benchmark rate replacement.

7 Effects on Small Banks and the Borrower Side

The previous section shows that after SOFR was announced as the successor to LIBOR, large banks with heavier reliance on the repo market offered lower interest spreads and consequently gained market share. The transition to SOFR benefited large banks but disadvantaged smaller banks. However, small and local banks provide personalized services and flexible financing options that larger banks often cannot. Could the benchmark rate replacement cause harm to borrowers through the bank lending channel? I explore the economic consequences by focusing on the sample period post-announcing SOFR as LIBOR's successor rate.

7.1 Bank Funding Structure as Instrumental Variable

To accurately assess the impacts of interest spread on borrower size, value, and employment, it is essential to address potential endogeneity issues in our empirical strategy. Endogeneity arises because the loan margin is usually determined by unobservable bargaining and loan market supply-demand dynamics, leading to biased estimates. In this context, the interest spread may also be endogenous due to unobserved factors affecting both the spread and borrower outcomes. To overcome this challenge, I employ a two-stage least squares (2SLS) approach using three measures for bank funding structure as instrumental variables (IVs) for the spread margin (Tables 7 and 8, Columns 2, 4, and 6). These three measures include the percentage of BHCs' funding costs exposed to SOFR, the percentage of BHCs' liabilities related to SOFR, and the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds.

The use of bank funding structure variables as IVs is advantageous for several reasons. First, these variables are plausibly exogenous to the borrower-specific outcomes like size, value, and employment. Banks' exposure to SOFR is primarily determined by their reliance on the secured market and other funding channels, which are independent of their borrowers' characteristics. This exogeneity ensures that the IVs are not directly related to the error term in the second-stage regression. Second, the funding structure variables, such as exposure to

SOFR, are strong predictors of the interest spread. As discussed in Section 7.1, banks with higher reliance on SOFR-related funding tend to offer lower loan spreads due to better management of funding costs and risks after the announcement. This strong correlation between the IVs and the endogenous variable (interest spread) satisfies the relevance condition for a valid instrumental variable.

Furthermore, using bank funding structure variables as IVs captures the broader economic implications of the transition from LIBOR to SOFR. By isolating the variation in interest spreads attributed to differences in funding structures, we can better understand how the transition impacts small banks and their borrowers through the lending channel. This approach enables us to test hypotheses about the real effects of the benchmark rate replacement on borrower size, value, and employment, offering insights into the distributional consequences of financial market reforms.

7.2 Effects on the Economy through Lending Channels

Small banks play a crucial role in the economy by utilizing relationships and soft information to provide personalized services to individuals and small businesses (Berger et al. (2005)). My results indicate that the ripple effects can harm the broader economy when small banks are disadvantaged due to benchmark rate mismatch risks. Small businesses, vital for economic growth and employment, may struggle to access the necessary financing, leading to slower growth and fewer job opportunities.

Together with the empirical analysis on interest spread of Section 7.1, in Table 7, Columns (1) and (2) show that the higher interest margins charged by smaller banks are typically associated with borrowers holding fewer assets. This indicates a stronger sorting effect after the announcement, where smaller banks increasingly lend to smaller businesses. As a result, larger banks are likely to capture the higher-quality borrowers who might have previously been served by smaller institutions. Columns (3) and (4) reveal that higher spreads charged by smaller banks are correlated with undervalued borrowers, measured by Tobin's Q. This suggests that smaller banks' borrowers tend to be undervalued, likely due to the lack of cheap liquidity. The higher borrowing costs imposed by smaller banks make it harder for these businesses to access the credit, potentially stunting their market valuation. Columns (5) and (6) suggest that smaller banks charging higher spreads are more likely to lend to firms with fewer employees. This trend could mean reduced employment opportunities, as these businesses face higher borrowing costs and limited access to affordable capital. These findings align with Chodorow-Reich (2014), who highlighted the detrimental impact of credit constraints on employment through the bank lending channel.

I further match the sample to the borrower's economic situation one year after receiving the loan to assess long-term effects. Comparing the coefficients' scale and significance in Tables 7 and 8, one can notice a persistent long-run impact on the borrower's size, value, and employment. Overall, while the transition to SOFR has benefitted large banks, it has challenged smaller banks. These challenges translate into real economic impacts, particularly for small businesses that rely on these banks for financing. The persistent results suggest that addressing these disparities caused by the benchmark rate replacement is essential for firm growth and employment. To better explain the economic impacts on the demand side, Appendix Section D extends the Section 4 exercise into a two-stage framework with one bank and one entrepreneur.

Previous results illustrate the dynamics of the intensive margin—conditional on obtaining a loan following the benchmark replacement. What about situations where banks could not access the liquidity, and therefore a tranche was not observed? In Table 9, I explore the effects on the extensive margin following the approach suggested by Chodorow-Reich (2014), utilizing the well-established fact that bank–borrower relationships are enduring in the syndicated loan market. In this scenario, firms that previously borrowed from banks with diminished lending activities in the SOFR era encountered increased difficulties in securing financing compared to those associated with larger, repo-financed lenders. Initially, I establish the borrower-lender relationships based on tranches originated before the announcement, spanning from the beginning of 2013 to the second quarter of 2017. I then investigate the impact of lenders' funding structures, averaged within each tranche at the activation date, on the changes in borrowers' asset sizes and employment levels before and after the announcement. This analysis includes control variables at the tranche and borrower levels with year-quarter, state, and industry fixed effects, and the standard errors are doubly clustered at the 2-digit SIC and lead lender levels.

Columns (1) and (3) of Table 9 indicate that if a lender's short-term funding costs are closely tied to the repo market, selecting a secured rate as the replacement benchmark leads to greater growth in asset size and employment opportunities for the borrower. These findings are consistent with those from the intensive margin; banks that are less well-hedged against benchmark rate risks, such as smaller institutions, might impose higher liquidity costs on their customers or, more critically, may deprive them of financing opportunities altogether. However, the coefficients related to OBFR-associated interest expenses appear to be statistically insignificant, underscoring a differential impact across lender types.

8 Optimal Benchmark Rate Choice

What would have been the optimal benchmark rate? From a social planner's view, the base rate of interest should be free from manipulation, easily verifiable, and reflective of market conditions and participants' diverse interests. However, 'optimal' varies depending on the objective—whether the goal is maximizing bank profitability, thus shareholder wealth, or ensuring borrower liquidity. The previous section discussed how all major currencies' LIBORs have transitioned into risk-free, transaction-based overnight rates, with differences between secured and unsecured markets. Given the need for a transaction-based, risk-free benchmark, incorporating elements from both secured and unsecured markets may provide a more robust and accurate measure of the true cost of borrowing. This section explores several optimal complex benchmark rate choices from these objectives by balancing the secured and unsecured market.

Secured markets, such as the SOFR-linked repo market, offer low-risk borrowing opportunities due to collateral backing. These transactions are less prone to volatility in periods of financial stress, making them a stable reference point for the benchmark. However, a purely secured-rate benchmark could underestimate the real costs faced by financial institutions that operate in unsecured environments. The OBFR-related unsecured markets reflect the funding costs faced by depository institutions, typically small and mid-sized financial intermediaries that borrow without collateral, capturing nuances of liquidity and credit conditions. I construct the hypothetical optimal benchmark rate by assigning a weight, γ, to

SOFR and $1 - \gamma$ to OBFR.

8.1 Pro-lender Targeted Optimal Weights

The model of Section 4.1 describes how the interest rate mismatch can subject banks to substantial risks, especially during periods of fluctuating market rates. By optimizing a reference rate that aligns closely with both asset and liability characteristics, banks can mitigate these risks, stabilizing their net interest margins and maintaining profitability. Financial literature underscores the importance of such mechanisms in ensuring the long-term sustainability of banks. Diamond and Dybvig (1983) highlight how mismatches in maturity structures can lead to liquidity risks, exacerbating financial instability. Similarly, Duffie and Stein (2015) emphasize the importance of having a reference rate that accurately reflects actual borrowing conditions in the market, which is crucial for protecting financial intermediaries' margins and ensuring that funding costs and asset returns remain balanced. For example, linking floating-rate loans to a benchmark like LIBOR, which reflects unsecured bank borrowing costs, allows banks to hedge against both general interest rate fluctuations and credit spreads changes.

There are two approaches to designing an optimal reference rate that maximizes overall bank shareholder wealth by reducing interest rate exposure. One straightforward way is to minimize the overall interest rate mismatch risks, characterized as the sum of the variance-covariance term across market participants j in the certainty-equivalent approach of equation (2). After eliminating the irrelevant terms such as the cost variation and risk-averse coefficient, also adding the covariance term between the two combined rates, the objective function becomes:

$$\min_{\gamma} \sum_{j} \left\{ \gamma^2 \sigma^2_{R_S} + (1-\gamma)^2 \sigma^2_{R_O} - 2[\gamma(1-\gamma)\sigma_{R_S,R_O} + \sum_{i} w_{ij}(\gamma \sigma_{R_S,c_{ij}} + (1-\gamma)\sigma_{R_O,c_i})] \right\} \tag{6}$$

This concave objective function has a closed-form unique solution that minimizes the sector's overall interest rate exposure. Assuming that the bank holding companies' funding structures w_{ij} remain stable within a given quarter, I calculate the variance and covariance between 1-

month reference rates and overnight funding costs using daily data. Table 12 optimal weights on the complex benchmark rate under multiple objectives and specifications. The first column shows the average effects of unhedged benchmark mismatch risks on a bank's profit under the certainty-equivalent approach, the calibrated optimal weight is $\gamma = 0.39$. Assuming to be $A = 1$, this is associated with -4.72 basis point loss per dollar invested, compared to the losses at -19.43 (-10.52) for only implementing SOFR (OBFR) as the reference rate.

One sophisticated way to determine the optimal weights is to relax the distributional assumption on the reference rate R and the overnight funding costs c_is. This general approach searches for the optimal weights by maximizing the aggregated expected profits of banks, as defined in equation (1). The objective is:

$$\max_{\gamma} \sum_{j} \left\{ \sum_{t} p_t (1 - e^{-A(r_j + \gamma R_{S,jt} + (1-\gamma) R_{O,jt} - \sum_i w_{ij} c_{ijt})}) / A \right\} \tag{7}$$

The numerical solution for the general form of expected profit is contingent on the value of the coefficient of absolute risk aversion. Since the interest spread r_j is not observable in the bank holding company data, I substitute it with a credit spread adjustment based on the gap between the weighted averages of the two rates. The adjustment is given by $\frac{1}{2}(\bar{R_S} + \bar{R_O}) - [\gamma \bar{R_S} + (1-\gamma)\bar{R_O}]$, where $\bar{R_S}$ and $\bar{R_O}$ represent the average 1-month SOFR and 1-month OBFR over the sample period. This adjustment is important as it neutralizes any preference for one rate over the other solely due to numerical differences in their average levels, rather than the variation. Normalizing the bank's overall funding costs $\sum_i w_{ij} = 1$, and based on the daily density p_t, the calibration produces an optimal weight on SOFR of $\gamma = 0.57$.

Column (3) of Table 12 reports that the optimal weight grants an average expected profit at 0.988 utils, which is nearly equivalent to the outcome of introducing OBFR as the LIBOR replacement rate. However, this represents a significant improvement over selecting SOFR alone. This result is primarily driven by the presence of numerous small and mid-sized banks in the sample, as the analysis is not influenced by bank size based on the profit function at the per dollar level. In contrast, as shown in Column (2) of Table 12, without accounting for the credit spread adjustment and relying solely on the raw data of the bank's funding structure, the optimal weight on SOFR drops to $\gamma = 0.33$. The difference between these two values is intuitive; the unsecured OBFR rate is mechanically higher than the collateral-backed SOFR rate. Without the spread adjustment and borrower-side modeling, more banks would favor OBFR over SOFR due to its higher average level and variance.

8.2 Pro-borrower Targeted Optimal Weights

Sections 6 and 7 show that the transition to SOFR has largely favored large financial institutions, allowing them to capitalize on the new benchmark's alignment with their funding strategies. Conversely, smaller banks have faced significant hurdles in adapting to the new rate, due to their reliance on different funding mechanisms. These difficulties not only influence the banking sector but also extend into the broader economy, particularly damaging small businesses that depend on these smaller banks for financing. The evidence suggests that the economic challenges created by this benchmark shift persist over time, affecting firm size, value, and employment. If we change the perspective to provide efficient liquidity to the borrower side, what would be the optimal weight γ?

To explore the optimal benchmark rate weight and its impact on borrowers, I use an instrumental variable (IV) estimation approach. This approach builds upon the method used in Section 7.1, which estimated the effects of benchmark rates on small banks and their borrowers using bank funding structures as IVs. Here, I replace the IV estimators with banks' engagement in the secured market, `Exposure`, interacting with quintile fixed effects based on the exposure distribution, and quarter fixed effects, `Quarter`. Quarter fixed effects capture lending market seasonality, correlating with interest spreads at tranche activation but likely exogenous to annual borrower outcomes. This ensures the instrument captures lending market variations without directly influencing borrower performance.

There are two key motivations for employing banks' exposure to the secured market, particularly following the announcement of SOFR, as the IV estimator. First, as outlined in the model—and as will be supported by the first-stage estimation results in Table 13, following the announcement of SOFR as the replacement for LIBOR, banks with higher exposure to the SOFR-linked repo market faced reduced interest rate mismatch risk. Consequently, these banks were able to offer lower interest spreads. Moreover, as shown in the second-stage estimation panel, the instrumented interest margins negatively correlate with borrower outcomes, such as firm size, market value, and employment. Second, adjusting the weight parameter γ allows for variation in borrowers' exposure to the hypothetical benchmark rate. Integrating this adjustment into the 2SLS estimation quantifies the aggregate effect of benchmark rate selection on borrower outcomes. Furthermore, the 2SLS approach isolates the exogenous variation in interest spreads, enabling a clearer calibration of how changes in loan pricing—driven by banks' exposure to different funding markets—translate into real economic effects on borrowers.

To be more specific, the first stage of the 2SLS approach estimates the relationship between the endogenous variable *log(Spread)* and the instrumental variables, along with the exogenous tranche-level controls. The first-stage regression is given by:

$$\mathit{log(Spread)}_{ijt} = \alpha_1 + \lambda_1 \texttt{Exposure}_{ijt} + \lambda_2 \texttt{Exposure}_{ijt} D_j + \delta_j + \delta_t + \mathbf{X}_{ijt} \cdot \boldsymbol{\beta}_1 + \epsilon_{it} \tag{8}$$

where $\mathit{log(Spread)}_{ijt}$ represents the interest spread on loan i issued at time t with the bank's $\texttt{Exposure}_{ijt}$ distributed at quintile j. $\texttt{Exposure}_{ijt}$ captures the bank's exposure to the secured market, which serves as our primary instrument. D_j is a set of dummy variables indicating the quintile of $\texttt{Exposure}_{ijt}$. δ_j represents quintile fixed effects to control for distribution-specific factors affecting the slope and spread. δ_t represents quarterly fixed effects to control for time-specific factors affecting spreads. $\mathbf{X}_{ijt}$ includes a set of tranche-level control variables such as the number of lenders and fixed effects for the deal purpose. ϵ_{ijt} is the error term. In the second stage, I use the predicted values from the first stage ($\widehat{\mathit{log(Spread)}}_{ijt}$) to estimate the effect of the spread margin on borrower outcomes:

$$\mathit{Borrower}_{ijt} = \alpha_2 + \theta \cdot \widehat{\mathit{log(Spread)}}_{ijt} + \mathbf{X}_{ijt} \cdot \boldsymbol{\beta}_2 + \eta_{ijt} \tag{9}$$

where $\mathit{Borrower}_{ijt}$ represents the borrower outcome of interest (e.g., firm size, value, or employment) for loan i at time t distributed at quintile j. η_{ijt} is the error term in the second stage. I cluster standard errors at the bank holding company level.

With estimated coefficients $\hat{\alpha_1}$, $\hat{\lambda_1}$, $\hat{\lambda_2}$, $\hat{\delta_j}$s, $\hat{\delta_t}$s, $\hat{\boldsymbol{\beta}}_1$ from the first stage and $\hat{\alpha_2}$, $\hat{\theta}$ and $\hat{\boldsymbol{\beta}}_2$

from the second stage, I can quantify the aggregate impact of benchmark rate selection on borrower outcomes by varying the weight γ. That is,

$$\max_{\gamma} \quad \sum_{i,j,t} \hat{Borrower}_{ijt}(\gamma) \tag{10}$$

$$\iff \quad \max_{\gamma} \quad \sum_{i,j,t} \left\{ \hat{\theta} \cdot [\hat{\lambda}_1 \texttt{Exposure}_{ijt}(\gamma) + \hat{\lambda}_2 \texttt{Exposure}_{ijt}(\gamma) D_j(\gamma) + \hat{\delta}_j(\gamma)] \right\} \tag{11}$$

where the second line follows the fact that the eliminated variables are independent of the weight γ. The numerical solution gives the optimal weight $\gamma = 0.49$, which provides the optimal amount of liquidity to the borrower side using the merged dataset.

Columns (4) to (6) of Table 12 outline the average effects of unhedged benchmark mismatch risks on the borrower's side. The findings indicate that the optimal weight at 0.49 minimizes the average benchmark mismatch risks across tranches, in which banks are inclined to charge the lowest possible spread. As a result, the borrower would expect a bigger firm size, higher market value, and more employment opportunities. In terms of relative scale, this is approximately three times more effective than implementing OBFR as the LIBOR successor and over five times more advantageous than SOFR. Another notable observation is that, even though the policymaker is restricted to making a binary choice between SOFR and OBFR, SOFR performs worse than OBFR regarding borrower-side effects. Together with the results in section 7, this suggests that smaller banks tend to favor OBFR, as their customers, often small and local businesses, are more sensitive to interest spread fluctuations. Selecting OBFR as the reference rate would likely offer greater benefits to their size, value, and employment margins than those received by large banks' business partners.

9 Equity Market

The announcement of SOFR as the successor rate to LIBOR had significant implications for the banking sector, particularly benefiting large banks that primarily fund through the repo market. There are several reasons why these large banks might experience abnormal returns in the stock market compared to small and mid-sized banks.

First, the transition reduces benchmark mismatch risks for large banks, enhancing their profitability and shareholder wealth. This is negatively pronounced for smaller banks exposed to unhedged interest risks. Large banks have advanced risk management and hedging capabilities, enabling them to handle the transition to SOFR and mitigate potential risks and volatility. Their ability to navigate the new rate environment helps them maintain and increase their profit margins. In contrast, small and mid-sized banks, which might lack sophisticated risk management tools, face more significant challenges and uncertainties, negatively impacting their stock performance. This likely boosted investor confidence in large banks, resulting in higher stock prices. As large banks lowered interest spreads and gained market share, these banks could leverage their return to scale to spread these costs over a larger base, making the transition more cost-effective per unit of operation. Small and mid-sized banks, lacking this advantage, faced proportionally higher costs, impacting their profitability and stock returns.

The transition to SOFR gave large banks distinct advantages, ranging from lower funding costs and enhanced risk management to greater investor confidence and competitive positioning. I hypothesize that these factors collectively contributed to the abnormal returns observed in the stock market for large banks after SOFR was announced as the successor to LIBOR. I apply a standard event-study approach to test the hypothesis. I set the event date to June 22, 2017, when the ARRC voted and announced SOFR as the alternative reference rate to replace USD LIBOR. Using WRDS default settings, I calculated abnormal returns with the CAPM and Fama-French three-factor models. I provide more details on the methodology in Appendix Section C.

In Table 10, Columns (1) and (4) show that the equity market cumulative abnormal returns of ARRC banks significantly jumped around 2-3% after announcing SOFR as the successor rate to LIBOR, compared to non-ARRC banks. In Columns (2) and (5), continuously measured by SOFR-related interest expenses, 10% more exposure to the repo market volatility leads to an average of 0.81%-0.84% higher returns from the stock. One standard deviation higher for a bank's SOFR-related Interest Expense distribution leads to a 0.67% gain of cumulative abnormal returns post-announcement. Specifically, Figure 5 shows the daily coefficients from OLS regression of Column (1), where we can see the ARRC banks' equity market underperformed relative to non-ARRC banks before the ARRC voting. Following the announcement, this relationship reversed. However, I do not observe such effects from OBFR-related interest expenses in Columns (3) and (6), both in terms of scale and statistical significance. These results illustrate that the shift to SOFR did not create a level playing field. Big banks' equity market returns benefited significantly from lower funding costs and better risk management, while smaller community banks struggled to compete and were ultimately squeezed. My review of ARRC archive and these stock market stylized facts suggest that the market did not anticipate SOFR's selection before the post-voting press meeting.

10 Conclusion

This study investigates the economic consequences of replacing LIBOR with SOFR as the new benchmark reference rate. The transition from LIBOR to SOFR emerged from concerns about LIBOR's manipulation and its lack of robustness during times of financial stress. While this transition intended to improve market stability and transparency, it had unintended consequences, particularly for smaller banks. The findings reveal that the shift to SOFR disproportionately benefited large banks with substantial exposure to the repo market, the underlying market for SOFR. These banks were able to leverage the new benchmark rate to reduce their funding costs and enhance risk management, leading to higher profitability and stock market returns.

Conversely, smaller banks, which rely primarily on unsecured overnight borrowing, faced difficulties adapting to the SOFR regime. The new benchmark rate did not align with their funding structures, exposing them more to interest rate mismatch risks. This forced these banks to charge higher interest spreads to compensate for the increased risk, making them less competitive in the market. Consequently, smaller banks lost market share and profitability as borrowers were drawn to the more favorable contracts offered by larger institutions. The model-based estimations suggest that the optimal benchmark reference rate allocates between 33% and 57% of its weight to SOFR, depending on whether the goal is to maximize bank profitability or to ensure adequate liquidity for borrowers, thereby promoting their growth, value, and employment.

Small banks play a crucial role by offering personalized services to individuals and small businesses. The disadvantages faced by small banks due to benchmark mismatch risks can harm the economy. Evidence indicates that higher spreads charged by smaller banks are linked to borrowers with fewer assets and firms with fewer employees. The transition to SOFR, while intended to strengthen the financial system, inadvertently exacerbated the competitive imbalance between large and small banks. This paper highlights the importance of considering market participants' diverse needs and characteristics when implementing regulatory changes.

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Appendix

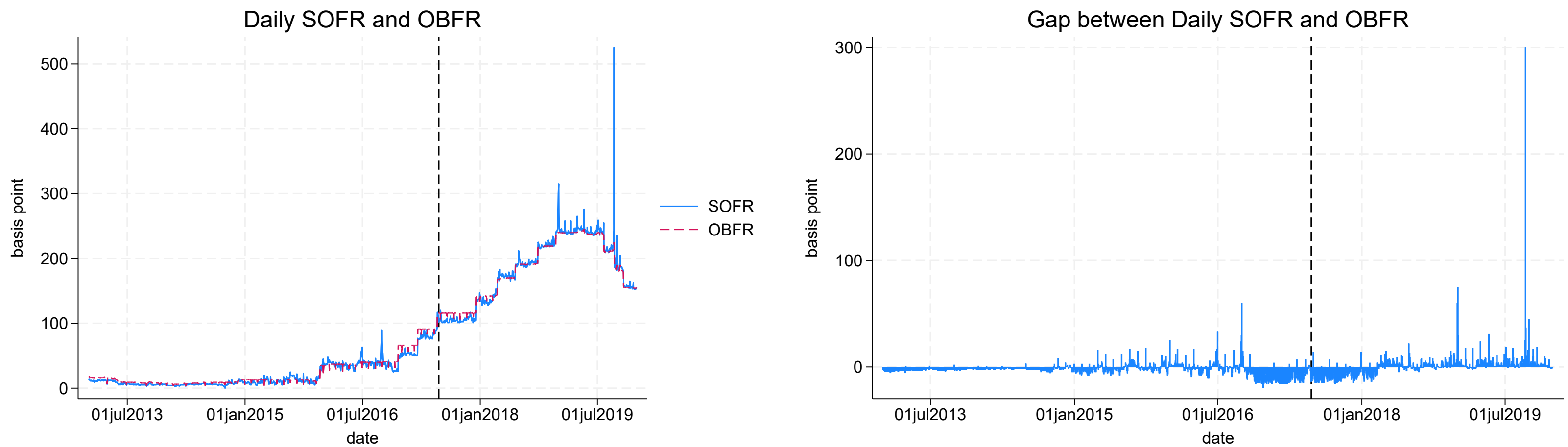

Figure 1: Overnight SOFR and OBFR

Note: The left figure shows the overnight SOFR and OBFR from January 2nd, 2013 to December 30th, 2019. The right figure shows the gap of the overnight SOFR minus OBFR. The FRBNY has officially released OBFR since March 1st, 2016, and SOFR since April 2nd, 2018. To best cover the sample period by public data, I also use the “brokered OBFR” and the “indicative SOFR” data, which are referenced as the historical OBFR and SOFR during the ARRC’s decision period. These recent and historical data cover OBFR for the entire research window and extend the availability of SOFR back to August 22nd, 2014. For the remaining unreported period from January 2nd, 2013, to August 21st, 2014, I use the cross-validation LASSO estimation to predict SOFR based on the time series of daily LIBOR, OBFR, and EFFR.

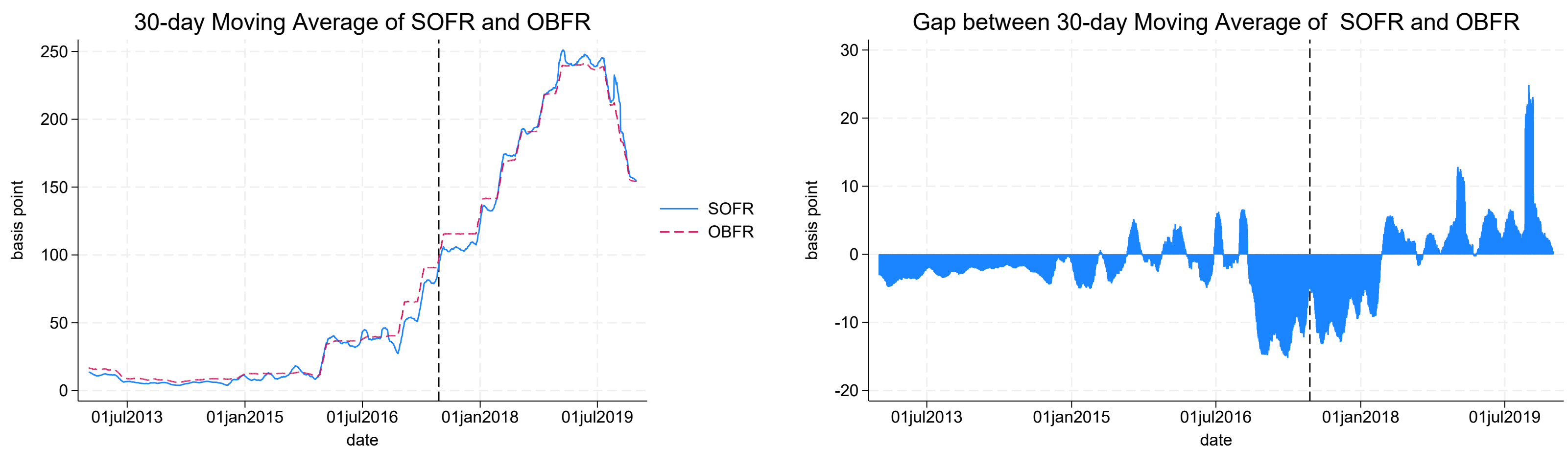

Figure 2: 1-month Moving Average SOFR and OBFR

Note: The left figure shows 1-month moving average of SOFR and OBFR from January 2nd, 2013 to December 30th, 2019. The right figure shows the gap of the 1-month moving average of SOFR minus OBFR. The FRBNY has officially released OBFR since March 1st, 2016, and SOFR since April 2nd, 2018. To best cover the sample period by public data, I also use the "brokered OBFR" and the "indicative SOFR" data, which are referenced as the historical OBFR and SOFR during the ARRC's decision period. These recent and historical data cover OBFR for the entire research window and extend the availability of SOFR back to August 22nd, 2014. For the remaining unreported period from January 2nd, 2013 to August 21st, 2014, I use the cross-validation LASSO estimation to predict SOFR based on the time series of daily LIBOR, OBFR and EFFR. I then calculate the 1-month moving average SOFR and OBFR based on the overnight SOFR and OBFR data.

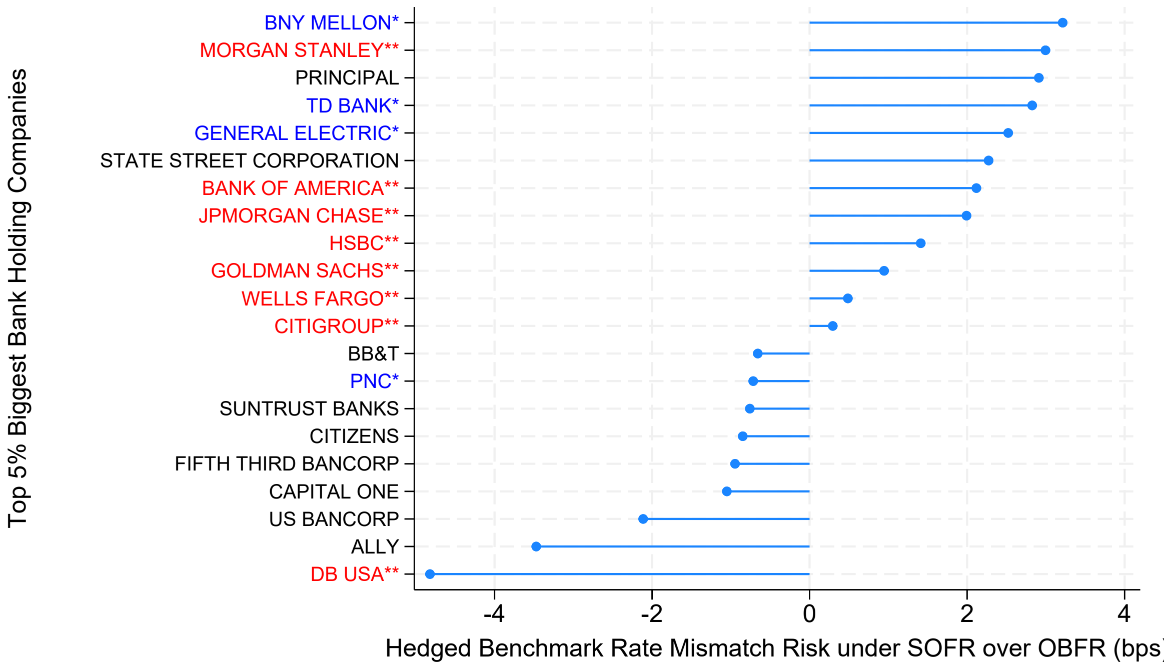

Figure 3: Calibration on SOFR vs OBFR

Note: The figure shows the counterfactual calibration results of the lobby incentive of the largest 5% of bank holding companies, measured by the asset size, when implementing SOFR versus OBFR as the LIBOR successor rate. The incentive, calibrated based on the model and measure described in Section 4, is the expected profit surplus for each bank holding company when selecting SOFR over OBFR, averaged from when the ARRC was formed in the first quarter of 2013 until the committee's voting date at the end of the second quarter of 2017. The further a bank's hedged benchmark rate mismatch risk stretched to the right (left), the more the bank prefers to execute SOFR (OBFR) as the new benchmark rate. Being positive on the right side of the panel represents that the bank will favor SOFR over OBFR, and vice versa. The banks highlighted in red with ** mark had voting rights and attended the ARRC meeting to decide between SOFR and OBFR on June 22, 2017. Additionally, the ARRC welcomed a small number of new banks to join the committee immediately after the decision and assigned them to subgroups to facilitate a smooth transition from LIBOR to SOFR. These banks are shown in blue with * mark.

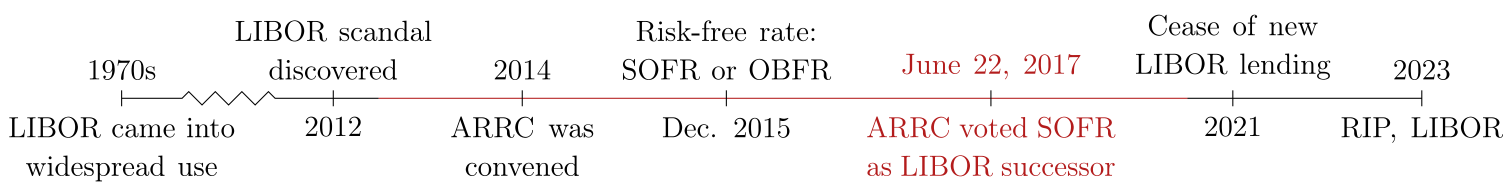

Figure 4: Key Milestones of USD LIBOR-SOFR Transition

Note: The figure shows the key milestones of USD LIBOR-SOFR transition. LIBOR came into widespread use in 1970s. The LIBOR scandal was discovered in 2012 suggesting that some major banks manipulated the LIBOR. In December 2014, the Alternative Reference Rates Committee (ARRC) was convened by the Fed to ensure a transition from USD LIBOR to a more robust benchmark rate. The ARRC decided to choose between two risk-free reference rates, SOFR and OBFR, as USD LIBOR successor rate. On June 22, 2017, the ARRC voted SOFR over OBFR to replace LIBOR. In October 2021, US regulators published their jointly statement to cease new LIBOR lending after December 31, 2021. The 12-Month USD LIBOR was ended on June 30, 2023. The 1-, 3-, and 6-Months USD LIBOR settings have been published on a 'synthetic', unrepresentative basis for a temporary period after end-June 2023 until end-September 2024. The event window of the paper starts from the January 1st, 2013, one year before the ARRC was convened, to December 31st, 2019, the last quarter before the COVID-19 pandemic. The key event date of the paper is on June 22, 2017.

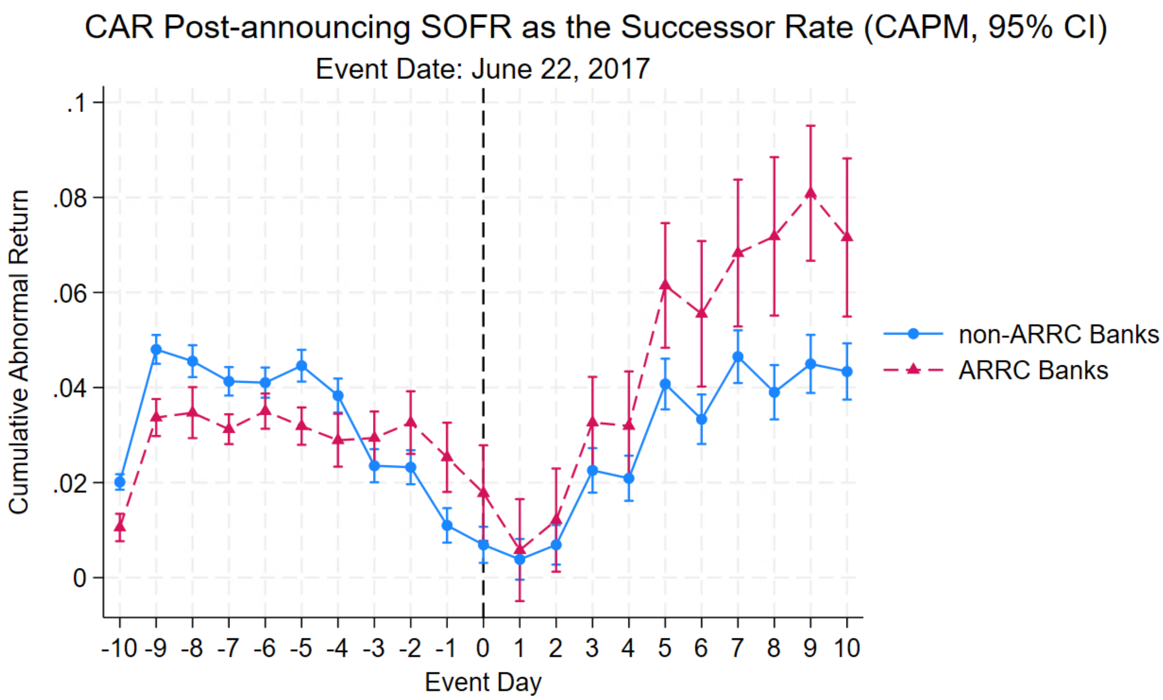

Figure 5: SOFR Announcement Effect on Equity Market

This Figure presents the daily coefficients from ordinary least squares regressions. The dependent variable is the stock market cumulative abnormal return (CAR) calculated based on the CAPM model. The red dashed line indicates the CAR for the Alternative Reference Rate Committee member banks, and the blue line indicates the rest banks.

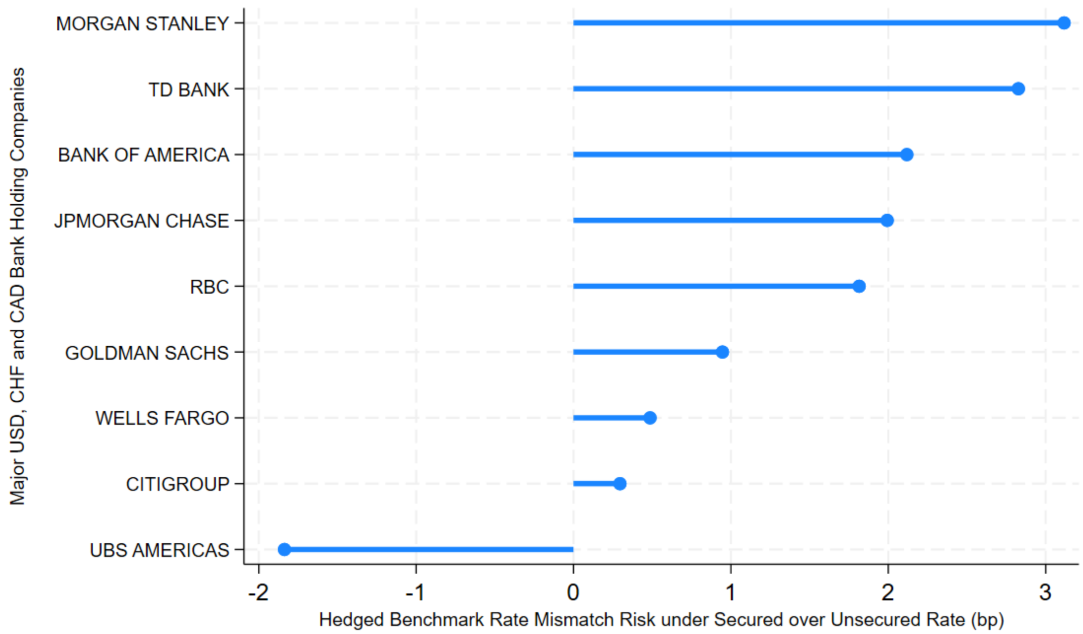

Figure 6: Calibration on Secured vs Unsecured Rates for Largest USD, CHF, and CAD Banks

Note: The figure shows the counterfactual calibration results of the lobby incentive of Largest USD, CHF and CAD Banks when implementing SOFR versus OBFR as the LIBOR successor rate. The incentive, calibrated based on the model and measure described in Section 4, is the expected profit surplus for each bank holding company when selecting a secured rate (SOFR) over an unsecured rate (OBFR), averaged from when the ARRC was formed in the first quarter of 2013 until the fourth quarter of 2019. The further a bank's hedged benchmark rate mismatch risk stretched to the right (left), the more the bank prefers to execute SOFR (OBFR) as the new benchmark rate. Being positive on the right side of the panel represents that the bank will favor SOFR over OBFR, and vice versa.

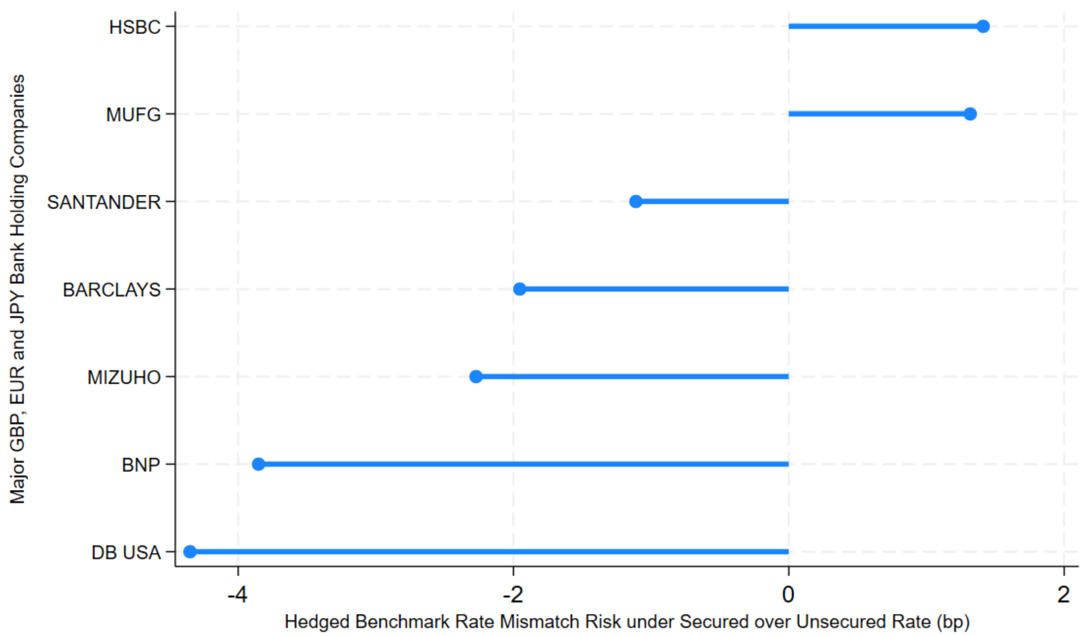

Figure 7: Calibration on Secured vs Unsecured Rates for Largest GBP, EUR and JPY Banks

Note: The figure shows the counterfactual calibration results of the lobby incentive of Largest GBP, EUR and JPY Banks when implementing SOFR versus OBFR as the LIBOR successor rate. The incentive, calibrated based on the model and measure described in Section 4, is the expected profit surplus for each bank holding company when selecting a secured rate (SOFR) over an unsecured rate (OBFR), averaged from when the ARRC was formed in the first quarter of 2013 until the fourth quarter of 2019. The further a bank's hedged benchmark rate mismatch risk stretched to the right (left), the more the bank prefers to execute SOFR (OBFR) as the new benchmark rate. Being positive on the right side of the panel represents that the bank will favor SOFR over OBFR, and vice versa.

Attendance for the June 22, 2017 Meeting
(page 1 of 2)

ARRC Member Attendees	
Bank of America	Jennifer Fortner
Barclays	Brian Rozen
BNP	David Moore
BNP	Simon Winn
Citigroup	Heraclio Rojas
CME	Agha Mirza
CME	Fred Sturm
Credit Suisse	Shane O' Cuinn
Credit Suisse	William Marshall
Deutsche Bank	Adam Eames
Deutsche Bank	Kayam Rajaram
DTCC	Dan Thieke*
Goldman Sachs	Ashok Varadhan
HSBC	Pieter van Vredenburch
ISDA	Anne Battle
JP Morgan	Alice Wang
JP Morgan	Emilio Jimenez*
JP Morgan	Thomas Hughes
JP Morgan	Sandra O' Connor
JP Morgan	Vickie Alvo
LCH	Phillip Whitehurst
Morgan Stanley	Maria Douvas
Morgan Stanley	Thomas Wipf
Nomura	Steve Licini
RBS	David Wagner
Société Générale	Subadra Rajappa
Société Générale	Sylvain Cartier
UBS	Christian Rasmussen
UBS	Giuseppe Nuti
Wells Fargo	Ben Bonner
Wells Fargo	Cronin McTigue

Figure 8: Attendance with Voting Rights on the ARRC June 22, 2017 Meeting when decided SOFR as LIBOR Successor

Note: The figure shows the full list of the Alternative Reference Rates Committee (ARRC) Member Attendees on the ARRC June 22, 2017 Meeting when decided SOFR as LIBOR Successor. These attendees are the agents who had the voting rights on selecting SOFR or OBFR as the LIBOR replacement. "page 2 of 2" includes the Ex Officio Member Attendees, who did not have voting rights. * indicates participation by phone. The original minute is archived at https://www.newyorkfed.org/medialibrary/microsites/arrc/files/2017/ARRC-Minutes-Jun-22-2017.pdf

Table 1: Summary Statistics

	ARRC banks			non-ARRC banks		
	N	Mean	SD	N	Mean	SD
SOFR IntExp.	38,791	0.13	0.08	10,908	0.01	0.02
SOFR Liability	38,791	0.09	0.04	10,908	0.01	0.01
UST. AFS. Sec.	38,791	0.22	0.24	10,908	0.07	0.09
OBFR IntExp.	38,791	0.10	0.08	10,751	0.09	0.07
$log(Spread)$	38,758	5.45	0.55	10,906	5.62	0.51
$log(Maturity)$	38,529	0.45	0.54	10,798	0.48	0.47
$log(Amount)$	38,774	5.71	1.37	10,907	4.61	1.46
#. lenders	38,758	7.62	5.96	10,908	6.01	4.72
Leverage	9,382	0.41	0.21	1,349	0.44	0.28
Cash Flow	9,382	1.02	1.99	1,349	0.93	2.10
Tangibility	9,382	0.28	0.25	1,349	0.26	0.25
Size	9,382	8.63	1.55	1,349	7.69	1.47
Q	9,382	1.98	1.30	1,349	1.91	1.07

Note: This table represents the number of observations (N), the mean (Mean), and the standard deviation (SD) for the contract level variables. *SOFR IntExp.* indicates the percentage of BHCs' funding costs exposed to SOFR. *OBFR IntExp.* indicates the percentage of BHCs' funding costs exposed to OBFR. *SOFR Liability* indicates the percentage of BHCs' liabilities related to SOFR. *UST. AFS. Sec.* measures the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds. $log(Spread)$ measures the logged interest spread margin at basis points. $log(Maturity)$ measures the logged tranche maturity at a number of months. $log(Amount)$ measures the logged tranche amount at thousand. *#. lenders* indicate the number of lenders within a tranche. *Leverage, Cash Flow, Tangibility, Size* and *Q* are measures for borrower side characteristics.

Table 2: Summary Statistics for Key Variables

	ARRC banks		*Non-ARRC banks*	
	2014Q1-2017Q2	2017Q2-2019Q4	2014Q1-2017Q2	2017Q2-2019Q4
As Share of Total Liabilities (%)				
Deposits	48.9	41.7	88.4	86.9
Federal funds and securities				
Federal funds purchased in domestic offices	0.4	0.4	0.3	0.3
Securities sold under agreements to repurchase	11.9	14.7	1.6	1.6
Trading liabilities	7.5	6.9	0.1	0.2
Other borrowed money	17.2	21.2	6.7	7.6
Subordinated notes	1.9	1.6	1.1	1.1
Other liabilities	12.2	13.5	1.8	2.3
Approx. SOFR related Liabilities (*SOFR Liability.*)	11.9	14.7	1.6	1.6
Approx. OBFR related Liabilities (*OBFR Liability.*)	21.1	13.4	11.6	11.5
Interest Expense to Total Liabilities (%)	0.2	0.4	0.1	0.2
As Share of Interest Expense (%)				
Deposits				
Domestic: Time deposits of $250k or less*	3	3.5	25.9	26
Domestic: Time deposits of $250k or more*	2.3	2.6	8.7	8.6
Domestic: Other deposits	7.8	12	35.6	34.3
In foreign offices	5.6	4.4	0.3	0.3
Federal funds and securities	15.2	23.8	2.7	2.9
Trading liabilities & Other borrowed money	58.7	42.3	17.5	18
Subordinated notes	10.7	4.7	2.8	3.2
Other interest expense	-3.3	6.7	6.5	6.7
Approx. SOFR related Interest Expense (*SOFR IntExp.*)	14.4	23.8	2.4	2.4
Approx. OBFR related Interest Expense (*OBFR IntExp.*)	8	6.9	19.6	9.4

Note: This table represents the mean for the key bank-level funding structure variables. The interest expense on securities sold under agreements to repurchase as a share of total interest expense shows the percentage of BHCs' funding costs exposed to SOFR as *SOFR IntExp.*. The sum of Federal funds purchased interest expenses, foreign offices deposit interest expenses, and over $250k deposits interest expenses as a share of total interest expense represents the percentage of BHCs' funding costs exposed to OBFR as *OBFR IntExp.*. The liabilities for securities sold under agreements to repurchase as a share of total liabilities show the percentage of BHCs' liabilities exposed to SOFR as *SOFR Liabilities*. The sum of Federal funds purchased liabilities, foreign offices deposit liabilities, and over $250k deposits liabilities as a share of total liabilities represents the percentage of BHCs' liabilities exposed to OBFR as *OBFR Liabilities.*. When the interest expenses (liabilities) indicator is unseparated from the FR Y-9 form, I use the details from the liabilities (interest expenses) to approximate the proportion. For instance, the FR Y-9C doesn't separately distinguish the share of federal funds and securities in total interest expense. In this case, I use the share between liabilities on the federal funds purchased in domestic offices and securities sold under agreements to repurchase as the approximation for these indicators.

Table 3: Correlation among key bank characteristics

	SOFR IntExp.	SOFR Liability	UST. AFS. Sec.	OBFR IntExp.	log(Asset)	Loan/Asset	Equity/Asset	Deposit/Liability	Risk Asset
SOFR Liability	0.70								
UST. AFS. Sec.	0.42	0.48							
OBFR IntExp.	-0.17	-0.05	-0.14						
log(Asset)	0.50	0.61	0.07	0.09					
Loan/Asset	-0.61	-0.82	-0.66	0.15	-0.50				
Equity/Asset	-0.29	-0.60	-0.30	0.12	-0.44	0.69			
Deposit/Liability	-0.57	-0.79	-0.74	0.25	-0.30	0.93	0.61		
Risk Asset	-0.73	-0.83	-0.46	0.10	-0.69	0.88	0.68	0.75	
Tier 1 Ratio	0.59	0.48	0.64	-0.12	0.24	-0.74	-0.28	-0.73	-0.69

Note: This table represents the correlation among key bank characteristics from the DealScan matched sample. *SOFR IntExp.* indicates the percentage of BHCs' funding costs exposed to SOFR. *OBFR IntExp.* indicates the percentage of BHCs' funding costs exposed to OBFR. *SOFR Liability* indicates the percentage of BHCs' liabilities related to SOFR. *UST. AFS. Sec.* measures the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds. log(Asset) is the log of total assets. Loan/Asset is the percentage ratio of total loans to total assets. Equity/Asset measures the percentage ratio of total equities to total assets. Deposit/Liability measures the percentage ratio of deposits to total liabilities. Risk Asset measures the percentage of risk-weighted assets to total assets. Tier 1 Ratio indicates the percentage of Tier 1 Capital to risk-weighted assets. The number of observations is 49,234.

Table 4: Effects on Interest Spread

	log(Spread)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SOFR IntExp.	-0.68***	-0.65**						
× post-SOFR	(0.24)	(0.27)						
SOFR IntExp.	0.41	0.71*						
	(0.55)	(0.42)						
SOFR Liability			-0.82	-1.26***				
× post-SOFR			(0.59)	(0.35)				
SOFR Liability			0.40	1.08*				
			(0.96)	(0.62)				
UST. AFS. Sec.					-0.16**	-0.30***		
× post-SOFR					(0.08)	(0.10)		
UST. AFS. Sec.					0.54***	0.50***		
					(0.12)	(0.16)		
OBFR IntExp.							-0.85	-0.26
× post-SOFR							(0.50)	(0.20)
OBFR IntExp.							-0.42	-0.16
							(0.48)	(0.40)
Borrower Controls		Yes		Yes		Yes		Yes
Tranche Controls		Yes		Yes		Yes		Yes
Year × Quarter FE.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	49,404	12,439	49,404	12,439	49,402	12,435	48,220	12,346
R^2	0.02	0.48	0.01	0.47	0.05	0.49	0.03	0.46

Note: This table presents the coefficients from ordinary least squares regressions. The dependent variable is $log(Spread)$ that measures the logged interest spread margin at basis points. *SOFR IntExp.* indicates the percentage of BHCs' funding costs exposed to SOFR. *OBFR IntExp.* indicates the percentage of BHCs' funding costs exposed to OBFR. *SOFR Liability* indicates the percentage of BHCs' liabilities related to SOFR. $UST.AFS.Sec.$ measures the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds. post-SOFR is a dummy variable that equals one for tranches activated after the second quarter of 2017. *Borrower Controls* include borrower's *Leverage, Cash Flow, Tangibility, Size* and *Q*. *Tranche Controls* include log maturity, log tranche Amount, number of lenders, and fixed effects for deal purposes. *Year × Quarter FE* are fixed effects for Year-Quarter interactions. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 5: Market Share

	Market Share %(Deal Amount)				
	(1)	(2)	(3)	(4)	(5)
ARRC	0.37***				
× post-SOFR	(0.08)				
SOFR IntExp.		1.50***			
× post-SOFR		(0.41)			
SOFR IntExp.		-0.35			
		(0.75)			
SOFR Liability			3.83***		
× post-SOFR			(0.88)		
SOFR Liability			1.25		
			(1.19)		
UST. AFS. Sec.				0.35*	
× post-SOFR				(0.20)	
UST. AFS. Sec.				-0.33	
				(0.24)	
OBFR IntExp.					0.05
× post-SOFR					(0.74)
OBFR IntExp.					-0.16
					(0.52)
BHC FE.	Yes	Yes	Yes	Yes	Yes
Year × Quarter FE.	Yes	Yes	Yes	Yes	Yes
Obs.	669	669	669	669	646
R^2	0.94	0.94	0.94	0.94	0.94

Note: This table presents the coefficients from ordinary least squares regressions. The dependent variable is each bank holding company's syndicated loan market share, which is calculated based on the deal amount in DealScan before merging to FR Y9-C data. *SOFR IntExp.* indicates the percentage of BHCs' funding costs exposed to SOFR. *OBFR IntExp.* indicates the percentage of BHCs' funding costs exposed to OBFR. *SOFR Liability* indicates the percentage of BHCs' liabilities related to SOFR. $UST.AFS.Sec.$ measures the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds. post-SOFR is a dummy variable that equals one for tranches activated after the second quarter of 2017. *ARRC* is a dummy variable that equals one if the bank holding company is an Alternative Reference Rate Committee member. *BHC FE.* and *Year × Quarter FE* are fixed effects for bank holding companies and Year-Quarter interactions, respectively. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 6: Inter-Loan Variation of Capital Structure

	sd(SOFR IntExp.)		*sd(OBFR IntExp.)*	
	(1)	(2)	(3)	(4)
log(#. Lenders)	-0.52***	-0.40**	-0.60***	-0.19
× post-SOFR	(0.10)	(0.18)	(0.15)	(0.19)
log(#. Lenders)	1.49***	1.39**	1.62***	0.93***
	(0.11)	(0.22)	(0.23)	(0.24)
Market Controls	Yes	Yes	Yes	Yes
Tranche Controls	Yes	Yes	Yes	Yes
Borrower Controls		Yes		Yes
Year × Quarter FE.	Yes	Yes	Yes	Yes
Obs.	15,643	4,986	15,491	4,975
R^2	0.24	0.25	0.49	0.54

Note: This table presents the coefficients from ordinary least squares regressions. The dependent variable is the standard deviation of lenders' percentage of funding costs exposed to SOFR within a given tranche for Columns (1) and (2). The dependent variable is the standard deviation of lenders' percentage of funding costs exposed to OBFR within a given tranche for Columns (3) and (4). log(#. Lenders) is the log of the number of lenders within the tranche. post-SOFR is a dummy variable that equals one for tranches activated after the second quarter of 2017. *Tranche Controls* include the average of lenders' percentage of funding costs exposed to SOFR within a given tranche, log maturity, log tranche Amount, number of lenders, and fixed effects for deal purposes. *Market Controls* include the average of lenders' percentage of funding costs exposed to SOFR in a given quarter for Columns (1) and (2), and average funding costs exposed to OBFR for Columns (3) and (4). *Borrower Controls* include borrower's *Leverage, Cash Flow, Tangibility, Size* and *Q*. *Year × Quarter FE* are fixed effects for Year-Quarter interactions. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 7: Effects on Borrower Size, Value, and Employment

	Firm Size$_t$		*Tobin's Q_t*		*Employment$_t$*	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Spread)	-1.22***	-1.76**	-0.76***	-1.82**	-0.90***	-1.82**
	(0.15)	(0.79)	(0.15)	(0.75)	(0.13)	(0.73)
Tranche Controls	Yes	Yes	Yes	Yes	Yes	Yes
Funding IV		Yes		Yes		Yes
Year × Quarter FE.	Yes		Yes		Yes	
Obs.	9,424	9,424	9,114	9,114	9,053	9,053
R^2	0.28	0.25	0.10		0.19	0.12
1st Stage F-test		12.06		12.63		10.84
RootMSE	1.28	1.31	1.31	1.40	1.44	1.50

Note: This table shows the effects of interest spread on borrower size, value, and employment. The sample period is from the third quarter of 2017 to the fourth quarter of 2019. Columns (1), (3), and (5) present the coefficients from ordinary least squares regressions. Columns (2), (4), and (6) present the coefficients from two-stage least squares regressions. The dependent variable is the log of the borrower's total assets for Columns (1) and (2). The dependent variable is the borrower's Tobin's Q for Columns (3) and (4). The dependent variable is the log of the number of employees on the borrower side for Columns (5) and (6). *Funding IV* is a set of instrumental variables that include the percentage of BHCs' funding costs exposed to SOFR, the percentage of BHCs' liabilities related to SOFR, and the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds and quarter-fixed effects. *Tranche Controls* include the number of lenders and fixed effects for deal purposes. *Year × Quarter FE* are fixed effects for Year-Quarter interactions. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 8: Dynamic Effects on Borrower Size, Value, and Employment

	Firm Size$_{t+1}$		*Tobin's Q*$_{t+1}$		*Employment*$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
log(Spread)	-1.25***	-2.29***	-0.87***	-2.14*	-0.96***	-2.13***
	(0.15)	(0.74)	(0.17)	(1.10)	(0.13)	(0.77)
Tranche Controls	Yes	Yes	Yes	Yes	Yes	Yes
Funding IV		Yes		Yes		Yes
Year × Quarter FE.	Yes		Yes		Yes	
Obs.	7,736	7,736	7,450	7,450	7,391	7,391
R^2	0.28	0.19	0.09	0.01	0.22	0.11
1st Stage F-test		17.00		16.23		17.00
RootMSE	1.33	1.41	1.96	2.05	1.42	1.52

Note: This table shows the dynamic effects of interest spread on borrower size, value, and employment. The sample period is from the third quarter of 2017 to the fourth quarter of 2019. Columns (1), (3), and (5) present the coefficients from ordinary least squares regressions. Columns (2), (4), and (6) present the coefficients from two-stage least squares regressions. The dependent variable is the log of the borrower's total assets for Columns (1) and (2). The dependent variable is the borrower's Tobin's Q for Columns (3) and (4). The dependent variable is the log of the number of employees on the borrower side for Columns (5) and (6). *Funding IV* is a set of instrumental variables that include the percentage of BHCs' funding costs exposed to SOFR, the percentage of BHCs' liabilities related to SOFR, and the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds and quarter-fixed effects. *Tranche Controls* include the number of lenders and fixed effects for deal purposes. *Year × Quarter FE* are fixed effects for Year-Quarter interactions. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 9: Effects on Borrower Growth and Employment (Extensive Margin)

	ΔBorrower Asset Size		*ΔBorrower Employment*	
	(1)	(2)	(3)	(4)
Avg. SOFR IntExp.	0.37**		0.86***	
	(0.17)		(0.33)	
Avg. OBFR IntExp.		-0.17		-0.41
		(0.24)		(0.31)
Tranche Controls	Yes	Yes	Yes	Yes
Borrower Controls	Yes	Yes	Yes	Yes
Year × Quarter FE.	Yes	Yes	Yes	Yes
State FE.	Yes	Yes	Yes	Yes
Industry FE.	Yes	Yes	Yes	Yes
Obs.	2,893	2,954	2,893	2,954
R^2	0.32	0.31	0.32	0.31

Note: This table shows the dynamic effects of interest spread on borrower size, value, and employment. The sample period is from the third quarter of 2017 to the fourth quarter of 2019. Columns (1), (3), and (5) present the coefficients from ordinary least squares regressions. Columns (2), (4), and (6) present the coefficients from two-stage least squares regressions. The dependent variable is the log of the borrower's total assets for Columns (1) and (2). The dependent variable is the borrower's Tobin's Q for Columns (3) and (4). The dependent variable is the log of the number of employees on the borrower side for Columns (5) and (6). *Funding IV* is a set of instrumental variables that include the percentage of BHCs' funding costs exposed to SOFR, the percentage of BHCs' liabilities related to SOFR, and the share of Available-for-Sale U.S. Treasury Securities in Total Securities the bank holds and quarter-fixed effects. *Tranche Controls* include the number of lenders and fixed effects for deal purposes. *Year × Quarter FE* are fixed effects for Year-Quarter interactions. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 10: Announcement Effects on SOFR over OBFR

	Cumulative Abnormal Return (%)					
	CAPM			*Fama-French 3 Factor*		
	(1)	(2)	(3)	(4)	(5)	(6)
ARRC	2.19***			2.95***		
× post-SOFR	(0.55)			(0.57)		
ARRC	-0.30			-0.81**		
	(0.24)			(0.35)		
SOFR IntExp.		8.10***			8.39***	
× post-SOFR		(2.41)			(2.56)	
SOFR IntExp.		5.09*			3.03	
		(2.74)			(2.19)	
OBFR IntExp.			-0.71			-1.15
× post-SOFR			(2.69)			(2.86)
OBFR IntExp.			0.64			0.47
			(2.02)			(1.80)
Event Date FE.	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	6,485	6,485	3,423	6,485	6,485	3,423
R^2	0.13	0.14	0.16	0.03	0.04	0.02

Note: This table presents the coefficients from ordinary least squares regressions. The dependent variable is the cumulative abnormal return calculated based on the CAPM model for Columns (1)-(3) and the Fama-French 3-Facctor model for Columns (4)-(6). *ARRC* is a dummy variable that equals one if the bank holding company is an Alternative Reference Rate Committee member. *SOFR IntExp.* indicates the percentage of BHCs' funding costs exposed to SOFR. *OBFR IntExp.* indicates the percentage of BHCs' funding costs exposed to OBFR. post-SOFR is a dummy variable that equals one for cumulative abnormal return after June 22, 2017. Event Date FE is the fixed effect for each day within the event window. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

Table 11: Successor Rates for Six Major Currencies

	SOFR-USD	SONIA-GBP	ESTER-EUR	TONAR-JPY	SARON-CHF	CORRA-CAD
Secured?	Yes	No	No	No	Yes	Yes
Overnight?	Yes	Yes	Yes	Yes	Yes	Yes
Transcation-based?	Yes	Yes	Yes	Yes	Yes	Yes
Risk-free?	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the newly replaced alternative reference rates for six major currencies.

Table 12: Optimal Weights on the Complex Benchmark Rate

	Average Effects of Benchmark Mismatch Risk on Measures					
	Bank side			*Borrower side*		
	Profits			*Asset Size*	*Tobin's Q*	*Employment*
Value of γ	(1)	(2)	(3)	(4)	(5)	(6)
0%	-10.52	0.986	0.95	-0.12	-0.12	-0.15
	(634,647)	(634,647)	(634,647)	(5,589)	(5,589)	(6,982)
100%	-19.43	0.084	0.62	-0.24	-0.25	-0.22
	(634,647)	(634,647)	(634,647)	(5,548)	(5,548)	(6,471)
39%	-4.72*					
	(634,647)					
33%		0.988*				
		(634,647)				
57%			0.98*			
			(634,647)			
49%				-0.04*	-0.04*	-0.04*
				(7,955)	(7,955)	(8,193)
Normal	No	No	Yes	No	No	No
Objective	Eq. 6	Eq. 7	Eq. 7	Eq. 11	Eq. 11	Eq. 11

Note: This table presents the calibrated average effects of unhedged benchmark mismatch risk on banks' profit in Columns (1) - (3) and on borrowers' size in Column (4), Tobin's Q in Column (5), and employment in Column (6). The effects of Columns (4) - (6) are calibrated based on the daily data of the full FR Y-9C sample from the 1st quarter of 2013 to the 4th quarter of 2019. The effects of Columns (4) - (6) are calibrated based on the significant coefficients from the IV estimations in Table 13 using the post-announcement FR Y-9C data merged with DealScan and Compustat from the 3rd quarter of 2017 to the 4th quarter of 2019. *Value of* γ is the hypothetical percentage of weights assigned to 1-month SOFR. The remaining is assigned to 1-month OBFR. *Normal* indicates if the bank's overall funding costs are normalized to one and the credit spread adjustment is added to compensate for the average gaps between the hypothetical reference rates. *Objective* indicates the objective function when solving the optimization problem. Values in the brackets are the numbers of observations. * indicates the effect of the optimal weight.

Table 13: Effects on Borrower Asset, Value, and Employment (Welfare Analysis)

	(1)	(2)	(3)
Second-Stage	*Asset Size*	*Tobin's Q*	*Employment*
log(Spread)	-1.595**	-1.652***	-1.151**
	(0.811)	(0.379)	(0.616)
Tranche Controls	Yes	Yes	Yes
Obs.	9,226	8,921	8,865
R^2	0.26	0.01	0.18
First-Stage IVs		*log(Spread)*	
SOFR-Exposure	-0.000	-0.000	-0.002
	(0.000)	(0.000)	(0.001)
SOFR-Exposure	0.001	0.001	0.002
× *QU-2*	(0.003)	(0.003)	(0.003)
SOFR-Exposure	-0.007	-0.006	-0.009**
× *QU-3*	(0.004)	(0.005)	(0.004)
SOFR-Exposure	0.007	0.010	0.009
× *QU-4*	(0.017)	(0.017)	(0.018)
SOFR-Exposure	-0.030***	-0.030	-0.031***
× *QU-5*	(0.003)	(0.003)	(0.003)
Quarter FE.	Yes	Yes	Yes
Quintile FE.	Yes	Yes	Yes
$F-test$	33.59	38.77	46.01
Adj. R^2	0.13	0.14	0.14

Note: This table shows the effects of interest spread on borrower size, value, and employment. The estimations use the post-announcement FR Y-9C data merged with DealScan and Compustat from the 3rd quarter of 2017 to the 4th quarter of 2019. The coefficients are from two-stage least squares regressions. The dependent variable is the log of the borrower's total assets for Columns (1), Tobin's Q for Columns (2), and the log of the number of employees for Columns (3). *SOFR-Exposure* captures the bank's interest expenses exposure to the 1-month SOFR reference rate. *QU-2*-*QU-5* are dummy variables indicating the quintile of *SOFR-Exposure* distribution. *Tranche Controls* include the number of lenders and fixed effects for deal purposes. *Quarter FE* are quarter fixed effects. Standard errors are clustered at the bank holding company level. * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$.

A Variables Definitions and Sources

Table 14: Key Variable Definitions and Sources

Variable	Definition	Source
SOFR IntExp.	((Liabilities on securities sold under agreements to repurchase 'BHCKB995' /(liabilities on Federal funds purchased and securities sold under agreements to repurchase 'BHDMB993'+ 'BHCKB995'))× Interest expense on federal funds purchased and securities sold under agreements to repurchase 'BHCK4180')/Total interest expense 'BHCK4073', use Interest expense on federal funds purchased and securities sold under agreements to repurchase 'BHCK4180"/Total interest expense 'BHCK4073' if previous measure is missing.	FR-Y9C
SOFR Liability	Liabilities on securities sold under agreements to repurchase 'BHCKB995'/ total liabilities 'BHCK2948'	FR-Y9C
UST. AFS. Sec.	U.S. Treasury securities available-for-sale 'BHCK1287'/Total securities available-for-sale 'BHCK1773' (fair value)	FR-Y9C
OBFR IntExp.	[(Interest expenses on deposits of more than $250,000 'BHCKHK04' + interest expenses in foreign offices 'BHCK4172') + ((federal funds purchased in domestic offices 'BHDMB993'/(federal funds purchased and securities sold under agreements to repurchase 'BHDMB993'+ 'BHCKB995'))× Interest expense on federal funds purchased and securities sold under agreements to repurchase 'BHCK4180')]/ total interest expense 'BHCK4073', use (Interest expenses on deposits of more than $250,000 'BHCKHK04' + interest expenses in foreign offices 'BHCK4172')/ total interest expense 'BHCK4073' if the previous measure is missing.	FR-Y9C
log(Spread)	Log of interest spread, 'margin_bps'	DealScan
log(Maturity)	Log of maturity length measured in month, ('tranche_maturity_date' - 'tranche_active_date')/(365/12)	DealScan
log(Amount)	Log of tranche amount, 'tranche_amount'	DealScan
#. lenders	Number of lenders, 'number_of_lenders'	DealScan
Size	Log of total asset 'at'	Compustat
Cash Flow	(Income before extraordinary items 'ib' + depreciation and amortization 'dp') / Total last year property, plant and equipment 'ppent'	Compustat
Tangibility	Total property, plant and equipment 'ppent' / total asset 'at'	Compustat
Leverage	(Total debt in current liabilities 'dlc' + Total long-term debt 'dltt') / total assets 'at'	Compustat
Tobin's Q	(total assets 'at' + (price close at annual fiscal year 'prcc_f'× common shares outstanding 'csho') - total common/ordinary equity 'ceq' - deferred taxes 'txdb') / total assets 'at'	Compustat
Investment	(Capital expend property, plant and equipment 'capxv' - sale of property 'sppe') / Total last year property, plant and equipment 'ppent'	Compustat
Z-Score	[3.3×pretax income 'pi' + sales/turnover 'sales' + 1.4×re 'retained earnings'+ 1.2×(current assets 'act' - current liabilities 'lct')] / total assets 'at'	Compustat
CAR	Cumulative abnormal return, see Appendix for construction details.	Compustat

B Evidence of the Lobbying Incentive and Possibilities

I examine the LIBOR-SOFR transition by reviewing open letters, Q&As, agendas, and minutes from the Alternative Reference Rate Committee (ARRC) meetings, as published on their official website (https://www.newyorkfed.org/arrc) from November 2014 to November 2023. My analysis reveals multiple pieces of evidence of lobbying incentives and opportunities during the committee's deliberations on candidate successor rates, as well as a notable misalignment between the interests of Wall Street and Main Street. I list a few examples in this section.

The following note highlights the ARRC's efforts to prevent new institutions from joining the deliberation process.

> "[ARRC] Members agreed the ARRC should have at least preliminary recommendations for a new rate and a more detailed implementation plan before inviting new members to join" (ARRC Minutes for the June 11, 2015 Meeting).

Another minute shows that the representatives' votes are expected to be consistent with their institutions' preferences, rather than the market interest, when choosing the replacement rate.

> "[The ARRC chair] reminded the ARRC member firms of the expectation that their representative's vote represents the view of their institution and has been appropriately discussed within their institution". (ARRC Minutes for the June 16, 2017 Meeting, the last meeting before the ARRC voted SOFR over OBFR to replace LIBOR)

The next message reveals a perception that SOFR primarily serves large banks' interests rather than the broader economy.

> "[These alternative reference rates] are heavily impacted by the large banks at month-end/quarter-end just as rate-setting is being established in contracts. This could result in perception of misalignment between Wall Street and Main Street all over again. These 2 attributes together may have the effect of confidence market participants will have for this product". (A question received at the ARRC Roundtable on November 2, 2017. The presenter did not provide an answer.)

C Event Study of Equity Market Response

To analyze the equity market response to the announcement of SOFR as LIBOR's successor rate, I employ a standard event-study approach. This methodology allows for the assessment of abnormal stock returns around the event date, providing insights into how the market perceived the impact of the transition on different banks. The event date is set to June 22, 2017, when the ARRC announced SOFR as the replacement for USD LIBOR.

The estimation window is set to 100 days ($T_E = 100$), and a gap of 50 days is included, with a requirement of at least 70 valid returns, following the WRDS Event Study default settings. The event window spans from 10 days before to 10 days after the announcement.

First, I estimate the parameters $\hat{\alpha}$ and $\hat{\beta}$s for both the Capital Asset Pricing Model (CAPM) and the Fama-French 3 Factor Model during the estimation window. The CAPM is specified as:

$$\pi = \pi_f + \widehat{\alpha_{\mathrm{M}}} + \widehat{\beta_{\mathrm{M}}}(\pi_m - \pi_f) + \epsilon,$$

where π is the return on the bank's stock, π_f is the risk-free rate, and π_m is the market return. The Fama-French 3 Factor Model is specified as:

$$\pi = \pi_f + \widehat{\alpha_{\mathrm{FF}}} + \widehat{\beta_{\mathrm{FF1}}}(\pi_m - \pi_f) + \widehat{\beta_{\mathrm{FF2}}}(SMB) + \widehat{\beta_{\mathrm{FF3}}}(HML) + \epsilon,$$

where *SMB* (Small Minus Big) represents the historic excess returns of small-cap over large-cap companies, and *HML* (High Minus Low) represents the historic excess returns of value stocks over growth stocks (high over low book-to-price ratio).

Next, I calculate the daily abnormal returns using the estimated parameters from both models. For the CAPM, the abnormal return is:

$$\widetilde{\pi_{\mathrm{M}}} = \pi - \widehat{\pi_{\mathrm{M}}},$$

where $\widehat{\pi_{\mathrm{M}}}$ is the expected return based on $\widehat{\alpha_{\mathrm{M}}}$ and $\widehat{\beta_{\mathrm{M}}}$. For the Fama-French 3 Factor Model, the abnormal return is:

$$\widetilde{\pi_{\mathrm{FF}}} = \pi - \widehat{\pi_{\mathrm{FF}}},$$

where $\widehat{\pi_{\mathrm{FF}}}$ is the expected return based on $\widehat{\alpha_{\mathrm{FF}}}$ and $\widehat{\beta_{\mathrm{FF1}}}$, $\widehat{\beta_{\mathrm{FF2}}}$, and $\widehat{\beta_{\mathrm{FF3}}}$.

Finally, I calculate the cumulative abnormal returns (CAR) by summing the daily abnormal returns over the event window. For the CAPM, the CAR is:

$$CAR_{\mathrm{M}} = \sum \widetilde{\pi_{\mathrm{M}}},$$

and for the Fama-French 3 Factor Model, the CAR is:

$$CAR_{\mathrm{FF}} = \sum \widetilde{\pi_{\mathrm{FF}}}.$$

By employing this event study methodology, I aim to capture the equity market's response to the SOFR announcement, highlighting the differential impacts on banks with varying reliance on the repo market and other funding structures.

D Extended Model with Demand Side

To better explain the economic impacts on the demand side, this part extends the Section 4 model into a two-stage framework with one bank and one entrepreneur. The entrepreneur has one project P that requires K amount of loan at the first stage. The project generates a return rate π with ex-ante expected value at μ_π and variation at σ_π^2. The bank side remains the same structure as in Section 4. The bank pays interest expenses c_i on each liability i, with overall funding costs at $C = \sum_i w_i c_i$. The funding costs are uncertain and not contractable ex-ante, with expected interest expense at μ_{c_i} and variance at $\sigma_{c_i}^2$ for each funding channel. For simplicity, I assume that the cost of borrowing from each liability c_i and the reference rate R_j are independent of the project's return π. The bank's funding structure is exogenously given[18].

The debt agreement contracts a loan amount of K and an interest rate with a fixed interest spread r and a floating reference rate R. The benchmark rate R is uncertain ex-ante with expectation at μ_{R_j} and variance at $\sigma_{R_j}^2$. I assume both the bank and entrepreneur are risk averse towards the rate mismatch risks with CARA-shaped functions and their coefficients of absolute risk aversion are $A^B > 0$ and $A^E > 0$, respectively. The timeline of the two-stage game is presented in Figure 2. In Stage 1, the loan amount is determined by the demand-supply system where the entrepreneur's demand equation is $K^D(r, A^E, \mu_\pi, \sigma_\pi^2, \mu_R, \sigma_R^2)$ and the bank's supply function is $K^S(r, A^B, w_i, \mu_{c_i}, \sigma_{c_i}^2, \mu_R, \sigma_R^2)$. In Stage 2, the project generates a return with profits π. The entrepreneur collects the profit of the project, and repays the debt K and the interests. The bank's long-run funding costs c_is were uncertain and uncontractable in Stage 1, but now realized in Stage 2. The bank collects the repayment from the entrepreneur and pays the financing costs to money market investors.

Suppose the benchmark rate R is exogenously chosen by the policy maker and the loan market is competitive, therefore, the interest spread is determined and the market participants are "interest" takers. I further assume the entrepreneur and the bank's outside options are at zero and $\mu_{pi} > \sum_i \mu_{c_i}$, which satisfies the individual rationality constraint. The en-

[18] I do not observe a significant empirical change in bank funding structure after announcing SOFR as the alternative reference rate. This suggests that banks do not reallocate the weights w_i across funding channels in dealing with the benchmark rate mismatch risk.

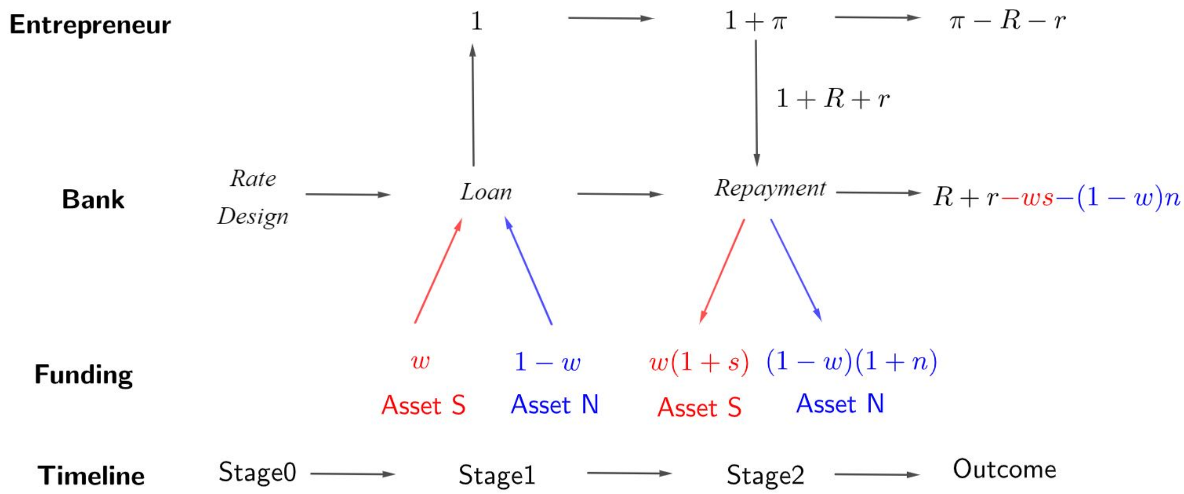

Figure 9: Timeline (need to update the notation)

trepreneur and the bank solve the following profit maximization problem:

$$U^E = \max_{K^D} K(\mu_\pi - \mu_R - r) - \frac{A^E}{2} K^2(\sigma_\pi^2 + \sigma_R^2) \tag{12}$$

$$U^B = \max_{K^S} K(\mu_R + r - \sum_i w_i \mu_{c_i}) - \frac{A^B}{2} K^2(\sigma_R^2 + \sum_i w_i^2 \sigma_{c_i}^2 - 2\sum_i w_i \sigma_{R,c_i}) \tag{13}$$

The first-order conditions characterize the loan demand and supply functions:

$$K^{D*} = \frac{\mu_\pi - \mu_R}{A^E(\sigma_\pi^2 + \sigma_R^2)} \tag{14}$$

$$K^{S*} = \frac{r + \mu_R - \sum_i w_i \mu_{c_i}}{A^B(\sigma_R^2 + \sum_i w_i^2 \sigma_{c_i}^2 - 2\sum_i w_i \sigma_{R,c_i})} \tag{15}$$

The supply function shows that, as the covariance between the benchmark reference rate and the overall weighted funding cost, $\sum_i w_i \sigma_{R,c_i}$, decreases, the supply curve shifts downward. This explains the economic mechanism behind the Section 7.2 empirical findings, where two financing costs—c_S and c_O—are considered. Banks that primarily raise funds from the unsecured overnight market, typically small and mid-sized institutions, have a higher weight on w_O compared to w_S. When the ARRC selected R_S as the base rate of interest, the correlation between the benchmark rate and their major funding costs, σ_{R_S,c_O}, weakened. Consequently, these banks reduced their loan supply. In contrast, banks that rely more on the secured markets benefited from the transition and were able to provide greater liquidity.

As the supply curve for smaller banks shifts downward, the loans available to their customers—primarily small and local businesses—decrease. This reduction in credit can lead to a decline in firm size and market value. Since the number of employees is often complementary to a firm's capital, this contraction could result in fewer job opportunities within those companies. Overall, while the transition to SOFR has benefitted large banks, it has challenged smaller banks. These challenges translate into real economic impacts, particularly for small businesses that rely on these banks for financing.