Deposit Market Power and Bank Risk-Taking[*]

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Abstract

We document a novel fact about the cross-section of banks' risk-taking behavior — banks with high deposit market power take on significantly less credit risk. In particular, the loan portfolios of high-market-power banks are much safer than those of low-market-power banks. This persistent relationship is not driven by the size, funding structure, loan market power, or geography of banks. Consequently, high-market-power banks earn higher profits, are less exposed to business cycle fluctuations, and sustain smaller losses in recessions. We propose a model where deposit market power increases banks' franchise value and induces them to take on less risk to avoid defaults.

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1 Introduction

Commercial banks issue safe deposits against risky loans. As of September 2022, banks in the US hold \$12.0 trillion loans (47% of GDP) and issue \$19.4 trillion deposits (75% of GDP). It has been argued that safety transformation is one of the main business models of modern commercial banks, and the associated risk-taking is an important driver of fragility within the banking sector (e.g., Calomiris and Mason, 2003; Admati and Hellwig, 2014; Brunnermeier and Sannikov, 2014; Baron, Verner and Xiong, 2021). Naturally, it is of great importance to understand the drivers of bank risk-taking.

In this paper, we identify a new cross-sectional pattern of bank risk-taking — banks that enjoy greater market power in deposit markets take on significantly less credit risk. As a result, high-market-power banks have lower regulatory asset risk weight and leverage ratio. On average, a one standard deviation increase in deposit market power is associated with a 7.2% decrease in a bank's risk-weighted assets to tier-1 capital ratio, one of the most widely adopted measures of bank soundness.

Importantly, high-market-power banks shed away from risk by reducing their portfolio weights on the riskiest loans. Consequently, they suffer from fewer loan losses, especially in recessions. In the Great Recession, banks in the top tercile of the deposit market power distribution sustained loan losses amounting to 0.83% of their assets. In contrast, banks in the bottom tercile experienced a loan loss rate of 1.33%. Moreover, the loan loss of high-market power banks is less exposed to business cycle fluctuations.

These findings have important implications for credit provision and the stability of the banking sector. In particular, they hint at a *competition-stability* trade-off. In more competitive markets, banks have less deposit market power and take on more risk by supplying more risky loans. However, the increased intermediation activities come at the cost of greater risk and more defaults on the asset side of the banks' balance sheets, which undermine the stability of those banks.

It is a well-studied fact that banks exhibit imperfect pass-through of the policy rate to retail deposit rates, and the degree of pass-through is tightly linked to concentration and market power.[1] Following Drechsler, Savov and Schnabl (2021), our baseline spec-

[1] See, e.g., Hannan and Berger (1991), Neumark and Sharpe (1992), Driscoll and Judson (2013), Drechsler, Savov and Schnabl (2017, 2021), Polo (2021), Gödl-Hanisch (2022), and Wang et al. (2022).

ification uses the banks' interest expense–federal funds rate (FFR) beta as the measure of deposit market power. Intuitively, a high beta means that the bank's deposit rate is more sensitive to the policy rate, indicating that the bank has little market power over depositors. We obtain bank balance sheet information from U.S. Call Reports and use the banks' asset risk weight and leverage ratio as measures of bank risk-taking.[2] Using data covering the period between 1996 and 2020, we show that the negative relationship between deposit market power and risk-taking is persistent over time and robust after controlling for bank size, funding structure, fee income, loan market power, and geographical distribution.

To address the measurement challenge that a bank's interest expense beta may reflect other unobserved characteristics than deposit market power, we further follow Drechsler, Savov and Schnabl (2021) to instrument the bank-level interest expense–FFR beta with a county-level retail deposit rate-FFR beta constructed from actual deposit rates, which measures the competitiveness of the local deposit markets each bank operates in. This instrument is based on the assumptions that the geographical distribution of banks and the competitiveness of county-level deposit markets are correlated with banks' deposit market power and that they only affect bank risk-taking through market power. Our main results remain robust in the two-stage least squares regression based on this instrument.

An obvious identification challenge is that risk-taking is affected by banks' investment opportunities, which might be correlated with their deposit market power as both can depend on their locations. We address this concern by examining one-county banks within the same county. After controlling for county-time fixed effects, we can compare banks that operate in the same location but differ in their deposit market power. The identification assumption is that banks in the same geographic area face the same borrowers and thus have similar investment opportunities. We show that the negative relationship between market power and risk-taking remains robust under this more restrictive specification.

[2]In this work, we focus on *credit risk* as it is one of the largest sources of risk facing modern commercial banks (e.g., Begenau, Piazzesi and Schneider, 2015). Complementary to this paper, a number of existing studies have investigated the relationship between deposit market power and *interest rate risk* (e.g., Li, Loutskina and Strahan, 2019; Whited, Wu and Xiao, 2021; Drechsler, Savov and Schnabl, 2021).

We also present a second identification scheme by examining the zero lower bound (ZLB) period. In practice, banks benefit from deposit market power as they can choose a deposit rate below the federal funds rate and earn a positive deposit premium (Drechsler, Savov and Schnabl, 2017). Hence, we expect that deposit market power becomes less relevant when the economy is at the zero lower bound where all banks must supply deposits at a rate of almost zero. Indeed, we find that the risk-taking gap between high-market-power banks and low-market-banks shrank substantially after 2009 when the federal funds rate hit zero.

We then build a model of bank franchise value to explain our empirical findings. Consistent with our measurements, high-market-power banks in the model charge higher deposit spreads and earn more profits. Banks also choose the amount of risk to take on. A riskier asset portfolio yields a higher risk premium but also increases the bank's default probability. Banks have limited liability in the event of default. Deposit market power boosts the banks' franchise value, the value of remaining in the market for the future. Thus, banks with high market power choose to take on less risk to avoid a potential default. The model has direct implications for bank competition and stability. In a highly competitive market, banks have low franchise value and are more willing to take on risk. In equilibrium, low market power results in more fragility in the form of greater default probability.

Related Literature. Our paper belongs to the burgeoning literature on bank deposit market power. Following Drechsler, Savov and Schnabl (2017), a number of studies have investigated the role of bank deposit market power in the transmission of monetary and fiscal policy (e.g., Xiao, 2020; Polo, 2021; Wang, Whited, Wu and Xiao, 2022; Li, Ma and Zhao, 2021; Gödl-Hanisch, 2022; Wang, 2022). However, such studies mostly focus on the liability side of bank balance sheets to study the pass-through of government policy to deposit rate and deposit quantity. Instead, we show that there exist important interactions between deposit market power and bank asset choice. In this regard, we share the same focus with Li, Loutskina and Strahan (2019), which emphasizes the maturity of bank assets and argues that deposit market power encourages banks to engage in long-term lending by reducing their funding risk. Similarly, Drechsler, Savov and Schnabl (2021) argues that deposit market power increases the duration of bank liabilities and that banks choose the duration of their assets to match the duration of their liabilities. In this paper, we instead focus on the risk of bank assets and show that deposit market power leads banks to behave more cautiously when choosing credit risk and leverage.

In a broad sense, our paper connects with the literature on the interactions between bank assets and bank liabilities. The seminal contributions of Diamond and Dybvig (1983) and Kashyap, Rajan and Stein (2002) have pointed out the fragility and synergy caused by lending and deposit-taking. Recently, Bolton et al. (2021) and Granja, Leuz and Rajan (2022) show that deposit inflows might depress bank lending and increase bank risk-taking. In this project, we demonstrate that risk-taking and deposit-taking can become substitutes when deposit market power elevates bank franchise value. That is, when banks earn high profits from deposit market power, they curb risk-taking to lower their likelihood of default.

We provide new insights into the long debate on the relationship between bank competition and financial stability.[3] Some have argued that a more competitive banking industry is also more fragile (e.g., Keeley, 1990; Demsetz, Saidenberg and Strahan, 1996; Beck, Demirgüç-Kunt and Levine, 2006; Jiménez, Lopez and Saurina, 2013; Berger, Klapper and Turk-Ariss, 2017; Carlson, Correia and Luck, 2022), while some suggest that competition does not necessarily lead to risk build-up in the banking sector (e.g., Allen and Gale, 2004; Boyd and De Nicolo, 2005; Boyd, De Nicolo and Jalal, 2006; Martinez-Miera and Repullo, 2010). Our paper provides new evidence that is supportive of the first view where competition leads to instability. However, instead of using bank valuation (e.g., Tobin's q) or profit markups (e.g., the Lerner index) as proxies for competition, we directly test the role of deposit market power. Further, we go beyond the overall level of bank risk (e.g., as measured by stock volatility and Z-scores) and examine the *source* of risk using bank balance sheet information. Our results suggest that low-market-power banks primarily take on more credit risk through loan issuance.

Our results also contribute to the emerging literature on the effect of a low-interest-

[3]See Vives (2016) for an overview of the literature.

rate environment on bank risk-taking. Existing research (e.g., Altunbas, Gambacorta and Marques-Ibanez, 2010; Maddaloni and Peydró, 2011; Jiménez, Ongena, Peydró and Saurina, 2014; Heider, Saidi and Schepens, 2019; Whited, Wu and Xiao, 2021) suggests that low nominal rates led to increased bank risk-taking, while we show that low rates can nullify the effect of deposit market power, reducing the difference in risk-taking between high-market-power banks and low-market-power banks.[4]

Outline. Section 2 describes the data used in the empirical analysis. Section 3 presents time series evidence, the empirical specification, main regression results, and various robustness checks. Section 4 examines the cross-sectional relationship between deposit market power and risk-taking in the zero lower bound period. Section 5 explains the findings with a tractable model of bank franchise value. Section 6 concludes.

2 Data and Measurement

2.1 Data Sources and Sample Selection

Our main source of data at the bank level is the quarterly U.S. Call Reports provided by Wharton Research Data Services. All U.S. commercial banks are required to file the report with balance sheet and income statement information. We use data from March 1996[5] to March 2020. For banks owned by bank holding companies, we aggregate the data to the holding company level.

For information at the bank branch level, our main source of data is the FDIC Summary of Deposits which reports the address and total deposits for each U.S. bank branch at the end of each June. We use the Summary of Deposits data from 1996 to 2020 and merge it to Call Reports using FDIC bank identifiers. For a part of our analysis, we also use deposit rate data from Ratewatch, which provides weekly branch-level deposit rates from 1998 to 2019 for a subset of bank branches.[6]

[4]Using a sample of Japanese banks, Balloch and Koby (2022) show that low rates weaken deposit market power and depress loan growth.

[5]Banks were required to report asset risk weight and risk-weighted leverage on section RC-R of call report starting in 1996Q1.

[6]Ratewatch provides deposit rates data for 63% of all U.S. bank branches in 2019. The majority of branches follow the rates set by a small number of "rate-setting branches." Among covered branches in 2019, only 11% set deposit rates by themselves.

We limit our main analysis sample to banks that have deposit-taking branches in at least two counties (at least one must be among the top 1000 counties by population) for at least five years from 1996 to 2019. We further require each bank-quarter observation to have at least \$10 million of total assets, \$1 million of loans, and \$1 million of deposits, and we require each bank to have at least 20 quarters of data for interest expense, risk-weighted assets, and tier-1 capital. The main analysis sample consists of 3437 banks (2969 bank holding companies and 468 non-BHC banks) and 195225 bank-quarter observations from 1996Q1 to 2020Q1. For the average quarter during this period, our main sample covers 72% of assets reported by all banks filing Call Reports. In Section 3.2.4, we examine a separate sample of one-county banks to address the identification challenge raised by the potential correlation between a bank's geographical distribution and its investment opportunities.

2.2 Measuring Bank Market Power

We follow the approach of Drechsler, Savov and Schnabl (2021) and use the sensitivity of a bank's interest expense to federal funds rate changes to measure the bank's deposit market power. Banks with higher market power can charge higher deposit spreads when the federal funds rate increases. Therefore, a low sensitivity of interest expense to the federal funds rate indicates high market power.

For each bank i, we estimate the response of the interest expense rate to the federal funds rate as follows:

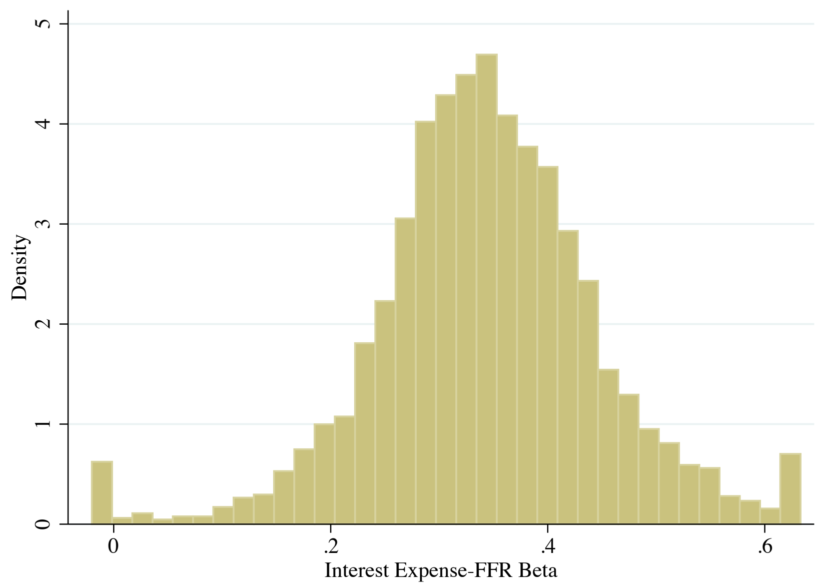
$$\Delta\text{IntExp}_{i,t} = \alpha_i + \sum_{\tau=0}^{3} \gamma_{i,\tau} \Delta\text{FFR}_{t-\tau} + \varepsilon_{i,t} \tag{1}$$

$$\text{IntExpBeta}_i := \sum_{\tau=0}^{3} \gamma_{i,\tau} \tag{2}$$

where $\text{IntExp}_{i,t}$ is bank i's interest expense rate in quarter t and FFR_t is the average of month-end federal funds rates in quarter t. We define the interest expense rate for a bank-quarter as quarterly interest expense divided by quarterly average total assets and multiplied by 4. The interest expense to FFR beta IntExpBeta_i (hereafter "interest expense beta") captures the total response of a bank's interest expense rate to changes in federal funds rate over the past year.

We require at least 20 observations for estimating equation (1) and winsorize the interest expense beta at 1% and 99% percentiles to avoid the impact of outliers. Figure 1 plots the histogram of interest expense beta across banks, and Table 1 provides summary statistics. Across 3437 banks in our main sample, the average interest expense beta is 0.343, and the standard deviation is 0.105 — i.e., the average bank in our sample increases its deposit rate by 0.343% in response to a 1% increase of federal funds rate over a year.

Figure 1: Distribution of Interest Expense to FFR Beta



Note: The interest expense-FFR beta at bank level estimated from Equations (1-2) for 3437 banks in the main sample and winsorized at 1% and 99% percentiles.

2.3 Measuring Bank Risk-Taking

Our main metric for bank risk-taking is risk-weighted leverage, defined as a bank's risk-weighted asset divided by tier-1 capital. It is the product of a bank's asset risk weight and leverage and thus summarizes a bank's risk-taking on both margins. The inverse of risk-weighted leverage is the Tier-1 Capital Ratio commonly used by regulators to judge a bank's capital adequacy.

$$\underbrace{\frac{\text{Risk-Weighted Assets}}{\text{Tier-1 Capital}}}_{\text{Risk-Weighted Leverage}} = \underbrace{\frac{\text{Risk-Weighted Assets}}{\text{Assets}}}_{\text{Asset Risk Weight}} \times \underbrace{\frac{\text{Assets}}{\text{Tier-1 Capital}}}_{\text{Leverage}}. \tag{3}$$

Each bank classifies its assets by four risk weight categories of 0%, 20%, 50%, and 100% on the call report and computes the risk-weighted asset by applying these risk weights and adjusting for off-balance-sheet exposure.[7] The instructions for call reports define the risk weight categories for each type of asset.[8] For example, the risk weight guidelines for loans in the June 2007 call report instructions are as follows:

- 0% for the guaranteed portion of SBA loans purchased in the secondary market.
- 20% for loans to other depository institutions, the guaranteed portion of FHA and VA mortgage loans, the guaranteed portion of SBA loans originated by the bank, and student loans insured by the U.S. government.
- 50% for loans fully secured by first liens on residential properties that are "prudently underwritten"[9] and not past due for more than 90 days.
- 100% for all other loans on the balance sheets (i.e., riskier mortgages and all commercial loans).

Table 1 provides summary statistics for risk-weighted leverage and its two components. For all of our analyses, we winsorize all three variables at 1% and 99% levels in each quarter to mitigate the impact of outliers. The average risk-weighted leverage in our main sample is 7.89, corresponding to a tier-1 capital ratio of 12.6%. The average asset risk weight is 70.8%, and the average raw leverage is 11.2. Risk-weighted leverage and its components all vary substantially across banks and over time.

[7] The reported off-balance sheet exposure is 3% of total assets for an average bank in the period from 2001Q1 to 2014Q4. This is very small compared to the on-balance-sheet risk-weighted asset, which is 68% of total assets for an average bank in the same period.

[8] According to the June 2007 call report instructions, risk weight categories 20%, 50%, and 100% can be considered as long-term credit rating AAA/AA, A, and BBB, respectively (https://www.ffiec.gov/PDF/FFIEC_forms/FFIEC031_041_200706_i.pdf).

[9] Prudent underwriting typically requires a loan-to-value ratio not exceeding 80% (75% for floating-rate loans).

For a part of our analysis, we also use loan loss provision as a measure of a bank's ex-post loss due to loan defaults. We calculate banks' loan loss rate as the quarterly loan loss provision divided by quarterly average assets, averaged across the past four quarters to adjust for seasonality. Table 1 shows that the average annual loan loss to asset ratio is 0.328% in our sample.

Table 1: Summary Statistics: Main Sample

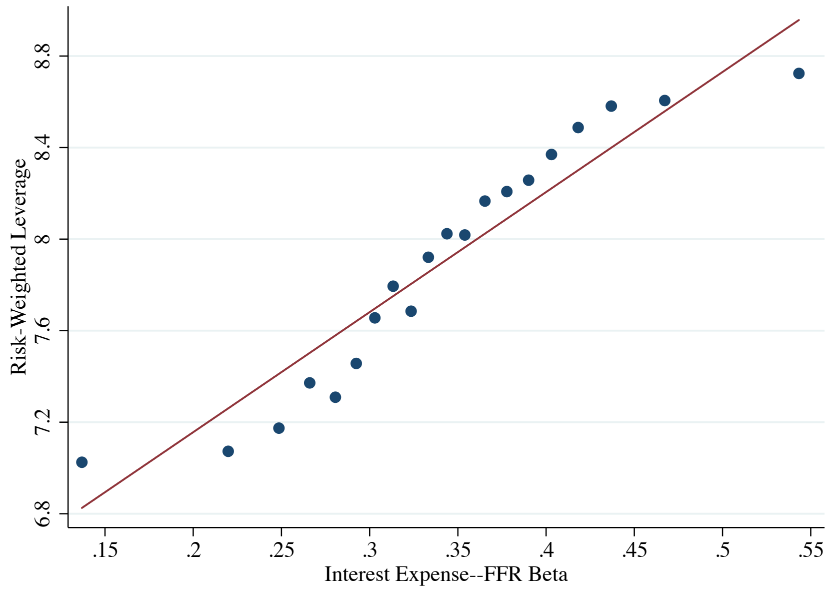
Variable	Level	*N*	Mean	SD	Q10	Q50	Q90
Interest Expense Beta	Bank	3437	0.343	0.105	0.226	0.341	0.469
Risk-Weighted Leverage	Bank-Quarter	195225	7.89	2.19	5.17	7.92	10.36
Asset Risk Weight (%)	Bank-Quarter	195225	70.8	11.4	55.7	71.6	84.9
Leverage	Bank-Quarter	195225	11.2	2.64	8.17	11.1	14.0
Annual Loan Loss Rate (%)	Bank-Quarter	194149	0.328	0.531	0	0.175	0.772

3 Main Results

3.1 Market Power and Risk-Taking Metrics

In this section, we examine the relationship between interest expense beta and risk-taking metrics in the cross-section of banks. To begin with, Figure 2 shows a binned scatter plot of risk-weighted leverage against interest expense beta. The plot shows a clear relationship where banks with lower interest expense beta — i.e., higher deposit market power — have lower risk-weighted leverage.

Figure 2: Risk-Weighted Leverage and Interest Expense to FFR Beta



Note: 20-point binned scatter plot with year-quarter fixed effects taken out. Data from 1996Q1 to 2020Q1 for 3437 banks.

We use the regression below to formally test the relationship between interest expense beta and risk-taking metrics:

$$\text{Risk}_{i,t} = \alpha_t + \beta \cdot \text{IntExpBeta}_i + \gamma' \boldsymbol{x}_{i,t} + \varepsilon_{i,t} \tag{4}$$

where $\text{Risk}_{i,t}$ is one of the risk-taking metrics for bank i in quarter t, α_t is a year-quarter fixed effect that ensures comparison in the cross-section of banks, $\boldsymbol{x}_{i,t}$ are control variables, and IntExpBeta_i is the interest expense beta for bank i. The parameter of interest is β, which measures the change of risk-taking behavior per one unit increase of interest expense beta.

3.1.1 Risk-Weighted Leverage

The regression results for risk-weighted leverage are presented in Table 2. Column (1) shows the regression results without controls, with log risk-weighted leverage as the risk metric. The coefficient β is 0.720 with a large t-statistic: in the cross-section of banks, 0.1 unit lower interest expense beta (one standard deviation) is associated with

7.2% lower risk-weighted leverage. Column (2) shows that the coefficient β is 0.570 after controlling for basic bank characteristics, including log assets, deposit-to-liability ratio, log total number of branches, and an indicator for having branches in multiple states. Column (3) shows that the coefficient is 0.557 after further controlling for two measures of non-interest income[10]: domestic deposit fee income and other non-interest income[11].

One potential omitted variable for our regression analysis is bank-specific investment opportunities related to geographical distribution. For example, banks with higher deposit market power might be located in high-income counties with an older population, where lending opportunities are safer. To address this concern, we construct bank-level measures about the riskiness of the counties the bank operates in. We first compute a "county business cycle beta" CountyBusBeta_c for each county c by regressing the county's real per-capita income growth $g_{c,t}$ onto the U.S. real per-capita income growth G_t using annual data from 1969 to 2019, as shown in Equation (5).

$$g_{c,t} = \alpha_c + \text{CountyBusBeta}_c \cdot G_t + \varepsilon_{c,t}. \tag{5}$$

We then aggregate this measure to the bank level by taking the average of county business cycle beta across all counties a bank operates in, weighted by the number of branches the bank has in each county, as shown in Equation (6).

$$\text{BankBusBeta}_{b,t} = \frac{\sum \#\,\text{Branch}_{b,c,t} \times \text{CountyBusBeta}_c}{\sum \#\,\text{Branch}_{b,c,t}}. \tag{6}$$

Similarly, we also construct the weighted average of per-capita income across counties a bank operates in, as shown in Equation (7).

$$\text{BankIncome}_{b,t} = \frac{\sum \#\,\text{Branch}_{b,c,t} \times \text{Per-Capita Income}_{c,t}}{\sum \#\,\text{Branch}_{b,c,t}}. \tag{7}$$

[10]Domestic deposit fee income is the service charges on domestic deposit accounts (RIAD4080) divided by a bank's total assets. Other non-interest income is all non-interest income minus the deposit fees (RIAD4079 minus RIAD4080), divided by a bank's total assets. We use annualized rolling 4-quarter averages of these two fee measures to adjust for seasonality.

[11]Notably, banks that earn high service fees from domestic deposit accounts also tend to have lower risk-weighted leverage and asset risk weight, as shown in columns 4 and 5 in Table 2. One can interpret the deposit fee income as an alternative measure of deposit market power, as banks with high market power over their depositors could charge higher service fees. Therefore, the negative association between deposit fee income and risk-taking is consistent with our main results.

Column (4) of Table 2 shows the regression results after controlling for the two bank-level measures defined above. Adding the controls does not meaningfully change our main coefficient β (from 0.557 to 0.554). As shown in columns (5-6), the average county business cycle beta is positively correlated with asset risk weight but not significantly correlated with bank leverage. Conditioning on county business cycle beta, average county per-capita income is also positively correlated with risk-taking, which might indicate that high-income counties offer more lending opportunities.

Table 2: Risk-Taking and Interest Expense Beta: Main Regression Results

	Dependent Variable: Risk Metrics					
	Log Risk-Weighted Leverage				Risk Weight	Log Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
IntExp-FFR Beta	0.720**	0.570**	0.557**	0.554**	0.221**	0.217**
	[12.70]	[10.28]	[10.04]	[10.03]	[10.81]	[5.341]
Log Assets		0.00807	0.00108	-0.0121	-0.00328	-0.00528
		[0.913]	[0.120]	[-1.297]	[-0.860]	[-0.760]
Deposit/Liability		-0.372**	-0.374**	-0.378**	0.00112	-0.362**
		[-5.818]	[-5.846]	[-5.966]	[0.0430]	[-8.134]
Log(# Branches)		0.0375**	0.0501**	0.0625**	0.0140**	0.0380**
		[3.298]	[4.260]	[5.201]	[2.900]	[4.324]
Multi State		-0.0114	-0.0114	-0.0134	-0.00150	-0.00869
		[-1.083]	[-1.119]	[-1.314]	[-0.335]	[-1.127]
Deposit Fee Income			-0.0777**	-0.0610**	-0.0556**	0.0194
			[-4.373]	[-3.359]	[-8.093]	[1.352]
Other Non-Interest Income			-0.00588	-0.00827	0.000700	-0.00801+
			[-0.906]	[-1.293]	[0.249]	[-1.764]
Log(County PC Income)				0.0763*	0.0336**	0.0354
				[2.616]	[2.989]	[1.587]
County Bus. Cycle Beta				0.0426**	0.0339**	-0.00342
				[2.812]	[5.478]	[-0.290]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Within R^2	.055	.104	.11	.117	.102	.066
# Banks	3437	3437	3437	3437	3437	3437
Observations	195225	195225	195225	195225	195225	195225

Note: Regressions based on Equation (4). "IntExpBeta" is the interest expense to FFR beta defined in Equations (1-2). "Multi State" is an indicator for having branches in multiple states. "County PC Income" is the average per-capita income in counties a bank operates in, defined by Equation (7). "County Bus. Cycle Beta" is the average county business cycle beta in counties a bank operates in, defined by Equation (6). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

3.1.2 Breakdown of Risk Components

To further examine which component of risk-taking is related to market power, we run the main regression (4) separately with asset risk weight and log leverage as dependent variables. Column (5-6) of Table 2 shows that with all the control variables, 0.1 unit lower interest expense beta is associated with 2.21 percentage point lower asset risk weight (3.1% compared to the overall average risk weight of 70.8 percent) and 2.17% lower raw leverage. Therefore, banks with higher market power choose both a safer asset portfolio and lower leverage; these two margins have a similar contribution to the overall relationship between market power and risk-weighted leverage.

Table 3 uses data from 2000Q1 to 2014Q4[12] to examine further breakdowns of asset composition. In columns (1-2), we separately examine the off-balance-sheet and on-balance-sheet asset risk weights, where the sum of these two equals the overall asset risk weight. For 0.1 unit lower interest expense beta across banks, off-balance-sheet risk weight reduces by 0.11 percentage points (compared to the average of 3%), and on-balance-sheet risk weight reduces by 2.43 percentage points (compared to the average of 68%). Therefore, both the average asset risk weight and its relationship with market power are mainly driven by the composition of on-balance-sheet assets.

Finally, we further separate on-balance-sheet assets into two categories: loans with 100% risk weight and all other assets. According to the June 2007 call report instructions, loans in the 100% risk category includes all mortgages not secured by first-lien or not "prudently underwritten" and all commercial-industrial loans. Loans in this category are, on average, 51% of the total assets in our subsample from 2000Q1 to 2014Q4, so they contribute the most towards overall asset risk weights. Column (3) of Table 3 shows that banks with higher market power allocate less of their portfolio in loans with 100% risk weight: 0.1 unit lower interest expense beta is associated with 3.48 percentage point lower portfolio weight in this category. Therefore, the relationship between market power and asset risk is primarily driven by portfolio allocation between risky, unsecured loans and other assets (non-loan assets and secured or guaranteed loans).

[12]This subsample period is limited by data availability. A detailed breakdown of assets into risk weight categories was only available since 2000Q1. Schedule RC-R of the call reports was substantially changed after 2015Q1, making some of the variables non-comparable.

Table 3: Interest Expense Beta and Asset Composition

	Dependent Variable: Risk Metrics			
	Off-Bal Risk Weight (1)	On-Bal Risk Weight (2)	100% Wgt Loan to Assets (3)	Avg. Risk Weight Other Assets (4)
IntExp-FFR Beta	0.0114*	0.243**	0.348**	0.0417**
	[2.016]	[11.17]	[11.33]	[3.199]
Log Assets	0.0115**	-0.0116**	-0.000644	-0.0203**
	[8.275]	[-2.957]	[-0.126]	[-9.491]
Deposit/Liability	-0.0252**	0.0458+	0.189**	-0.147**
	[-3.201]	[1.812]	[5.818]	[-8.253]
Log(# Branches)	-0.00368*	0.0151**	0.00743	0.0188**
	[-2.168]	[3.099]	[1.163]	[7.593]
Log(County PC Income)	0.0168**	0.0147	0.0553**	-0.0454**
	[5.463]	[1.317]	[3.549]	[-5.328]
County Bus. Cycle Beta	-0.000543	0.0347**	0.0609**	-0.00904+
	[-0.335]	[5.724]	[7.619]	[-1.885]
Multi State	0.000269	-0.00721	-0.00394	-0.00984**
	[0.213]	[-1.627]	[-0.655]	[-3.236]
Deposit Fee Income	-0.000240	-0.0529**	-0.0647**	-0.0181**
	[-0.128]	[-7.871]	[-7.125]	[-3.990]
Other Non-Interest Income	0.00477**	-0.00593*	-0.0123**	0.00499**
	[5.791]	[-2.013]	[-3.215]	[2.826]
Year-Quarter FE	✓	✓	✓	✓
Within R^2	.235	.093	.142	.058
# Banks	3395	3395	3395	3395
Dep. Var. Mean	.03	.68	.51	.36
Observations	124377	124377	124377	124377

Note: Regressions based on Equation (4). "Off-Bal Risk Weight" is off-balance sheet risk exposure divided by assets. "On-Bal Risk Weight" is the average risk weight of all assets reported on the balance sheet. "100% Wgt Loan to Assets" is the fraction of assets in the "100% risk-weight loan" category. "Avg. Risk Weight Other Assets" is the average risk weight of all assets excluding 100% risk-weight loans. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

3.2 Robustness

The previous section shows our main result that banks with higher market power take less risk both by choosing a safer asset portfolio and by taking on less leverage.

In this section, we first show that our results are robust to controlling for loan market power. We also show that our results hold for both small and large banks. We then use a two-stage least squares specification based on variations of retail deposit rates across counties to address concerns about measurement error. We finally examine a separate sample of one-county banks to address identification concerns regarding the unobserved geographical distribution of investment opportunities. Appendix B provides more robustness results.

3.2.1 Loan Market Power

One potential concern for our main results in Table 2 might be driven by banks' loan market power instead of deposit market power. Holding borrower characteristics constant, a bank with higher loan market power could charge higher loan spreads and thus earn higher interest income. If deposit market power and loan market power are positively correlated, as both could be driven by a bank's geographical distribution, then the negative relationship between deposit market power and risk-taking might be confounded by loan market power.

To address this concern, we construct a proxy for loan market power based on the HMDA data for mortgage originations[13] from 1996 to 2019. For each county in each year, we compute the county-level HHI based on the loan amounts originated by each bank. We then aggregate the county-level HHI to the bank level by taking a loan-amount-weighted average of HHI across all counties in which a bank originates mortgages. We use the resulting bank-level measure of *mortgage HHI* as a proxy for a bank's loan market power[14]. A high mortgage HHI indicates that a bank issues more mortgages in counties with concentrated mortgage markets.

In our analysis sample, mortgage HHI can be computed for 87.4% of banks (constituting 98.8% of total assets) in an average quarter. The correlation between mortgage

[13]The HMDA data provides loan-level origination records for mortgages. We include all mortgages for home purchasing, or refinancing originated from all lenders reporting to HMDA. We require the loans to have a FIPS code within the 50 U.S. states and require the loan amount to be between 10,000 and 10,000,000 dollars.

[14]We use a 5-year rolling average of mortgage HHI in regression analysis in order to mitigate the issue of missing data. The rolling average also takes into account the fact that HMDA captures the flow of mortgage originations rather than the stock of all outstanding mortgages held by each bank.

HHI and interest expense beta is 0.04, and the correlation between mortgage HHI and the deposit HHI measure of Drechsler, Savov and Schnabl (2017) is 0.39. These results show that the correlation between loan market power and deposit market power is moderate at best.

Table 4 shows the results of our main regression with mortgage HHI as an additional control. Comparing with results in Table 2, we find that the coefficient on interest expense beta only reduces slightly after the control. For example, the coefficient for interest expense beta in the regression for log risk-weighted average decreases from 0.554 ($t = 10.0$) to 0.519 ($t = 9.2$) after adding the control. The results are similar for the two components of the risk-weighted average.

Table 4 also shows that mortgage HHI is positively associated with risk weight, negatively associated with log leverage, but not significantly associated with risk-weighted leverage. However, we note that the coefficients on mortgage HHI in Table 4 are very small in magnitude: for example, 1-standard deviation higher mortgage HHI is only associated with 0.5 percentage point higher risk weight and 0.8% lower leverage. Overall, these results suggest that mortgage market power has a small impact on banks' risk-taking and franchise value.[15]

Finally, Table 16 in the appendix shows that our results based on deposit HHI as a measure of deposit market power are also robust after controlling for mortgage HHI.

[15] We note that there are at least two potential reasons why high mortgage market power may not translate into high bank franchise value. On the one hand, banks may not have much pricing power over conforming mortgages sold to GSEs. On the other hand, mortgages may be more nationally priced than deposits (e.g., Hurst et al., 2016).

Table 4: Robustness: Controlling for Mortgage Market Power

	Dependent Variable: Risk Metrics		
	Log Risk-Wgt Lev. (1)	Risk Weight (2)	Log Lev. (3)
IntExp-FFR Beta	0.519**	0.206**	0.208**
	[9.205]	[9.672]	[5.036]
Log Assets	-0.00967	-0.00272	-0.00456
	[-0.921]	[-0.644]	[-0.595]
Deposit/Liability	-0.359**	0.0140	-0.361**
	[-5.514]	[0.522]	[-7.885]
Log(# Branches)	0.0547**	0.0122*	0.0345**
	[4.128]	[2.341]	[3.590]
Log(County PC Income)	0.0677*	0.0346**	0.0236
	[2.202]	[2.885]	[1.001]
County Bus. Cycle Beta	0.0434**	0.0354**	-0.00500
	[2.696]	[5.293]	[-0.406]
Multi State	-0.00539	-0.000249	-0.00342
	[-0.544]	[-0.0565]	[-0.441]
Deposit Fee Income	-0.0806**	-0.0570**	0.00194
	[-4.096]	[-7.676]	[0.125]
Other Non-Interest Income	-0.00467	0.00242	-0.00767
	[-0.761]	[0.926]	[-1.629]
Mortgage HHI (STD)	0.000109	0.00557**	-0.00806*
	[0.0240]	[3.592]	[-2.297]
Year-Quarter FE	✓	✓	✓
Within R^2	.112	.099	.064
# Banks	3197	3197	3197
Observations	171501	171501	171501

Note: Regressions based on Equation (4) with additional control of mortgage HHI defined in the text. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

3.2.2 Subsample by Bank Size

One potential concern is that the results in Table 2 might mostly be driven by small banks that only constitute a small portion of the banking sector. In this subsection, we examine the samples of large banks and small banks separately and show that the relationship between deposit market power and bank risk-taking holds for both types of banks.

We first rank the 3437 banks in our main sample by size, defined as a bank's share of total assets average across time. We then estimate the main regression (Equation 4) separately for the 500 largest banks and the rest. The 500 largest banks constitute 94.0% percent of all assets on average in our sample period, which reflects the high concentration of the banking industry.

Columns (1-2) of Table 5 show that the main coefficient of interest expense β for risk-weighted leverage is 0.251 for the top 500 banks and 0.613 for the rest, smaller banks. Therefore, the negative relationship between market power and risk-taking holds for both large and small banks but is stronger among small banks. Columns (3-4) show that the coefficient for asset risk weights is similar for large and small banks (0.173 and 0.228), and columns (5-6) show that the coefficient for log leverage is only positive and statistically significant for small banks. These results indicate that higher market power is associated with a safer asset portfolio across both large and small banks, although the relationship with raw leverage is only present for small banks.[16]

[16] It has been documented that large banks and small banks have different leverage dynamics (e.g., Kalemli-Ozcan, Sorensen and Yesiltas, 2012; Coimbra and Rey, 2022). A handful of factors might lead to these differences, including regulatory burdens, access to government bailouts, and (decreasing) return to scale for banks.

Table 5: Robustness by Bank Size: 500 Largest and Other Banks

	Dependent Variable: Risk Metrics					
	Log Risk-Weighted Lev.		Asset Risk Weight		Log Leverage	
	Top 500	Other	Top 500	Other	Top 500	Other
	(1)	(2)	(3)	(4)	(5)	(6)
IntExp-FFR Beta	0.251*	0.613**	0.173**	0.228**	-0.000484	0.265**
	[2.384]	[10.10]	[3.630]	[10.46]	[-0.00592]	[5.889]
Log Assets	-0.0183	0.0115	-0.0158*	0.00988*	0.00474	-0.00155
	[-1.073]	[1.119]	[-2.019]	[2.479]	[0.307]	[-0.207]
Deposit/Liability	-0.128	-0.490**	0.104+	-0.0690*	-0.290**	-0.360**
	[-1.316]	[-5.993]	[1.921]	[-2.257]	[-3.666]	[-6.497]
Log(# Branches)	0.0710**	0.0541**	0.0259**	0.00433	0.0301	0.0434**
	[3.411]	[4.285]	[3.111]	[0.889]	[1.624]	[4.679]
Log(County PC Income)	-0.0200	0.108**	-0.0523	0.0582**	0.0670	0.0298
	[-0.321]	[3.378]	[-1.605]	[5.077]	[1.514]	[1.202]
County Bus. Cycle Beta	0.0522	0.0387*	0.0651**	0.0268**	-0.0372	0.00293
	[1.427]	[2.391]	[3.392]	[4.240]	[-1.190]	[0.232]
Multi State	0.00210	-0.00869	0.0177*	-0.00563	-0.0199	0.00104
	[0.116]	[-0.727]	[2.115]	[-1.086]	[-1.297]	[0.119]
Deposit Fee Income	-0.0664+	-0.0425*	-0.0598**	-0.0456**	0.0193	0.0228
	[-1.721]	[-2.272]	[-4.038]	[-6.541]	[0.554]	[1.512]
Other Non-Interest Income	-0.0106	-0.00670	-0.00216	0.00208	-0.00512	-0.00873
	[-0.879]	[-0.965]	[-0.284]	[0.804]	[-0.818]	[-1.604]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Within R^2	.103	.104	.085	.117	.091	.044
# Banks	500	2937	500	2937	500	2937
Observations	31074	164151	31074	164151	31074	164151

Note: Regressions based on Equation (4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

3.2.3 Instrument with County-Level Retail Deposit Beta

The sensitivity of a bank's interest expense to federal funds rate may be driven not only by the bank's market power in deposit markets but also by factors including the bank's funding structure, depositor composition (institutional v.s. retail), types of deposit products the bank offers, and other unobserved bank characteristics. In addition, the estimation of interest expense beta on at most 24 years of quarterly data also introduces measurement error. In order to address these concerns, we follow Drechsler, Savov and Schnabl (2021) to construct an instrument using the sensitivity of retail deposit rate to federal funds rate at the county level and banks' geographical distribution across counties, based on recent empirical findings that local markets are important for bank deposit rate setting (e.g., Drechsler, Savov and Schnabl, 2017; Levine et al., 2021; Dlugosz et al., 2022; Gödl-Hanisch, 2022).

Methodology. For this exercise, we use published rates of $25,000 money market savings accounts at the branch level provided by RateWatch.[17] We aggregate the original weekly RateWatch data to the monthly level in order to reduce noise from reporting delays. First, we estimate a "county-level retail deposit beta" using data for all bank branches in a county:

$$R_{i,c,t} = \alpha_{i,c} + \text{RetailBeta}_c \cdot \text{FFR}_t + \varepsilon_{i,c,t} \tag{8}$$

where $R_{i,c,t}$ is the deposit rate for branch i in county c in month t, $\alpha_{i,c}$ are branch fixed effects, and the regression is estimated separately for each county. We winsorize the reported deposit rates $R_{i,c,t}$ at 99% percentile for each month to mitigate the impact of outliers, and we limit our sample to counties with at least two banks and 60 months of data and to branches with at least 20 months of data. The coefficient RetailBeta_c is the "county-level retail deposit beta," which measures the sensitivity of deposit rates in county c to the federal funds rate. We interpret counties with lower RetailBeta_c as having less competitive deposit markets, which enable banks to charge higher deposit spreads when the federal funds rate increases.

Second, we aggregate the county-level retail deposit beta RetailBeta_c to the bank level by taking a branch-weighted average across all counties for each bank:

$$\text{RetailBeta}_{b,t} = \frac{\sum \#\, \text{Branch}_{b,c,t} \times \text{RetailBeta}_c}{\sum \#\, \text{Branch}_{b,c,t}}. \tag{9}$$

Finally, we compute the time series average RetailBeta_b for each bank to use as our instrument for bank-level interest expense beta.

Identification Assumptions. A bank's retail deposit beta RetailBeta_b is determined by two sources: the bank's distribution across counties and the competitiveness of the

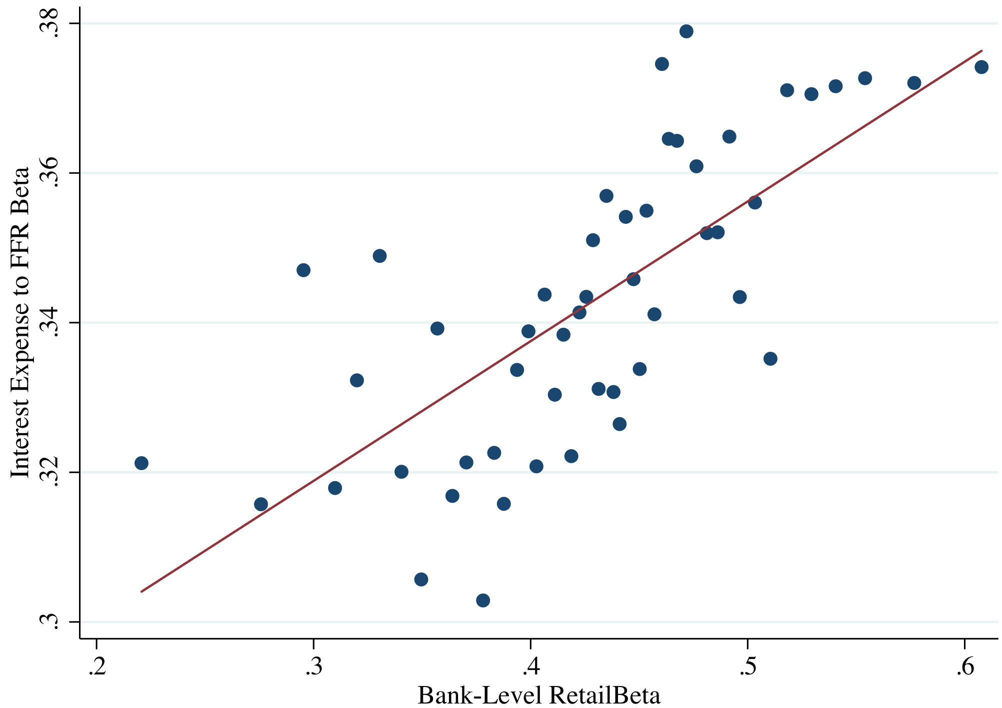
[17] We only use data for "rate-setting branches" that set deposit rates on their own.

retail deposit market in each county. The relevance assumption for this instrument is that banks operating in counties with less competitive deposit markets have higher market power and, thus, a lower interest expense beta. The exclusion restriction is that both the geographical distribution of banks and the competitiveness of local deposit markets only affect bank risk-taking through market power.

We note that the exclusion restriction relies on the strong assumption that the bank's geographical distribution is exogenous to risk-taking. The assumption is violated if investment opportunities in high-market-power counties are inherently less risky. Therefore, the retail beta instrument does not address this specific threat to the identification. However, we address this issue in two ways: first, by controlling for county-level riskiness defined in Section 3.1.1, and second, by examining a separate sample of one-county banks in Section 3.2.4 below.

Results. We first show the first-stage relationship between our instrument RetailBeta_b and interest expense beta IntExpBeta_b as a binned scatter plot in Figure 3, which shows a positive correlation between the two variables. A bank-level regression of IntExpBeta_b onto RetailBeta_b has a coefficient of 0.186 with F-statistic of 63.44 under robust standard errors, which exceeds the conventional threshold values of Stock and Yogo (2005).

Figure 3: First Stage: Interest Expense Beta and Bank Retail Beta



Note: 50-point binned scatter plot on data for 3430 banks.

Table 6 shows the 2SLS regression results. Column (1) shows that the 2SLS estimation for our main coefficient of interest (β of Equation 4) is 1.711 for log risk-weighted leverage: i.e., 0.1 unit lower interest expense beta is associated with 17% lower risk-weighted leverage. The coefficient is statistically significant with $t = 6.56$ with clustered standard errors at the bank and quarter level and is much larger than the OLS estimate of 0.554 in Table 2. Columns (2-3) show that the 2SLS coefficient of 0.793 for asset risk weight and 0.489 for log leverage are both statistically significant and larger than the OLS point estimates in Table 2.

Table 6: Risk Regression: 2SLS Results

	Dependent Variable: Risk Metrics		
	Log Risk-Wgt Lev.	Risk Weight	Log Lev.
	(1)	(2)	(3)
IntExp-FFR Beta	1.711**	0.793**	0.489*
	[6.555]	[7.529]	[2.614]
Log Assets	-0.0428**	-0.0185**	-0.0124
	[-3.440]	[-3.497]	[-1.456]
Deposit/Liability	-0.265**	0.0561*	-0.335**
	[-3.829]	[2.005]	[-6.843]
Log(# Branches)	0.0860**	0.0257**	0.0433**
	[5.906]	[4.249]	[4.479]
Log(County PC Income)	0.122**	0.0564**	0.0460*
	[3.830]	[4.388]	[1.989]
County Bus. Cycle Beta	0.0122	0.0190**	-0.0108
	[0.682]	[2.643]	[-0.833]
Multi State	-0.0289*	-0.00930+	-0.0122
	[-2.432]	[-1.790]	[-1.470]
Deposit Fee Income	-0.0326	-0.0417**	0.0264+
	[-1.625]	[-5.367]	[1.739]
Other Non-Interest Income	-0.00972	0.0000541	-0.00846+
	[-1.445]	[0.0178]	[-1.848]
Year-Quarter FE	✓	✓	✓
1st Stage F	149.097	149.097	149.097
# Banks	3430	3430	3430
Observations	194930	194930	194930

Note: Two-staged least squared regression based on Equation (4), with IntExpBeta instrumented by RetailBeta. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

3.2.4 One-County Banks with County-Time Fixed Effects

In order to further address the threat to identification due to the unobserved variation of investment opportunities and bank characteristics across geographical areas, we examine a separate sample of 2232 banks (1444 BHCs, 788 non-BHC banks) that only have deposit-taking branches in one county from 1996 to 2019. With the assumption that the one-county banks mainly take deposits and lend in the same county, we can add county-times-quarter fixed effects to the main regression (4) to absorb the unobserved county-level investment opportunities.

To begin with, Table 7 shows summary statistics for the one-county banks. These banks are generally smaller, accounting for 4.5% of total call report assets in an average quarter. Compared to the main-sample banks (Table 1), the one-county banks take slightly less risk: the average risk-weighted leverage is 6.32 for the one-county banks and 7.89 for the main sample banks, and the one-county banks also have a lower average loan loss rate. The one-county banks have a slightly lower average interest expense beta (0.318) compared to the main-sample banks (0.343).

Table 7: Summary Statistics: One-County Sample

Variable	Level	*N*	Mean	SD	Q10	Q50	Q90
Interest Expense Beta	Bank	2232	0.318	0.135	0.181	0.317	0.471
Risk-Weighted Leverage	Bank-Quarter	123333	6.32	2.49	3.28	6.15	9.48
Asset Risk Weight (%)	Bank-Quarter	123333	64.9	14.5	45.9	65.1	83.5
Raw Leverage	Bank-Quarter	123333	9.69	3.06	6.01	9.61	13.2
Annual Loan Loss Rate (%)	Bank-Quarter	122042	0.285	0.572	0	0.107	0.721

Table 8 shows the regression results for one-county banks. Among the control variables we use, only log assets and deposit-to-liability ratio vary within counties; we also control for an indicator of having only one branch. Column (1) shows the regression results for log risk-weighted leverage with only quarter fixed effects, and column (2) shows the results with county-times-quarter fixed effects. Comparing columns (1) and (2), we find that adding county-times-quarter fixed effects only reduces the main coefficient from 0.796 to 0.730, and the coefficient in column (2) is still highly significant with a *t*-statistic of 9.56. The results for asset risk weight and leverage in columns (3-6) show the same finding for these two components of risk.

Therefore, our results show that among the one-county banks, the relationship between market power and risk-taking is not driven by county-specific investment opportunities. We note two limitations of this analysis: first, the county-time fixed effects approach relies on the assumption that banks that take deposits in the same county also lend to clients in the same county; second, we cannot apply this approach to the main-sample banks that operate in multiple counties due to the lack of county-level asset-side data with risk metrics, and the results for one-county banks may not necessarily generalize to multi-county banks.

Table 8: Risk Regression: One-County Banks

	Dependent Variable: Risk Metrics					
	(1) Log Risk-Wgt Lev.	(2) Log Risk-Wgt Lev.	(3) Risk Wgt	(4) Risk Wgt	(5) Log Lev.	(6) Log Lev.
IntExp-FFR Beta	0.796**	0.730**	0.214**	0.182**	0.468**	0.442**
	[10.61]	[9.556]	[8.174]	[7.376]	[8.460]	[7.293]
Log Assets	0.0462**	0.0447**	0.0151**	0.00856*	0.0246**	0.0302**
	[5.229]	[4.557]	[4.348]	[2.315]	[3.604]	[3.626]
Deposit/Liability	-0.590**	-0.448**	-0.180**	-0.0870*	-0.325**	-0.354**
	[-5.163]	[-4.472]	[-3.982]	[-2.238]	[-3.978]	[-4.561]
Deposit Fee Income	0.0661*	0.127**	-0.0414**	-0.00632	0.124**	0.118**
	[2.566]	[4.247]	[-4.934]	[-0.580]	[6.445]	[5.802]
Other Non-Interest Income	0.00149	-0.0178	0.0173**	0.00500	-0.0240*	-0.0252**
	[0.121]	[-1.590]	[4.189]	[1.270]	[-2.331]	[-2.673]
Only One Branch	-0.150**	-0.136**	-0.0159**	-0.0206**	-0.116**	-0.0991**
	[-9.561]	[-9.438]	[-2.977]	[-4.021]	[-10.03]	[-8.642]
Time FE	✓		✓		✓	
County-Time FE		✓		✓		✓
Within R^2	.139	.116	.101	.046	.105	.09
# Banks	2232	2232	2232	2232	2232	2232
Observations	123333	123333	123333	123333	123333	123333

Note: Regressions based on Equation (4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

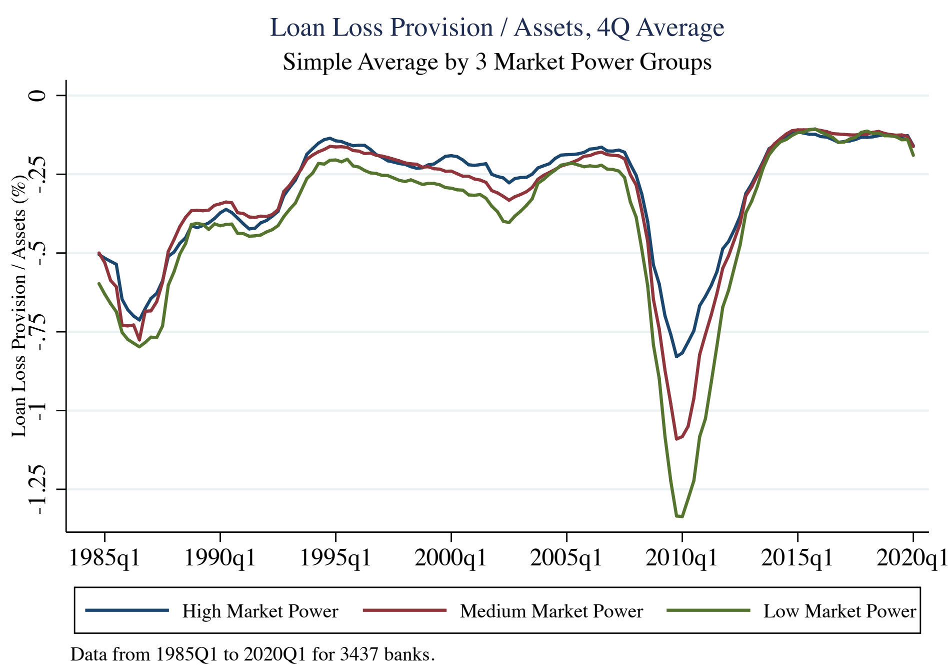
3.3 Market Power and Ex-Post Loan Loss

In this section, we examine the relationship between market power and ex-post loan loss and show that banks with higher market power have both lower levels and lower cyclicality of loan loss. These results complement our main finding on asset risk weight, which is an ex-ante measure of risk. Our results here also augment the similar findings of Li, Loutskina and Strahan (2019) with a different specification and different measure of market power.

We use the item "provision for loan and lease losses" on call reports (hereafter loan loss provision) to measure a bank's loss due to default. For each bank-quarter, we compute the ratio of loan loss provision to quarterly average assets and then take its average over the past 4 quarters to account for seasonality in the reporting of loan losses. Table 1 shows that for observations in our main sample, the average annual loan loss is 0.328% of total assets.

To begin with, we sort the 3437 banks in our main sample by their interest expense beta into 3 equal-sized groups, and compute the average loan loss to asset ratio for each group and quarter, as plotted in Figure 4. The comparison between groups shows that banks with high market power had significantly less loan loss during the financial crisis. From 2009Q1 to 2009Q4, the average loan loss is 0.83% of assets for the high market power banks and 1.33% of assets for the low market power banks. Moreover, the negative relationship between loan loss and market power is persistent over time.

Figure 4: Loan Loss Provision Rate and Market Power



Note: We sort banks into 3 equal-sized groups by interest expense beta. For each group-quarter, we compute the average loan loss to asset ratio and plot the rolling 4-quarter averages. Negative values indicate loan losses. Data covers 3437 banks in the main sample from 1985Q1 to 2020Q1.

We then formally test how market power is related to the level of loan loss. Table 9 shows results from running the main regression (4) with loan loss rate as the dependent variable (signed so that the losses are negative values). Column (2) of the table shows that after including all the main control variables—including measures of risk related to geographical distribution—a 0.1 unit lower interest expense beta is associated with 2.7

basis points lower loan loss, which is sizable compared to the average loan loss level of 32.8 basis points. In addition, columns (3-4) of the table shows regression results using data from 1996Q1 to 2006Q4, which shows that our results are persistent over time and are not simply driven by the financial crisis.

Table 9: Market Power and Loan Loss Level

	Dependent Variable: Loan Loss / Asset (%, Negative = Loss)			
	(1) 1996-2020	(2) 1996-2020	(3) 1996-2006	(4) 1996-2006
IntExp-FFR Beta	-0.418**	-0.269**	-0.332**	-0.321**
	[-5.606]	[-4.899]	[-6.363]	[-6.277]
Log Assets		-0.0284**		-0.00148
		[-2.739]		[-0.179]
Deposit/Liability		-0.0826		-0.0376
		[-1.390]		[-0.747]
Log(# Branches)		0.00956		0.00660
		[0.791]		[0.601]
Log(County PC Income)		0.185**		0.121**
		[6.065]		[4.874]
County Bus. Cycle Beta		-0.154**		-0.0522**
		[-5.487]		[-3.690]
Multi State		-0.0260*		0.00132
		[-2.312]		[0.123]
Deposit Fee Income		0.0472^{+}		-0.0550**
		[1.778]		[-3.548]
Other Non-Interest Income		-0.0123		-0.0599**
		[-1.136]		[-5.444]
Sample Period	1996-2020	1996-2020	1996-2006	1996-2006
Year-Quarter FE	✓	✓	✓	✓
Within R^2	.007	.02	.011	.04
# Banks	3437	3437	2682	2682
Observations	194149	194149	78665	78665

Note: Regressions based on Equation (4). The dependent variable is the loan loss provision divided by assets, signed so that negative values represent losses. The sample period is 1996Q1-2020Q1 for columns (1-2), and 1996Q1-2006Q4 for columns (3-4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Finally, we use the following regression to test how market power is related to the cyclicality of loan loss:

$$\text{Loss}_{i,t} = \alpha_i + \delta_t + \beta \cdot \text{IntExpBeta}_i \cdot \Delta_4 y_t + \gamma_1' x_{i,t} + \gamma_2' x_{i,t} \cdot \Delta_4 y_t + \varepsilon_{i,t} \tag{10}$$

where $\Delta_4 y_t$ is the real GDP growth rate from $t-4$ to t, α_i are bank fixed effects, and δ_t are quarter fixed effects. With bank fixed effects, the coefficient β captures how the *co-movement* between a bank's loan loss and GDP relates to the bank's interest expense beta: a higher β means banks with lower market power have more cyclical loan losses. The control variables $x_{i,t}$ are both directly included and interacted with GDP growth. Note that the GDP growth $\Delta_4 y_t$ and interest expense beta IntExpBeta_i are not included in the regression because they are absorbed by the fixed effects.

The estimates for β from regression (10) are reported in Table 10. Column (1) shows that the loan loss to GDP beta is increasing in interest expense beta, which confirms that banks with higher market power have less cyclical loan loss. Column (2) shows that the relationship survives direct and interacted controls, and columns (3-4) show that the result is robust in the 1996-2006 period and thus not purely driven by the financial crisis of 2007-2008.

Table 10: Market Power and Loan Loss Cyclicality

	Dependent Variable: Loan Loss / Asset (%, Negative = Loss)			
	(1) 1996-2020	(2) 1996-2020	(3) 1996-2006	(4) 1996-2006
$\Delta_4 y_t \times \text{IntExpBeta}_i$	0.176**	0.0533*	0.0687**	0.0585*
	[5.018]	[2.079]	[2.862]	[2.461]
Sample Period	1996-2020	1996-2020	1996-2006	1996-2006
Year-Quarter FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Basic Controls		✓		✓
Within R^2	.004	.036	.001	.009
# Banks	3437	3437	2672	2672
Observations	194149	194149	78655	78655

Note: Regressions based on Equation (10). Only the core coefficient of interest β is reported. The sample period is 1996Q1-2020Q1 for columns (1-2) and 1996Q1-2006Q4 for columns (3-4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

In summary, we show in this section that banks with higher market power have both lower levels and lower cyclicality of loan loss. These results show that the relationship between deposit market power and risk-taking is not limited to the ex-ante regulatory risk measure, but has a real impact on the financial performance of banks — and therefore the overall stability of the banking sector.

4 Zero Lower Bound

Banks benefit from deposit market power by charging a deposit rate lower than the market short rate. During the zero lower bound period from 2009Q1 to 2015Q4, the federal funds rate was kept at 0-0.25%, and the 1-year treasury yield was also near zero. Deposit market power becomes less relevant in this environment because there is little room for banks to charge positive deposit spreads. If banks expect the low-rate environment to persist, we should find a weakened link between deposit market power and risk-taking.

In this section, we show that the relationship between market power and risk-taking is indeed stronger when the interest rate is higher. In particular, the regression coefficient of log risk-weighted leverage on interest expense beta is 35% lower during the ZLB period compared to the non-ZLB period. These results support our main findings by showing that the market short rate — which determines the effectiveness of bank market power — plays an important role in the relationship between market power and risk-taking.

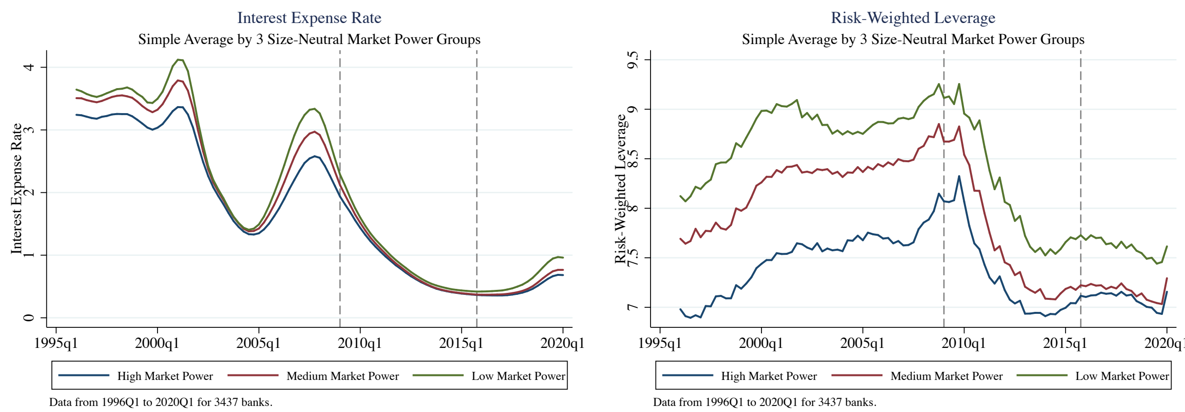
Motivating Evidence. To begin with, we sort the 3437 banks in our main sample into 3 size-neutral groups[18] by interest expense beta. For each of the 3 market power groups, we compute the average interest expense rate and average risk-weighted leverage for each quarter.

The left panel of Figure 5 plots the interest expense rates. The plot shows clearly that high market power banks could only charge significantly higher deposit spreads (i.e.

[18]We first sort the banks by their average assets into 5 groups. Within each size group, we then sort by interest expense beta into 3 groups. Each of the 3 groups by interest expense beta thus contains both small and large banks.

lower interest expense rates) when the interest rate is higher. During the ZLB periods, the interest expense rates for all banks are near zero, and there is little difference between high- and low-market-power banks. The right panel of Figure 5 then shows that the difference of risk-weighted leverage between high and low market power banks also shrinks during the ZLB period.

Figure 5: Market Power and Interest Expense (Left) / Risk-Weighted Leverage (Right)



Note: We sort banks into three size-neutral groups by interest expense beta. For each group-year, we compute the average interest expense rate (left, four-quarter averages) and risk-weighted leverage (right). Data covers 3437 banks in the main sample from 1996Q1 to 2020Q1.

Regression Analysis. We then formally test the difference between non-ZLB and ZLB periods by adding an interaction term to our main regression in Equation (4):

$$\begin{aligned}\text{Risk}_{i,t} = {} & \alpha_t + \beta_1 \cdot \text{IntExpBeta}_i + \beta_2 \cdot \text{IntExpBeta}_i \times 1\{\text{ZLB}\}_t \\ & + \gamma_1' \boldsymbol{x}_{i,t} + \gamma_2' \boldsymbol{x}_{i,t} \times 1\{\text{ZLB}\}_t + \varepsilon_{i,t} \end{aligned} \tag{11}$$

where $1\{\text{ZLB}\}_t$ is an indicator for the ZLB period from 2009Q1 to 2015Q4. Coefficient β_1 captures the relationship between interest expense beta and risk-taking in the non-ZLB period. Coefficient β_2 captures the additional relationship during the ZLB period. $\boldsymbol{x}_{i,t}$ includes the full set of control variables listed in Table 2. To ensure the interaction effect between ZLB and interest expense beta is not driven by other bank characteristics, we also include interacted controls $\boldsymbol{x}_{i,t} \times 1\{\text{ZLB}\}_t$ in some specifications.

Table 11 shows the coefficients β_1 and β_2 from the regression. Column (2) shows that in the specification with interacted controls, $\beta_1 = 0.654$ and $\beta_1 + \beta_2 = 0.386$ for risk-weighted leverage. That is, 0.1 unit lower interest expense beta is associated with 6.54% lower risk-weighted leverage in non-ZLB periods, but only 3.86% lower risk-weighted leverage in ZLB periods. Therefore, the relationship between market power and risk-taking is significantly muted during the ZLB period (by $\beta_2/\beta_1 = -41\%$).

Columns (4) and (6) further show that the ZLB interaction effect is present for both asset risk weight and leverage. In fact, the effect is stronger for leverage. Figure 7 in Appendix A shows that the difference in leverage between high and low market power banks gradually disappeared during the ZLB period. One explanation of this result might be that leverage is easier to adjust than the riskiness of long-term assets.

Table 11: Risk Regression: ZLB Interaction

	Dependent Variable: Risk Metrics					
	(1) Log Risk-Wgt Lev.	(2) Log Risk-Wgt Lev.	(3) Risk Wgt	(4) Risk Wgt	(5) Log Lev.	(6) Log Lev.
IntExp-FFR Beta	0.654**	0.645**	0.250**	0.252**	0.282**	0.271**
	[10.37]	[9.984]	[11.32]	[11.12]	[6.163]	[5.857]
IntExp-FFR Beta × 1{ZLB}	-0.268**	-0.233**	-0.0770**	-0.0800**	-0.174**	-0.133*
	[-4.192]	[-3.422]	[-3.530]	[-3.367]	[-3.448]	[-2.589]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Interaction Ctrls		✓		✓		✓
Within R^2	.119	.125	.103	.107	.067	.071
Observations	195225	195225	195225	195225	195225	195225

Note: Regressions based on Equation (11). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Further, the role of the market short rate in mediating the market power and risk-taking relationship is not limited to the ZLB period. To show this, we run the regression (11) with 4-quarter average federal funds rate FFR_t instead of the ZLB indicator. Columns (1-3) of Table 12 show the regression results for the entire main sample, and columns (4-6) show the regression results *outside* the ZLB period. For example, column (1) shows that the baseline association between interest expense beta and log risk-weighted leverage is 0.362, and this coefficient increases by 0.099 per 1 percentage point increase of federal funds rate; and column (4) shows that this result is robust over the non-ZLB period.

Table 12: Risk Regression: FFR Interaction

	Dependent Variable: Risk Metrics					
	Full Sample			Excluding ZLB (09Q1-15Q4)		
	(1) Log Risk-Wgt Lev.	(2) Risk Wgt	(3) Log Lev.	(4) Log Risk-Wgt Lev.	(5) Risk Wgt	(6) Log Lev.
IntExp-FFR Beta	0.362**	0.179**	0.0825+	0.306**	0.204**	0.00272
	[6.212]	[7.426]	[1.829]	[3.715]	[5.819]	[0.0543]
IntExp-FFR Beta × FFR	0.0985**	0.0216**	0.0696**	0.111**	0.0159*	0.0873**
	[6.985]	[3.654]	[6.287]	[6.277]	[2.099]	[7.682]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Interaction Ctrls	✓	✓	✓	✓	✓	✓
Within R^2	.128	.107	.073	.159	.117	.104
Observations	195225	195225	195225	130283	130283	130283

Note: Regressions based on Equation (11), with a 4-quarter average federal funds rate in place for the ZLB indicator. The sample period is 1996Q1-2020Q1 for columns (1-3) and is 1996Q1-2008Q4 and 2016Q1-2020Q1 (i.e., excluding the ZLB period) for columns (4-6). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

In summary, we show in this section that the relationship between market power and risk-taking is strongly driven by the short-term interest rate. In a higher-rate environment, banks benefit more from their market power by charging higher deposit spreads. At the same time, they make more prudent risk-taking decisions. These results provide further support that our results are driven by banks' deposit market power rather than other potential forces.

5 Model

In this section, we use a static model of bank franchise power to explain the relationship between deposit market power and bank risk-taking. In the model, deposit market power reduces the sensitivity of household deposit demand to deposit rate, allowing banks to charge higher deposit spreads and earn more profits. Banks face limited liability in the event of a default and deposit market power raises the franchise value of the banks. Expecting higher future profits, high-market-power banks choose to reduce their exposure to default risk by holding safer assets.

5.1 Model Setup

Deposit Demand. The deposit market consists of I identical depositors indexed by $i \in \{0, 1, ..., I\}$ and N banks indexed by $j \in \{0, 1, ..., N\}$. Bank j offers a deposit rate r_j^d and has other characteristics x_j. Deposit i receives utility $u_{i,j}$ if she deposits her wealth with bank j where

$$u_{i,j} = \eta_j r_j^d + (1 - \eta_j) x_j + \xi_{i,j}.$$

Depositors put a weight η_j on the deposit rate and a weight $(1 - \eta_j)$ on the bank's other characteristics (e.g., quality of service). The demand shocks $\xi_{i,j}$ are independent and follow a type-I generalized extreme value distribution with the cumulative distribution function $F(\xi) = \exp(-\exp(-\xi))$. By standard arguments, the probability of depositor i choosing bank j is given by the following logit choice model

$$s_j(r_j^d; \eta_j) = \frac{\exp(\eta_j r_j^d + (1 - \eta_j) x_j)}{\sum_k \exp(\eta_k r_k^d + (1 - \eta_k) x_k)}.$$

We consider the case where the number of depositors is large (i.e., $I \to \infty$) so that we can interpret $s_j(r_j^d; \eta_j)$ as the market share of bank j. The depositors' demand elasticity is given by

$$\frac{\partial s_j}{\partial r_j^d} \frac{r_j^d}{s_j} = \eta_j r_j^d (1 - s_j).$$

All else equal, depositors are less sensitive to bank j's deposit rate if η_j is low. Hence, we identify banks with lower η_j as having greater deposit market power.

Bank Risk-Taking. In addition, banks choose the riskiness of their asset portfolio. The return on bank j's assets is $(r + \theta_j)$ where r is the Fed Funds rate and θ_j is the risk premium earned by holding riskier assets.

However, risk-taking increases the likelihood of bank failures. The *survival* probability of bank j is given by the function $p(\theta_j)$. As in Allen and Gale (2004) and Boyd and De Nicolo (2005), we impose the following restrictions on $p(\cdot)$,

$$p'(\cdot) < 0, \quad p''(\cdot) \leq 0, \quad p(0) = 1, \quad p(\bar{\theta}) = 0.$$

First, $p(\cdot)$ is a decreasing function, as risk-taking increases the probability of bank failure. Second, $p(\cdot)$ is concave, which signifies a "decreasing return to risk-taking." As the risk premium θ_j rises, the bank needs to entail greater default risk in exchange for an additional risk premium. This condition is necessary to ensure that banks do not take on an infinite amount of risk. Third, if the bank invests all of its deposits in fed funds, it is free from default risk. Lastly, there exists an upper bound of risk-taking $\bar{\theta}$ such that the bank fails with certainty if $\theta_j \geq \bar{\theta}$. Importantly, these requirements imply that $-p'(\cdot)/p(\cdot)$ is an increasing function. For tractability, we will assume the following functional form of $p(\cdot)$ for some of the results proven in Section 5.2.

Assumption 1 *The survival probability is given by* $p(\theta_j) = 1 - \psi\left[\exp(\kappa\theta_j) - 1\right]$.

It is easy to verify that this function satisfies the four requirements on $p(\cdot)$ for positive values of ψ and κ. In this case, the risk-taking limit is $\bar{\theta} = \frac{1}{\kappa}\ln(1 + \frac{1}{\psi})$.

Bank's Problem. Bank j chooses its deposit rate r_j^d and risk-taking θ_j to maximize its expected profit

$$\max_{r_j^d,\, \theta_j} \quad p(\theta_j)(r + \theta_j - r_j^d)s_j(r_j^d; \eta_j), \tag{12}$$

which is the product of the bank's survival probability $p(\theta_j)$, its profit margin $(r + \theta_j - r_j^d)$, and its market share $s_j(r_j^d; \eta_j)$.

Banks face two trade-offs. First, by offering a higher deposit rate, the bank captures a larger share of the deposit market, but the profit margin shrinks. Second, by taking on more risk, the bank earns a higher risk premium on its deposit base, but the probability of default also heightens, in which case it has to forfeit profit $(r + \theta_j - r_j^d)s_j(r_j^d; \eta_j)$.

Market Power and Market Share. One might expect that high-market-power banks also have larger market shares, as market share and franchise value typically move in the same direction. Indeed, as shown in Table 13 in Appendix A, banks' market share and deposit market power are strongly and positively correlated in our sample. In the model, the market share of bank j is related to its deposit market power by

$$\frac{\mathrm{d}s_j(r_j^d;\eta_j)}{\mathrm{d}\eta_j} = s_j(1-s_j)\left(r_j^d + \eta_j\frac{\partial r_j^d}{\partial \eta_j} - x_j\right).$$

To replicate the empirical relationship between market power and market share, we assume that x_j is large enough so that $\mathrm{d}s_j/\mathrm{d}\eta_j < 0$.

Assumption 2 *The value of x_j is large enough so that $\mathrm{d}s_j/\mathrm{d}\eta_j < 0$ for all banks.*

5.2 Model Results

Deposit Rate. Now, we illustrate the key implications of deposit market power. Solving problem (12), the first-order condition with respect to the deposit rate r_j^d is,

$$(r + \theta_j - r_j^d)\eta_j(1-s_j) = 1. \tag{13}$$

The right-hand side represents the interest expense saved per unit of deposit when the bank lowers the deposit rate by a marginal unit. The left-hand side is the revenue lost because the bank's deposit base shrinks when it lowers the deposit rate. In particular, $\eta_j(1-s_j) = (\partial s_j/\partial r_j^d)/s_j$ is the response of depositors' demand to a decline in the deposit rate, divided by the deposit stock. In equilibrium, we have the following results regarding bank deposit rate setting.

Proposition 1 (Deposit Spread) *Bank j's deposit spread is increasing in its market power*

$$\frac{\partial(r - r_j^d)}{\partial \eta_j} < 0.$$

Proposition 2 (Interest Expense Beta) *Bank j's interest expense-FFR beta is decreasing in its market power*

$$\frac{\partial}{\partial \eta_j}\left(\frac{\partial r_j^d}{\partial r}\right) > 0.$$

High-market-power banks exploit depositors' insensitivity to their deposit rates and charge higher deposit spreads in equilibrium. In turn, the deposit rates they set are less sensitive to changes in the Fed Funds rate, which justifies our use of the interest expense-FFR beta as a measure of deposit market power. In this sense, deposit market power grants banks *franchise value* — if the bank does not fail, it can enjoy high profits derived from the market power.

Bank Risk-Taking. The first-order condition with respect to risk-taking is

$$p'(\theta_j)(r + \theta_j - r_j^d) + p(\theta_j) = 0. \tag{14}$$

The first term reflects the fact that default is more likely when the bank takes on more risk, in which case it forgoes the profit $(r + \theta_j - r_j^d)$. The second term is the extra profit earned through risk-taking, which only materializes if the bank does not fail. Intuitively, when a bank has greater deposit market power, its profit margin widens as the deposit spread $(r - r_j^d)$ is high. In this case, the first term in (14) becomes more dominant, and banks take on less risk to preserve their franchise value.

Formally, we have the following result that explains the cross-sectional relationship between deposit market power and bank risk-taking presented in Section 3.

Proposition 3 (Bank Risk-Taking) *Banks take on less risk when they have greater deposit market power*

$$\frac{\partial \theta_j}{\partial \eta_j} > 0.$$

Zero Lower Bound. We are also able to incorporate a zero lower bound on the deposit rate into the model. In practice, bank deposit rates are almost always between zero and the Fed Funds rate. In the model, it translates to the following constraint

$$1 \le r_j^d \le r.$$

When the Fed Funds rate approaches zero, all banks have to offer a deposit rate that is almost zero. In this case, deposit market power no longer matters. Plugging $r - r_j^d = 0$ into (12), the banks' problem becomes

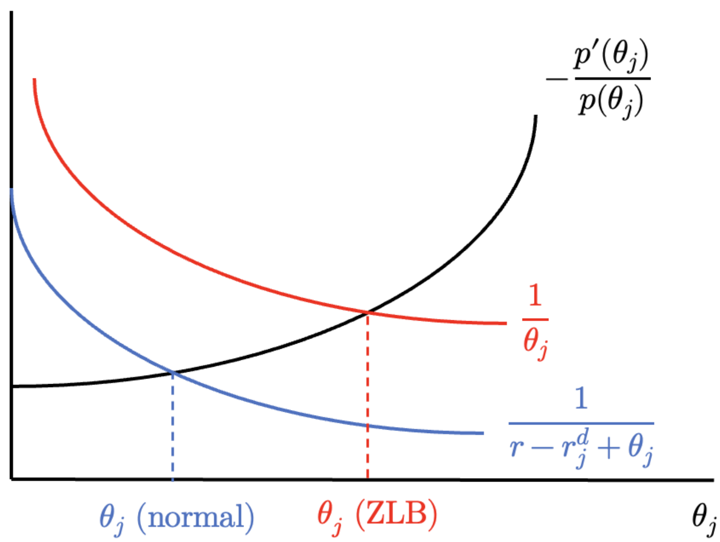
$$\max_{\theta_j} \quad p(\theta_j)\theta_j.$$

The optimal risk-taking now satisfies

$$p'(\theta_j)\theta_j + p(\theta_j) = 0. \tag{15}$$

Comparing the first-order conditions (14) and (15), it is clear that the zero lower bound forces the banks to charge a zero deposit spread, which depresses their franchise value and encourages risk-taking. We can immediately see the effect of a zero lower bound in Figure 6, a graphic representation of the equilibrium conditions (14) and (15).

Figure 6: Equilibrium Risk-Taking



Proposition 4 (Zero Lower Bound) *Banks take on more risk at the zero lower bound. Further, deposit market power has no predictive power of bank risk-taking at the zero lower bound.*

Ceteris paribus, a low-rate environment stimulates bank risk-taking, which is in line with existing studies (e.g., Whited, Wu and Xiao, 2021).[19] Furthermore, consistent with the empirical evidence presented in Section 4, deposit market power has less predictive power of bank risk-taking when the Fed Funds rate reaches zero.

[19] As shown in Figures 4 and 5, banks' risk-weight leverage and loan default rate have declined during the zero lower bound period. This is not necessarily contradictory to Proposition 4 as it is important to notice that banks also faced more stringent regulations and worse lending opportunities after the Great Recession, which we abstracted away in the model. Instead, we view the fact that deposit market power has less predictive power in this period as supportive evidence for the franchise value channel of deposit market power.

In practice, the effect of the zero lower bound will also depend on its duration, as banks base their risk-taking decisions on the present value of their future deposit market power. As shown in Section 4, low rates attenuated rather than completely nullified the effect of deposit market power. A potential explanation is that banks expect the low-rate environment to be persistent but not permanent, which is a distinction that we omitted in this static model.

Market Structure. Our theory suggests that deposit market power plays a disciplinary role in shaping bank risk-taking. Apart from the cross-sectional relationship between deposit market power and bank risk-taking, we can also leverage the model to examine the relationship between the competitiveness of the deposit market and the aggregate level of bank risk. To do so, we consider a symmetric equilibrium where banks are identical.

Assumption 3 *All banks have the same market power and other characteristics. That is,* $\eta_j = \eta, x_j = x$ *for all* j.

In this case, the market share of every bank is $s_j = 1/N$. We can consolidate the first-order conditions (13) and (14) into

$$-\frac{p'(\theta)}{p(\theta)} = \frac{N-1}{N}\eta.$$

Since $-p'(\cdot)/p(\cdot)$ is an increasing function, we see that banks take on more risk when their deposit market power is low or when the number of banks is large (e.g., when η or N increases). Both forces reduce banks' franchise value — a higher η indicates that depositors are more sensitive to deposit rates, and a higher N lowers the market share of the banks.

Proposition 5 (Market Competitiveness) *A more competitive deposit market is associated with greater bank risk and higher bank default probability (i.e.,* θ *is increasing in* η *and* N*).*

Therefore, our model implies a *competition-stability* trade-off. When the deposit market is more competitive, banks charge a lower deposit spread, and the pass-through of monetary policy to deposit rate is higher. In the meantime, banks have lower franchise value and take on more credit risk.

6 Conclusions

In this paper, we establish that banks with high deposit market power take on less risk. In particular, they choose lower leverages, safer loan portfolios, and sustain fewer loan losses. We provide various identification schemes and robustness checks to rule out endogeneity concerns. Our results shed light on an important interaction between deposit-taking and risk-taking — when market power increases profits from deposit-taking, banks curb their risk-taking in order to avoid default, so they can stay in the market and exploit their deposit market power. We illustrate this mechanism through a tractable model of bank franchise value, and our findings suggest that deposit market power plays a disciplinary role in shaping bank risk-taking.

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A Supplementary Results

Table 13 demonstrates the relationship between banks' local deposit market share and their deposit market power. The result suggests that deposit market power strongly and positively predicts county-level bank market share. Intuitively, large banks are more likely to have market power in the local deposit market.

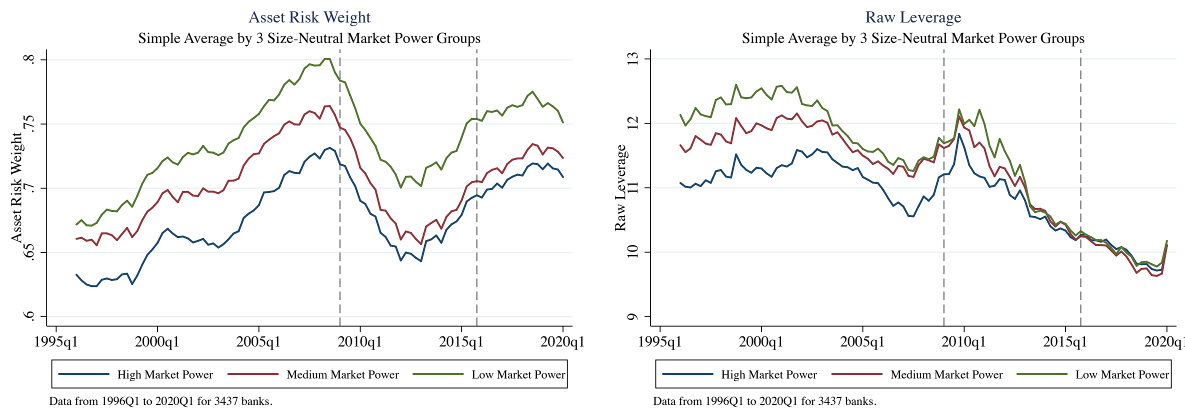
Table 13: Deposit Market Share and Interest-Expense Beta

	Dep Var: Log Avg. Deposit Mkt Share at Bank-Year Level	
	(1) Branch-Wgt	(2) Deposit-Wgt
IntExp-FFR Beta	-1.003**	-1.085**
	[-3.125]	[-3.281]
Log Assets	0.178**	0.183**
	[9.454]	[10.41]
Year FE	✓	✓
Within R^2	.035	.034
# Banks	3437	3437
Observations	50308	50308

Note: We use the Summary of Deposits data to compute market share at bank-county-year level, and then aggregate to bank-year level using the number of branches (column 1) or amount of deposits (column 2) as weights. We then regress log of average bank-level market share on interest expense beta and log assets, with year fixed effects to ensure cross-sectional comparison. t-statistics based on standard errors clustered at bank and year level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Figure [7](#) plots the time series of bank asset risk weight and raw leverage. The gaps between high-market-power banks and low-market-power banks narrowed significantly during the zero lower bound period, especially for raw leverage.

Figure 7: Market Power and Asset Risk Weight (Left) / Leverage (Right)



Note: We sort banks into three size-neutral groups by interest expense beta. For each group-year, we compute the average asset risk weight (left) and raw leverage (right). Data covers 3437 banks in the main sample from 1996Q1 to 2020Q1.

B More Robustness Results

In this appendix, we show that our results are robust to two alternative measures of deposit market power.

First, Table 14 replicates the main regression results (Table 2) using the deposit market Herfindahl Index (HHI) as the measure of deposit market power. Following Drechsler, Savov and Schnabl (2017) and Li, Loutskina and Strahan (2019), we first construct a county-level deposit market HHI using the FDIC Summary of Deposits data, which we then aggregate to the bank level using the number of branches as weights, as shown in Equations (16-17). A higher bank HHI means that a bank has more branches in counties with concentrated deposit markets.

$$\text{CountyHHI}_{c,t} = \sum_b \left(\frac{\text{Deposits}_{b,c,t}}{\sum_b \text{Deposits}_{b,c,t}} \right)^2 \tag{16}$$

$$\text{BankHHI}_{b,t} = \frac{\sum_c \#\text{Branch}_{b,c,t} \times \text{CountyHHI}_{c,t}}{\sum_c \#\text{Branch}_{b,c,t}} \tag{17}$$

Table 14: Main Risk Regression with Bank HHI as Market Power Measure

	Dependent Variable: Risk Metrics		
	(1) Log Risk-Wgt Lev.	(2) Risk Weight	(3) Log Lev.
BankHHI	-0.0278**	-0.0118**	-0.00987*
	[-5.348]	[-5.991]	[-2.584]
Log Assets	-0.000715	0.00121	-0.000688
	[-0.0773]	[0.317]	[-0.0993]
Deposit/Liability	-0.436**	-0.0222	-0.385**
	[-6.668]	[-0.825]	[-8.536]
Log(# Branches)	0.0568**	0.0119*	0.0355**
	[4.830]	[2.487]	[4.050]
Log(County PC Income)	0.00753	0.00493	0.0102
	[0.245]	[0.408]	[0.437]
County Bus. Cycle Beta	0.0438**	0.0340**	-0.00245
	[2.853]	[5.344]	[-0.209]
Multi State	-0.00291	0.00277	-0.00470
	[-0.282]	[0.612]	[-0.606]
Deposit Fee Income	-0.0738**	-0.0607**	0.0144
	[-4.082]	[-8.846]	[1.006]
Other Non-Interest Income	-0.00852	0.000574	-0.00807+
	[-1.311]	[0.201]	[-1.775]
Year-Quarter FE	✓	✓	✓
Within R^2	.095	.08	.06
# Banks	3437	3437	3437
Observations	195225	195225	195225

Note: Regression based on Equation (4), with bank-level deposit HHI (Equation 17) as measure of market power. HHI is cross-sectionally standardized for each quarter. t-statistics based on standard errors clustered at bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Second, other studies have also used the level of deposit spread as proxy for deposit market power (e.g., Balloch and Koby, 2022). Table 15 replicates the main results using the deposit spread as a measure of market power. We define deposit spread for a bank-quarter as the difference between the 4-quarter average Federal Funds Rate and the 4-quarter average of the bank's deposit expense rate, where the deposit expense rate is a bank's interest expense on deposits divided by total deposits. Banks with higher deposit market power will charge higher deposit spreads.

Table 16 further shows that the results based on bank HHI are robust to controlling for mortgage HHI, which proxies for a bank's loan market power.

Table 15: Main Risk Regression with Deposit Spread as Market Power Measure

	Dependent Variable: Risk Metrics		
	(1) Log Risk-Wgt Lev.	(2) Risk Weight	(3) Log Lev.
Deposit Spread	-0.114**	-0.0458**	-0.0445**
	[-10.92]	[-11.82]	[-6.419]
Log Assets	-0.00392	-0.0000614	-0.00196
	[-0.418]	[-0.0161]	[-0.281]
Deposit/Liability	-0.307**	0.0298	-0.334**
	[-4.807]	[1.144]	[-7.351]
Log(# Branches)	0.0645**	0.0151**	0.0384**
	[5.367]	[3.161]	[4.306]
Log(County PC Income)	0.108**	0.0465**	0.0480*
	[3.719]	[4.193]	[2.135]
County Bus. Cycle Beta	0.0578**	0.0398**	0.00286
	[3.867]	[6.445]	[0.244]
Multi State	-0.0148	-0.00210	-0.00919
	[-1.461]	[-0.477]	[-1.189]
Deposit Fee Income	-0.00178	-0.0319**	0.0430**
	[-0.0940]	[-4.540]	[2.955]
Other Non-Interest Income	-0.00283	0.00286	-0.00584
	[-0.452]	[1.045]	[-1.288]
Year-Quarter FE	✓	✓	✓
Within R^2	.122	.108	.067
# Banks	3437	3437	3437
Observations	194149	194149	194149

Note: Regression based on Equation (4), with deposit spread (federal funds rate minus bank deposit expense rate) as a measure of market power. *t*-statistics based on standard errors clustered at bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 16: Additional Robustness for Loan Market Power

	Dependent Variable: Risk Metrics		
	(1) Log(RWA/T1 Cap)	(2) Risk Weight	(3) Log(Asset/T1 Cap)
BankHHI	-0.0305**	-0.0149**	-0.00840*
	[-5.485]	[-6.788]	[-2.068]
Log Assets	0.00277	0.00192	0.000829
	[0.266]	[0.457]	[0.109]
Deposit/Liability	-0.402**	-0.00239	-0.379**
	[-5.977]	[-0.0869]	[-8.162]
Log(# Branches)	0.0487**	0.0104*	0.0313**
	[3.727]	[2.018]	[3.247]
Log(County PC Income)	0.00745	0.00730	0.00414
	[0.234]	[0.582]	[0.170]
County Bus. Cycle Beta	0.0462**	0.0354**	-0.00227
	[2.844]	[5.195]	[-0.184]
Multi State	0.00205	0.00280	-0.000569
	[0.204]	[0.628]	[-0.0733]
Deposit Fee Income	-0.0921**	-0.0612**	-0.00307
	[-4.725]	[-8.334]	[-0.198]
Other Non-Interest Income	-0.00555	0.00196	-0.00788+
	[-0.877]	[0.724]	[-1.665]
Mortgage HHI (STD)	0.0120**	0.0110**	-0.00432
	[2.648]	[6.998]	[-1.232]
Year-Quarter FE	✓	✓	✓
Within R^2	.093	.084	.058
# Banks	3197	3197	3197
Observations	171501	171501	171501

Note: Regression based on Equation (4), with bank-level deposit HHI (Equation 17) as a measure of market power, and with additional control of mortgage HHI as a measure for loan market power. Both HHI measures are cross-sectionally standardized for each quarter. t-statistics based on standard errors clustered at bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

C Proofs

In this appendix, we present proofs of Propositions 1-3, while the proofs of Propositions 4 and 5 are straightforward and already given in the main text. We start from the first-order conditions (13) and (14),

$$(r + \theta_j - r_j^d)\eta_j(1 - s_j) = 1,$$
$$p'(\theta_j)(r + \theta_j - r_j) + p(\theta_j) = 0.$$

Proofs of Propositions 1 and 3. Differentiating the first-order conditions with respect to η_j, we get,

$$\frac{\partial r_j^d}{\partial \eta_j} = \frac{\frac{r+\theta_j-r_j^d}{\eta_j}\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r+\theta_j-r_j^d)+2\right)\left(1+\eta_j(x_j-r_j^d)s_j\right)}{\left(1+(r+\theta_j-r_j^d)\eta_j\right)\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r+\theta_j-r_j^d)+1\right)+(r+\theta_j-r_j^d)\eta_j},$$

$$\frac{\partial \theta_j}{\partial \eta_j} = \frac{\frac{r+\theta_j-r_j^d}{\eta_j}\left(1+\eta_j(x_j-r_j^d)s_j\right)}{\left(1+(r+\theta_j-r_j^d)\eta_j\right)\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r+\theta_j-r_j^d)+1\right)+(r+\theta_j-r_j^d)\eta_j}.$$

Under Assumption 2, $x_j > r_j^d$, so

$$\frac{\partial r_j^d}{\partial \eta_j} > 0, \quad \frac{\partial \theta_j}{\partial \eta_j} > 0.$$

Proof of Proposition 2. Differentiating the first-order conditions with respect to r, we get

$$\frac{\partial r_j^d}{\partial r} = \frac{\frac{p''(\theta_j)}{p'(\theta_j)}(r+\theta_j-r_j^d)+1}{\left(1+(r+\theta_j-r_j^d)\eta_j s_j\right)\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r+\theta_j-r_j^d)+1\right)+(r+\theta_j-r_j^d)\eta_j s_j}.$$

Plugging in (13) and simplifying,

$$\frac{\partial r_j^d}{\partial r} = \frac{\frac{p''(\theta_j)}{p'(\theta_j)}(1-s_j)+\eta_j(1-s_j^2)}{\frac{p''(\theta_j)}{p'(\theta_j)}+\eta_j(1-s_j^2)}.$$

Under Assumption 1, the expression above becomes

$$\frac{\partial r_j^d}{\partial r} = \frac{\kappa(1-s_j) + \eta_j(1-s_j)^2}{\kappa + \eta_j(1-s_j^2)}.$$

Differentiating once more with respect to η_j,

$$\frac{\partial^2 r_j^d}{\partial \eta_j \partial r} = \frac{\kappa s_j(1-s_j^2) + \left[2\eta_j(\eta_j+\kappa_j)(1-s_j)^2 + \kappa^2 + \kappa\eta_j(1-s_j^2)\right](-\frac{\partial s_j}{\partial \eta_j})}{\left[\kappa + \eta_j(1-s_j^2)\right]^2}.$$

Under Assumption 2, $\partial s_j/\partial \eta_j < 0$, so

$$\frac{\partial^2 r_j^d}{\partial \eta_j \partial r} > 0.$$