Bye Bye Beta: Deposit Duration with Fixed Spreads

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Abstract

I document that deposit rates follow risk-free rates with fixed spreads of approximately 2 ppt and nearly complete long-run pass-through at high rates, challenging the conventional "deposit beta" framework. Valuing deposits using derivative pricing methods, I show that this option-like behavior alone generates large negative duration at low rates, without requiring negative cash flows or deposit runoff. These duration estimates successfully predict bank stock responses to monetary policy shocks ($R^2 = 10\%$), while existing measures fail. The framework resolves why deposit franchises switch from hedging to amplifying asset risk, why asset duration doesn't predict bank stock sensitivity, and why banks accumulated long-term securities when yield curves were flattest (2010–2021).

Keywords: duration, interest rate risk, deposit pricing, deposit spreads, franchise value

JEL classification: G12, G21

Are very low interest rates bad for banks? Banks and analysts seemed to think so — a typical equity analyst report from early 2022 lists "rates normalization" as a "reason for hope" for bank stocks (Morgan Stanley & Oliver Wyman, 2022).[1] And this fear of low rates motivated the dangerous build-up of long-term securities in Silicon Valley Bank (Federal Reserve Board, 2023).

But a straightforward look at the income statements of banks makes it hard to see why. DeMarzo et al. (2024) decompose bank income into a fixed positive stream and a floating positive stream. Fixed income values increase when rates fall, and floating income values remain constant. So the value of the bank should always benefit from lower rates. Were banks and analysts simply mistaken? Should regulators be assuming that interest rate cuts always increase bank equity value?

This paper shows that very low interest rates do indeed lower the value of banks, and that this emerges naturally from the structure of deposit interest payments. Specifically, I make three novel empirical claims. First, long-term pass through of the risk-free rate to demand deposit rates is higher than the banking literature has argued when interest rates are high, but nearly 0 when interest rates are near zero. Second, when deposits are modeled with this varying pass-through, the deposit franchise value drops at very low interest rates (i.e. duration can become negative) even before considering any fixed costs or deposit runoff. Third, interest rate exposure (duration) modeled on this basis closely matches the effect of rate changes on bank stock prices, identified from monetary policy shocks. This time-varying interest rate sensitivity explains why banks bought long-term securities when yield spreads were at their lowest in 2020-2021: as a hedge against interest rates staying low.

The mechanism can be illustrated by a simple example with a permanent depositor in a bank. Suppose the interest rate received by the depositor is some function of the risk-free rate: $f(r_t^f)$, and the risk-free rate is fixed at some low rate ε with certainty until time T.

[1] DeMarzo, Krishnamurthy, and Nagel (2024) also document that bank 10K disclosures state that higher rates will increase equity values

If we denote the value at time T of all future interest payments after time T by FV_T, then the value of the deposit interest payments is:

$$PV_0 = \underbrace{\frac{f(\varepsilon)}{\varepsilon} \times (1 - e^{-\varepsilon T})}_{\text{Value up to time T}} + \underbrace{FV_T \times e^{-\varepsilon T}}_{\text{Value after time T}}$$

The effect of a small increase in the near-term rate ε when ε is low will be:

$$\lim_{\varepsilon \to 0} \frac{\partial PV_0}{\partial \varepsilon} = T\left(f'(0) - FV_T\right)$$

If deposit interest rates are exactly linear, as in the standard "deposit beta" model in which $f(r) = \beta \times r$, then this derivative is zero and the value of deposits is always β (e.g. Drechsler, Savov, and Schnabl, 2021; DeMarzo et al., 2024).

However, the banking literature has shown that the "pass-through" of interest rates to deposit rates, $f'(r_t^f)$, varies depending on the interest rate (e.g. Kang-Landsberg, Luck, and Plosser, 2023; Greenwald, Schulhofer-Wohl, and Younger, 2023). In particular, pass-through seems to be near zero at very low rates, as deposits are squeezed up against the lower bound, i.e., $f'(0) \approx 0$. In this case, the value of the derivative will be negative. Increasing interest rates will drive down the value of deposits and increase in the value of the bank.

For illustration, consider if rates are held at 0 for 10 years ($T = 10$), pass-through is 0 at the zero lower bound ($f'(0) = 0$), and the value of a dollar of deposit interest rates after rate normalization is 80 cents ($FV_T = 0.8$). Then $\frac{\partial PV_0}{\partial \varepsilon} = -8$, and a 1 ppt increase in the interest rate will lower the value of bank deposit liabilities by 8%. If the bank is 10× leveraged, this translates to an 80% increase the value of equity. Higher interest rates drive up the value of the bank deposit franchise through the discount rate channel but drive down the value through the cash flow channel. If deposit rates are pinned at 0 and not sensitive to small changes in rates, then the discount rate effect dominates, leading to a large negative bank duration.

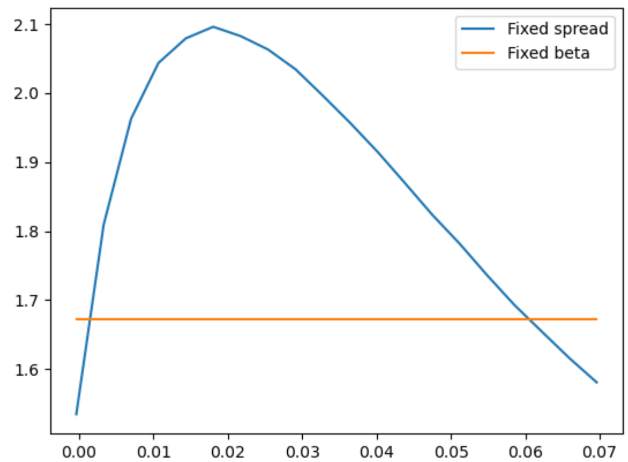

Figure 1: **Deposit value as a function of interest rate with fixed spread or fixed beta**. The blue line plots estimated franchise value of all US demand deposits divided by total book equity in 2019 Q4 if interest rates were shifted up or down from the actual rate of 1.6%, as calculated in this paper. The orange plots the value if calculated using a fixed deposit beta of 0.65 instead.

The rest of this paper calculates these deposit values and durations under realistic parameters, using real banking data and market prices, and level shifts of the whole yield curve. The intuition remains with this added complexity. The blue line in Figure 1 plots the estimated aggregate value of the deposit "franchise value" (i.e. $1 - PV(r_t^d)$) in 2019, scaled by book equity, if interest rates are shifted up or down. As rates become very low, the value of the bank deposit franchise can decrease sharply.

Other papers have also proposed that low interest rates can hurt bank valuations (e.g. Drechsler, Savov, Schnabl, and Wang, 2023; Greenwald et al., 2023). But they ultimately rely on either negative fixed cash flows or shrinking deposits to deliver the negative duration (DeMarzo et al., 2024). This paper demonstrates that low interest rates can lower bank value even though banks' deposit base is growing and fixed cash flows are positive. Greenwald et al. (2023) also considers the duration effects of varying deposit pass-through rates. But their framework values deposits assuming a constant interest rate, and so finds that deposit franchise duration is always positive when deposit runoff rates are 0.

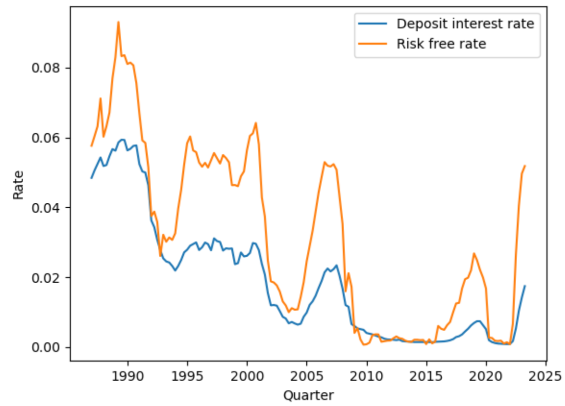

Figure 2: **Demand deposit rate and risk-free rate rate.** Aggregate quarterly rate of interest income on interest-paying savings and transaction deposits from the FFIEC call reports vs 1-quarter risk-free spot rate from Gürkaynak et al. (2007), 1987-2023.

The first step to calculate this negative bank duration is to model the deposit interest function. I find that in the long-term, savings deposit interest rates are better approximated by fixed spreads floored at zero, rather than fixed betas. That is $f(r_t^f) \approx \max\{r_t^f - \delta, 0\}$, instead of βr_t^f. The pass-through is roughly zero at low rates and one at high rates.

This pattern is supported by the time series of deposit interest rates from 1987–2023 (see Figure 2). While short-term pass-through is low (consistent with Drechsler et al., 2021), long-term pass-through is near complete. Viewed peak-to-peak or trough-to-trough, there seems to be a roughly consistent spread between deposit and risk-free rates from the high-interest-rate 1980s to today. A flexible econometric model that nests both fixed betas and fixed spreads strongly rejects low long-term betas, instead finding fixed spreads of around 2 ppt with substantial pass-through delays.

Valuing deposits with fixed spreads thus requires treating them as non-linear interest rate derivatives rather than simple floating-rate liabilities. Deposit rates function as call options on interest rates (or "caps" in fixed-income terminology), and their duration must be calculated using derivative pricing tools. I employ common, modern fixed-income derivative pricing tools calibrated to match prices of traded interest rate caps, allowing me to compute

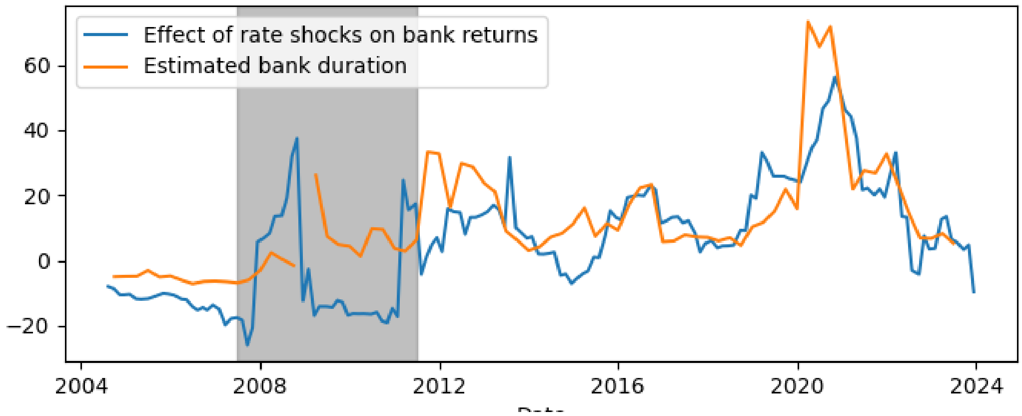

Figure 3: **Predicted (orange) vs observed (blue) effect of rate shocks on bank values.** The orange line shows the predicted interest rate risk of banks (i.e. negative duration – see Section E for details). The blue line shows the effects of high frequency monetary shocks to long-term yields on bank returns, measured by a rolling 2 year regression (details in Section 3). The financial crisis (2007 H2 - 2009 H1) is shaded in grey.

the market value and interest rate sensitivity of each bank's deposits in every quarter.

I then validate these duration estimates using high-frequency monetary policy shocks around FOMC announcements. The model's predictions match observed bank stock price responses with correct sign, magnitude, and high statistical significance ($R^2 = 10\%$ for announcement-day returns, excluding the financial crisis), as shown in Figure 3. In contrast, all existing bank duration measures—including those from DeMarzo et al. (2024), Begenau, Piazzesi, and Schneider (2015), and Haddad and Sraer (2020)—either fail to predict returns or predict them with the wrong sign. They fail because they focus on asset duration while missing the large, time-varying deposit franchise duration that dominates total bank interest rate exposure.

This framework resolves three puzzles about bank interest rate risk. First, it resolves whether the deposit franchise hedges asset interest rate risk (Drechsler et al., 2021) or amplifies it (DeMarzo et al., 2024). I show it can do both: it hedges when rates are low but adds risk when rates are high. Second, it explains why asset duration fails to predict bank stock price response to rate changes (Haddad and Sraer, 2020). Deposit duration is far more variable and ultimately more important. Third, it answers why banks accumulated long-term securities during 2010–2021 despite flat yield curves. These securities hedged their increasingly negative duration as rates fell.

The paper proceeds as follows. Section 1 presents the empirical model of deposit rates and estimation results. Section 2 develops the valuation framework and calculates deposit duration over time. Section 3 validates the duration measure against stock price reactions to monetary shocks. Section 4 examines the connection to banks' long-term securities purchases. Section 5 concludes.

1 Deposit spreads

Empirical work on bank deposits often assumes that deposit spreads are proportional to risk-free rates, i.e. a fixed deposit beta (e.g. Drechsler et al., 2021; DeMarzo et al., 2024).

However, this is not the only or obvious outcome of theory. Discrete choice models used in the industrial organization literature tend to deliver spreads that are roughly constant with respect to the risk-free rate. This is true for both simple logit-based exercises (e.g. Dick, 2008) and more thorough modeling of the competition between deposits and cash (Wang, Whited, Wu, and Xiao, 2022).[2]

This section therefore differentiates between the "fixed beta" and "fixed spread" models by testing a general model that allows deposit spreads to be fixed or proportional, and to have an arbitrary lag. In Appendix A I show that the empirical model can be derived from a discrete-choice model of bank competition with a zero lower bound.

1.1 Model

In this section I specify the simplest time-series model of deposits that allows for a) a delay in deposit pass-through, b) a 0 floor on deposit interest rates, and c) either fixed or

[2]E.g. figure 4 from Wang et al. (2022) shows that modeled pass-through is approximately 1 when the risk-free rate is over 2%.

proportional spreads

The time series of deposit rates, shown in Figure 2, clearly shows greater long-term than short-term pass-through — for example, deposit rates pictured in Figure 2 showed a small response to the sudden drop in risk-free rates in 2001, but seem to have mostly followed the long decline from 1990 to 2010. I therefore allow average deposit rates to follow a simple AR1 relationship with the short-term risk-free rate:

$$r_t^d = \gamma r_{t-1}^d + \beta(1-\gamma)(r_t^f - \delta) + \varepsilon_t \tag{1}$$

Where r^d is the rate of a deposit and r^f is the risk-free rate.

This is a standard AR1 equation with one exogenous variable. I have simply expressed the constant parameter as $\beta(1-\gamma)\delta$ and the coefficient of the exogenous variable as $\beta(1-\gamma)$ to give the variables intuitive interpretations. The parameter δ represents the long-term fixed spread between deposit rates and the risk-free rate, as we would expect in a simple discrete-choice model. The parameter β represents the long-term proportional spread as in Drechsler et al. (2021). And γ allows for delays in deposit pass-through, which have been empirically well documented since at least Hannan and Berger (1991).

If $\delta > 0$ this model would lead to negative deposit rates when the risk-free rate is low. Since in reality we do not observe any significant negative deposit rates, I add a second equation imposing that no depositors are paid less than 0. This can be interpreted as the result of competition with cash, or institutional or legal restrictions.

Since I only observe deposits at a bank level, aggregated across many types of depositors paid different rates (small, large, corporate, retail, etc), I must assume that there is some unobserved heterogeneity in rates represented by a depositor-specific error term (η_j). The observed deposit rate r_t^o is therefore given by:

$$r_t^o = E\left(\max\left\{r_t^d + \eta_j, 0\right\}\right)$$

Where E denotes the cross-sectional expectation across depositors.[3]

If I assume the cross-sectional distribution of deposit errors, η, is normal with variance s^2, then the observed rate is given by:

$$r_t^o = \beta(\widetilde{r}_t - \delta) \underbrace{\Phi\left(\frac{\widetilde{r}_t - \delta}{s}\right)}_{\text{Share paid} > 0} + \underbrace{\beta s \phi\left(\frac{\widetilde{r}_t - \delta}{s}\right)}_{\text{Adjustment from censoring lowest-paid}} \tag{2}$$

Importantly, this model nests the simple constant β model used in Drechsler et al. (2023), DeMarzo et al. (2024), and other papers, if $\delta = 0$ and $s = 0$.

While the motivation for the model is primarily empirical, I microfound this pattern of deposit rates from a simple discrete choice model in Appendix A.

1.2 Estimation

I fit equations 1 and 2 onto quarterly deposit interest rate data from 1987 Q1 to 2023 Q2 using maximum likelihood estimation. Bank Data is compiled from the FFIEC call reports.[4] For the bank-level analysis, I include data quality filters described in Appendix C.1. For quarterly risk-free rates, I use the treasury curve data from Gürkaynak et al. (2007).

I estimate the deposit rate function for interest-paying demand deposits only, covering approximately 70% of domestic deposits 2002–2023.[5] Time deposits and non-interest-paying demand constitute another 30% of deposits and are included separately in the calculation of bank value in Section 3.

[3]The contemporaneous paper Xu (2024) takes a similar approach to estimating deposit rate response to interest rate changes.

[4]The starting point for the SAS code to download the call report data was taken from Alexi Savov's website. I am grateful to Alexi and coauthors for making this code available.

[5]I combine savings accounts and interest-paying transaction accounts because the regulatory distinction between these accounts disappeared during the period under study.

Coefficient & description	Beta $\neq 1$	Beta $= 1$
δ Fixed spread	0.019	0.022
	(0.005)	(0.005)
β Long-term pass-through	0.940	1
	(0.110)	
γ Pass-through delay	0.788	0.788
	(0.031)	(0.040)
s Zero bound phase-in rate	0.017	0.019
	(0.004)	(0.006)
σ Error standard deviation	0.002	0.002
	(0.000)	(0.000)

Table 1: **Aggregate deposit parameter estimates.** Estimates from maximum likelihood estimation of model specified in Section 1.1 on the time-series of quarterly aggregate commercial-bank data from US call reports, 1987-2023. The right column shows the estimation restricted to impose a beta of 1. Numbers in parentheses show GMM Newey-West standard errors with 4 lags.

1.3 Results

Table 1 reports the estimated coefficients. It turns out that the fixed spread (δ) and pass-through rate (γ) parameters are tightly identified by the data. We can conclusively reject a 0-fixed-spread model for savings deposits with a high degree of statistical significance.

The long-term profitability and value of deposits comes from a fixed spread of approximately 2%. If we assume for some back-of-the-envelope calculations that the long-term discount rate is 5%, then the value of a permanent flow of the fixed spread would be $\frac{2\%}{5\%} = 40\%$ of the total book value of demand deposits. Hence the compression of this fixed spread as rates go to 0 will have a large impact on the value of the bank, as I will show in Section 2.

The long-term pass-through at high rates (β) does not seem to as important. The estimate is near 1. Indeed, the model restricted to impose $\beta = 1$ shows slightly better out–of–sample prediction ability (see results in Section 1.5). I therefore use the $\beta = 1$ model as the baseline for my calculations in the remaining section. At low rates, pass-through will be somewhat lower than 1 due to the zero floor and the cross-sectional variance.

I also estimate bank-specific coefficients, with results summarized in Appendix C.3. The average bank results are similar to the aggregate, although with considerable cross-sectional standard deviation. High δ is correlated with large size and high fixed costs, although, surprisingly, not with local branch concentration.

1.4 Comparison with Drechsler et al. (2021) and DeMarzo et al. (2024)

Previous work has found instead that deposits have a low β to the risk-free rate and no fixed spread. Drechsler et al. (2021) estimate that average bank interest expense has a beta of just 0.35, and DeMarzo et al. (2024) estimate that average deposit betas are approximately 60%.[6]

My findings differ for three reasons. First, I allow for spreads to follow an autoregressive process. Figure 4 plots the value of demand deposit rates vs the risk-free rates, with sequential points connected. Visually, the low short-term pass-through traces out a series of shallow lines with a slope of $< \frac{1}{2}$, but the long-term trend moves up down a much steeper slope of roughly 1. Drechsler et al. (2021) regress annual changes in deposit rates on risk-free rates, and thus measure this low short term pass-through instead of the long-term relationship. Their average β of 0.35 resembles the 1-year pass-through rate implied by my estimation of $\gamma^4 = 0.4$.

Second, I allow for a zero lower bound and non-linearity. There are no observations with negative deposit rates and a number of quarters with 0 risk-free rates. So a linear

[6] Aggregate deposit spreads are estimated as $r^f \times 0.24 \times assets$. Deposits are 60% of assets on average during the period, implying $1 - \beta \approx 40\%$

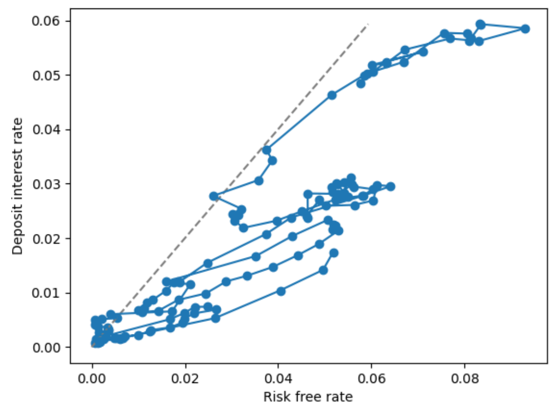

Figure 4: **Demand deposit rate and risk-free rate.** Aggregate quarterly rate of interest income on interest-paying demand deposits from the FFEIC call reports vs quarterly risk-free rates, 1987-2023. The dotted line shows the 45 degree line where $r^d = r^f$.

regression in levels will always find that the intercept (i.e. fixed spread) is 0. In other words it will interpret the fact that deposit rates did not become negative when risk-free rates were near–0 as proof that long-term pass-through is low rather than proof of a distinct lower bound.

DeMarzo et al. (2024) find a higher pass-through than Drechsler et al. (2021) because they run their regression in levels and allow for some time-series dynamics by incorporating swap rates. However, they still assume a linear relationship and hence find no fixed spread and a low pass-through.

Third, I run my analysis on interest-paying demand deposits only, whereas Drechsler et al. (2021) and DeMarzo et al. (2024) include all deposits. Aggregating all deposits would drive my β estimate down to roughly 0.8, but is problematic because it mixes long-term secular trends on deposit types with interest rate effects.

The share of domestic deposits that paid no interest saw a steady decline throughout the 1990s and 2000s from a peak of 23% in the late 1980s to 8% just before the financial crisis in 2007. This change mechanically increased the aggregate deposit rates as interest rates lowered. E.g. in 1989 savings deposits rates are 30 basis points above the aggregate deposit rate, but by 2007 they are 60 bp below it.

If we value a static deposit quantity based on this historical aggregate deposit rate rate, we would be implicitly assuming that if rates increase to their early 1990s levels, the share of non-interest-paying deposits will *increase.* This assumption seems implausible, since we would expect that a higher rate environment will lead depositors to be less willing to hold non-interest-paying deposits.

1.5 Goodness of fit

The censored autoregressive model fits the data well, even far out of sample. A more standard linear model, either estimated in levels or first differences, shows much greater prediction error.

Table 2 shows the R^2 and prediction error of the fitted model for savings deposit rates as well as simple linear regressions of savings deposit rates on the fed funds rate in levels and differences. In sample, the R^2 of the censored autoregressive model is 0.997, making its error variance 20× lower than the linear regression in levels.

To ensure that I am not overfitting, I test the out-of-sample prediction with a "leave-one-out," "leave-five-year-out," and "leave-ten-year-out" approach. For each quarter, I split the data into (a) an out-of-sample dataset of the following 1 quarter or 5 years of data and (b) an in-sample dataset of the rest. I then fit the model on the in-sample set and calculate the residuals for the last out-of-sample quarter.

The censored autoregressive model predictions hold up well even 5 years out of sample, with a $R^2 > 0.98$, and prediction error variance that is almost 4× lower than the linear model in levels and 6× lower than the linear model in differences.[7]

[7] The linear model in first differences works well over 1 quarter because of the high autocorrelation of the time series. But over the long term it fares poorly because it underestimates long-term pass through and predicts negative rates.

(a) In sample

	R^2	MAPE (ppt)
Censored AR model	0.997	0.102
Linear model	0.932	0.512

(b) Five year out of sample

	R^2	MAPE (ppt)
Censored AR model	0.951	0.268
Censored AR model (beta != 1)	0.950	0.275
Linear model (levels)	0.852	0.486
Linear model (differences)	0.726	0.597

(c) Ten year out of sample

	R^2	MAPE (ppt)
Censored AR model	0.938	0.248
Censored AR model (beta != 1)	0.936	0.252
Linear model (levels)	0.807	0.430
Linear model (differences)	0.304	0.947

Table 2: **In and out of sample goodness of fit statistics for linear models and the censored autoregressive model from Section 1.1**. Panel (a) provides the simple in-sample R^2 and mean average percentage error (i.e. average of the absolute value of fitted deposit rates minus observed deposit rates). Panel (b) provides results from a leave-one-quarter-out analysis. Panel (c) provides results from a leave-five-year-out analysis, using the residuals from the last quarter of the five-year out-of-sample period. Panel (d) provides the same for 10 years. The first quarter of data is dropped from panel (b), the first 5 years from panel (c), and the first 10 for panel (d)

2 Deposit value & duration

Fixed spreads have very different implications for value and duration than the deposit beta model. In this section I calculate the no-arbitrage value of deposit spreads modeled in Section 1 using derivative valuation tools and show that they can become highly sensitive to the risk-free rate. The value of the bank declines at either very low or very high rates. At low rates this effect hedges the interest-rate risk of bank assets. However the sensitivity can become so large that it "over-hedges" and the duration of the whole bank becomes negative.

2.1 Mechanism

When rates are very high, the value of deposit payments increases (and thus the value of the bank declines) because the payments become large. On the other hand, when rates are very low for a long time, the value can also increase because the value of future payments becomes large.

A simple example can illustrate this effect. Suppose a bank has 1 dollar of deposits, paid rate $r^d = r^f - \delta$. The deposit is invested into an asset paying r^f. Interest rates are known with certainty and will remain at a level $r^f = \epsilon < \delta$ for the next T years, after which, it will switch to its long-term permanent value of $r^f = 5\%$.

Because $\epsilon < \delta$, the bank is not paying any interest before time T. So any increase in the near-term risk-free rate ϵ just lowers the value of future deposit payments. Specifically, the value of a unit of permanent deposits is:

$$PV(r^d) = \left(\frac{1}{1+\epsilon}\right)^T \times \frac{5\% - \delta}{5\%}$$

Clearly this is a decreasing function of ϵ. And thus bank value is increasing in risk-free rates.

On the other hand, the the value of the assets' payment of the risk-free rate is always

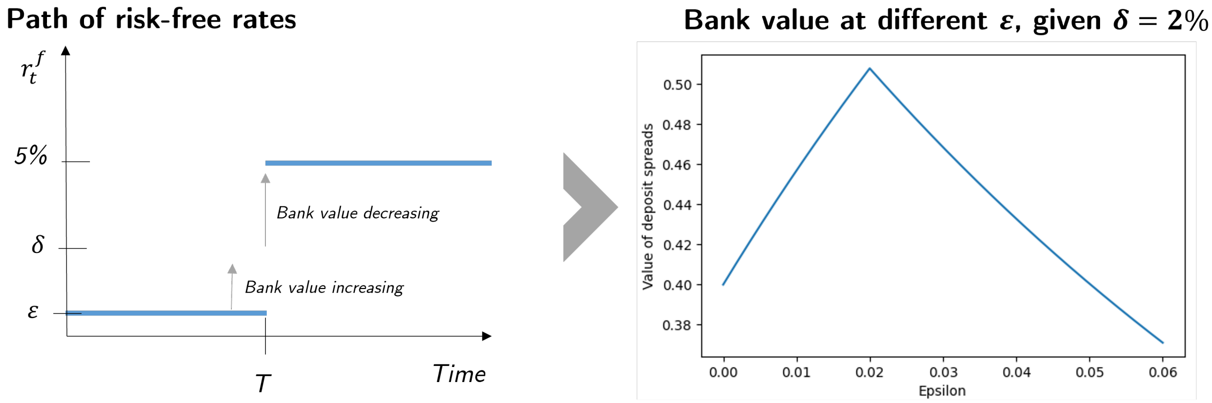

Figure 5: **Illustrative example of bank value under changes in the risk-free rate.** The left hand side shows the path of interest rates in the example described in the main body text. The right hand side shows the value of the bank if $\delta = 2\%$ and $T = 10$.

1. For example, applying the usual standard pricing formula in this case gives:

$$PV(r^f) = \left(1 - \left(\frac{1}{1+\epsilon}\right)^T\right) \times \frac{\epsilon}{\epsilon} + \left(\frac{1}{1+\epsilon}\right)^T \times \frac{5\%}{5\%} = 1$$

So the value of the deposit spreads (and thus the bank) is $1 - PV(r^d)$ and is increasing in the risk-free rate.

However, once near-term risk-free rate ϵ crosses above δ, the bank will start to pay deposit interest out in the near term, and any further increase will lower the value of the bank. So the value of the bank is "hump shaped" with respect to the risk-free rate with a maximum at $\epsilon = \delta$. Figure 5 plots this relationship if $\delta = 2\%$ and $T = 10$.

This hump shape does not depend on the particulars of the example — it applies for a very general structure of the forward curve, when interest rates is unknown, and there are a range of customers with different fixed spreads. It also applies to a level shift in both the short and long-term interest rate. In Appendix B I state and prove a general statement that low enough risk-free rates will always drive up the value of a permanent call option on the risk-free rate.

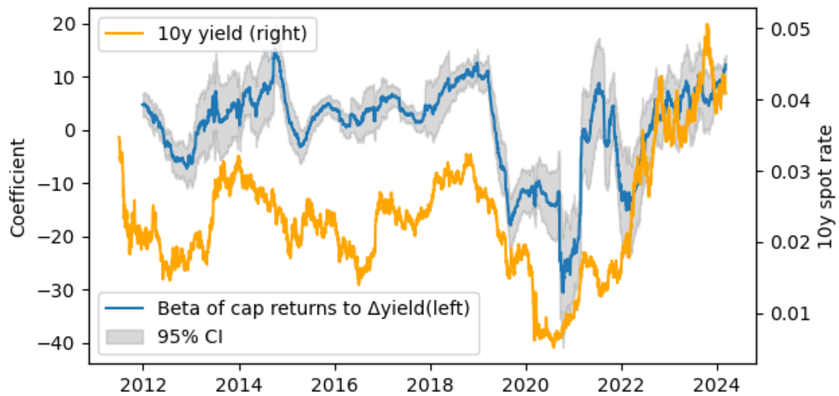

Figure 6: **Rolling regression of changes in permanent cap prices on changes in risk-free rates.** The blue line shows the coefficient from a regression of 1 quarter of daily changes in the price of a permanent 3% interest rate cap on daily changes in 10 year treasury yields. The orange line shows the 10 year treasury yield.

As a simple test that this hump effect is relevant empirically, we can check the quoted prices of caps from Bloomberg. Caps are quoted up to 30 years, so I create a simple "model-free" estimate of the value of a permanent cap, by taking the quoted price for a cap from 25–30 years at a 2% strike and assuming the forward price of the cap remains constant after 25 years.

Figure 6 shows a daily rolling regression of changes in the price of the permanent cap on changes in the 10 year treasury yield. As predicted, when interest rates are at their lowest, as in 2021, a decline in rates is associated with a decline in the call option value. And when rates are higher, an increase in rates is associated with a rise in the call option value.

2.2 Valuation methodology

Model

To calculate the value and duration of deposits, I need to calculate the value of a call options on the interest rates with a lag. I can estimate the price of a simple call option directly from quoted interest rate derivatives, but I will need to use an interest rate model to estimate the effects of changes in the risk-free rate (i.e. the duration).

Valuation also requires a few assumption about discount rates and growth rates. I follow DeMarzo et al. (2024) and value the deposits as a static quantity discounted at the risk-free rate. This is equivalent to assuming the growth rate and discount banks are equal. The aggregate book equity of banks has grown at a 7% average rate since 1987, which is within the range of typical equity risk premium assumptions. The constant growth assumption is a reasonable approximation because deposit interest rates are simply far more variable than balances and account for the vast majority of changes in cash flows. Deposit interest rates plus a fixed growth rate account for 98% of the time-series variance in the level of demand deposit cash flows since 1987.[8]

The financial industry has a set of common and well understood tools to measure the value and duration of interest rate derivatives. I use a Brace, Gątarek, and Musiela (1997) model, also known as the "LIBOR market model," one of the most popular interest rate derivative pricing models used in banks and investment firms (Brigo and Mercurio, 2007).

The advantage of this model is that it allows me to:

1. Measure the effects of arbitrary shocks to the yield curve
2. Exactly match quoted prices of interest rate caps from 1 to 30 years at a particular strike
3. Guarantee forward rates remain positive, or above some small negative number

I add two standard extensions to the model to better match quoted option prices: a "constant elasticity of variance" (CEV) and a shift of 1%.

In this model, each quarterly forward rate from 3 months to 30 years has a separate but correlated source of risk dB_t^T. Under the time T forward measure, the price of the forward

[8] R^2 from a regression of log dollar deposit interest expense on log deposit interest expense rate and year is 0.98.

expiring at time T follows the process:

$$dF_t^T = \left(F_t^T + 1\%\right)^{\eta} \sigma_T dB_t^T$$

The parameters of this model are:

- σ_T: volatility of the 3 month forward rate expiring at time T.
- 1%: A shift parameter to allow for small negative interest rates
- η: the CEV parameter and governs how the instantaneous volatility of forward relates to their level. If $\eta = 1$, the model is lognormal, if $\eta = 1$ it is normal and if $\eta = 0.5$ it is a square root process. This parameter is important to calculating the duration of the option — the lower the value of η, the less the value of a call option will increase when rates rise.
- The correlation matrix of the brownian motions for the different forward rates

Under any other measure, no arbitrage restrictions give a drift term to each forward rate that depends on their correlation. Collectively the forward rates can vary independently, but exhibit mean reversion. More details on the functioning of the Brace et al. (1997) model can be found in fixed-income derivative textbooks or MFE teaching material, for example Brigo and Mercurio (2007) or Lesniewski (2019).

The value of call options (i.e. caplets) can be calculated in closed form. If $\eta = 1$, they would follow the Black Scholes formula. With $\eta \in (0, 1)$ they follow a slightly different expression involving the χ^2 distribution that can be found in standard textbooks. Valuing the delay effect of deposit rates (i.e. γ from Section 1) requires a Monte Carlo simulation of interest rates.

Yield curve and cap price data is only available out to 30 years. I therefore assume the forward rates and forward prices of call options are constant after 30 years.[9]

[9] A short-lived dislocation in bond markets at the end of 2008 means that the estimated 30 year forward rate from Gürkaynak et al. (2007) at the end of 2008 is just 0.6%. This leads to very large estimates for

Calibration

The forward rates in each period are taken from the Gürkaynak et al. (2007) yield curve data. The correlation matrix of interest rate shocks is also calculated from the same data.

I choose the values of σ in each period that best prices 1–30 year interest rate caps with strikes from 1% to 3%, since this resembles the structure of the fixed spread value. Interest rate cap data is taken from the Bloomberg "Volatility Cube" and based on broker quotations.

Finally the CEV parameter η is calibrated from a regression of daily squared changes in forward rates on the level of forward rates. Taking the log of the squared forward rate process gives us:

$$\log\left(\left(\Delta F_t^T\right)^2\right) \approx \eta \times \log\left(\left(F_t^T + 1\%\right)^2\right) + \log\left(\sigma_T^2 \Delta t\right)$$

η can therefore be recovered from a regression of the log of daily changes in forward rates on the shifted log level. The calibrated value is 0.35, implying the process is somewhere between a normal and square root processs.

The model matches the market prices of call options whose payoffs very closely resemble deposit rates. So while it is not a perfect description of reality, I am only asking it to describe prices well locally around a specific set of quoted strikes and instruments.

Value calculations performed for interest rates far away from observed market rates, as in the illustrations in Figure 1 and 7, depend more on the accuracy of the model far away from quoted derivatives. They should be treated as conceptual illustrations rather than actual predictions of behavior under very large rate shocks.

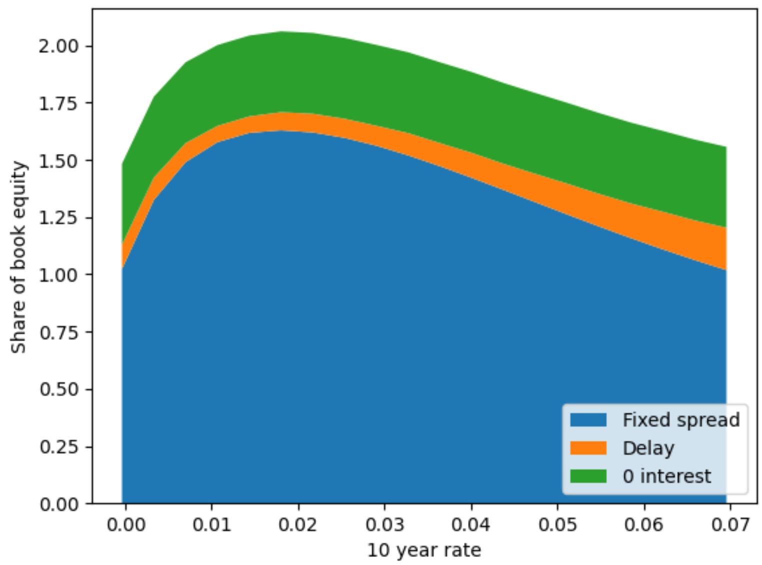

Figure 7: **Demand deposit value at different interest rates**. This figure plots what the estimated value of the deposit franchise would be after level-shifting the yield curve up and down, starting from 2019 Q4 values. The x-axis shows the 10 year spot rate after the level shift, and the y-axis shows the valuation as a share of book equity. The blue area shows the value of interest-paying demand deposits if the pass-through delay parameter (γ) were 0. The orange area shows the extra value from the pass-through delay. The green area shows the value of non-interest paying deposits.

2.3 Value and duration

Figure 7 shows how the value of deposits changes when the interest rate level is shifted up or down. To construct this figure I start with the banking system at year end 2019, shift the entire yield curve up or down, and recalculate the value of deposits. The x-axis denotes the 10-year spot rate after shifting the curve. The true 10 year spot rate was 1.6%.

The blue area shows the value of interest-paying demand deposits from the "pure call option" — i.e. the value if the pass-through delay parameter γ were 0. The orange area shows the value of the pass-through delay. The green shows the value of non-interest-paying transaction deposits. These have a franchise value equal to their book value because they never pay interest.

Four observations arise from the chart. The first is that the value of deposit spreads is large. We should expect any swings in its valuation to have large effects on bank wealth. On average 2002-2023, the value of deposit spreads is is 1.8× book equity. This is consistent with the average value calculated by DeMarzo et al. (2024).[10]

Second, most of the value comes from the interest rate cap. The delay is relatively unimportant. To a first approximation, the value of demand deposits is given by the value of a permanent call option.

Third, the values show the same hump shape described in Section 2.1. Value is maximized around $r^f = 2\%$ and declines at high or low rates. So the bank's risk and hedging incentives flip signs depending on the level of rates.

Fourth, the hump shape is much steeper on the low side. So the bank should be more concerned about interest rates in a very low rate environment as in 2021 than a very high one as in the 1990s. Although the specifics of the slope will depend on the full yield curve and the shape of th eshock being considered.

perpetuity values that likely do not reflect true discount rates. I therefore exclude this single quarter from the duration charts in the rest of this section.

[10] DeMarzo et al. (2024) calculate value before tax is 25% of tangible assets. Adjusting for a leverage ratio of 10× and a tax rate of 25% gives deposit value of 1.9× book equity.

This pattern helps explain a common sentiment in the industry and markets that low very low risk-free rates were bad for banks. For example, a typical equity analyst report from early 2022 lists "rates normalization" as a "reason for hope" for bank stocks, and sets price targets for on that basis (Morgan Stanley & Oliver Wyman, 2022). Similarly, DeMarzo et al. (2024) document that bank risk disclosures generally reported that they stood to benefit from interest rate increases during the low rate period.

3 Predicting the effects of monetary policy

Central banks need to be able to understand and predict how monetary policy will affect bank wealth and stock prices, both to monitor systemic financial stability, and to predict monetary policy transmission to credit provision (i.e. the bank balance sheet channel of monetary policy, as in Bernanke and Gertler, 1995; Jimenéz, Ongena, Peydró, and Saurina, 2012).

Fortunately, the effects of monetary policy shocks are measurable in retrospect because we know exactly when some of them occur. I follow the high frequency identification literature (e.g. Nakamura and Steinsson, 2018; Gürkaynak, Karasoy-can, and Lee, 2022) and treat 30 minute changes in interest rates around Federal Open Market Committee (FOMC) announcements as exogenous monetary shocks. We can then identify the effect on the value of publicly listed banks by simply regressing stock returns on these shocks. Public banks account for approximately 80% of bank assets, so this gives us a reasonable picture of the overall market.

I therefore start this section by constructing a measure of the expected effect of a "typical" monetary policy shock on total bank wealth. To do so, I calculate the duration of assets and other income sources of banks and add this to my measure of deposit duration.

I then show that this measure predicts the observed effects of monetary policy with the right scale and a high degree of statistical significance. In contrast, existing bank interest rate risk measures all fail to even predict returns with the correct sign. This prediction exercise validates that my measure of deposit value and interest rate risk is accurate.

This exercise also resolves the puzzle from Haddad and Sraer (2020): why does the duration of maturity and statutory assets not predict how market value of banks responds to interest rate changes? The answer, at least for recent years, is that the variation in deposit franchise duration measured in these paper overwhelms the asset effects measured by Haddad and Sraer (2020).

3.1 Constructing a measure

A typical monetary shock

To predict the effect of a monetary shock on bank value I first need to know how they change the yield curve. It is not exactly right to measure the effects of level changes to the yield curve as in Section 2, since monetary shocks are typically larger at the short end than the long of the curve (Jarocinski, 2024).

As a measure of "typical" monetary shock, I use using the first principal component of shocks to 4 different yields, accounting for 70% of variance. More specifically, I use the fed funds futures rate and 5, 10, and 30 year treasury futures, 2002Q3–2023Q2. Principal components of the fed funds forward and 5, and 10 year are often used to summarize and categorize monetary shocks (e.g. Swanson, 2021; Jarocinski, 2024). I add the 30 year rate as well because long-term yields are particularly important for bank and deposit valuation. Shock data is taken from Gürkaynak et al. (2022) up to 2019 and Jarocinski (2024) thereafter. I scale the principal component such that the effect on the 2 year treasury rate is 1.[11]

The deposit valuation described in Section 2 allows me to calculate the effect of arbitrary shocks to the yield curve. Since the high frequency data only identifies shocks to a few points on the curve, I need to fit some function to connect these points and fill-in the rest

[11] The long-term shocks to interest rates will be some combination of quantitative easing and forward guidance and information effects. I do not try to separate these because my interest rate risk measures are based on no arbitrage prices, and work equally well for risk-premium-driven shifts and expectation shifts.

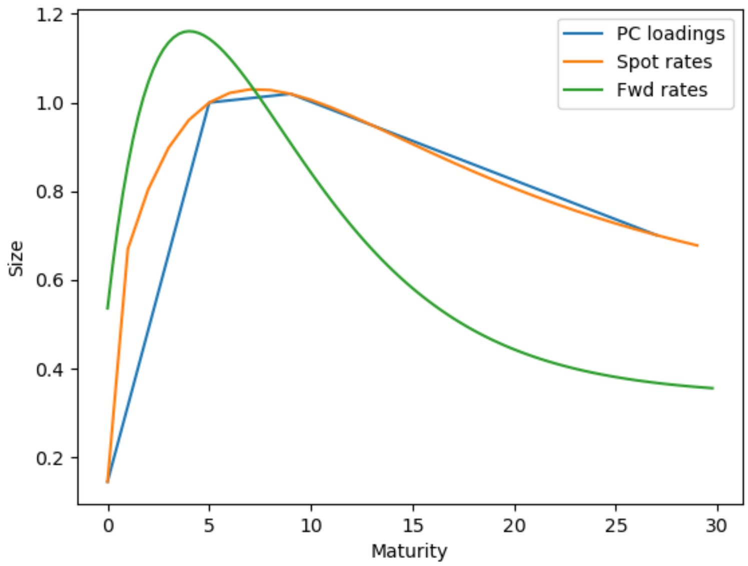

Figure 8: **1st principal component of rate shocks, and fitted shock to forward rates**. The blue line plots the first principal component of high frequency shocks to the fed funds futures rate and the 5, 10, and 30 year treasury futures rate. The orange line plots the fitted shock to the spot curve and the green plots the fitted shock to the forward curve.

of the rate-shocks. I fit a a Nelson-Siegel function that exactly matches the shape of the principal component.

Figure 8 shows the first principal component of observed shocks, and the fitted yield curve shocks. The shock is scaled to have size 1 at 5 years and follows the Nelson-Siegel function:

$$fwd_t = \beta_0 + \beta_1 e^{-t/\lambda} + \beta_2 \left(t/\lambda\right) e^{-t/\lambda}$$

I use daily bank stock returns to measure the effect of these returns on banks. Returns data is taken from CRSP and linked to call report data using the RSSD ID to permco linking file provided by the New York Fed. I use daily changes in bank stock prices instead of returns from the 30 minute announcement window. This adds noise but should not introduce any endogeneity problems and has the benefit of allowing for banks that might not have high liquidity during 30 minute windows.

Total bank duration

A full picture of the effects of monetary policy on bank wealth requires us to calculate the contribution of assets, and all other sources of bank income and costs.

I calculate the duration of the assets on the balance sheet using data on maturities and interest income from the Call Reports. I use standard bond pricing formulas to calculate the value and duration of non-mortgage loans and securities and use mortgage-backed security (MBS) index pricing data for mortgage loans and securities. Appendix D describes the methodology and results. In total, asset duration rises from roughly 1 year in 2002 to 2 years in 2023. Since banks are leveraged roughly 10× on average, this adds 10-20 years to bank duration.

The duration of non-asset, non-deposit cash flows is more challenging to estimate. These include costs, fees, profitability of new loans, any future governmental transfers or levies, etc. In my base case I assume that all of these sum to a perpetuity in expectation. I narrow my focus to publicly listed banks (representing roughly 80% of bank assets) and calculate the perpetuity size that delivers the market capitalization of the bank. The perpetuity duration is then my estimate of duration for the non-asset, non-deposit value. This approach of choosing a constant long-term cash flow to match equity prices is analogous to the approach used in the equity implied duration literature, specifically Dechow, Sloan, and Soliman (2004) and Weber (2018).

The estimated perpetuity value is around 0.2% of assets pre-crisis and around −0.8% of assets post-crisis. The net impact is that estimated bank duration is lower post-crisis. This is reasonable, because the drop in market prices of banks after the financial crisis must translate to higher discount rates or low cash flow expectations, either of which lowers duration.

My estimation is relatively robust to the choice of assumption on non-asset non-deposit duration. DeMarzo et al. (2024) instead use historical regressions to estimate that the long-term value of lending spreads minus costs is around 0 for the average bank. As a robustness test, Figure 15 in Appendix F calculates the measure of monetary policy sensitivity with this 0 assumption instead. The results are broadly similar — the choice of assumption will shifts duration up or down, but not change the overall pattern. A full description of the methodology and its results are in Section E.

For the regression analysis, I use estimated sensitivities using the last complete quarter of balance sheet data before the date of the FOMC announcement (e.g. I use March data and duration estimates for an announcement in April). Cash flow sensitivity parameters are estimated for each bank using the whole time series of data, as described in Section 1. This is meant to capture the best possible estimate of deposit sensitivity — investors may have information on deposit interest rate sensitivity available to them through annual reports, analyst calls, and customer surveys that is richer than the simple time series employed in this analysis. As a robustness test in Appendix H I recalculate the aggregate regressions using expanding window estimates that do not use any future data.

3.2 The duration time series

Figure 3 plots the resulting estimate of the effect of monetary shocks on deposit value and on total bank value. As in the stylized example from Section 2.1, the exposure of the bank to a rate rise is positive when rates are low and a small negative when rates are high. The overall bank duration time series resembles the deposits-only time series, but scaled up somewhat due to the effect of the non-asset non-deposit income perpetuity assumption.

The peak values are large relative to the value of banks — in 2020 they imply that a single percentage point drop in interest rates would lead to up to a 75 ppt drop in the market-to-book of banks. As a comparison point, the drop in bank market to book during the Covid pandemic was just 60 ppt from Q4 2019 to Q1 2020. The interest rate hedging incentives of banks therefore change dramatically over time.

The swings in duration are also macroeconomically large in dollar terms. At peak, in

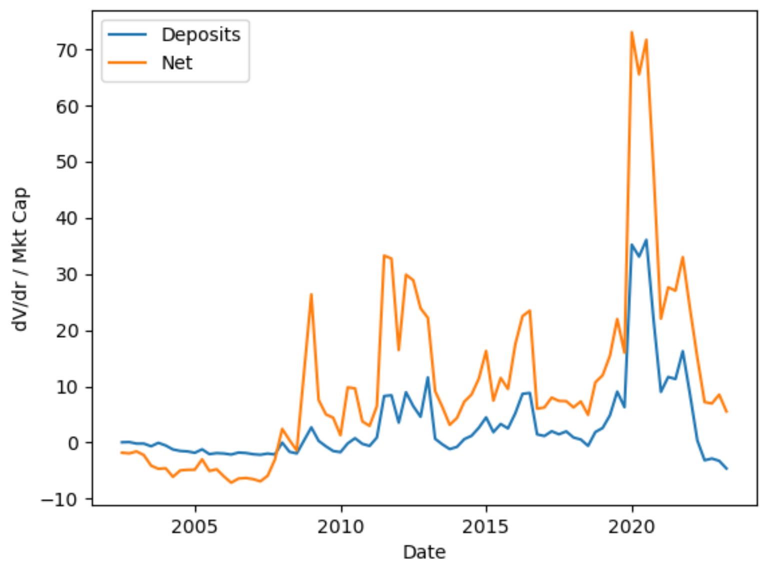

Figure 9: **Aggregate duration of deposits and of the total bank, scaled by market cap, 2002 Q3 – 2023 Q2**. The blue line plots the estimated derivative of deposit value with respect to a monetary shock, divided by market cap (i.e negative duration) of all publicly listed US banks. The orange line plots the the total duration including assets ans non-asset non-deposit income.

2020 the aggregate value of banks increased approximately \$14 BN per basis point rise in rates. By the 2023, that number dropped down to \$1.3 BN. For comparison, the dollar duration per basis point of all Fed holdings as of 2023 are only roughly \$4.5 BN[12]. So in a few years the swing in in public bank interest rate sensitivity added more than twice as much duration to the public balance sheet all aggregate QE had removed.

This variation in bank interest rate risk is substantially larger than any other important sources of time-variation in duration identified in the finance literature. Mortgage-backed-securities prepayment risk and insurance company convexity and duration mismatch are two key factors often credited for driving investor interest rate exposure and long-term yields (e.g. Hanson, 2014; Carboni and Ellison, 2022; Domanski, Shin, and Sushko, 2017). In Appendix G I show that swings in bank duration are larger and more persistent than either of these sources, with variation around 10× higher.

3.3 High frequency regression

Aggregate results

Figure 3 compares the effect of interest rate shocks, measured using a rolling regression of 20 announcements (2.5 years), to my measure of bank interest rate risk. There is a clear and consistent relationship between my measure and the effects of shocks outside of the financial crisis period. This result is not just a peculiarity of the announcement days. In Appendix H, I repeat this plot using all days and show it follows the same pattern.

To confirm and test this relationship, Table 3 shows a time-series regression of banking sector returns on the interaction of measured interest rate risk with rate shocks. If the duration measure is accurate, then the coefficient on the interaction term should be near one and highly significant.

The results are highly significant, all with p values under .01. They are also of the correct scale, with coefficients of almost exactly 1. Of course it might be possible to

[12] Wan and Becker (2024) estimates fed holdings as \$5.5 TN in 10-year Treasury equivalents. I assume 10-year Treasuries have a duration of 8 for this simple calculation

	Full Sample			Fin. Cris. excluded		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Rate sens. × rate shock	1.274**	1.082**	0.442**	1.169***	1.194***	0.607***
	(0.416)	(0.330)	(0.152)	(0.313)	(0.350)	(0.163)
Rate shock	-7.417	-9.214+	2.934	-4.650+	-6.172*	2.404
	(7.432)	(5.239)	(2.375)	(2.377)	(2.771)	(2.077)
Rate sensitivity	0.003	0.005	-0.002	0.005	0.004	-0.001
	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
ΔIG spread		23.603***	12.062***		11.783	10.133
		(4.849)	(2.533)		(16.912)	(9.300)
ΔHY spread		-10.219*	-2.889		-3.348	-2.383
		(5.148)	(1.869)		(3.786)	(1.738)
Market return			1.527***			1.249***
			(0.144)			(0.117)
Intercept	0.179	0.013	-0.132	0.103	0.095	-0.057
	(0.178)	(0.202)	(0.081)	(0.128)	(0.126)	(0.071)
Num.Obs.	168	168	168	152	152	152
R2	0.062	0.197	0.839	0.104	0.117	0.735

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: **Aggregate measured duration predicts bank stock price response to interest rate shocks.** This table shows results from regressions of banking sector returns on FOMC announcement days on monetary shocks to long-term interest rates, Q3 2002 – Q2 2023. "Rate sensitivity" is the measured interest rate exposure of the aggregate banking system, described in Section E. "Rate Shock" is the change in the 10 year treasury yield in the 1-hour window around FOMC announcements from Gürkaynak et al. (2022). "Δ IG spread & HY spread" denote controls for daily changes in the ICE BofA option adjusted investment grade or high yield credit spread index. "Market return" is a control for the CRSP total market daily return. All columns exclude duration calculated using Q4 2008 and columns 4–6 exclude H2 2007 – H1 2009. All standard errors are Newey West with 3 lags.

arrive at similar interest rate risk predictions by some other means (e.g. high fixed costs or discount rates), but this at least serves as some validation that the deposit valuation calculations from sections 1 and 2 are not unreasonable.

Effects are generally more robust when the financial crisis and its immediate aftermath are excluded (columns 4-6). Bank stocks were highly volatile during this period and investors were likely to be parsing federal reserve announcements for information about the nature of bank assistance programs, adding noise and possibly endogeneity into the relationship.

The effects are also quantitatively important for explaining the overall variation in the value of banks. Excluding the financial crisis, the duration and the 1 hour interest rate shock explains a full 10% of the variance in daily bank returns (see R^2 in column 4). This is not just because interest rate shocks are large on FOMC days — a simple regression of all daily stock returns on daily rate changes $\times$ duration also shows a similar R^2.

One potential concern could be that monetary shocks impact bank value through credit spreads and loan default expectations rather than interest rates. I control for this channel by adding daily changes in high yield and investment grade credit spreads (the ICE BofA option adjusted spread index) into the regression as controls in columns 2 and 5, with little effect.

I also control for market returns in columns 3 and 6 to demonstrate that the observed patterns reflect bank-specific effects rather than solely general market movements. Other stocks of course have interest rate risk as well, so the coefficient after controlling for market returns should be interpreted with caution — it no longer represents a pure bank interest rate risk measure.

Bank-level results

Table 4 shows the results of a regression of individual bank returns on interest rate shocks interacted with measured bank duration. The coefficient on the interaction term is again highly significant, although with a coefficient closer to 0.5 than 1 (columns 1 and 4).

To show that the effects are not purely driven by the time-series, i.e. that cross-sectional differences in measured interest rate risk predict cross-sectional differences in share price response, columns 2 and 5 include time fixed effects. After excluding the volatile financial crisis period, the cross-sectional results are borderline significant, although substantially less than 1, perhaps due to measurement error.

Just as for the time-series results, the results are not driven by credit spreads or whole market returns. Columns 3 and 6 show the results including bank-specific controls for credit spreads and market returns (i.e. interactions of bank dummies $\times$ spread changes or returns), which remain significant when excluding the financial crisis period.

To avoid the results being skewed by small banks with low daily liquidity and non-standard business models, the regressions in Table 4 is weighted by each bank's share of total sector market capitalization. I have also excluded a few banks with non-commercial-banking business models (e.g. investment banks, custodians).

Comparison with other duration measures

Other measures of bank duration in the finance literature tend to move in the opposite direction from this paper's results because they do not include the large, concave deposit value. They do not match the high frequency shock data — in fact most tend to predict bank stock price reactions in the wrong direction.

I consider three alternative bank interest rate risk measures that I can reproduce or extract from other papers: the measures calculated in DeMarzo et al. (2024) and Begenau et al. (2015), and the "income gap" used, for example in Haddad and Sraer (2020). Figure 10 plots these measures together — it is clear that they reach their minima as this paper's measure reaches its maxima.

These measures move in the opposite direction from mine because they are focused on the bank's assets rather than its franchise. DeMarzo et al. (2024) estimate that for the

	Full Sample			Fin. Cris. excluded		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Rate sens. × rate shock	0.523**	0.071+	0.067+	0.684**	0.125+	0.119*
	(0.180)	(0.038)	(0.035)	(0.207)	(0.068)	(0.059)
Rate shock	-5.271			-3.837		
	(6.645)			(2.873)		
Rate sensitivity	0.003	0.003	0.004	0.005	0.003	0.005
	(0.009)	(0.003)	(0.003)	(0.010)	(0.003)	(0.004)
Intercept	0.302+			0.117		
	(0.174)			(0.134)		
Num.Obs.	55230	55230	55230	49698	49698	49698
R2	0.027	0.768	0.804	0.047	0.736	0.765
R2 Within		0.002	0.003		0.003	0.004
FE: Date		X	X		X	X
FE: Bank			X			X
Bank × spread & market			X			X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: **Value-weighted duration of all public banks predicts stock price response to interest rate shocks.** This table shows results from regressions of the returns of 15 large commercial banks on FOMC announcement days on monetary shocks to long-term interest rates, Q3 2002 – Q2 2023, weighted by share of total market cap. Banks with non-commercial business models are excluded as described in Section 3.3 and the rate sensitivity measure is winsorized at 1%. "Rate sensitivity" is the measured interest rate exposure of the aggregate banking system, described in Section E. "Rate Shock" is the change in the 10 year treasury yield in the 1-hour window around FOMC announcements from Gürkaynak et al. (2022). Date fixed effects are included in models 2, 3, 5, and 6. "Bank × spread & market" denotes that controls have been added for bank id interacted with daily changes in IG and HY credit spreads (using the ICE BofA index) and CRSP total market returns. All columns exclude duration data calculated using Q4 2008 and columns 4–6 exclude H2 2007 – H1 2009. All standard errors are clustered by date.

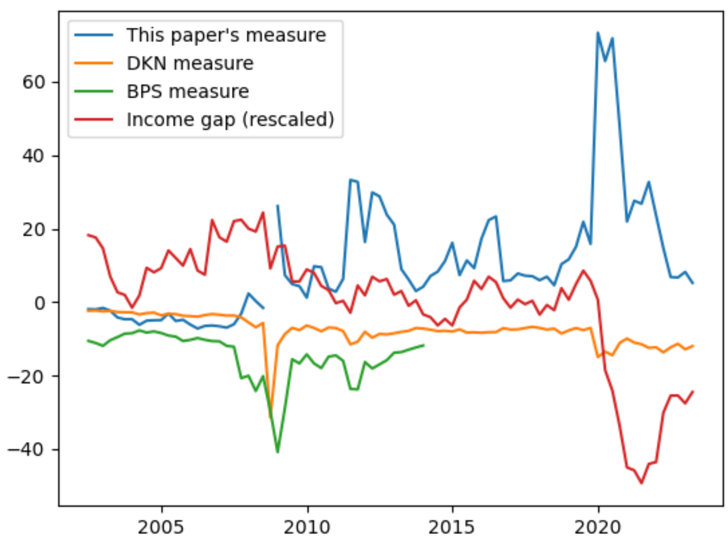

Figure 10: **Different bank interest rate risk measures**. This chart shows calculated interest rate sensitivity (i.e. negative duration) estimated from this paper (see section E), DeMarzo et al. (2024), Begenau et al. (2015), and Haddad and Sraer (2020). The income gap measure is rescaled to match the mean and variance of this paper's measure.

average bank in 2021, the interest-rate-sensitive portion of bank franchise value amounts to a very small perpetuity, of just 0.07%. So most of the interest rate exposure comes from the asset book. Begenau et al. (2015) focus on the assets and statutory liabilities, treating savings deposits as zero-duration. And the income gap used in Haddad and Sraer (2020) is similarly only a measure of the interest rate exposure of assets and statutory liabilities.

The time series of bank duration (and thus these other measures) is negatively correlated with asset duration because banks have accumulated more long-maturity assets over the years as interest rates declined.

I calculate the DeMarzo et al. (2024) measure by using my estimate of security duration and their estimate of the franchise perpetuity. For the Begenau et al. (2015) metric, I collect aggregate interest rate factor exposures up to 2014 from their paper (figure 8) and divide by aggregate bank market capitalisation.[13] And I calculate income gap using the standard definition applied to the aggregate bank balance sheet. The figures may not exactly match the respective authors calculations but they should at least be highly correlated.

In Table 11, I repeat the time-series duration regression from Table 3 for each of the alternative duration measures shown in Section 11. All measures have the wrong sign — more positive measured interest rate exposure is associated with more negative response of stock prices to positive interest rate shocks.

The coefficient on the DeMarzo et al. (2024) and Begenau et al. (2015) measures are significant when excluding the financial crisis. Both measure the duration of assets. The fact that they have a negative, significant sign suggests that banks tend to allow their asset duration to move in the opposite direction from their franchise duration, consistent with their time-varying hedging motive.

[13] Interest rate factor exposures are calculated in units of exposure to the 5 year interest rate swap. To convert to a duration measure I multiply by 5 as a rough estimate of interest rate swap duration.

Panel a: Full sample

	DKN measure	DKN (eq wtd)	BPS measure	Income gap
Rate sens. × rate shock	0.330	0.098	0.443	-3.826
	(0.456)	(0.158)	(0.311)	(3.670)
Rate shock	-1.117	-1.402	-2.347	119.057
	(9.615)	(3.700)	(6.992)	(117.178)
Rate sensitivity	-0.184	-0.065	-0.146*	0.029
	(0.115)	(0.041)	(0.060)	(0.096)
Intercept	-1.009	-0.260	-1.495+	-0.609
	(0.821)	(0.291)	(0.763)	(3.060)
Num.Obs.	170	152	96	170
R2	0.107	0.055	0.128	0.032

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel b: Financial crisis period excluded

	DKN measure	DKN (eq wtd)	BPS measure	Income gap
Rate sens. × rate shock	-3.260**	-1.705*	-2.654***	-0.368
	(1.031)	(0.786)	(0.579)	(1.876)
Rate shock	-18.066***	-9.917*	-35.775***	13.368
	(4.964)	(4.014)	(5.917)	(60.853)
Rate sensitivity	0.000	-0.021	-0.044	-0.045
	(0.044)	(0.043)	(0.030)	(0.082)
Intercept	0.165	-0.076	-0.186	1.637
	(0.281)	(0.283)	(0.358)	(2.678)
Num.Obs.	152	137	78	152
R2	0.059	0.031	0.156	0.005

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: **Alternative interest rate risk measures do not predict bank stock price reaction to interest rate shocks with the right sign.** This table repeats the regressions in Table 3 using different alternative bank interest rate risk measures described in Section 3.3. Columns 1, 3, and 4 use value-weighted bank stock returns as the dependent variable, while column 2 uses equal-weighted returns. "Rate sensitivity" is the measured interest rate exposure, based either on DeMarzo et al. (2024), Begenau et al. (2015), or Haddad and Sraer (2020). "Rate Shock" is the change in the 10 year treasury yield in the 1-hour window around FOMC announcements from Gürkaynak et al. (2022). Panel b exclude H2 2007 – H1 2009. All standard errors are heteroskedasticity–robust.

4 Duration and long-maturity asset holdings

At very low interest rates, bank duration becomes negative, as shown in Section 3. The sensitivity of short-term deposit interest expense to income also drops. Depositors who already paid 0 will see no decrease in rates if rates decline further, so the larger the share of unpaid depositors, the lower the interest rate sensitivity.[14]

So if banks are risk averse with respect to their stock price (as in Haddad and Sraer, 2020), or their interest income (as in Drechsler et al., 2021), they have reason to buy longer maturity assets when rates are low. If they are hedging their equity value, then long-term assets will appreciate in value when their deposit franchise value drops. If they are hedging their short term cash flows, then long-term assets will match the insensitivity of their deposit interest income. These motives will be particularly strong for banks with large savings deposit quantities, and large fixed spreads (δ).

This time variation in hedging motives helps explain why banks bought large quantities of long-term securities during the zero rate period, and particularly when long rates were at their lowest in 2020-2021. Figure 11 shows the time series of the share of bank balance sheet that is invested in securities with maturities over 15 years, the longest maturity bucket available in the call reports data. When rates were low, these assets (primarily MBS) constituted under 7% of balance sheet. They rose up to 9% at the end of 2019 and then shot up to over 11% at the end of 2021. Drechsler, Savov, Schnabl, and Supera (2024) document that bank MBS constituted an increasing share of the total economy-wide mortgage holdings during this period.

This increase does not seem to be explained by credit demand, since it was driven by securities rather than lending. Nor does not seem to be consistent with the simplest versions of the "reach for yield" story (Hanson and Stein, 2015). The yield curve became flatter over this period, so their was less and less yield to reach for. From 2010 to 2020 the

[14]Differentiating the deposit interest rate function from Section 1.1 tells us deposit interest sensitivity is exactly proportional to the share of depositors paid 0: $\frac{\partial r_t^d}{\partial r_t^f} = \beta(1-\gamma)\Phi(\frac{\widetilde{r}_t - \delta}{s})$

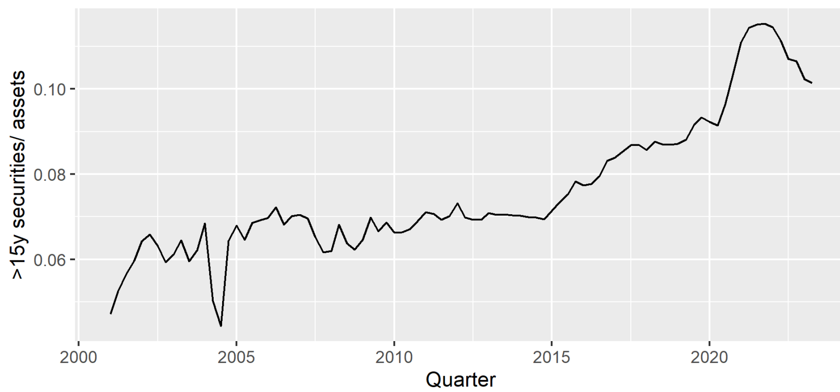

Figure 11: **Total securities with $> 15y$ maturities as a share of all bank assets, 1997-2023**. All commercial banks from the FFIEC call reports.

difference in yield between a 10 year and 3 month treasury bond steadily decreased 3.8% to -0.2%.[15]

But the data is consistent with the interest-rate-risk driven story. The banks with the most demand deposits and with the largest fixed spreads, whose spreads were most squeezed against 0 were precisely those that bought the most long-term securities. In Figure 12 panel (a) I show the coefficients from quarterly regressions of the share of assets held in $> 15y$ maturities on the estimated savings deposit fixed spreads for each bank (i.e. the δ from Section 1.3). Panel (b) does the same exercise but using demand deposits as a share of income as the regressor.

When rates were higher, there was little relationship. But as banks accumulate their long-term securities, a relationship appears, with the highest-δ and highest deposit share banks holding the most long-term securities. At peak, in Q2 2022, the R^2 from this single-regressor is 11%. To ensure that the data is not driven by small with little effect on aggregate securities holdings, I weight the regression by the bank's share of total banking system assets.

Drechsler et al. (2024) argue that banks' increase in MBS holdings 2019-2021 was driven by the large increase in savings and transaction deposits over the same period. Banks

[15] Data series T10Y3M from the Federal Reserve Bank of St Louis, FRED

simply matched their new low-interest-rate-sensitivity deposit funding with low-interest-rate-sensitivity MBS.

This explanation is not inconsistent with this paper — if banks are hedging their interest rate risk, then they should care about both the changes in deposit quantity deposit interest-rate-risk characteristics.

This dual explanation seems to fit with the available evidence. The increase in the holdings of the longest-maturity securities was even larger than the growth in savings and transaction accounts. From 2015 Q4 to 2021 Q2 the ratio of $> 15y$ maturity securities to savings and transaction deposits rose from 12.5% to 16.5%

Additionally, the relationship between savings deposit quantities and long-term security holdings strengthened as rates fell. This change is easily explained if the interest-rate sensitivity of those deposits changed, as described in this paper — i.e. the hedging motive per dollar of deposits strengthened. Figure 12 panel (b) plots the coefficient from quarterly regressions of $> 15y$ maturity security holdings on savings and transaction deposits. Before 2010 there is a weak and usually not-significant relationship. After 2010, the relation becomes stronger, peaking in 2021.

5 Conclusion

The past few decades have seen a great deal of uncertainty about bank interest rate risk. The correlation of bank returns with interest rate changes has gone from negative to positive and back again. And academics and regulators have variously argued that it should be positive, negative, or near 0.

The challenge of determining the risk lies in the deposits, where statutory maturity differs from behavioral. A low "deposit beta" is supposed to lower the sensitivity of interest expenses to the risk-free rate and thus allow banks to hold longer term assets without taking interest rate risk (Drechsler et al., 2021). But from a valuation point of view, the value of a fixed beta to interest rates is constant and shows no interest rate risk, so how

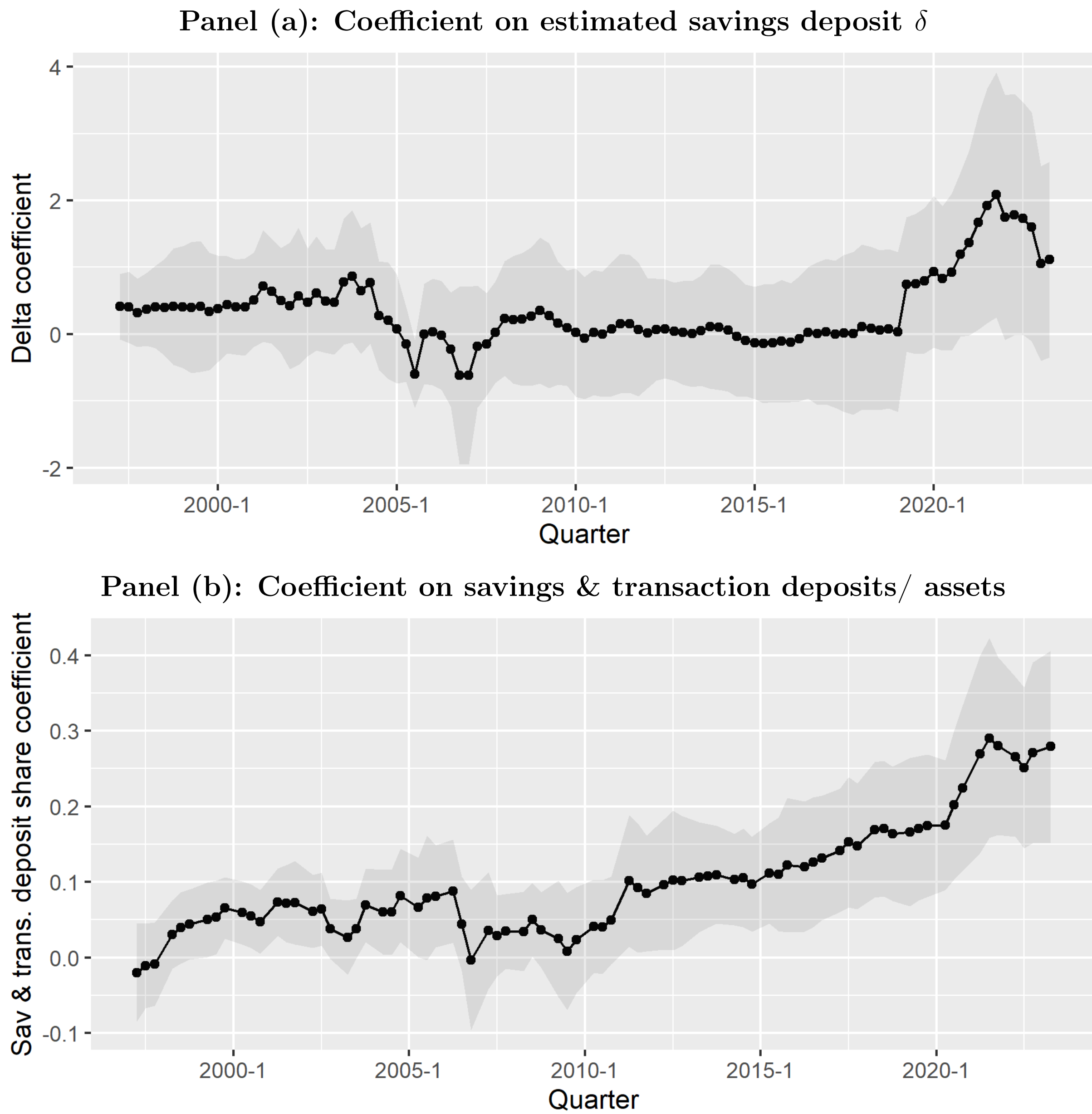

Figure 12: **Coefficients from quarterly regressions of $> 15y$ maturity securities as a share of assets on explanatory variables, all banks 1997-2023.** Regressions are weighted by share of total assets, and standard errors are heteroskedasticity-consistent. Estimated δ is winsorized at the 1% level.

can it hedge long-term loans (DeMarzo et al., 2024)?

By breaking the assumption of a fixed deposit beta and using slightly more sophisticated asset pricing tools to value deposits, I show that the deposit spreads themselves can deliver positive interest rate exposure even before considering fixed costs. Furthermore when long-term rates become very low, they will dramatically "over-hedge" and the bank gains a large positive exposure to interest rates.

To check that the importance of this dynamic, I conduct a realistic, quarterly quantification of the value and interest rate sensitivity of banks using my model of deposit interest. The result matches high-frequency response to monetary shocks well. The fixed spreads explain why investors seem to have "changed their minds" on bank interest rate exposure

This time variation in interest rate risk presents a potentially powerful motive for banks to change their holdings in a low rate environment. Low long-term rates should mean more savings deposits are put into long-term assets. This is consistent with the time series and cross-sectional dynamics observed in the data.

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Appendices

A A model of discrete depositor choice

The motivation for this model is primarily practical and empirical, but it can also be microfounded with a simple model of consumer choice. In this section, I derive the model from setup where depositors a discrete choice among banks with different quality levels. The only departure from a standard "logit" model as in McFadden (1973) that is needed to match the empirical model from Section 1.1 is that consumers pay more attention to prices when rates are falling than rising.

I focus in this model on depositors optimization over which bank to choose, rather than depositors choice of deposit quantity. This focus is justified if depositors choice of banks is much more elastic to individual bank deposit rates than depositors choice of overall savings quantities. Or in plainer English, I assume that when banks set their deposit rates they are primarily worried about customers moving to a different bank, not customers saving less in total.

Suppose there are N depositors indexed by j and M banks indexed by i, where N and M are both large. Each depositor chooses a single bank. The depositor's utility from each bank depends on the deposit pricing (r^d_{it}), but also on the quality of the services provided by that particular bank (ξ_{it}) and some random error-term for that bank–customer combination (ε_{jit}) that follows an extreme value distribution. If the bank pays less than 0 interest, the depositor will choose to hold cash instead of deposits, but still retain the benefit of the bank relationship.

The depositor therefore chooses bank i to solve:

$$\max_i U_{jt} = \max\{r^d_{it} - r^f_t, 0\} + m_t\left(\xi_{it} + \varepsilon_{jit}\right)$$

The variance of the quality and error terms are scaled by a potentially time-varying weight m_t, which can be interpreted as how much attention the depositor pays to price or how hard she searches.

Following standard results, the share of deposits demanded from bank i is a logit function of prices:

$$D_{it} = \frac{exp\left(\left(r^d_{it}\right)/m_t + \xi_{it}\right)}{\sum_{k=1}^{M} exp\left(\left(r^d_{kt}\right)/m_t + \xi_{kt}\right)}$$

Each bank therefore chooses deposit rates to maximize its total profit vs funding at the risk-free rate:

$$\max_{r^d_{it}} D_{it}\left(r^f_t - r^d_{it}\right)$$

The bank's first-order condition, after some rearranging, is:

$$r^d_{it} - r^f_t = \frac{-m_t}{1 - D_i t}$$

Since M is large, each bank's share of deposits (D_{it}) is small, so the equilibrium deposit rate is approximately:

$$r^d_{it} \approx r^f_t - m_t$$

If m_t is constant, banks will have fixed deposit spreads. In reality, as documented in Section 1.1, we tend to observe wider spreads when rates have recently risen. This effect suggests that bank market power, and thus m_t, is greater when banks rates have recently risen.

I therefore assume depositors have some lagging perception of the true level of risk-free rate, gleaned from social networks, news, etc, given by:

$$\hat{r}_t = \gamma\hat{r}_{t-1} + (1-\gamma)\,\beta r^f_t + \varepsilon_t$$

When the true risk-free rate is below the perceived rate (i.e. m_t is low), the depositor thinks she is getting a bad deal and so searches harder and puts more emphasis on price.

Hence the bank market power m_t is given by:

$$m_t = \delta + r_t^f - \hat{r}_t$$

This effect could also be seen as a reduced form for a more complicated model with search costs and frictions where customers are more likely to look into switching banks when they are notified of a rate cut on their account.

It may seem counterintuitive to suggest depositors focus more on price when rates have fallen, since most of us have been more likely to check our bank rates in the past 2 years when rates have increased. But this is a function of 1) the 0 floor on deposit rates which pinned spreads near 0 in an exogenous fashion when rates were low, and 2) the equilibrium pricing behaviors of banks. Banks respond to the lower price-attentiveness of customers in rising rate periods by increasing spreads until depositor choices remain the same.

With this form for m_t, the equilibrium bank deposit rate becomes:

$$\max\{r_{it}^d, 0\}$$

Where

$$r_{it}^d \approx \gamma r_{it-1}^d + \beta\left(1-\gamma\right)\left(r_t^f - \delta\right)$$

Which is the same as equationa 1 and 2 for an individual depositor.

The parameters (γ, δ) here are characteristics of the depositors not the bank, and thus all banks charge the same rate in this model. To think about different banks with different parameters, as I estimate in Section 1.1, we should consider multiple product and regional markets with different customer parameters. Each bank has a different exposure to different markets, so faces different parameters. Different product markets also delivers a range of δ values within a bank, which allows for the "phased in" truncation from equation 2.

B Proof of negative deposit duration at low rates

Denote the value of a continuous call option at from time 0 to T given a path of instantaneous forward rates $\{f_t\}_0^\infty$ as :

$$V_C\left(0, T, \{f_t\}_0^T\right) = \int_0^T P(0,t)C(t, f_t)dt$$

Proposition 1:

Let the path of forward rates $\{f_t\}_0^\infty$ be such that:

- Forward rates are held below some value $\eta > 0$ from time 0 to some time T:

$$\forall t \in [0, T] : \ 0 < f_t < \eta$$

- After T, rates are high enough that the perpetuity rate is at least $\overline{r}$ and the value of the permanent call before discounting is at least $\overline{V}$:

$$\int_T^\infty P(T, s) \leq \frac{1}{\overline{r}}$$

$$V\left(T, \infty, \{f_t\}_T^\infty\right) = \int_T^\infty P(T, s)C(s, f_t) \geq \overline{V}$$

And let the C follow a few simple conditions appropriate for a call price:

- $C(t, f_t) \geq 0$ and $\frac{\partial C}{\partial f_t}(t, f_t) \in [0, 1]$ for all $t \in [0, \infty)$ and $f_t \in (0, \infty)$
- As $f \to 0$, either the call option price is bounded below or it smoothly approaches 0:

$$\forall f > 0, t > 1 : \ C(t, f) > C_0 > 0$$

or

$$\forall t > 0: \lim_{f \to 0} C(t,f) = 0; \lim_{f \to 0} \frac{\partial C}{\partial f_t}(t,f) = 0$$

Then there exists a value of η low enough and T large enough that a positive level shock to forwards rates will have an arbitrarily negative effect on the value of the permanent call — i.e. duration is arbitrarily positive:

$$\forall D < 0,\ \exists \eta, T\ s.t.\ \frac{\partial}{\partial \varepsilon}\Big|_{\varepsilon=0} V_C\left(0, \infty, \{f_t + \varepsilon\}_0^\infty\right) < D$$

Where:

$$V_C\left(0, \infty, \{f_t + \varepsilon\}_0^\infty\right) = \int_0^\infty P(0,t) C(t, f_t) dt$$

Proof:

Separate the value of the call by time into three portions, splitting at time 1 and T:

$$V_C\left(0, \infty, \{f_t + \varepsilon\}_0^\infty\right) = v_0^1 + v_1^T + v_T^\infty$$

Where

$$v_A^B = P(0,A) V_C\left(0, 1, \{f_t + \varepsilon\}_A^B\right)$$

And note that the derivative of each w.r.t. the rate shock (i.e. the negative duration) is given by:

$$\frac{\partial}{\partial \varepsilon}\Big|_{\varepsilon=0} V_A^B = P(0,A)\left(\int_A^B P(A,t)\left(\frac{\partial C}{\partial f_t}(t,f_t) - tC(t,f_t)\right) dt - A V_C\left(A, B, \{f_t\}_A^B\right)\right)$$

I will show the duration of each of the three parts is either bounded or goes to infinity as $\eta \to 0$ and $T \to \infty$. Thus the total duration goes to infinity.

v_0^1: The portion from 0 to 1 must have a derivative ≤ 1 because the $\frac{\partial C}{\partial f_t}$ is bounded above at 1 and C is bounded below at 0:

$$\frac{\partial}{\partial\varepsilon}\bigg|_{\varepsilon=0} v_0^1 \le \int_0^1 P(0,t)1dt \le 1$$

v_T^∞: As $\eta \to 0$, the portion after T has a duration that becomes arbitrarily large as T increases, because the value is bounded below at $\overline{V}$:

$$\begin{aligned}\lim_{\eta\to 0}\frac{\partial}{\partial\varepsilon}\bigg|_{\varepsilon=0} v_T^\infty &= \int_T^\infty P(T,t)\left(\frac{\partial C}{\partial f_t}(t,f_t) - tC(t,f_t)\right)dt - TV\left(T,\infty,\{f_t\}_T^\infty\right)\\ &\le \int_T^\infty P(T,t)1dt - T\overline{V} \le \frac{1}{\overline{r}} - T\overline{V}\end{aligned}$$

v_1^T: Depending on the behavior of the call function as $f \to 0$, the duration of portion between 1 and T will either approach 0, or have an arbitrarily large value as T gets large.

If the value is bounded below (as in the Vasicek model), then:

$$\begin{aligned}\lim_{\eta\to 0}\frac{\partial}{\partial\varepsilon}\bigg|_{\varepsilon=0} v_1^T &= \int_1^T \frac{\partial C}{\partial f_t}(t,f_t) - tC(t,f_t)dt - V\left(1,T,\{f_t\}_1^T\right)\\ &\le \int_1^T 1 - tC_0 dt \le\ T - 1 - \frac{C_0}{2}(T-1)^2\end{aligned}$$

Which is arbitrarily negative as $T \to \infty$

If the value and derivative of the call option approach 0 as $f \to 0$ (as in a model where rates are lognormal, for example):

$$\lim_{\eta\to 0}\frac{\partial}{\partial\varepsilon}\bigg|_{\varepsilon=0} v_1^T = \int_1^T 0dt - 0 = 0$$

Hence as $\eta \to 0$ the derivative of the call option w.r.t. to rates becomes arbitrarily negative as T increases.

C Details of deposit model estimation

C.1 Data filters

For the bank-level analysis I conduct the same estimation separately for each bank. For data quality purposes I drop from the individual analysis:

- Banks with less than 50 quarterly observations
- Micro-banks, defined as those with under \$100 MM assets in Q1 2023, or the equivalent percentile of total banking system assets for previous quarters
- Banks with deposits under 1/3 of assets
- Banks which ever report paying deposit rates >3 ppt above the Fed Funds rate, or a 2 ppt jump in rates that reverses the next quarter
- Banks that report negative or exactly 0 rates (just 64 small banks)
- Banks-quarter observations that have a >50 bp jump that reverses the next quarter

C.2 Likelihood function

To estimate the model, I numerically maximize the joint likelihood of the observed deposit rates. The conditional log likelihood of deposit rates can be derived as:

$$L\left(r^d_{t+1}\middle| r_{d,t}, r^f_{t+1}, \hat{\gamma}, \hat{\beta}, \hat{\delta}, \hat{\sigma}, \hat{s}\right) = \log\left(\frac{1}{\hat{\sigma}}\phi\left(\frac{\hat{\varepsilon}_{t+1}}{\hat{\sigma}}\right)\right) - \log\left(\Phi\left(\frac{f^{-1}\left(r^d_{t+1}\right)}{\hat{s}}\right)\right)$$

Where

$$\hat{\varepsilon}_{t+1} = f^{-1}\left(r^d_{t+1}\right) - \hat{\gamma} f^{-1}\left(r^d_t\right) - (1-\hat{\gamma})\left(\hat{\beta} r^f_{t+1} - \hat{\delta}\right)$$

And f^{-1} is the inverse of the censoring function from equation 2.

The optimization can be sped up by noting that conditional on s, the maximum likelihood solutions for $(\hat{\gamma}, \hat{\beta}, \hat{\delta}, \hat{\sigma})$ are given by the OLS estimator for equation 1, plugging in

$f^{-1}\left(r_t^d\right)$ for $\widetilde{r}_t$. Hence I can conduct a fast univariate optimization over $\hat{s}$, plugging in the OLS solutions for the other parameters for each guess for $\hat{s}$.

C.3 Bank-level results

Summary statistics for the coefficients estimated from the bank-level analysis for all demand deposits are shown in Table 6. The cross-sectional means are similar to the aggregate estimates, with relatively high δs and βs near one. Fixed spreads (δ) are generally substantial and statistically significant.

The association of δ with bank characteristics, also shown in Figure 6, is mostly consistent with market-power and cost-to-serve interpretations of the fixed spreads. High spreads are correlated with the bank cost base (e.g. from branch costs) and amount of small depositors, measured as share of deposits under the FDIC insurance thresholds. Surprisingly, high local market concentration is actually correlated with a low delta.

	Summary stats			Regression coefficients			
	Mean	Stdev	PctSignificant	Log assets	Cost/ assets	Insured share	Cty HHI
δ	0.028	0.017	0.738	-0.179	0.067	0.053	-0.112
γ	0.859	0.080	0.963	-0.835	-0.040	2.243	0.607
s	0.030	0.019	0.789	0.143	0.111	0.299	-0.061
σ	0.003	0.001	0.922	-0.013	0.005	-0.023	-0.002

Table 6: **Summary statistics for bank–level estimates of deposit parameters**. 3,374 banks are included in the savings deposit results and 912 in the transaction deposits. "Share signif" shows the percent that pass a t-test at a 95% confidence level. Parameters and bank characteristics are winsorized at the 1% level. Columns labeled "regression coefficients" show the results of a regression of bank-level average characteristics on the estimated bank-level coefficients. "Insured share" is the share of deposits consisting of balances under the FDIC insurance thresholds ($100 K before 2009 and $250 K after). Characteristics labeled "Cty" are branch-weighted averages of county characteristics. "HHI" is a measure of local market concentration, specifically the Herfindahl-Hirschman index of bank branches. "Age" and "income" are the average age and income of counties from census data

D Asset duration

A full picture of the interest rate risk of the bank requires us to also calculate asset duration. I do so using call report data on maturities and interest income and applying standard bond pricing formulas and mortgage-backed security (MBS) index pricing data. Asset varies between 1 and 2 and does not change enough to counteract the swings in deposit duration described in Section 2

D.1 Methodology & assumptions

Unlike for instant-access deposits, I focus on valuing the stock of existing assets rather than the permanent flow of loans. I treat time deposits the same way. I use a different approach for two reasons. First, unlike for instant access deposits, there is rich information available about the maturity of loans and time deposits. There is no need to try to estimate interest rate exposure from the time series of interest income when we can measure it directly from maturity.

Second, interest rates on assets are above the risk-free rate, not below it. So assets will not show the same spread compression dynamics that are described in Section 1 when interest rates approach 0. Estimation of the duration of expected spreads on new loans is therefore performed in a simple fashion in Section E.

The call reports provide maturity data on three types of assets: non-mortgage loans (constituting 43% of assets 2002-2023), mortgage loans (11%), mortgage backed securities (11%) and treasuries (9%). A further 25% of assets has not maturity data, and largely consists of cash and deposits. The average interest income rate is also provided for each of these products.

I estimate the value and duration of non-mortgage loans, treasuries, and time deposits by assuming they consist of a series of coupon bonds. The call reports provide data on the book value of loans maturing in 6 different maturity buckets (e.g. <3 months, 3m – 1 year, etc). I assume the balance in each bucket matures at the mid-point of the bucket.

I use the average interest income of the product as the coupon rate. For non-mortgage loans, I apply a credit spread equal to the ICE Bank of America high yield bond credit spread index. Duration is generally close to the maturity for coupon bonds, and so is relatively insensitive to coupons or spreads.

Estimating the value duration of mortgages and MBS is more complicated because of the prepayment option embedded in the product. Fortunately, there are widely available indices used to track the price and duration of mortgage backed securities (e.g. as used in Hanson, 2014). I apply price and duration estimates from the Bloomberg Barclays MBS indices to the bank mortgage holdings.

D.2 Results

The time series of estimated asset duration and the contribution of each type of product is shown in Figure 13. Unsurprisingly, asset duration is relatively stable over time and does not flip signs like deposit spread duration does.

Average asset duration over the decade ending in 2023 was 2. This estimate is approximately half the size of the most recent and widely used estimates from Jiang, Matvos, Piskorski, and Seru (2023). The differences are explained in appendix [X] but come down to a misreading of how the call report maturity data applies to amortising assets. My estimates are in line with the average bank disclosures that securities duration is approximately 4 years[16] and are roughly in-line with the "conservative" set of estimates that Jiang et al. (2023) provide based on actual MBS transactions.

Short term trends in duration (e.g. the large increase 2022-3) are driven by mortgage convexity. When the interest rate moves down, borrowers tend to refinance their mortgages, lowering the duration of existing mortgages.

There is also a long-term secular increase in asset duration post-crisis. This has two

[16] Jiang et al. (2023) also justify their estimates based on these figures, but appear to have misread the bank disclosures. Banks provide estimates of security duration, not overall assets. Security duration is about twice as high as overall asset duration by my estimates.

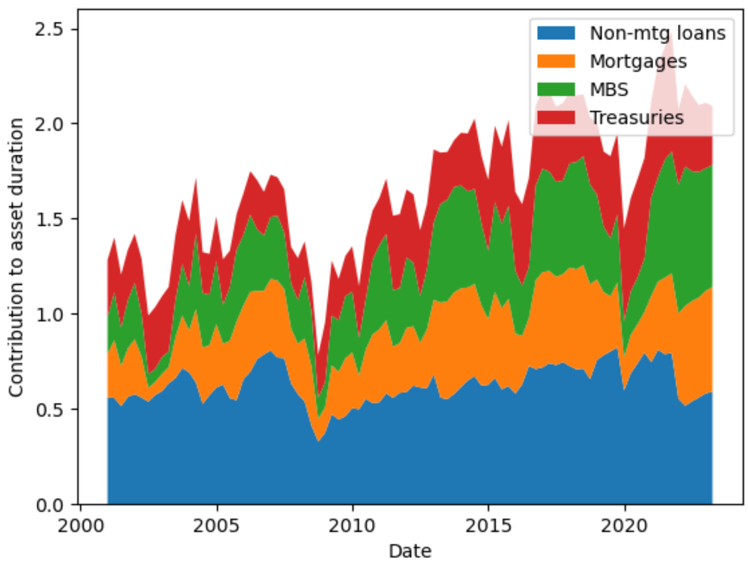

Figure 13: **Aggregate duration of bank assets 2002 Q3 – 2023 Q2**. The total stacked height shows the aggregate duration of all assets. Each color shows the contribution of a specific product. Duration is defined as $\frac{\partial Value/\partial r}{Value}$. Details of the estimation methodology are in Section D.

sources. First, banks increased their holdings of long-maturity assets, particularly around 2020. MBS and treasury holdings rose around 20% at the start of 2019 to 26% at the end of 2021.

Second, the duration of mortgages and mortgage backed securities themselves increased from an average of 2 in 2000-2010 to an average of 3.6 2013-2023, as adjustable rate mortgages and shorter term fixed rates have been replaced by 30 year fixes. The Bloomberg Barclays index of fixed rate maturities increased its average duration from 3 to 4 during this period, and I estimate that the share of adjustable rate mortgages has fallen from 25% to 6%. These estimates are in line with the federal home finance agency monthly interest rate survey shows ARM shares fluctuating between 20-30% pre-crisis and dropping to $< 10\%$ post-crisis (Moench, Vickery, and Aragon, 2010).

E Total bank duration

The bank does have other expected cash flows besides the deposits and loans: costs, fees, profitability of new loans, any future governmental transfers or levies, etc. A full accounting of bank interest rate risk requires some assumption on the duration of this residual component. In my base case I assume that the residual costs constitute a perpetuity. My estimation is relatively robust to this choice — the exact choice of assumption will tend to shift duration up or down, but not change the overall pattern.

E.1 Methodology & assumptions

We can check the scale of the residual bank value by comparing my estimates of deposit and asset value to the market value of public banks.

A regression of aggregate bank stock prices onto the measured asset and deposit values in Table 7 shows that these two measures alone explain just under half of the variation in bank valuation over the past 20 years.[17]

[17] The regression in levels is only run post-crisis because of the large shift in the level of market-to-book pre- and post-crisis

=

	Levels (post-crisis)	Annual changes
(Liab value - book) / book equity	0.282***	0.737***
	(0.051)	(0.212)
(Asset value - book) / book equity	0.465***	0.590**
	(0.090)	(0.173)
Intercept	1.541***	-0.099+
	(0.168)	(0.051)
Num.Obs.	58	80
R2	0.495	0.365
Std.Errors	Newey-West (L=4)	Newey-West (L=4)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: **Regression of aggregate bank market-to-book on estimated deviations of asset and deposit value from book value, 2022Q3 - 2023 Q2**. Regressors are scaled by aggregate book equity. Estimation of of asset and deposit franchise value is described in sections 2 and D. The regression in levels is performed on data from 2009 to 2023 Q2 because of the large level shift in market-to-book around the financial crisis (e.g. on the full sample, a simple pre-post-crisis dummy alone has an R2 60%).

However, there is a large unexplained portion of bank value. For my main estimation I simply assume that this residual value in each period is composed of a perpetuity c_t, discounted at the same 2% risk premium as the rest of the bank cashflows. The full detail of this simple calculation as well as the calibrated values are shown in Appendix F.

The resulting value of aggregate c_t is 0–0.2% of assets pre-crisis and around -0.5% post-crisis. The net impact is that estimated bank duration is lower post-crisis. This is reasonable, because the drop in market prices must translate to higher discount rates or low cash flow expectations, either of which lowers duration.

This approach of choosing a constant long-term cash flow to match equity prices is analogous to the approach used in the equity implied duration literature, specifically Dechow et al. (2004) and Weber (2018). I leave ρ constant and vary c_t for numerical simplicity and consistency with the existing literature. If I varied ρ instead, the results would likely be similar – higher market to book would imply higher duration in both cases.

The assumption behind this approach is that the residual cash flows are not a function of interest rates. For operational costs, this assumption is relatively uncontroversial, and is also made for example in Drechsler et al. (2023); DeMarzo et al. (2024); Begenau and Stafford (2018).

For spreads on new lending, the evidence points toward only very modest effects of the interest rate level. A regression of the spread between new mortgage loans (accounting for 30% of aggregate lending) and MBS yields increase just 0.05 ppt for each 1 ppt increase in the fed funds rate. These effects are small enough that they could be accounted for by prepayment option effects or borrowers shifting to higher fee products. DeMarzo et al. (2024) also find that loan spreads have a loading of just 0.05 on the interest rate.[18].

Replacing some of the c_t perpetuity with a floating-rate spread would just shift up or down the duration, with little change in the overall pattern. In Appendix F I include an estimation of duration if we assume that the residual value comes entirely from floating rates, and the value of c_t is 0.[19]

What would change the overall pattern of duration would be a strong non-linear response of loan spreads to interest rates — for example if loan spreads exactly cancel out the compression of deposit spreads at low interest rates. However the recent path of net interest margin suggests this is not the case: from Q1 to Q4 2022 as rates rose, the spread between bank loan and deposit rates rates rose by over a full percentage point.[20]

I also show in Appendix F that there is no correlation between changes in the c_t estimates and changes in interest rates. This suggests that I am not systematically over- or under-estimated the residual duration.

[18]Wang (2020) shows that loans spreads increase as rates lower, but only for two relatively small loan categories: ARMs and vehicle loans.

[19]This is similar to DeMarzo et al. (2024)'s estimation of a nearly 0 fixed franchise perpetuity for the average bank

[20]The drop in interest rates in 2009 was not associated with a drop on net interest margin, most likely due to large one-off increase in (a) credit spreads and (b) term premia after the financial crisis.

F Details of residual value estimation and robustness

I define the future "remaining cashlows" $C_{t,T}$ at time t of each bank such that:

$$P_t = V_{A,t} + V_{DF,t} - V_{L,t} + \int_t^\infty e^{-(T-t)r_{t\to T}} E_t^*(C_{t,T})dT$$

Where P_t is the pre-tax market price of bank equity, V_A is the value of assets, V_{DF} the value of the deposit franchise, V_L the book value of liabilities, and $r_{t\to T}$ the spot rate from time t to T.

The pre-tax market price of bank equity is calculated as $P_t = \frac{MktCap}{1-\tau}$, where $MktCap$ is the market capitalisation observed on CRSP and τ is the corporate tax rate, assumed here to be 0.25.

I assume that at time t the expected future remaining cash flows are a constant share c_t of bank assets A_t, and are discounted at a constant rate ρ, net of asset growth:

$$E^*(C_{t,T}) = e^{-(T-t)\rho} A_t c_t$$

I find c_t by matching the value of the observed market price of the bank in each period:

$$c_t = \frac{P_t - V_{A,t} - V_{DF,t} + V_{L,t}}{A_t \int_t^\infty e^{-(T-t)(r_{t\to T}+\rho)}dT}$$

I plug in a typical equity discount rate for ρ. As described in Section 2 I use $\rho = 2\%$, based on an average bank stock excess return of 7% minus a 5% growth rate.

I test the approach by checking for correlation between changes in c_t estimates and changes in interest rates. If I systematically over-estimated duration, then I would find that the value of the bank is higher than predicted after rates increase. This would mean that there should be a correlation between changes in interest rates and changes in the value of c_t. Table 8 reports the coefficients from a regression of changes c_t on changes in

Table 8: **Regression of annual changes in aggregate c_t on annual changes in interest rates, 2003 Q3 - 2023 Q2.** c_t is the estimated residual cash flow perpetuity described in Section E. Regressors are changes in the federal funds rate and the yield on 10 year treasury securities. c_t and yields are both expressed in whole numbers, so a coefficient of 0.01 implies a 1 ppt increase in rates is associated with a .01 ppt increase in c_t.

Summary stats	Summary stats	Correlations	Correlations
# obs	34604.00	Log assets	0.04
# banks	942.00	Cost/ assets	0.05
Avg obs per qtr	407.11	Maket-to-book	0.57
Mean c_t (ppt)	-4.07	(Liab value - book) / BE	-0.09
Std of c_t (ppt)	21.18	(Asset value - book)/ BE	-0.05
Cross-sectional std c_t	19.28		

Table 9: **Summary statistics for estimates of residual cash flow perpetuities c_t for public banks, 2002 Q3 - 2023 Q2.** c_t is the estimated residual cash flow perpetuity described in Section E. Parameters and bank characteristics are winsorized at the 1% level. Columns labeled "Correlations" show the correlation of parameters with the average across quarters of different bank characteristics.

short and long-term interest rates. The point estimates are close to 0 and insignificant and the 95% confidence intervals do not include any large effects.

The estimated values for aggregate rate of expected cash flows c_t for all public banks is shown in Figure 14. The most striking feature of the time series is the drop in expected remaining cash flows around the global financial crisis. Prior to 2007, c_t remained in the range of 0–0.2% of assets, whereas from 2010 onwards it was generally below -0.4%.

Summary statistics for the panel of c_t estimates is shown in Table 9. The cross-sectional standard deviation is high, at 1.5 ppt on average 2003-2023. c_t shows intuitive negative correlations with assets and cost — i.e. smaller higher-cost banks have less residual cash flow expectation. Unsurprisingly, since c_t is constructed as the portion of market to book not explained by liability and asset valuations, it also shows strong positive correlations with market to book and negative correlations with deposit franchise value and asset value.

While c_t plays an important role in determining average duration, its time-series varia-

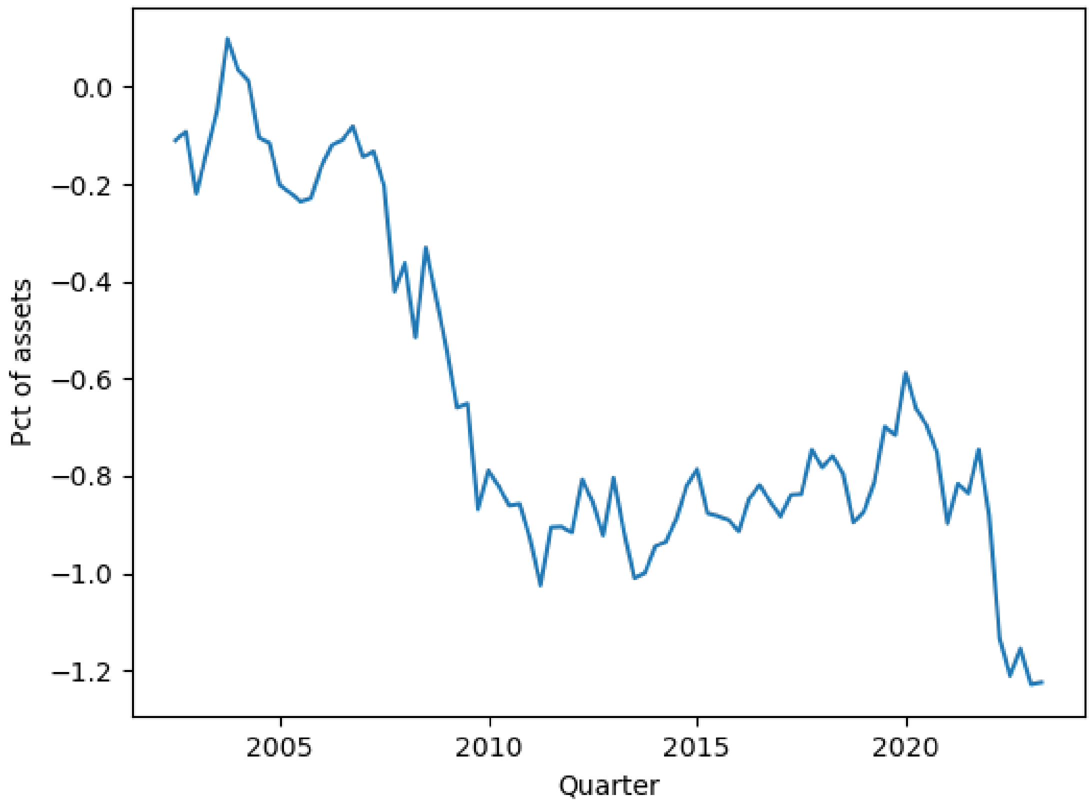

Figure 14: **Fitted values for the residual cash flow expectation perpetuity** c_t**, 2002 Q3 – 20023 Q2**. See Section E for description of methodology.

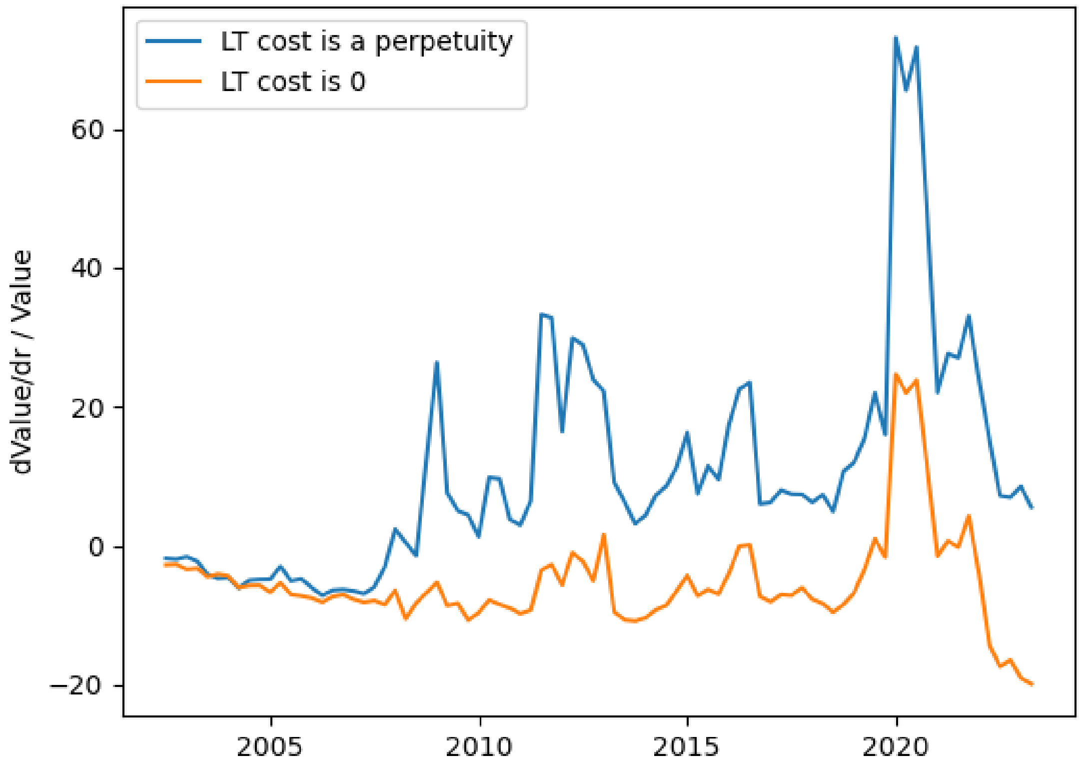

Figure 15: **Aggregate (negative) duration of public banks using a a perpetuity duration or 0 duration for remaining value, 2002 Q3 – 2023 Q2**. This figure recreates panel b from Figure **??**, but assuming the residual cash flow perpetuity c_t is 0.

tion is relatively unimportant. As a robustness test, Figure 15 plots the time series of bank duration if we assume that c_t is instead either (a) equal to it's time-series average(around -0.3%) or (b) 0. The overall picture is similar, with peaks in interest rate sensitivity when long rates are low and the floor is valuable.

G Comparison to other sources of variation in aggregate duration

Mortgage-backed-securities prepayment risk and insurance company convexity and duration mismatch are two key factors often credited for driving investor interest rate exposure and long-term yields (e.g. Hanson, 2014; Carboni and Ellison, 2022; Domanski et al., 2017). Figure 16 plots the aggregate duration created by these two sources over the past 20 years vs the bank duration described in this paper, and shows that swings in bank duration are larger and more persistent. The standard deviation of total bank duration is approximately 3–4× higher than either MBS or insurer duration.

H Additional stock return validation tests

Figure 17 compares the measured banking sector duration from Section E to the coefficients from a simple rolling 1 quarter regression of daily bank stock returns on changes in the 10 year rate, with no high frequency identification.

The stock prices price behavior shows the same patterns and scale as this paper's duration measure. When yields were low and interest rate floors expense, the relationship between yields and bank stock prices became positive.

In Table 11, I repeat the time-series duration regression from Table 3 for each of the alternative measures. All measures have the wrong sign — more positive measured interest rate exposure is associated with more negative response of stock prices to positive interest rate shocks. The coefficient on the DeMarzo et al. (2024) and Begenau et al. (2015) measures are significant when excluding the financial crisis. Both measure the duration of assets. The fact that they have a negative, significant sign suggests that banks tend to allow their asset duration to move in the opposite direction from their franchise duration. In Section 4 I explore the hedging interpretation of this finding.

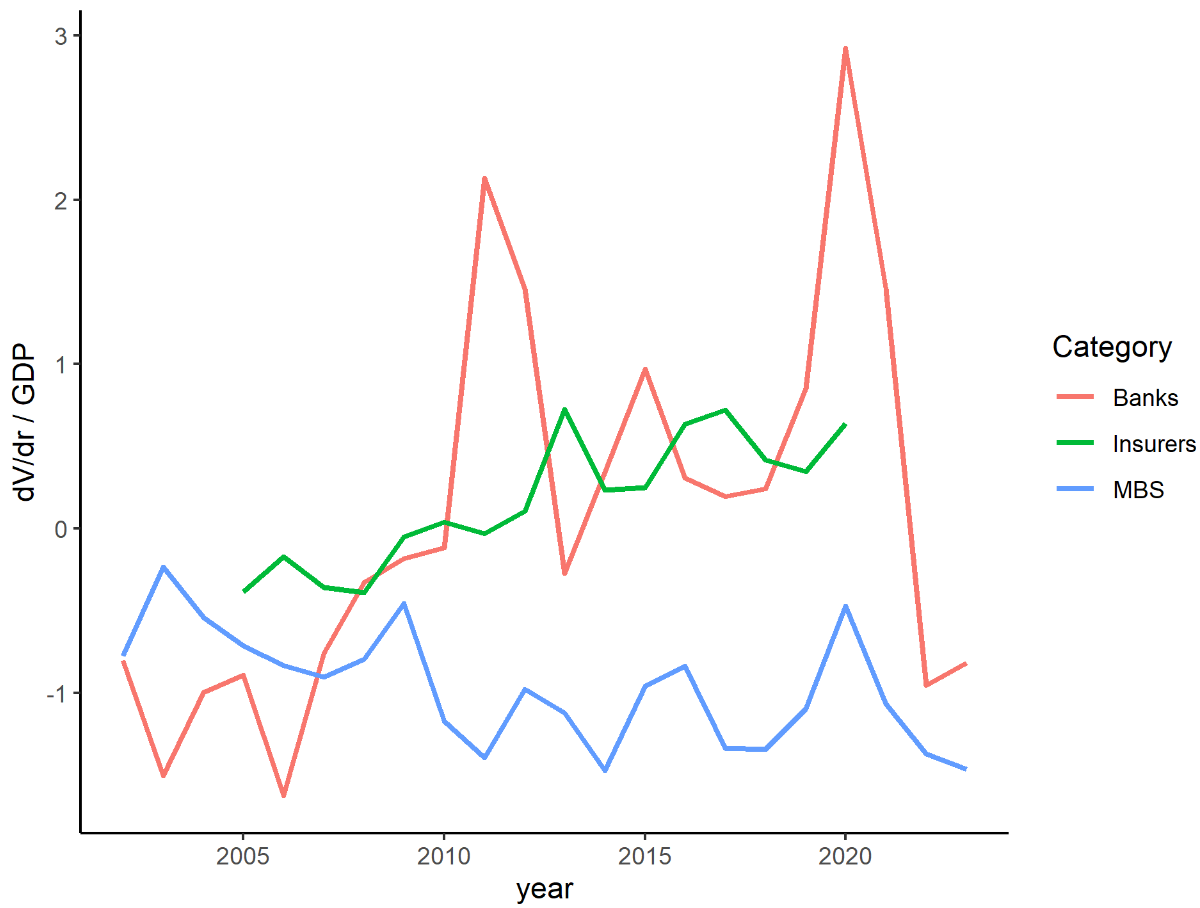

Figure 16: **Comparison of time-series of total dollar duration from the bank mechanism described in this paper, insurers, and mortgage-backed securities, 2002-2023**. The y axis shows the negative of dollar duration, scaled by GDP. Insurer duration is taken from Huber (2022). MBS duration is provided by the Bloomberg Barclays aggregate MBS index and matches the figures used in Hanson (2014). Bank dollar duration is estimated on publicly listed banks and then scaled up to all bank using the ratio of all bank assets to public bank assets.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Rate sens. × rate shock	1.216**	1.089***	0.429*	1.162***	1.197***	0.638***
	(0.377)	(0.282)	(0.170)	(0.330)	(0.341)	(0.185)
Rate shock	-4.802	-7.155	3.759	-1.944	-3.674	3.601+
	(6.851)	(5.160)	(2.466)	(2.637)	(2.957)	(2.165)
Rate sensitivity	0.003	0.003	-0.001	0.005	0.004	0.000
	(0.009)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
ΔIG spread		23.747***	12.283***		10.975	10.683
		(5.005)	(2.582)		(17.900)	(9.222)
ΔHY spread		-10.340*	-2.967		-3.615	-2.565
		(5.084)	(1.900)		(3.814)	(1.805)
Market return			1.524***			1.246***
			(0.146)			(0.119)
Intercept	0.185	0.035	-0.147+	0.120	0.115	-0.071
	(0.168)	(0.190)	(0.078)	(0.128)	(0.127)	(0.065)
Num.Obs.	168	168	168	152	152	152
R2	0.062	0.200	0.839	0.104	0.119	0.738

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: **Out of sample aggregate measured duration, calculated using expanding windows predicts bank stock price response to interest rate shocks.** This table repeats the regressions in Table 3 using bank duration measures calculated from expanding window estimates of bank interest rate sensitivity that do not use any data from after the date of the relevant interest rate shock. "Rate sensitivity" is the measured interest rate exposure of the aggregate banking system, described in Section E, and calculated without any out of sample data. "Rate Shock" is the change in the 10 year treasury yield in the 1-hour window around FOMC announcements from Gürkaynak et al. (2022). "Δ IG spread & HY spread" denote controls for daily changes in the ICE BofA option adjusted investment grade or high yield credit spread index. "Market return" is a control for the CRSP total market daily return. Columns 4–6 exclude H2 2007 – H1 2009. All standard errors are heteroskedasticity–robust.

Panel a: Full sample

	DKN measure	DKN (eq wtd)	BPS measure	Income gap
Rate sens. × rate shock	0.330	0.098	0.443	-3.826
	(0.456)	(0.158)	(0.311)	(3.670)
Rate shock	-1.117	-1.402	-2.347	119.057
	(9.615)	(3.700)	(6.992)	(117.178)
Rate sensitivity	-0.184	-0.065	-0.146*	0.029
	(0.115)	(0.041)	(0.060)	(0.096)
Intercept	-1.009	-0.260	-1.495+	-0.609
	(0.821)	(0.291)	(0.763)	(3.060)
Num.Obs.	170	152	96	170
R2	0.107	0.055	0.128	0.032

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel b: Financial crisis period excluded

	DKN measure	DKN (eq wtd)	BPS measure	Income gap
Rate sens. × rate shock	-3.260**	-1.705*	-2.654***	-0.368
	(1.031)	(0.786)	(0.579)	(1.876)
Rate shock	-18.066***	-9.917*	-35.775***	13.368
	(4.964)	(4.014)	(5.917)	(60.853)
Rate sensitivity	0.000	-0.021	-0.044	-0.045
	(0.044)	(0.043)	(0.030)	(0.082)
Intercept	0.165	-0.076	-0.186	1.637
	(0.281)	(0.283)	(0.358)	(2.678)
Num.Obs.	152	137	78	152
R2	0.059	0.031	0.156	0.005

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: **Alternative interest rate risk measures do not predict bank stock price reaction to interest rate shocks with the right sign.** This table repeats the regressions in Table 3 using different alternative bank interest rate risk measures described in Section 3.3. Columns 1, 3, and 4 use value-weighted bank stock returns as the dependent variable, while column 2 uses equal-weighted returns. "Rate sensitivity" is the measured interest rate exposure, based either on DeMarzo et al. (2024), Begenau et al. (2015), or Haddad and Sraer (2020). "Rate Shock" is the change in the 10 year treasury yield in the 1-hour window around FOMC announcements from Gürkaynak et al. (2022). Panel b exclude H2 2007 – H1 2009. All standard errors are heteroskedasticity–robust.

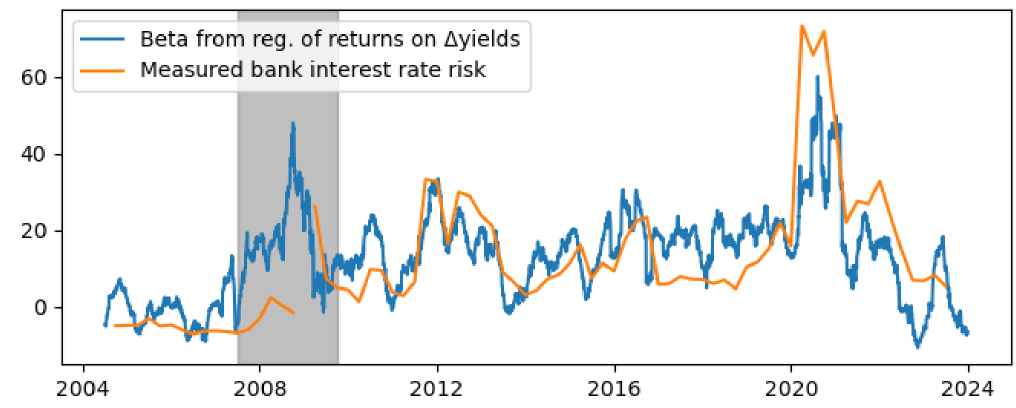

Figure 17: **The bank interest rate risk measure closely tracks the relationship of daily yield changes on daily bank returns.** The orange line shows the aggregate interest rate sensitivity of public banks. Sensitivity is calculated as the negative duration of all bank equity (details in Section E). The blue line shows the coefficient from a rolling 1-quarter regression of 1-day banking sector stock returns on 1 day changes in the 10 year treasury yield. Data from the financial crisis (2007 H2 - 2009 H1) is shaded in grey.