Bank Convexity Risk*

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Abstract

Nothing exemplifies bank exposure to interest rate risk better than the U.S. banking crisis of March 2023, when monetary policy tightening due to high inflation caught several regional banks off-guard. These banks experienced massive losses in asset values, which were not hedged with interest rate derivatives. Uninsured depositors – a significant source of funding for these banks – became increasingly concerned about potential losses, prompting a classic bank run. Regulators quickly intervened as they feared that interest rate exposures of some banks could undermine bank sector financial stability. We analyze bank exposure to interest rate variability in the context of these recent events. We begin by documenting that banks are exposed to not only interest rate changes (i.e., duration risk) but also interest rate volatility or uncertainty (i.e., convexity risk). Higher interest rate uncertainty, as measured by higher implied volatility of options on Treasury futures ('yield implied volatility' or 'YIV'), is associated with the higher volatility of both bank assets (loans and liquid assets including securities) and bank liabilities (deposits). Since this variation in the value of bank assets and liabilities can lead to financial instability and potentially cause bank runs (as in Jiang, Matvos, Piskorski, and Seru (2023)), we then introduce a new measure, YIV-Beta, that captures individual banks' exposure to interest rate uncertainty, – convexity risk – i.e., bank stock return's sensitivity to changes in YIV. An application of our methodology to a case study of Silicon Valley Bank shows the bank had built up substantial exposure to interest rate variability starting in 2020, and that SVB's high YIV-Betas could have served as an advanced warning signal to regulators that something was amiss at the bank. More generally, in the cross-section of banks, higher convexity risk exposure is associated with an increase in the volatility of deposits, credit, and liquid assets. The predictive power of YIV-Beta holds after controlling for duration risk exposure. Our results suggest that bank exposure to interest rate uncertainty is key to understanding the full picture of bank exposure to interest rate variability with implications for financial stability.

JEL Codes: E4, E43, E58, G0, G2, G21.

Keywords: Banks, Interest rate risk, Options markets, Implied volatility, Convexity risk.

*...All errors are our responsibility.

Introduction

Given banks' pivotal position in the financial system and in transmission of monetary policy, risk assessment of banks has been central to policy design and regulations, especially after the Global Financial Crisis. Particularly, interest rate risk is a normal part of banking business and banks' exposure to interest rate risk could impose significant risk to the economy. Nothing exemplifies this better than the U.S. banking crisis of March 2023, when monetary policy tightening in response to high inflation caught several regional banks, such as Silicon Valley Bank and First Republic Bank, off-guard. Further, uninsured depositors, which represented a significant source of funding for these banks, became increasingly concerned about potential losses, prompting them to withdraw their funds, spurring a classic bank run. Regulators reacted quickly with an array of interventions as they feared that interest rate exposures of some regional banks could easily undermine confidence among other banks, resulting a full-blown banking crisis.

That interest rate risk can significantly impact the value of bank assets is not particularly surprising. Funded by short-term deposits, traditional banks engage in maturity transformation, issuing short-term liabilities and investing the proceeds in illiquid, long-term, fixed-income securities and assets. Surprisingly, the extant literature on banks' interest rate risk exposures focuses only on duration risk, i.e., the duration (mis)match between banks' assets and liabilities. For example, the widely used income gap measure of Flannery and James (1984b) and Gomez, Landier, Sraer, and Thesmar (2021) captures this maturity mismatch by subtracting the dollar value of liabilities subject to repricing within one year from the dollar value of assets subject to repricing within one year.

In this paper, we document that banks are exposed not only to changes in interest rates (duration risk) but interest rate uncertainty as well, which we term as bank convexity risk.[1] Results in studies such as Hanson, Shleifer, Stein, and Vishny (2015), Collin-Dufresne and Goldstein (2002), and Hoffmann, Langfield, Pierobon, and Vuillemey (2019) directly motivate banks exposure to interest rate uncertainty. Hanson, Shleifer, Stein, and Vishny (2015) model banks as patient, fixed-income investors whose asset values can fluctuate substantially with interest rates (i.e., market conditions). Collin-Dufresne and Goldstein (2002) show that in incomplete markets, such convexity risk is not completely spanned and thus cannot be easily hedged by a portfolio consisting solely of bonds. Finally, convexity risk can be particularly relevant for banks with substantial exposure to interest rate derivatives via their off-balance-sheet

[1] In fixed income markets, convexity is one measure of the relation between bond prices and bond yields. Throughout this paper, we use convexity risk to refer to banks' exposure to interest rate uncertainty. We use the terms 'exposure to interest rate uncertainty', 'exposure to interest rate volatility,' and 'convexity risk' interchangeably throughout the paper.

activities, or using such derivatives for increasing risk exposures (Hoffmann, Langfield, Pierobon, and Vuillemey (2019)). To the best of our knowledge, this is the first paper that examines banks' exposure to convexity risk, introduces a simple way to measure such risk at the individual bank level that is based on market prices and thus forward-looking, and highlights that bank exposure to convexity risk is important to understand and predict future volatility of bank balance sheets.

Following Cremers, Fleckenstein, and Gandhi (2021), our measure of aggregate interest rate uncertainty is the implied volatility from the Treasury derivatives market (YIV), which captures the expected volatility of interest rates. Cremers, Fleckenstein, and Gandhi (2021) establish that higher YIV is strongly associated with deteriorating future economic conditions and increased future macroeconomic volatility, e.g., as reflected in the growth and volatility of gross domestic product.

YIV is an ideal proxy for measuring interest rate uncertainty, particularly in a study focused on banks, for several reasons. First, YIV is estimated directly from option contracts on Treasury note and bond futures, and although these contracts are not identical to options written directly on Treasury notes or bonds themselves, they serve much the same purpose and are similarly priced.[2] Second, YIV not only reflects the market's expectation of interest rate uncertainty but also embeds the cost of hedging such uncertainty. Third and finally, banks are among the most active traders in the market for options on Treasury note and bond futures as well as the underlying futures contracts. Therefore, YIV, to a large extent, directly captures banks' collective expectations of the prospect of interest rate uncertainty, the cost of hedging such uncertainty, and its relation to the broader economy.

We begin by showing that for the aggregate U.S. bank sector, higher interest rate uncertainty predicts higher volatility of bank deposits, higher volatility of credit, and higher volatility of liquid assets, as well as lower bank stock returns and higher bank stock volatility. We focus on bank deposits, credit, and liquid assets as, collectively, these three variables account for more than 80% of the bank's liabilities or assets, on average.[3] A one-standard deviation increase in YIV is associated with increases in the future volatility of deposits of 0.36% over a one-year horizon, which amounts to 12% of average annual volatility of deposits in our sample. YIV by itself explains nearly 17% of the future variation in the volatility of deposits over a one-year horizon.

[2]This is because spot and futures prices of Treasury notes and bonds are highly correlated. See, for example, Mizrach and Neely (2008). Options written directly on Treasury notes and bonds trade mostly in over-the-counter and transaction prices for these are generally not available to researchers.

[3]See Hanson, Shleifer, Stein, and Vishny (2015). The average bank finances nearly 80% of its assets with deposits. Bank credit and liquid assets account for nearly 90% of the average bank's book value of assets.

Similarly, a one-standard deviation increase in YIV also implies increases in future volatility of credit (by 0.3276%, which is 8% of the sample volatility) and liquid assets (by 2.0728%, which is 11% of the sample volatility), such that these results are also economically significant. Over a one-year horizon, YIV by itself explains approximately nearly 18% and 16% of the variation in the future volatility of credit and liquid assets, respectively. Finally, we find that interest rate uncertainty also helps predict bank stock returns. In predictive regressions, using a value-weighted index of common stock returns for all publicly listed banks in the U.S., a one-standard deviation increase in YIV is associated with an 1.50% increase in the volatility of returns (22% of the sample volatility) and 5.28% lower abnormal returns (35.48% of the sample mean) at the one-year horizon.

These results for the aggregate U.S. bank sector are robust to numerous changes in empirical design, such as varying the forecasting horizons for the predictive regressions, excluding data for the global financial crisis of 2008–2009, using non-overlapping observations, and out-of-sample tests. Furthermore, the results are also robust to controlling for the implied volatility from options on the two-year, ten-year, T-bond (long-term) U.S. Treasury note and bond futures, or employing the Treasury implied volatility measure from Choi, Mueller, and Vedolin (2016). Using non-parametric vector auto-regressions, we show that YIV has significant predictive ability (i.e., Granger causality) extending up to 20 months for subsequent volatility of bank deposits, credit, and liquid assets, but the volatility of any bank variables does not have predictive ability for the YIV.

We then propose a new measure for interest rate uncertainty or convexity risk for individual banks. We estimate this measure by regressing individual banks' daily stock returns on daily (negative) changes in YIV to estimate each individual bank's exposure to changes in aggregate interest rate uncertainty. That is, we regress individual banks' daily stock returns on daily changes in YIV multiplied by (-1). We term this exposure the bank's 'YIV-Beta'. Intuitively, YIV-Beta gauges the sensitivity of the bank's stock return to changes in interest rate uncertainty. Since we multiply changes in YIV by minus 1, a (more) positive YIV-Beta for a bank implies that increases in interest rate uncertainty are associated with (more) lower equity excess returns, and is thus indicative of greater exposure to movements in interest rate uncertainty or YIV.[4]

On average, YIV-Beta is negative at -0.40% indicating that for the average bank an increase in YIV is associated with higher realized contemporaneous stock returns. The slightly negative mean YIV-Beta

[4]Thus, multiplying changes in YIV by minus 1 makes our interpretation of YIV-Beta consistent with the loading of excess bank equity returns on any risk factor.

for the cross-section of banks is consistent with the idea that the average bank may have hedged their exposure to interest rate uncertainty either using a portfolio of interest rate derivatives or by matching the interest rate exposures of assets and liabilities.

YIV-Beta's vary substantially in the cross-section with a standard deviation of 6.91% and an interquartile range of 4.24%, which is an order of magnitude higher than the mean value of YIV-Beta. Next, the product of changes in YIV and YIV-Beta – i.e., the change in the aggregate interest rate uncertainty times the bank's exposure to changes in those levels – serves as our proxy for each individual bank's exposure to aggregate interest rate uncertainty, i.e., our proxy for each bank's convexity risk.

Our novel proxy of bank's convexity risk complements current measures of bank risk and offers several advantages. First, as mentioned earlier, the existing literature on bank exposure to interest rate risk emphasizes duration risk, i.e., to changes in the level of interest rates. For example, Flannery and James (1984a) measure bank interest rate risk by regressing bank stock returns on interest rate changes, where the regression coefficient —- often referred to as the interest-rate beta —- provides an estimate for the average exposure of the bank's overall value to interest rate changes. Gomez, Landier, Sraer, and Thesmar (2021) build on this approach and develop alternative performance measures such as changes in interest income or earnings as a fraction of assets. In contrast, we focus on changes in the implied volatility of interest rate derivatives, and therefore YIV-Beta represents banks' exposure to convexity risk.

Second, other measures for banks' exposure to interest rate risk, use data for only 'on-balance-sheet' items and do not incorporate exposure to interest rate risk via 'off-balance-sheet' activities. For instance, the widely used maturity gap measure is estimated as the difference between bank assets and liabilities that mature or reprice within one year (Flannery and James (1984b) and Flannery and Sorescu (1996)). However, banks often have substantial exposure to interest rate risk via their off-balance-sheet activities via loan commitments, lines of credit, and interest rate derivatives. Venkatachalam (1996) and Acharya, Engle, and Steffen (2021) show the size of such off-balance-sheet risk exposures for banks have increased dramatically in recent years. For the largest banks, the size of their off-balance-sheet activities is an order of magnitude larger than that their on-balance-sheet activities.[5] By directly regressing bank stock returns on changes in aggregate convexity risk (i.e., the YIV), our measure accounts for both on- and off-balance sheet positions.

[5]Consider, for example, J.P. Morgan Chase (NYSE ticker: JPM), the largest commercial bank in the U.S. by book value of assets. In 2021, JPM's book value of assets equals $3.74 trillion, but just the notional value of its interest rate derivatives positions is ten times higher at $37.18 trillion. Source: FRY9-C report released by the Federal Reserve Board, available at https://www.ffiec.gov/npw/Institution/TopHoldings.

Third and finally, banks typically assess how interest rate uncertainty affects them via computing and continuously monitoring their portfolio value at risk (VaR).[6] However, for most banks, VaR computations are at best available at a quarterly frequency. Further, Begley, Purnanandam, and Zheng (2017) show that banks' VaR computations are typically restricted to assessing the risk of their trading books, and they argue that banks have an incentive to underreport their true VaR risk. In contrast, our measure is estimated using market-based equity returns and implied volatilities, is straightforward to compute, and serves as a comprehensive measure of banks' exposure to convexity risk that can be computed at a relatively high frequency. Since the YIV is forward-looking, YIV-Beta may be especially useful in predicting the volatility of banks' balance sheets and stock returns and how banks would react to an increase in interest rate uncertainty.

To illustrate how our measure of interest rate exposure (i.e., the YIV-Beta) differs and relates to other popular measures of interest rate risk, we apply our methodology to a case study of Silicon Valley Bank. To compute the YIV-Beta for SVB, we collect daily excess returns for the bank for all years for which such data is available in CRSP. We then regress SVB's daily excess stock returns on daily changes in YIV multiplied by (-1) with each year (as well as the daily excess return on an index of all stocks and daily changes in the yield-to-maturity on the 5-year Note issued by the U.S. Treasury) to get an annual 'YIV-Beta' for SVB for each year. As above, since we multiply changes in YIV by minus 1, a (more) positive YIV-Beta for SVB indicates that the bank had a greater exposure to increases in interest rate uncertainty.

Figure 1 plots the annual YIV-Beta for SVB for each year for which its stock returns are available for the full year. In the Figure, the blue bar plots the magnitude of the annual YIV-Beta for SVB for that year. The red line plots an alternative measure of interest rate risk for banks that is currently used in the literature –i.e., the income gap of Gomez, Landier, Sraer, and Thesmar (2021). Higher values of both income gap and interest sensitivity indicate greater exposure of a bank to interest rate risk.

Figure 1 suggests that YIV-Beta correlates well with income gap as a measure of interest rate risk. For instance, for SVB, YIV-Beta's and income gap both decline in 2001 as well as in 2003, indicating that the bank had lower exposure to both interest rate changes as well as interest rate uncertainty. However, in certain cases, these measures of interest rate risk diverge. As an example, in 2007, the YIV-Beta for SVB declines while its income gap increases. The divergence of YIV-Beta and income gap for SVB could partly

[6] For instance, using a limited sample of 8 banks over a six-year period from 1994–2000, Jorion (2002) shows that individual bank estimates for VaR predict the variability in their future trading income.

be attributed to the fact that income gap is based on the difference in book value of assets and liabilities scheduled to be repriced within one year, and often does not take into account the a bank's off-balance sheet positions in interest rate derivatives. Such positions could be substantial for a large bank such as SVB, and would be adequately captured by SVB's YIV-Beta whose computation relies on the reaction of stock market prices to changes in YIV.

The plot in Figure 1 also indicates that YIV-Betas sometimes lead income gap as a measure of interest rate risk. For instance, in 2009, the decline in YIV-Beta for SVB precedes a decline in its income gap, both of which indicate lower exposure to interest rate risk. More interestingly, in the runup to the most recent crisis (i.e., in the years 2020 - 2022), income gap for SVB is either flat or falling, indicating a lower exposure to interest rate risk. In 2020 and 2021, the YIV-Beta for SVB is above 4.00%, which is nearly 10 times higher than the sample cross-sectional mean of 0.40%, indicating SVB had substantial exposure to interest rate variability. Even though the YIV-Beta for SVB falls to 2.00% in 2022, this is still nearly 5 times higher than the YIV-Beta for the average bank in our sample.

The large positive YIV-Betas for SVB in the years 2021–2022, combined with the fact that over these years, the annual change in YIV exceeded 3% and 2%, respectively, indicates that SVB was building up substantial exposure to interest rate variability in the run up to the crisis. Thus, YIV-Betas and our measure of bank exposure to interest rate uncertainty could have served as advanced warning signals to regulators and market participants that something was amiss at SVB, and that an intervention to rake in interest rate exposure may have been necessary.

Equipped with this new measure of convexity risk for individual banks, we show that for banks with more exposure to aggregate convexity risk (i.e., with more negative YIV-Betas), an increase in YIV is associated with an increase in the volatility of the year-on-year growth of deposits, credit, and liquid assets. In terms of economic magnitude, a one-standard deviation increase in YIV, is associated with nearly 0.16% (0.36%) higher future volatility of bank deposits (credit) for banks with YIV-Betas at the 75^{th}-percentile (i.e., higher YIV-Betas and thus higher convexity risk). These numbers can be compared to the sample volatility of 2.12% and 2.37% for bank deposits and credit, respectively. Similarly, a one-standard deviation increase in YIV is associated with nearly 1.08% higher volatility of liquid assets for banks with YIV-Betas at the 75^{th}-percentile. This can be again compared to the sample volatility of 1.71% for the growth of bank liquid assets.

These results survive when we control for duration risk as measured by the coefficients in a regression of individual banks' daily stock returns on daily changes in the 5-year Treasury rate. Our results are also robust to controlling for current measures of bank risk, such as the income gap of Gomez, Landier, Sraer, and Thesmar (2021), the difference in the book value of assets and liabilities that are scheduled to be repriced within on year (Flannery and James (1984b)), and the notional value of interest rate derivatives used for hedging normalized by the book value of assets as in Purnanandam (2007). The inclusion of any or all of these variables does not affect the economical or statistical significance of the relation between YIV-Betas and future volatility of bank deposits, credit, liquid assets, and interest income.

In our final test, we investigate how interest rate uncertainty impacts the year-on-year growth of bank deposits, credit, and liquid assets themselves For the aggregate U.S. bank sector, we find that a one-standard deviation increase in YIV is associated with an -0.0953% decrease in credit and an 0.5398% increase in liquid assets over the next one year horizon. While this amounts to only a 2.00% and a 10.00% change in credit and liquid assets as compared to respective sample means, the results are economically significant in dollar terms. For instance, the total book value of all bank loans issued by all domestically chartered banks in the U.S. was $11.23 trillion as of July 2023. A 0.0953% reduction in the growth of bank credit implies that the dollar amount of total bank credit over the next one year will be a nearly $11 billion lower collectively for all banks in the U.S.

For the aggregate U.S. bank sector, there is no statistically significant relation between YIV and the year-on-year growth of bank deposits over any horizon. This suggests that bank depositors may not care about banks' exposure to interest, and such behavior can be rational for small depositors in a world with deposit insurance. However, as the regional banking crisis of U.S. of March 2023 indicates, it is still possible that interest rate uncertainty significantly impacts the year-on-year growth of large bank deposits that are less likely to be covered by deposit insurance, and this is exactly what we find. An increase in YIV is associated with lower growth of large bank deposits (defined as those with a value of $100,000 or higher) over the next one year. The coefficient on YIV for all horizons is negative and statistically significant. In terms of economic significance, a one-standard deviation increase in YIV is associated with a nearly 0.1864% decline in the year-on-year growth of large bank deposits, and this number can be compared to sample average growth of 1.44%, indicating that the results are economically significant.

In our final test, we verify that the impact of YIV on the growth of bank deposit, credit, and liquid assets holds in the cross-section. In the cross-section, an increase in YIV causes a reduction in the growth of bank deposits, credit, and liquid assets for banks with greater exposure to interest rate uncertainty.

These results again survive numerous changes in the empirical specification, and are also robust or even stronger when we control for duration risk or other existing measures of bank interest rate risk exposures.

Overall, our paper contributes to the existing literature on bank risk assessment and management, and present evidence that interest rate uncertainty matters for banks. Our measure of banks' exposure to interest rate uncertainty is easily estimated using publicly-available, market-based, equity returns and implied volatilities, and allows assessment of banks' exposure to interest rate uncertainty at a relatively high frequency. To our knowledge, we are the first to focus exclusively on how interest rate uncertainty impacts banks, and the first to establish a link between financial market volatility and the volatility of bank balance sheets. Finally, our study also contributes to the current debate in the literature on whether interest rate risk matters for banks (see literature review below) by highlighting a new perspective: that banks' exposure to interest rate risk has two distinct components, duration risk and convexity risk.

1 Related literature

This paper relates to several strands in the literature. First, we contribute to the literature on how to assess bank risk, which was one of the key questions coming out of the financial crisis of 2008. Post crisis, regulators developed frameworks to encourage banks to be adequately capitalized, hold sufficient liquid assets, and maintain their funding stability. They also focused on developing several measures of bank tail risk that could potentially provide early warning systems (Acharya, Pedersen, Philippon, and Richardson (2017), Kelly, Lustig, and Van Nieuwerburgh (2016)). Further, regulators introduced stress tests requiring banks to assess their performance under various tail risk scenarios. Our paper complements these studies and suggest that incorporating interest rate uncertainty is likely to be useful in these stress test scenarios.

Second, our work is closely connected to the literature on risk-management practices in banking. Important papers in this area include Begley, Purnanandam, and Zheng (2017), Ellul and Yerramilli (2013), Jorion (2002), and Berkowitz and O'Brien (2002). One methodology that banks may currently use to assess how interest rate volatility or uncertainty impacts them is via monitoring their portfolio value at risk (VaR). However, Jorion (2002) and Liu, Ryan, and Tan (2004) show that VaR only estimates variability in banks' future trading income. In addition, Begley, Purnanandam, and Zheng (2017) document that banks have an incentive to underreport their true VaR exposure. In contrast, our measure of banks' exposure to interest rate uncertainty (i.e., the YIV-Beta) is easily estimated using publicly-available, market-based equity returns and implied volatilities and allows regulators and investors to asses banks' exposure to interest rate uncertainty at a relatively high frequency.

Third, we contribute to the literature that attempts to understand how monetary policy and interest rates impacts bank balance sheets. Important models in this literature include Bernanke (1983), Bernanke and Blinder (1988), Bernanke and Gertler (1995), Kashyap and Stein (1995), and Stein (1998). In this literature, monetary policy impacts bank lending and balance sheets because of market frictions, such as, the existence of reserve requirements. Our results provide a possible alternative channel, i.e., an increase in interest rate uncertainty increases volatility of value of bank assets, which in turn impacts their discretionary lending decisions. Our results are thus consistent with Bernanke and Gertler (1989), Kiyotaki and Moore (1997), Adrian and Shin (2010), He and Krishnamurthy (2011, 2013), and Gertler and Kiyotaki (2015), where higher interest rate uncertainty around monetary policy announcements causes bank balance sheets to contract. More recently, Ghironi and Ozhan (2020) develop a formal model for how central banks can employ interest rate uncertainty to discourage inefficient investments.

Finally, our study contributes to the recent debate between two major opposing views on whether banks bear interest rate risk. Under the 'traditional view', buying long-term assets funded by short-dated deposits exposes banks to interest rate uncertainty that cannot be perfectly hedged (Flannery and James (1984a), Begenau, Piazzesi, and Schneider (2015), Gomez, Landier, Sraer, and Thesmar (2021), Rampini and Viswanathan (2010), Rampini and Viswanathan (2013)). To the extent that banks cannot fully hedge this risk, the impact of interest rate risk on banks' balance sheets propagates through the real economy by contracting the supply of loans (Bernanke and Gertler (1995) and Jiménez, Ongena, Peydró, and Saurina (2012)). In extreme cases, the exposure to interest rate risk can lead to bank failures and poses a threat to financial stability, as was the case for regional banks in the U.S. in March 2023.

Alternatively, the 'matching view' states that banks can match their exposure to interest rate risk of their assets and liabilities and that, therefore, banks are not exposed to interest rate risk. In Hellwig (1994), banks extend variable-rate loans and rely on variable-rate deposits. Kirti (2017), provides empirical evidence to support such a view: banks offer variable-rate loans due to their own exposure to variable-rate liabilities. Recently, Drechsler, Savov, and Schnabl (2021) argue that banks' market power in the deposits market leads to limited pass-through of market rates to deposit rates, and therefore deposits effectively serve as long-term fixed-rate liabilities. Consequently, it is optimal for banks to match deposits with long-term assets, and this maturity mismatch reduces the risks of banks, and therefore, banks do not take on interest rate risk. This view is challenged by Begenau and Stafford (2021) and Jiang, Matvos, Piskorski, and Seru (2023). In particular, Jiang, Matvos, Piskorski, and Seru (2023) argues that substantial presence of uninsured deposits can cause the deposit franchise channel to break down.

We contribute to this debate by highlighting a new perspective: banks' exposure to interest rate risk has two distinct components, duration risk and convexity risk. While the existing literature exclusively focuses on duration risk, our results show that regardless of whether banks bear duration risk, convexity risk matters for banks. Such exposure is also more difficult to hedge using a linear combination of bonds (Collin-Dufresne and Goldstein (2002)). To our best knowledge, we are the first to construct a market-based and forward looking measure of banks' exposure to convexity risk.

Overall, our results for how YIV impacts levels of bank credit and liquid assets are consistent with the literature that shows higher cash flow uncertainty and volatility is associated with lower discretionary investments (Stulz (1990), and Froot, Scharfstein, and Stein (1993), Minton and Schrand (1999), Shapiro and Titman (1986), among others). In addition, Acharya and Skeie (2011) show how higher uncertainty can increase rollover risk for banks causing them to reduce lending and increases their precautionary demand for liquid assets, consistent with our results.

2 Data and summary statistics

In this section, we describe our data sources and the methodology used to calculate the Treasury yield implied volatility, and provide summary statistics for the main variables in the analysis. We follow Cremers, Fleckenstein, and Gandhi (2021) to construct our measure of aggregate interest rate uncertainty, which is the implied volatility from the Treasury derivatives market or the YIV. We begin by collecting transaction data for call and put options on U.S. Treasury note and bond futures contracts traded on the Chicago Mercantile Exchange (CME). The buyer of a call (put) option on a U.S. Treasury futures contract has the right to buy (sell) the underlying futures contract at the strike price on any business day before expiration. The U.S. Treasury note and bond futures contracts underlying the options contracts themselves are standardized contracts for the future purchase and sale of Treasury notes and bonds.

Although an option on Treasury note or bond futures contracts is not identical to an option on a Treasury note or bond, it serves much the same purpose and is similarly priced, as spot and futures prices of Treasury notes and bond are highly correlated (Mizrach and Neely (2008)). We use options on U.S. Treasury note and bond futures as these are exchange-traded, while options on actual notes and bonds trade in over-the-counter markets, and transaction data for the latter are not readily available

(Choudhry (2010) and Hull (2016)). The markets for options on Treasury notes and bond futures and for the underlying futures contracts themselves are among the largest and most liquid in the world. Volume is concentrated in four contracts: two-year, five-year, ten-year Treasury notes, and long-term Treasury bonds (with about 20 years to maturity). The average daily trading volume for these futures (options) contracts is over 2 million (450,000) contracts per day, concentrated mostly in the five-year and ten-year contracts. Average daily notional traded in these markets is $300 billion, which amounts to more than 80% of the daily volume in Treasury cash bonds.

While the pricing of Treasury note and bond futures contracts is complex and impacted by delivery options, the pricing of options on these futures contracts is relatively straightforward, i.e., through standard option pricing (Hegde (1988), Burghardt and Belton (1994), and Fleming and Sarkar (1999)). We estimate the implied volatility for the selected options on each day by solving the Black (1976b,a) commodity option pricing model for the standard deviation of the log Treasury notes futures prices.

We focus on options on the five-year Treasury note futures, although in robustness tests we also use data for options on the two-year, ten-year, and long-term Treasury notes and bond futures. As explained in Cremers, Fleckenstein, and Gandhi (2021), there are two reasons for primarily using data for options on the five-year Treasury note futures. First, the market for options and futures on the five-year Treasury note is the largest and the most liquid.[7] Second, Brandt, Kavajecz, and Underwood (2007) and Mizrach and Neely (2006) show that price discovery in the Treasury futures market takes place primarily in the five-year Treasury notes futures contracts.[8]

We obtain the time-series of option implied volatilities on the five-year Treasury note futures using price of two call and put options with exercise price closest to the price of the near-term five-year Treasury note futures contracts in the March, June, September, and December cycle (i.e., those options whose exercise prices are closest to at-the-money relative to the next closest Treasury note futures in the quarterly cycle). This choice is motivated by Ederington and Lee (1993, 1996), who argue that this process ensures the strongest link between spot and futures markets, so that options on futures are very close to options on

[7] For example, in 2016 average daily trading volume for the five-year note futures exceeded 750,000 contracts per day, accounting for nearly 40% of the overall volume in the Treasury note and bond futures market.

[8] Brandt, Kavajecz, and Underwood (2007) show that trading in the five-year futures contracts is of central importance to the [price impact] in both the Treasury futures and cash market. Similarly, Mizrach and Neely (2006) find that the contribution of trading in the five-year futures contracts to intra-day price discovery increases significantly after 1999 and, by 2001, exceeds that of the ten-year contracts. While trades in both the two- and five-year futures are significantly related to price movements, the price impact of trading in the ten-year and long-term futures contracts is less pronounced. In addition, options on the two-year Treasury note futures contracts are less liquid than those on five-year Treasury notes, and are available over a much shorter data sample.

the actual Treasury notes and bonds themselves. The selected options are generally also the most liquid and informationally efficient and the first to adjust to macroeconomic news, typically within the first ten seconds (Ederington and Lee (1996)).

Next, we compute the moneyness-weighted average of the implied volatilities, resulting in a daily time-series of option implied volatility on the five-year Treasury note futures contract. We average this time-series within each month to obtain a monthly time-series from May 1990 through December 2019, spanning a period of nearly 30 years with several major economic and financial events.[9] Henceforth, we denote this monthly time-series as the YIV.[10]

Figure 2 plots the time series of the option yield implied volatilities. Each panel plots the YIV from options on a distinct futures contract. The top right panel plots the YIV, i.e., the implied volatilities derived from options on the 5-year Treasury note futures. In each panel, the grey regions represent NBER recessions. Figure 2 indicates that YIV is highly counter-cyclical, peaking during almost all business cycle downturns. However, YIV also displays several distinct peaks unrelated to U.S. business cycles. For example, YIV peaks in February 1997 during the Asian Financial Crisis and again in August 1998 as news about losses incurred by the hedge fund Long Term Capital Management became public. Similarly, YIV (as well as the implied volatility derived from options on the 2-year, 10-year, and long-term Treasuries) has been increasing post-2021 and coincides with the period of high inflation post the COVID-19 pandemic. Thus, it seems YIV is useful indicator of not only deteriorating economic conditions (as in Cremers, Fleckenstein, and Gandhi (2021)), but also correlates with the stability of the global banking and financial systems as well with periods of high inflation and hence high interest rate uncertainty.

Panel A of Table 1 reports the mean, standard deviation, minimum, 25th-percentile, median, 75th-percentile, and maximum values of YIV over the entire sample period. YIV has a mean value of 3.26% and a standard deviation (i.e., volatility of implied volatility) of 1.15%. Its maximum value in our sample equals 9.21, which is nearly 3 times its mean value, and occurs during the global financial crisis of 2008–2009. The last column shows that YIV is highly persistent with a first-order autocorrelation of nearly

[9]For example, our sample period spans key events such as, Black Wednesday (September 1992) when the U.K. withdrew from the European Exchange Rate Mechanism; the collapse of Askin Capital Management (April 1994), which sent a shock wave through the mortgage markets; the Mexican Peso Crisis (December 1994); the Asian Financial Crisis (July 1997); the Russian default (August 1998); the Long-Term Capital Management crisis (August 1998); the subprime mortgage crisis (October 2007); the Lehman Brothers bankruptcy (September 2008); the European Debt Crisis (starting in May 2010); and the downgrade of the U.S. credit rating by S&P (August 2011).

[10]For further details regarding the transaction data for options on Treasury notes and bonds futures, the process for selecting options closest to the price of the near-term five-year Treasury note futures contract, the methodology for backing out the implied volatilities, and the robustness of YIV as a measure of interest rate uncertainty we refer the reader to Cremers, Fleckenstein, and Gandhi (2021).

73%.

To investigate the link between interest rate uncertainty and bank activities, we collect aggregate data for all domestically-chartered commercial banks in the U.S. We exclude data for all U.S. based branches, subsidiaries, and agencies of foreign banks. This data on the aggregate U.S. bank sector is available via a monthly (and weekly) report on the 'Assets and Liabilities of Commercial Banks in the U.S.' (statistical release H.8) issued by the Board of Governors of the Federal Reserve System (FED). The H.8 release is primarily based on data that are reported weekly by a sample of approximately 815 domestically-chartered banks.

While more than 5,000 FDIC insured commercial banks operate in the U.S., the largest 803 banks control nearly 93.75% of all bank assets in the U.S., so that the banks captured by our data serve as a proxy for the aggregate bank sector in the U.S.[11]

The FED carries out a series of checks and balances to ensure the accuracy of the data in the H.8 release. For instance, the FED regularly benchmarks the H.8 data against the mandatory quarterly 'Report of Condition and Income' (hereafter the Call Report) required to be filed accurately by all FDIC-insured banks on a quarterly or semi-annual basis. Further, to maintain historical continuity, the FED adjusts the time series data for all variables to remove the estimated effects of mergers and acquisitions, again using data obtained from the quarterly Call Reports.

From the H.8 release, we collect data for three key variables that summarize the essence of the business model of traditional banks: deposits, bank credit, and liquid assets, capturing the two distinct types of activities that traditional banks engage in: deposit-taking and lending. Deposits is the dollar amount of interest-bearing deposits held in all domestic offices (H.8 item code B1058NDMDM). Credit is the credit extended by all commercial banks in the U.S. to non-financial entities, including commercial and industrial loans, real estate loans, and consumer loans, but excluding interbank loans, repurchase agreements, Federal Funds holdings, derivative positions, and unearned income on loans (H.8 item code B1001NDMDM). To construct liquid assets, we follow Kashyap and Stein (2000), Berger and Bouwman (2009), and Stulz, Taboada, and van Dijk (2023) and use the sum of dollar amount of Treasury securities (H.8 item code B1003NDMDM), agency securities (H.8 item code B1302NDMDM), agency mortgage backed securities (H.8 item code B3092NDMDM), securities purchased with a commitment to resell (H.8

[11]See for example, data for all FDIC-insured institutions, page 7, 'Quarterly Banking Profile', for the fourth quarter 2022, issued by the Federal Deposit Insurance Corporation and available at https://www.fdic.gov/analysis/quarterly-banking-profile/index.html.

item code B1003NDMDM), and cash (H.8 item code B1048NDMDM) held by a bank. Stulz, Taboada, and van Dijk (2023), Kashyap and Stein (2000), and Berger and Bouwman (2009) argue that the items included in the definition of liquid assets all bear low credit risk and can either be sold outright or used for repurchase agreements when banks face financial constraints. For all items from the H.8 release, we use non-seasonally adjusted data collected in billions of dollars. All the assets we include in the definition trade in liquid markets, have little or no credit risk, and can easily be used for repurchase agreements.

The first three rows of Panel B of Table 1 reports the summary statistics for data for the aggregate U.S. bank sector for the year-on-year growth of bank deposits, credit, and liquid assets. For the aggregate bank sector, on average, the year-on-year (i.e., annual) growth of deposits, credit, and liquid assets equals about 6.10%, 6.01%, and 9.10%, respectively. The volatilities for the year-on-year growth of deposits and credit for the aggregate U.S. bank sector range are low, on the order of from 2.95-3.99%, respectively. Conversely, the volatility for the year-on-year growth of liquid assets equals 18.18%. The higher volatility of the year-on-year growth of liquid assets (as compared to that for deposits and credit) could partly be due to the fact that securities comprising liquid assets are periodically marked-to-market, while the both deposits and credit reflects are recorded at historical values in bank balance sheets. Note that all growth rates are highly persistent with first order autocorrelations that are above 95% in all cases. Such persistent makes it important to controlled for lagged growth rates and volatilities, and we are careful to do so in all our empirical tests below.

Panel B also reports the summary statistics for a value-weighted index of all publicly-listed banks in the U.S. To construct this index, we collect data for banks' stock prices, holding period returns including dividends, and total shares outstanding from the Center for Research on Security Prices (CRSP). For identifying banks in CRSP, we follow Gandhi and Lustig (2015) and select all firms with the two-digit header standard industrial classification (SIC) code of 60 or a four-digit SIC code of 6712.[12] We use data for share prices and total shares outstanding to compute the market capitalization for each individual bank for each month in our sample. Daily (monthly) returns for the bank index is constructed by value-weighting daily (monthly) holding period returns by individual banks' market capitalization. In addition, we use the daily returns for bank index to compute a monthly time-series of the stock return volatility of an index of all publicly-traded banks in the U.S.

[12] To identify banks in CRSP, several studies also use four-digit SIC codes ranging from 6000–6199. Gandhi and Lustig (2015) show that SIC codes from 6000–6199 sometimes misses selecting bank holding companies as they are usually listed under the four-digit SIC code 6712. By using the two-digit header standard industrial classification (SIC) code of 60 or a four-digit SIC code of 6712, our selection includes all publicly-listed bank holding companies in the U.S.

The last two rows in Panel B in Table 1 lists the mean, standard deviation, minimum, 25th-percentile, median, 75th-percentile, maximum values as well as the first-order auto-correlation of monthly returns and volatility for the index of bank stocks. The annualized mean and standard deviation for bank stock returns over the full sample equal 14.88% and 23.34%, respectively, and thus are higher than that of the average non-financial firm in the CRSP value-weighted index (7.64% and 18.90%, respectively). Higher return and volatility for the index of bank stocks may partly reflect the fact that the typical bank is much more leveraged than the typical non-financial firm. The last columns indicate that while returns for banks are not persistent (first-order autocorrelation of approximately 3%), volatility is highly persistent (first-order autocorrelation of nearly 82%), which is also the case for non-financial firms.

To investigate the relation between interest rate uncertainty and individual banks in the cross-section, we gather quarterly bank balance sheet and income statement information at the bank holding company (henceforth banks) level from the FR Y-9C, i.e., the 'Consolidated Financial Statements for Bank Holding Companies'. Panel C of Table 1 reports the summary statistics for the year-on-year growth of bank deposits, credit, and liquid assets at the bank level. Since a bank's size can substantially influence the growth of its deposits, credit, and liquid assets, in panel B, all growth variables are normalized by lagged book value of assets. In addition, to understand how interest rate uncertainty may impact bank cash flows, we also gather data for each individual bank's net interest income. Details regarding how each of these variables is constructed using data from the FRY9-C are provided in Table A1 in the Appendix.

Panel C indicates that for the average bank in the U.S., the year-on-year growth of deposits and credit both equal about 1.39% and 1.20%, respectively. However, these growth rates vary quite a bit over time and in the cross-section, with standard deviations of higher than 2% in each case. The average year-on-year growth for bank liquid assets is smaller (in comparison to the year-on-year growth of deposit and credit) and equals about 0.30%. The volatility of the year-on-year growth of liquid assets is also slightly lower at 1.71%. Finally, the last column of Panel C indicates that balance sheet growth variables at the individual bank level are not particularly persistent, with first order autocorrelations ranging from 10.23% – 46.84%.

The last panel of Table 1 (Panel D) presents the summary statistics for several stock and bond market variables that serve as controls in our empirical tests. We collect data for yield-to-maturity on the 3-month Bill and the 10-year Note issued by the U.S. Treasury, the Chicago Board of Options Exchange (CBOE) volatility index, and credit spreads. Data for yield-to-maturity on Treasury bonds is from the

Federal Reserve Economic Data at the Federal Reserve Bank of St. Louis available at https://research.stlouisfed.org/andhttps://fred.stlouisfed.org/. We use these yield-to-maturities to compute the term spread, defined as the yield spreads between the 10-year Treasury Note and the 3-month T-bill (term spread). We also use the yield-to-maturity on the 3-month Treasury Bill to compute changes in the short-term interest rates, i.e., the change in the yield-to-maturity on 3-month T-bills (Δ Rate). Data for the CBOE volatility index (denoted as VIX) is from Wharton Research Data Services. Finally, credit spreads are measured using the option-based methodology for analyzing credit risk from Culp, Nozawa, and Veronesi (2018) (denoted as CREDIT-SPREAD).

3 Results

In this section, we first assess the predictability of interest rate uncertainty for the aggregate U.S. bank sector. We then move to the bank level analysis in the cross-section, construct our measure of individual banks' exposure to interest rate uncertainty, i.e., the YIV-Beta, and show how interest rate uncertainty forecasts the volatility of bank balance sheets in the cross-section.

3.1 Aggregate bank sector results

We begin by plotting the YIV along with the volatility of bank deposits, credit, and liquid assets in Figure 3. Each panel in this figure presents the result for a different bank variable, with the gray-shaded bars representing periods of NBER recessions. The blue lines are the moving average of YIV (computed over 12-month moving windows) and the red lines are volatilities of the year-on-year growth of bank deposits, credit, and liquid assets for the aggregate U.S. bank sector (also computed over 12-month moving windows).

Figure 3 shows that increases in YIV are generally accompanied by an increase in the volatility of bank deposits, credit, and liquid assets. More importantly, the change in YIV tends to precede changes in volatilities of bank balance sheet items, suggesting predictive power of YIV. This positive correlation among YIV and volatility of bank variables is particularly visible during the recent financial crisis and recession of 2008–2009, when the value of YIV more than doubles from 3.44% in March of 2008 to 7.50% in November of the same year. Over the same period, the volatilities of the year-on-year growth of deposit, credit, and liquid assets also increases substantially. For instance, the volatility of the year-on-year growth of deposits nearly triples from 1.00% in March 2008 to nearly 3.00% in November 2008. Panels B and

C of Figure 3 depict that the volatility of the year-on-year growth of credit increases by nearly 150% from 0.74% to 1.12%, and that for liquid assets is nearly 8 times higher (from 1.92% to 16.27%) over this period.

The positive correlation between the YIV and volatility of bank variables is not confined to the recent financial crisis. For instance, during the bursting of the 'tech bubble' (from March 2001 to November 2001) and the accompanying recession, the value of YIV increases by nearly 20% and this is accompanied by a 52.78%, 10.62%, and a 169.10% increase in the volatility of the year-on-year growth of deposits, credit, and liquid assets, respectively. Similarly, in the post-pandemic period after COVID-19, an increase in YIV from 2.60% to 5.04% is accompanied by substantial increases in the volatility of the year-on-year growth of deposits, credit, and liquid assets. Sharp increases in YIV in May 2010 (the European Debt Crisis) and August 2011 (the downgrade of the U.S. credit rating by S&P) were also accompanied by sharp increases in the volatilities of growth rates of bank deposits, credit, and liquid assets. Thus, while the 2001 and the 2008 recessions provide the most striking evidence for the relation between YIV and volatility of bank variables, the relation holds outside of economic contractions,

We empirically assess whether YIV predicts the volatility of the year-on-year growth rates of bank deposits, bank credit, and liquid assets by running predictive regressions as follows:

$$\sigma BANKVAR_{t+H} = \alpha_H + \beta_H YIV_t + Lag + Controls + \epsilon_{t+H} \tag{1}$$

where $\sigma BANKVAR_{t+H}$ is either the volatility of the year-on-year growth rates of deposits, credit, or liquid assets computed over the months t - $t + H$. In all regressions, we control for lagged outcome variables to incorporate the persistence of volatilities for of aggregate U.S. bank sector variables. The key coefficient of interest is β_H, which captures the relationship between YIV measured at time t and the future volatility of bank variables of the subsequent H months.

Since bank balance sheets are impacted by business cycles, all regressions include a set of control variables that previous literature has shown to predict business cycles, including the change in the short rate, the term spread, the implied volatility of the stock market, and credit spread. All right-hand-side variables are standardized by subtracting the mean and dividing by the standard deviation. The standard errors are adjusted for heteroscedasticity, autocorrelation, and overlapping data using the Newey-West correction with up to 12 lags. All results are also robust to using Hansen-Hodrick errors (with 12 lags) that correct standard errors for overlapping data.

Table 2 presents the estimates for regression (1) from 3 to 12 months ahead, with each panel relating to the volatility of a different bank variable. In all three panels and across all tested horizons, the coefficients on YIV are positive and statistically significant at the 10% level or better, indicating that higher YIV is associated with higher future volatility of growth rates of bank deposits, credit, and liquid assets. For instance, Panel A indicates that when predicting the volatility of bank deposits, the coefficient on YIV ranges from 0.1112% at the 3-month horizon to 0.1313% at the 12-month horizon (with t-statistics ranging from 1.70 to 3.96, indicating statistical significance at the 10% level or better). Similarly, in panels B and C, the coefficients on YIV ranges from 0.1181% to 0.3276% and 1.0547% to 2.072%, respectively, over 3- to 12-month windows, when predicting the volatility of bank credit and bank liquid assets, respectively. All coefficients in panels B and C remain significant at the 10% level or better.

The coefficients on YIV in Table 2 indicate that the documented predictability is also economically significant. In panel A, the coefficient on YIV at the 12-month horizon is 0.3578% when predicting the volatility of bank deposits, such that a one-standard deviation increase in YIV is associated with a 0.3578% increase in the volatility of deposits over a one-year horizon. As the volatility of deposits in our sample period is 2.95%, this implies a 12% increase in volatility of the year-on-year growth of bank deposits as compared to its sample mean. Similarly a one-standard deviation increase in YIV is associated with a 0.3276% (2.0728%) increase in the volatility of credit (liquid assets) over a one-year horizon, or a 8% (11%) higher volatility of credit (liquid assets) as compared to their sample means of 3.99% and 18.18%, respectively.

In all cases, the signs and significance of the coefficients on the control variables (not reported in Table 2) are as expected. For example, when predicting the volatility of bank credit, the coefficient on CREDIT-SPREAD or the option-based credit spread from Culp, Nozawa, and Veronesi (2018) is positive and statistically significant at all horizons, indicating that higher credit risk or higher credit spreads, which are usually associated with worsening macro-economic outcomes, are associated with higher volatility of bank credit over a horizon of three to twelve months. Similarly, when predicting the volatility of bank liquid assets, the coefficient on the change in the short-rate, as measured by the first difference in the level of the yield-to-maturity on the 3-month bill issued by the U.S. Treasury, is positive. This indicates that an increase in the level of rates (which is usually accompanied by an increase in the volatility of rates as in Longstaff and Schwartz (1992)) is associated with a future increase in the volatility of bank liquid assets.

There are several potential economic channels that can drive the predictability in Table 2. Why YIV predicts the volatility of bank liquid assets is arguably the most straightforward. Bank liquid assets include both held-to-maturity and held-for-trading Treasury securities. Banks are required to adjust the values for such securities and mark these to market on nearly a daily basis. Since interest rate volatility is a key variable in pricing contingent claims such as Treasury securities and fixed income bonds, it is not surprising that YIV matters for future volatility of bank liquid assets.

Similarly, YIV can lead to higher volatility of bank credit if higher interest rate uncertainty is associated with higher volatility of income or cash flows. For instance, Thakor, Hong, and Greenbaum (1981) argue that higher interest rate volatility strongly impacts the value of bank commitments.[13]. Higher YIV is also associated with higher volatility of deposits, and since deposits are the primary source of funds for bank deposits, such higher funding volatility implies that a bank is more likely to have periods of internal cash flow shortfalls, and in response chooses to forego discretionary investment (i.e., providing credit) rather than raising costly external capital (Myers and Majluf (1984)).

Finally, in the absence of deposit insurance, a higher YIV may also impact depositors, who may worry about how such interest rate uncertainty impacts bank asset values and solvency risk. Acharya and Mora (2015) show that nearly 62% of bank deposits are not covered by deposit insurance. They also document that during the financial crisis of 2008–2009, as solvency risks for some banks increased, they could only attract or retain credit by offering substantially higher rates, indicating that in the cross-section, bank depositors are responsive to bank risk exposures.

3.2 Robustness tests

The results in Table 2 relating YIV to future volatility of bank deposits, credit, and liquid assets are robust to several changes in the empirical design and specification. We present the results for several additional robustness tests in Tables in the Appendix. Table A2 uses YIV to predict the volatility of bank deposits, credit, and liquid assets over longer horizons of 15 - 24 months. In general, the economic or statistical significance of the coefficient on the YIV is stronger over longer horizons. For example, over a horizon of two years, a one-standard deviation increase in YIV is associated with nearly a 0.39%, 0.43%, and 3.25% increase in the volatility of bank deposits, credit, and liquid assets, or a 13%, 11%, and 18% higher volatility of deposits, credit and liquid assets as compared to their sample means of 2.95%, 3.99%

[13]Such commitments only accounted for 15% of bank assets in the 1980s, but their importance for bank balance sheets has recently increased. See, for example, Acharya, Engle, and Steffen (2021)

and 18.18%, respectively. All coefficients are significant at the 1% level or better. More importantly, the predictive relation between YIV and volatility of bank variables does not reverse and persists for a horizon of up to 24 months.

In Table A4 in the Appendix we present the baseline results excluding data for the years covering the most recent financial crisis of 2008–2009. We find that the results are largely robust. The recent crisis provides one of the most dramatic examples of a period in which the value of the YIV increased dramatically by more than 200%, and was accompanied by substantially higher values of volatility of bank deposits, credit, and liquid assets. Finding that our results are not driven solely by this period is thus reassuring.

Tables A6 - A8 in the Appendix control for implied volatilities from options on the 2-year, 10-year, and long-term Treasury note and bond futures.In almost all cases, the coefficients on YIV (which is derived from options on the 5-year Treasury note futures) are statistically significant, and the magnitudes of these coefficients are comparable to those in baseline regressions. Thus, the coefficient estimates on the YIV are robust to inclusion of additional implied volatilities. Moreover, the YIV is the only variable that consistently predicts the volatility of bank variables across all horizons and across all three bank balance sheet variables. This is not surprising given the results in Cremers, Fleckenstein, and Gandhi (2021). The results in Tables A6 - A8 also suggest that the negative predictive relation between the YIV and future volatility of bank variables is unlikely due primarily to a time-varying variance risk premium. Put differently, if changes in the YIV primarily capture changes in the variance risk premium, we should find that an increase in other implied volatilities also predicts an increases in bank balance sheet volatility, but this is not the case.

Appendix Table A12 shows the results for predictive regressions with non-overlapping observations to address concerns that Newey-West adjustments may be insufficient to address autocorrelation or persistence in small samples. Using non-overlapping observations significantly reduces the number of observations in our sample, and this can affect the statistical power of our empirical analysis, especially over longer horizons. Nevertheless, the results in Table A12 indicate strong predictability over horizons beyond three months.

Appendix Table A14 considers out-of-sample performance, comparing the model including YIV and all control variables from the baseline regression in Table 2 (YIV & Controls) with a model containing all control variables but excluding the YIV (Ex. YIV); a model containing only the lagged volatility of the dependent variable (Naïve); and a model containing only YIV (YIV only). For each specification, we measure to what extent a market participant could have predicted the volatility of each bank variable in real time, using the data available to that point in time. That is, we first run forecasting regressions with the selected variables over a window from May 1990 to month $t-1$. We then use the estimated parameters of the model to predict the volatility of bank deposit, credit, and liquid assets for months t through $t+24$.

Our out of sample forecasts start in January 1996, when we have 60 observations of data to estimate up to 12 parameters of the model. In all cases, we estimate the root mean squared error (i.e., the RMSE), which is defined as the square root of the squared differences between the actual (i.e., realized) and predicted values of volatility of the bank variables. The results in Panels A – C of Table A14 indicate that when forecasting the volatility of bank variables at various horizons, the YIV only model generally outperforms the other models. For example, when predicting future volatility of deposits at the 12-month horizon in Panel A, the YIV only model has the lowest RMSE (0.8910%) compared to all other models, including the Naïve model with just the lagged volatility (RMSE of 0.9267%). This conclusion also holds true in Panels B and C of Table A14. In fact, the YIV only model outperforms the full model including all control variables, but excluding the YIV (i.e., the Ex. YIV model) when predicting the volatility of any bank variable at almost all horizons. This result is consistent with the finding in Ang, Piazzesi, and Wei (2006b) that in out-of-sample predictive tests, it is often the more parsimonious model (such as the one with single variables) that performs well.

In our last robustness test, we employ a reduced-form vector autoregression framework (VAR) to determine Granger causality between YIV and the volatility of bank deposits, credit, and liquid assets. The VAR allows us to investigate whether it is YIV that predicts the volatility of bank variables, or whether it is exogenous shocks to banks (say, an exogenous shock to bank capital or net worth) that simultaneously results in an increase in YIV as well as an increase the volatility of bank variables. This is important in light of the recent literature on intermediary asset pricing models, which suggests that in asset markets, financial intermediaries themselves are very important traders (see He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and He, Kelly, and Manela (2017), among many others). These papers suggest that financial intermediaries' net worth (or, their capital ratios) is a key determinant of the marginal value of wealth, and thus in determining asset prices. In other words, when financial intermediaries experience negative shocks to their net worth or equity capital, their risk bearing capacity is impaired, and (because these intermediaries are collectively so large) this impacts prices of assets they trade. Given that the market for interest rate derivatives such as that for options on Treasury notes and bonds futures, from which the YIV is derived, is dominated by banks, it is thus useful to check Granger causality. We estimate an unrestricted (i.e., a reduced-form) VAR given by the following equation:

$$Y_t = \alpha + \sum_{i=1}^{4} B_i Y_{t-i} + \epsilon_t \tag{2}$$

where the Y_t variables are the YIV, the volatility of bank deposits, credit, or liquid assets, and bank net worth or the intermediary capital risk factor from He, Kelly, and Manela (2017). Thus, we estimate three independent VAR systems, and each VAR system includes three variables: the YIV, volatility of one of the bank variables (either deposits, credit, or liquid assets), and an additional control variable, which is the intermediary asset pricing factor. We include four lags for each variable. The four-lag structure for all VAR systems is suggested according to the minimum score of the Akaike Information Criterion (AIC). We present the results for the Granger causality tests for the VAR system in Table A15, reporting the p-values of the Wald test (i.e., the χ^2 test) that the column variable has marginal predictive power for the row variable. We do not present the estimated coefficients of Equation (2), as the significance and the size of these coefficients are hard to interpret.

The first row of each panel shows that only the volatility of bank deposits and volatility of liquid assets both have predictive ability (i.e., Granger causality) for predicting YIV. The relation is significant with p-values of 1.21% and 4.75%, respectively. In contrast, YIV has significant predictive ability for the volatility of all three bank variables at the 1% level or better. When using YIV to predict future volatility of bank deposits, credit, and liquid assets the p-values range from a minimum of 0.01% to a maximum of 0.97%.

Using these VAR regressions, Figure A1 plots the responses of volatility of bank deposits, credit, and liquid assets to a one-standard deviation shock increase to YIV. In all cases, positive shocks to YIV are followed by a sustained increase in the volatility of bank deposits, credit, and liquid assets. The increase in volatility lasts for about one year (i.e., the response functions peak at a horizon of 6–8 months), and in most cases the response to a shock to YIV only tapers over a horizon of 20 months. Overall, the response of volatility of bank variables to a shock to YIV is not transitory but persisting for some time, which is consistent with the results of the predictive regression in Table 2.

3.3 Bank stock return volatility and returns

So far, we establish that higher interest rate uncertainty leads to higher volatility of bank balance sheets, thereby increasing risk for banks, consistent with the results in Cremers, Fleckenstein, and Gandhi (2021), who show that higher YIV negatively predicts future real economic activity. In this section, we investigate the ability of YIV to predict bank stock volatility and returns. Our goal here is not to assess if interest rate uncertainty is priced in the cross-section of stock returns for banks (a question we leave for future work). We instead simply check if bank investors care about and respond to variation in interest rate uncertainty.

Table 3 presents the results for such a predictive regression. Panel A and B of this table test if interest rate uncertainty helps predict the volatility and cumulative abnormal returns for this index, respectively. First in panel A of Table 3. we find that higher YIV is associated with higher volatility of bank stock returns. When using the YIV to predict monthly volatility, the coefficient at the one-year horizon is 0.4338%, which implies that a one-standard deviation increase in YIV is associated with 1.50% higher annualized volatility (i.e., $0.4388 \times \sqrt{12}$) for an index of bank stocks. Similarly, Panel B of Table 3 indicates that when predicting cumulative abnormal returns, the YIV coefficient at the one year horizon is -2.6276%, indicating that a one-standard deviation increase in YIV is associated with nearly 5.28% lower cumulative abnormal returns (annualized) for an index of bank stocks over a 12-month horizon. Relative to their sample means (Table 1) a one-standard deviation increase in YIV is associated with nearly 22.26% higher volatility and 35.48% lower returns for the value-weighted index of bank stocks. The results of the predictive regressions in Table 3 are consistent with the idea that bank investors in bank stocks care about and respond to variation in interest rate uncertainty.

3.4 A measure of bank exposure to convexity risk (YIV-βs)

In this section, we turn to data for individual banks, and examine how interest rate uncertainty impacts banks in the cross-section. We develop a methodology to measure the exposure of each individual bank to convexity risk.

Motivated by the APT (Ross (2013)) and the asset pricing models in Merton (1973) and Cox, Ingersoll Jr, and Ross (1985), seminal papers such as Fama and Schwert (1977), Fama and Gibbons (1982), Flannery and James (1984a), and Chen, Roll, and Ross (1986) regress equity returns for individual firms on changes in interest rates (and other macroeconomic factors). They argue that in these regressions, the coefficient on changes in interest rates provides an unbiased measure of how changes in nominal rates impact individual firms.

We follow a similar approach by estimating the sensitivity of bank stock returns to changes in YIV, which we propose as a measure of individual bank exposure to changes in interest rate uncertainty, i.e., convexity risk. While previous empirical studies suggest that there are many other cross-sectional factors that have explanatory power for the cross-section of returns, such as the size and value factors of the Fama and French (1993), we do not directly control for all such factors (except the market risk factor). Rather, we follow Ang, Hodrick, Xing, and Zhang (2006a), who argue that controlling for these additional factors when measuring sensitivity to a particular factor (in our case interest rate uncertainty) adds noise. Specifically, we estimate the following regression to estimate a bank's sensitivity to changes in interest rate uncertainty:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{YIV} \Delta YIV_t \times (-1) + \beta_{5YR} \Delta r_{5,t} + \beta_{MKT} MKT_t + \epsilon_t \tag{3}$$

where $r_{i,t}$ measures the holding period return on common stock for bank i, $r_{f,t}$ is the risk-free rate, ΔYIV_t is the first-order difference in the daily YIV, $\Delta r_{5,t}$ is the first-order difference in the yield-to-maturity on the 5-year note issued by the U.S. Treasury, and MKT_t is the holding period return on the value-weighted index of all stocks traded on the NYSE, NASDAQ, and AMEX. The main coefficient of interest in Equation (3) is the coefficient on ΔYIV, which we term as the β_{YIV} or 'YIV-Beta'.

Typically, increases in YIV correspond with periods of high interest rate uncertainty and are thus 'economically bad times' for banks. In equation (3), since we multiply ΔYIV by minus 1, a (more) positive YIV-Beta for bank i implies that increases in interest rate uncertainty are associated with (more) lower contemporaneous equity excess returns for bank i, and is thus indicative of greater exposure to movements in interest rate uncertainty or YIV. Thus, multiplying ΔYIV by minus 1, makes our interpretation of β_{YIV} consistent with the loading of excess bank equity returns on risk factors commonly used in the asset pricing literature.

We use daily data, and regression (3) is contemporaneous with all variables being measured at time t. The set of individual banks is restricted to those for whom both stock return as well as balance sheet information (i.e., their FRY-9C reports from the Federal Reserve Board) are available. In addition, we remove data for banks that trade infrequently (defined as banks with less than 100 observations in each year).

We estimate Equation (3) within each year using daily data, producing an annual time-series of β_{YIV}, for each bank. Since coefficients in regression (3) using individual bank level data can be subject to substantial measurement error, we follow Blume (1971), Vasicek (1973), Fama and MacBeth (1973), Jagannathan and Wang (1996), and Levi and Welch (2017) to shrink the betas.[14]

Figure 4 presents the distribution of the coefficient on the daily changes in YIV, i.e., the YIV-Beta for the cross-section of all banks across all years in our sample. This figure also presents the summary statistics for the YIV-Beta's for the time-series and the cross-section of banks. For the average bank in our sample YIV-Beta is negative at -0.40%. The slightly negative mean YIV-Beta for the cross-section of banks is consistent with the idea that the average bank may have hedged their exposure to interest rate uncertainty using a portfolio of interest rate derivatives. However, there is also substantial time-series and cross-sectional variation in banks' exposure to interest rate uncertainty. In Figure 4, the standard deviation of YIV-Betas (across time and across banks) is 6.91%, and the interquartile range is 4.24%, both of which are an order of magnitude higher than the average YIV-Beta of -0.40%. The highest YIV-Beta in our sample is 1.1413 indicating that some banks may have very high exposure to interest rate variability some of the times.

We investigate what drives YIV-beta for a bank to vary over time and in the cross-section. That is, what factors cause the YIV-Beta for a particular bank to be higher or lower at a particular point in time. Using a standard panel regression framework, we regress YIV-Beta at the individual bank level on a select number of balance sheet and income statement variables. We focus specifically on independent variables which may intuitively drive banks' exposure to interest rate uncertainty. Table 4 presents the results. Each column in this table presents the results for a separate regression specification. We relate banks' YIV-Betas to the year-on-year growth of loans, deposits, and liquid assets (Column (1)); to the year-on-year growth of income derived from various sources (Column (2)); to the year-on-year growth of several different categories of loans (Column (3)); and finally, to the year-on-year growth of notional value of interest rate derivatives held by the bank (Column (4)). The last column of this Table presents the result for a kitchen sink regression using all of the explanatory variables from Columns (1) – (4). Since

[14] Blume (1971) is the first to point out that coefficients in a regression using individual firm stock returns can be mean reverting and suggests a linear shrinkage adjustment. Vasicek (1973) builds on Blume (1971) and proposes a Bayesian shrinkage estimator. Levi and Welch (2017) compare competing approaches for estimating sensitivity of stock returns for individual firms to systematic risk factors.

bank size can influence the growth of all our explanatory variables, we normalize all explanatory variables by lagged total book value of assets.

In Table 4, a positive (negative) coefficient on any independent variable implies that higher values of that variable are associated with higher (lower) YIV-betas, and thus higher (lower) sensitivity of banks' excess stock returns to changes in the YIV. For instance, in column (1), the coefficient on liquid assets is negative and statistically significant at the 10% level, implying that higher year-on-year growth of liquid assets is associated with lower YIV-Beta and thus lower sensitivity of banks' stock returns to changes in interest rate uncertainty. Similarly, the coefficient of 2.24% on the year-on-year growth of deposits (statistically significant at 10% with a t-statistic of 1.87) indicates that an increase in the book value of deposits for bank is associated with an increase in its exposure to interest rate uncertainty.

In column (1), the positive coefficient on the year-on-year growth of deposits at first may seem surprising as it indicates that an increase in deposit funding is associated with higher YIV-Betas and greater exposure to interest rate uncertainty. This result contrasts with Drechsler, Savov, and Schnabl (2021) and Egan, Hortaçsu, and Matvos (2017) who argue that deposit franchise may allow banks to pay deposit rates that are low. They further show that this insensitivity in the deposit rates may allow banks that derive a greater proportion of their funding from deposits to hedge some of the banks' exposure to interest rate variability. However, Jiang, Matvos, Piskorski, and Seru (2023) show that the deposit franchise channel can collapse when uninsured deposits become a significant source of funding for commercial banks. They also argue that uninsured depositors are particularly sensitive to bank exposure to interest rate risk and can withdraw funds, causing bank runs.

Column (2) relates banks' YIV-Betas to income derived from various sources. Here, the independent variables include the year-on-year growth of net interest income, interest income, trading income, and non-interest rate income. While the coefficient on both the year-on-year growth of net interest income and interest income is not statistically significant at conventional levels, both coefficients are positive, indicating that an increase in either the year-on-year growth of net interest income or net income is associated with higher YIV-Betas, and thus greater exposure to interest rate uncertainty. The coefficient on both the year-on-year growth of trading income and non-interest income is negative and significant at the 5% level or better. Thus, an increase in either trading income or non-interest income for banks lowers a bank's exposure to interest rate uncertainty. This latter result is consistent with the literature that shows diversification by banks into non-core activities (defined as activities not related to deposit-taking or lending) can reduce risk of financial distress.[15]

We next regress banks' YIV-Betas on the year-on-year growth of loans classified according to various lending activities (Column (3). That is, in Column (3) the independent variables include the year-on-year growth of commercial, real estate, and personal loans. The only coefficients that is marginally statistically significant at the 10% level here is that on the year-on-year growth of real estate loans. The coefficient is negative, again indicating that an increase in real estate loans is associated with higher YIV-Betas and hence higher exposure to interest rate uncertainty. The positive coefficients make sense if (as is often the case) real estate loans are issued at fixed rates that are locked over long horizons. That is, the positive coefficient on real estate loans is consistent with the idea that banks with greater long-term, fixed-rate loans are more sensitivity to changes in interest rate uncertainty, much like fixed income market investors of long-term fixed coupon rate bonds who are naturally more exposed to convexity risk.

Finally, column (4) investigates how a banks portfolio of interest rate derivatives impacts its YIV-Beta. The independent variables in column (4) include the the year-on-year growth of notional value of interest rate forwards, futures, options bought, options sold, and interest rate swaps. The only variables that have a statistically significant relation with YIV-Betas are the changes in the notional value of interest rate futures, options bought and sold by banks. The coefficient on the notional value of futures and interest rate options bought by the bank is negative indicating higher growth for these variables is associated with lower YIV-Betas and lower exposure to interest rate uncertainty. Conversely, the positive coefficient on interest rate options sold is consistent with the idea that when writing (i.e., selling) interest rate options, interest rate risk transfers from the buyers of such options to the sellers, in turn resulting in increased sensitivity of banks stock returns to interest rate uncertainty.

The last column of Table 4 presents the results for a kitchen-sink regression including all independent variables covered in Columns (1) – (4). Comparing the coefficients in the comprehensive regression to those in the other four columns, we note that all our results survive, and the statistical significance as indicated by the t-statistics either remains comparable to the regressions in Columns (1) – (4) or becomes slightly stronger. The only exception is that the coefficient on the year-on-year growth of real estate loans is no longer statistically significant at conventional levels in Column (5).

Overall, the coefficients in Column (5) are also economically significant. For instance, in Column (5),

[15]See, for example, Smith and Stulz (1985), Diamond (1984), Ramakrishnana and Thakor (1984), Boyd and Prescott (1986), Diamond (1991), Rajan (1992), Saunders and Walter (1994), and Stein (2002)who show that diversification can help banks by reducing the cost associated with financial distress.

the coefficient on non-interest income is -0.3311. The standard deviation of this variable is 0.005. This suggests that a one-standard deviation increase in the year-on-year growth of non-interest income decreases the sensitivity of a bank's stock return to interest rate uncertainty by nearly 40% (= -0.3311×0.005, divided by the sample mean YIV-beta of 0.0040 equals -0.4139 or -41.39%). Similarly, a one-standard deviation increase in the year-on-year growth of interest rate options bought (standard deviation of 0.1069) decreases the sensitivity of a bank's stock return to interest rate uncertainty by nearly 65.48%. This result stands in contrast to that for interest rate options sold (standard deviation of 0.0962), where a one-standard deviation increase in the variable is associated with a nearly 43% increase in the sensitivity of a bank's stock return to the YIV. That is, as expected, the notional value of interest rate options bought and sold by a bank are the most significant drivers of its YIV-Beta.

3.5 Evidence from the cross-section of banks

Next, we relate banks YIV exposures to the future volatility of bank deposits, credit, and liquid assets in the cross-section in order to test if banks with greater exposure to interest rate uncertainty display higher volatility of balance sheets in the future. Our proxy for an individual bank's exposure to interest rate uncertainty is the product of YIV-Beta and ΔYIV. That is, we multiply the level of interest rate uncertainty times the bank's exposure to changes in those levels to estimate each individual bank's exposure to aggregate interest rate uncertainty, i.e., convexity risk. We then use a standard panel regression framework to explore how exposure to convexity risk is related to future volatility of the year-on-year growth of bank deposits, credit, and liquid assets. In particular, we relate each bank's exposure to interest rate uncertainty at year t to the volatility of the year-on-year growth of deposits, credit, and liquid assets measured over year $t+1$. Our exact specification is:

$$Y_{i,t+1} = \alpha + \gamma_{YIV}\Delta YIV_t + \gamma_{YIV-Beta}\beta_{YIV,i,t} + \gamma_{EXP}\beta_{YIV,i,t} \times \Delta YIV_t + Controls + \epsilon_{t+1} \quad (4)$$

Here, $Y_{i,t+1}$ is either the volatility of the year-on-year change in deposits, credits, or liquid assets for bank i, measured over year $t+1$, ΔYIV_t is the annual change in the yield implied volatility measured during year t, and $beta_{YIV,i,t}$ is the sensitivity to interest rate uncertainty measured for bank i at time t as described in the last section. All regressions include bank fixed effects and control for bank capital and log of book value of bank assets. As above, all growth variables are normalized by lagged total book value of assets. Statistical significance is computed using standard errors clustered at the bank level.

The main coefficients of interest are γ_{YIV} and γ_{EXP}, i.e., the coefficient on ΔYIV_t and the interaction term $\beta_{YIV,i,t} \times \Delta YIV_t$, respectively. We expect the sign on both γ_{YIV} and γ_{EXP} to be positive. First, for the aggregate U.S. bank sector, higher YIV is associated with higher future volatility of growth of bank deposits, credit, and liquid assets. A positive sign on the coefficient for YIV_t would extend this result for individual banks. Second, we expect the coefficient on the interaction term $\beta_{YIV,j,t} \times \Delta YIV_t$ to be positive, indicating that whenever interest rate uncertainty increases, banks with higher YIV-Betas (i.e., banks with more greater exposure to yield implied volatility) experience higher future volatility of the year-on-year growth of bank deposits, credit, and liquid assets, as compared to banks with lower YIV-Betas (i.e., banks with lower exposure to yield implied volatility).

Table 5 presents the estimates for the regression in Equation (4). Each column in Table 5 presents the results for a different dependent variable. The first column presents the results for the volatility of deposits, and the remaining two columns refer to results for the volatility of credit and liquid assets, respectively. We find that the sign of the coefficients rate uncertainty is associated with higher volatility of deposits, credit, and liquid assets for individual banks (as is the case for the aggregate U.S. bank sector) over the subsequent year. The coefficient on ΔYIV_t ranges from 0.0035 in column 1 for volatility of bank deposits to 0.0315 in column 3 for volatility of bank liquid assets. The t-statistics indicate significance at the 10% level or better, ranging in value from 1.67 to 10.48. Further, the coefficient on the interaction term $\beta_{YIV} \times \Delta YIV$ is positive. This indicates that banks with greater exposure to interest rate uncertainty as measured by YIV-Betas experience higher future balance sheet volatility whenever YIV levels increase.

To estimate the economic significance of these coefficients we compute the impact of a one-standard deviation increase in YIV on the volatility of the year-on-year growth of deposits, credit, and liquid assets for the banks in our sample. Column (1) of Table 5 indicates that the coefficients on YIV, β_{YIV}, and the interaction term $\beta_{YIV} \times \Delta YIV$ are 0.0035, 0.0008, and 0.1060, respectively. For the banks in our sample, YIV-beta equals -1.68% and 2.56% at the 25^{th}-percentile and 75^{th}-percentile, respectively. This implies that a one-standard deviation increase in ΔYIV is associated with a nearly 0.16% increase in volatility of deposits for banks with YIV-Betas at the 75^{th}-percentile. Since the sample volatility of the year-on-year growth of deposits in our cross-section of banks is 0.0212, this computation implies that a one-standard deviation increase in YIV is associated with nearly 8% higher volatility of bank deposits for banks with YIV-Betas at the 75^{th}-percentile as compared to the sample mean. Similar computations for the year-on-year growth of bank credit and liquid assets suggest that a one-standard deviation increase in YIV is associated with nearly 15% higher volatility of bank credit and nearly 64% higher volatility for bank liquid assets as compared to their sample means.

In Table 6 , we control for a proxy for duration risk, namely, β_{5YR}, or the sensitivity of the bank's stock return to changes in the 5-year interest rate (which we also control for when estimating YIV-Betas). Controlling for a bank's exposure to changes in the level of interest rates hardly impacts the results of Table 5. In all cases, the coefficient on YIV_t is always positive and statistically significant at the 1% level or better. The coefficient on the interaction term, $YIV \times \beta_{YIV}$, is also always negative indicating that higher YIV leads to higher volatility of the year-on-year growth of deposits, credit, and liquid assets for banks with greater exposure to interest rate uncertainty. The economic significance of these results also hardly changes. For bank with YIV-Betas at the 75^{th}-percentile, a one-standard deviation increase in YIV is associated with 8%, 12%, and 72.31% higher volatility of deposits, credit, and liquid assets, respectively.

In Table 7, we control for three other common measures of banks exposure to interest rate risk, namely, the banks income gap, the notional dollar value of interest rate derivatives that a bank uses for hedging, and the banks book value of net interest sensitive assets. These three measures are defined as follows: (a) the income gap (see Gomez, Landier, Sraer, and Thesmar (2021)) is measured as the difference between the dollar amount of assets that reprice or mature within one year and the dollar amount of liabilities that reprice or mature within one year, normalized by total assets; (b) the banks net exposure to interest rate risk (see Purnanandam (2007)) is defined as the difference in the notional dollar value of interest rate derivatives used by the bank for hedging and the notional dollar value of interest rate derivatives used for trading; and finally, (c) the banks interest sensitivity (see Flannery and James (1984b)) is defined as banks assets, interest bearing deposit liabilities, long-term debt, variable-rate preferred stock, and long-term debt that either reprices or is scheduled to mature within one year. We find that the results in Table 5 are robust to the inclusion of these variables.

3.6 Impact on levels

Does interest rate uncertainty risk also impact the year-on-year growth of bank deposits, credit and liquid assets themselves? We begin by examining the link between interest rate uncertainty and the year-on-year growth of bank deposits, credit, and liquid assets, for the aggregate U.S. bank sector. Figure 5 plots the YIV along with the year-on-year growth of bank deposits, credit, and liquid assets. Each panel in this figure presents the result for a different bank variable. Thus, the top-left panel presents the result for bank deposits and the remaining two panels depict plots for credit and liquid assets. In each panel, the gray-shaded bars represent periods of NBER recessions. In all plots, the blue line refers to the moving average of YIV (computed over 12-month moving windows) and the red line refers to the average year-on-year growth of of bank deposits, credit, and liquid assets for the aggregate U.S. bank sector (also computed over 12-month moving windows).

Figure 5 suggests that while the year-on-year growth of bank liquid assets tends to increase with YIV, the growth of bank credit is negatively correlated with interest rate uncertainty. The clearest example of this positive (negative) relation between YIV and bank liquid assets (bank credit) is again during the recent financial crisis of 2008–2009, but as was the case for volatilities, it also holds during other periods of market turmoil, such as the dot com bubble of 2001 and the European debt crisis of 2011 as well. For instance, from March to December 2008, an increase in YIV from 3.44% to 7.50% was accompanied by an increase in the growth of bank liquid assets from -6.19% to 7.36% and a decline in the year-on-year growth of bank credit from 9.74% to 7.81%.

The relation between YIV and the growth of bank deposits is more ambiguous. During March to December 2008, an increase in YIV was accompanied by an increase in the growth of bank deposits from 5.75% to 7.58%. Similarly, during the recession of 2001, an increase in YIV (from 3.03% to 3.67%) was accompanied by an increase in the growth of deposits from 8.09% to 8.58%. However, during the early days of the COVID-19 pandemic, a decrease in YIV from 2.75% to 2.51% (from January to June of 2020) was accompanied by an increase in the year-on-year growth of bank deposits from 5.97% to 12.77%. During other periods movements in YIV do not appear to be correlated with the growth of bank deposits for the aggregate U.S. bank sector in any significant way. During other periods movements in YIV do not appear to be correlated with the growth of bank deposits for the aggregate U.S. bank sector in any significant way.

Next, we estimate the predictive regression given by the following equation:

$$\sum_{j=1}^{j=H} \log(1 + BANKVAR_{t+j})/j = \alpha_H + \beta_H YIV_t + Lag + Controls + \epsilon_{t+H} \tag{5}$$

Here, $BANKVAR_{t+j}$ is the year-on-year growth of either deposits, credit, or liquid assets for all domestic banks in the U.S. at time $t + j$. We divide the left-hand-side by j so that the dependent variable in all cases is the average monthly year-on-year growth of total deposits, credit, or liquid assets. As above, in all regressions, we include the lagged outcome variables (i.e., either the current value of year-on-year growth of bank deposits, credit, and liquid assets) to account for the fact that for the aggregate U.S. bank sector, year-on-year growth rates of bank deposits, credit, and liquid assets are highly persistent, with first-order autocorrelation values of above 90%. We also control for business cycles variables, and right-hand-side variables are standardized by subtracting the mean and dividing by the standard deviation. We account for heteroscedasticity, autocorrelation, and overlapping data when computing standard errors.

Table 8 presents the estimates for the regression in Equation (5) from 3 to 12 months ahead. Panels A, B, and C of this table present results for the year-on-year growth rates of deposits, credit, and liquid assets, respectively. The results from the predictive regressions support our conclusions from Figure 5. Panel A of this table indicates that there is no statistically significant relation between YIV and the year-on-year growth of bank deposits for the aggregate U.S. bank sector for any horizon. In Panel B, for the year-on-year growth of bank credit, the coefficients on YIV are negative and statistically significant at the 1% level or better across all tested horizons, indicating that higher YIV is associated with lower future growth of bank credit. Finally, coefficients across all tested horizons on YIV are positive and statistically significant at the 1% level or better in Panel C, confirming that higher YIV predicts higher future growth of bank liquid assets.

In terms of economic significance, the results in Table 8 indicate that at the one-year horizon, a one-standard increase in YIV is associated with a -0.0953% drop in the year-on-year growth of bank credit and an 0.5398% increase in year-on-year growth of liquid assets. This amounts to nearly 2% and 10% of the sample means for bank credit and liquid assets, respectively. However, these results are still economically significant. For instance, the total dollar value of all bank credit outstanding for U.S. domestic chartered banks in the US is approximately $11.23 trillion as of July 2023. Thus, a drop of -0.0953% in the year-on-year growth of bank credit implies a reduction of bank credit by nearly $10.71 billion, such that the reduction in the year-on-year growth of bank credit seems economically significant in the aggregate.

Cremers, Fleckenstein, and Gandhi (2021) show that higher interest rate uncertainty is associated with future lower real economic activity. The results above suggest an important channel through which interest rate uncertainty may harm the economy is – bank liquidity hoarding – i.e., banks either reducing the amount of credit they provide or increasing the amount of liquid assets that they hold in response to higher convexity risk. There may be several reasons why banks may hoard liquidity if interest rate uncertainty increases. For instance, banks may supply less credit whenever YIV increases (thereby causing the inverse relation between bank credit and the YIV above) as this could exactly be the time when nonfinancial firms seek to take out fixed-rate, long-term loans, but banks may wish to only extend floating rate loans (or loans where the interest rate frequently resets) in order to manage their interest rate uncertainty exposures. In addition, banks may anticipate that real economic activity will fall as well as the cost of hedging interest rate uncertainty will increase as YIV spikes, and may respond by reducing the quantity or increasing the price of credit they are willing to provide either through commercial, industrial, consumer, or real estate loans or in the form of loan commitments, standby letters of credit, or other similar financial guarantees.

The positive predictive relation between the YIV and bank liquid assets suggests that banks choose to hold more liquid assets when interest rate uncertainty increases to protect against increased risks of liquidity shocks and anticipated funding difficulties that may otherwise require them to sell illiquid assets at fire-sale prices or miss out on profitable future loan opportunities (Diamond and Rajan (2011)). Banks may also choose to hold more liquid assets to absorb higher expected loan losses or a potential decline in the mark-to-market values of their other assets as real activity contracts with higher interest rate uncertainty.

Table 8 documents that for the aggregate U.S. bank sector, higher YIV does not predict the growth of deposits at any horizon, suggesting that bank depositors may not care about banks' exposure to interest rate uncertainty. This behavior can be rational in a world with deposit insurance and is consistent with the model of banks in Hanson, Shleifer, Stein, and Vishny (2015) who show that while traditional banks hold illiquid, long-term, fixed-income assets, deposit insurance and a costly bank equity capital buffers allows bank depositors to ignore transient fluctuations in the market value of bank assets. However, it is still possible that interest rate uncertainty significantly impacts the year-on-year growth of large bank deposits that are less likely to be covered by deposit insurance, and we turn to this question next.

Table 9 shows the results for the predictive regression when the dependent variable is the year-on-year growth of large bank deposits, defined as those with a book value of $100,000 or more, which are either likely to be partially covered or not covered at all by deposit insurance. Data for large bank deposits for the aggregate bank sector is only available from 2011, hence the sample period for the predictive regression in Table 9 is 2011 – 2023.[16]

Table 9 clearly indicates that an increase in yield implied volatility is associated with lower growth of large bank deposits over the next one year. The coefficient on YIV for all horizons is negative and statistically significant at the 10% level or better. In terms of economic significance, at the 12-month horizon, a one-standard deviation increase in YIV is associated with a nearly 0.1864% decline in the year-on-year growth of large bank deposits. Since the sample average for the year-on-year growth of large bank deposits is nearly 1.44%, the decrease in the year-on-year growth of large bank deposits implied by its coefficient at the one-year horizon accounts for nearly 13% of the sample mean.

The results in Table 9 are also consistent with recent studies that analyze the impact of recent rise in interest rates on the value of bank assets and financial stability. In Section 3.1 above we already document that higher yield implied volatility is associated with higher volatility of bank liquid assets over the next one-year horizon. Jiang, Matvos, Piskorski, and Seru (2023) present a model that shows how uninsured depositors can become concerned about potential losses when the value of bank assets varies in response to changes in interest rates. They also document that uninsured depositors represent a significant source of funding for commercial banks accounting for nearly half of their total deposits and a total of $9 trillion of their liabilities. Thus, a run by these uninsured depositors can be a significant source of risk for banks as the value of their assets varies in response to interest rate volatility, and this is what the results in Table 9 also indicate.

Next, we relate each individual bank's exposure to interest rate uncertainty at year t to the future year-on-year growth of deposits, credit, and liquid assets over year $t+1$. Our exact specification is:

$$Y_{i,t+1} = \alpha + \gamma_{YIV}\Delta YIV_t + \gamma_{YIV-Beta}\beta_{YIV,i,t} + \gamma_{EXP}\beta_{YIV,i,t} \times \Delta YIV_t + Controls + \epsilon_{t+1} \quad (6)$$

where $Y_{i,t+1}$ is either the year-on-year growth of bank deposits, credits, or liquid assets for bank i, over year $t+1$, ΔYIV_t is the change in yield implied volatility measured at year t, $beta_{YIV,i,t}$ is the sensitivity to interest rate uncertainty measured for bank i at time t (as described in the last section). All regressions include bank fixed effects and control for bank capital and log of book value of bank assets. Statistical

[16] Prior to the financial crisis of 2008–2009, FDIC insurance limits applied to deposits of $100,000 or less. During the financial crisis, in order to prevent a run by deposits, insurance limits were increased to $250,000. Thus, not all deposits above $100,000 suffer from a lack of FDIC insurance during 2011 – 2023.

significance is computed using standard errors clustered at the bank level.

As above, the main coefficient of interest is that on $\beta_{YIV} \times \Delta YIV$. We expect the sign of the coefficient on ΔYIV to be negative for bank deposits and credit, but positive for liquid assets, i.e., an increase in YIV should be associated with lower future year-on-year growth of bank deposits and credit, but higher future year-on-year growth of bank liquid assets and the effect is stronger for banks with greater exposure to interest rate uncertainty. Table 10 presents the estimates for the regression in Equation (6), where each column presents the results for a different dependent variable. As is clear from this table, the sign of the coefficients on the variables of interest are all as expected. The coefficient on the interaction term $YIV \times \beta_{YIV}$ is negative for bank deposits and credit, indicating that banks with greater exposure to interest rate uncertainty as measured by YIV-Betas experience lower growth of bank deposits and credit whenever YIV increases. While the coefficient for deposits (Column (1)) is not statistically significant at conventional levels, the results are statistically significant for both bank credit and liquid assets.

To judge the economic significance of these coefficients we can again compute the impact of an increase in YIV on the volatility of balance sheet items for a bank in our sample with a YIV-Beta at the 75^{th}-percentile. For deposits, this computation implies that a one-standard deviation increase in YIV is associated with a nearly 0.03% lower year-on-year growth of bank deposits as compared to its sample mean of 1.39% (although the coefficient on the interaction term is not statistically significant). Similarly, a one-standard deviation increase in YIV implies that for a bank with a YIV-Beta at the 75^{th}-percentile the year-on-year growth of bank credit falls by 0.11% (with the coefficient on the interaction term statistically significant at the 1% level). This can be compared to the sample average of 1.20%. Finally, for bank liquid assets, where we find that a one-standard deviation increase in YIV implies that for the average bank in our sample the year-on-year growth of liquid assets increases by nearly 0.07% (as compared to its sample mean of 0.30%).[17]

Tables 11 and 12 repeats the analysis in Table 10, but now either controls for bank exposure to interest rate duration risk (i.e., the change in the yield-to-maturity on the 5-year Note issued by the U.S. Treasury in Table 11) or alternative measures of interest rate risk exposures of banks such as the income gap, the net notional dollar value of derivatives held for hedging, and the net value of assets and liabilities that are scheduled to be repriced or mature within one year (in Table 12). Not only do all of our

[17]Note that in Table 10 the coefficient on ΔYIV is positive in all cases, although it is more than an order of magnitude smaller than the coefficient on the interaction term, indicating that effect of increases on YIV on the year-on-year growth rates of bank deposits, credit, and liquid assets can be derived from focusing only on the interaction term, as we do above.

results survive when we include these additional controls, but in some cases their economic and statistical significance increases. For example, in Table 10, the coefficient on the interaction term $\beta_{YIV} \times \Delta YIV$ is not significant when the dependent variable is the year-on-year growth of bank deposits. In Tables 11 and 12, the coefficient on interaction term is statistically significant at the 10% level or better for bank deposits, indicating that an increase in YIV is associated with lower year-on-year growth of bank deposits for banks with greater exposure to interest rate uncertainty. The coefficient of -0.0690 on the interaction term in Column (1) of Table 11 implies that a for a bank in our sample with a YIV-Beta at the 75^{th}-percentile, a one-standard deviation increase in YIV is associated with a nearly 0.05% lower year-on-year growth of bank deposits as compared to its sample mean of 1.39%.

Why is the case that in Table 8, for the aggregate U.S. bank sector, higher YIV does not predict the year-on-year growth of deposits at any horizon, but that in Tables 11 and 12, the coefficient on the interaction term is statistically significant at conventional levels. One reason could be that while interest rate uncertainty may not impact the total deposit levels for the aggregate bank sector, in the cross-section, depositors may transfer funds from banks that are more to banks that are less exposed to interest rate uncertainty, as YIV increases.

Finally, note that all of the results for the levels are consistent with the theoretical and empirical literature which documents that in response to economic and financial uncertainty banks hoard liquid assets by holding more cash (Diamond and Rajan (2011), Acharya, Gromb, and Yorulmazer (2012), Gale and Yorulmazer (2013), and Heider, Hoerova, and Holthausen (2015)), increasing reserve balances (Acharya and Merrouche (2013)), reducing lending (Acharya and Skeie (2011)), increasing their liquid assets (Cornett, McNutt, Strahan, and Tehranian (2011), Berrospide (2013), and Acharya and Mora (2015)), varying the prices and quantities of funds they are willing to provide in interbank markets (Afonso, Kovner, and Schoar (2011)), seeking more deposits at times by offering higher deposit rates (Berrospide (2013) and Acharya and Mora (2015)), and finally reducing the amount of the loan commitments they are willing to underwrite (Cornett, McNutt, Strahan, and Tehranian (2011), Berrospide (2013), and Acharya and Mora (2015)).

4 Conclusion

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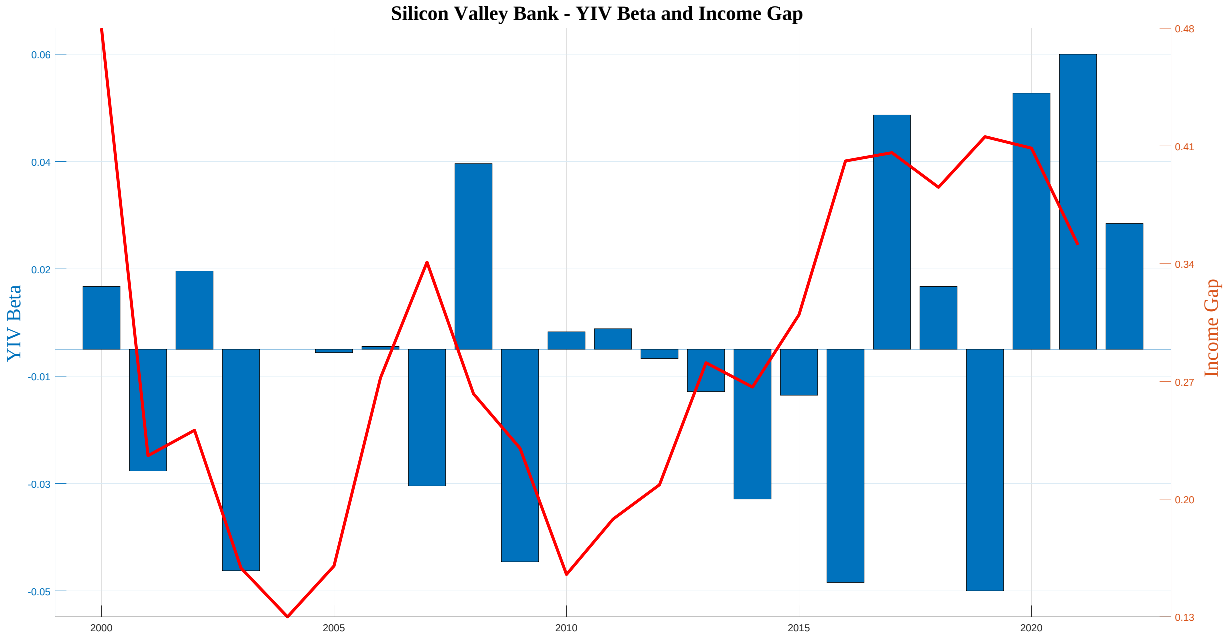


Figure 1. Silicon Valley Bank: Measures of interest rate risk exposures.

Notes: This figure plots how the interest rate risk exposures of Silicon Valley Bank evolved prior to its failure in March 2023. The blue bars plot the within-year YIV Betas computed using daily returns for each calendar year, and the red line plots a balance sheet measure of interest rate risk exposure – the income gap measure from Gomez, Landier, Sraer, and Thesmar (2021). Data for income gap is averaged for all quarters within each calendar year.

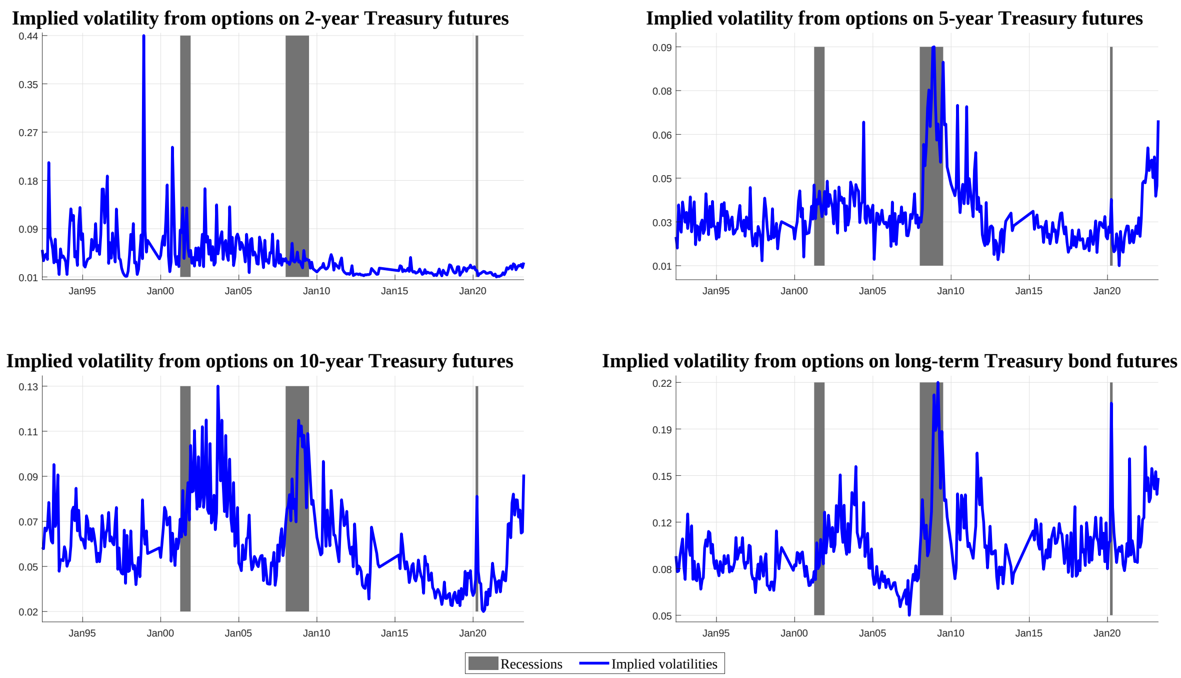


Figure 2. Time series plot of implied volatility from options on Treasury futures.

Notes: This figure plots the time-series of implied volatility from options on 2-year, 5-year, 10-year, and long-term Treasury note and bond futures. In each panel, the blue solid line plots the implied volatility. The grey shaded regions represent National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Monthly data, 1990 – 2023.

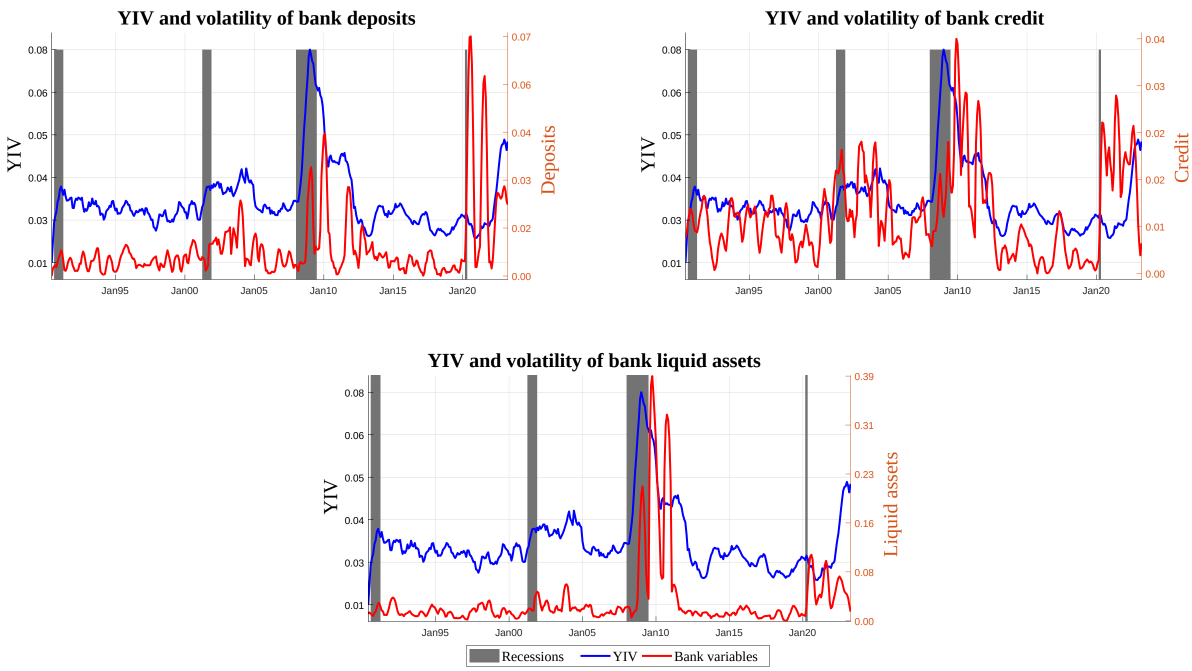
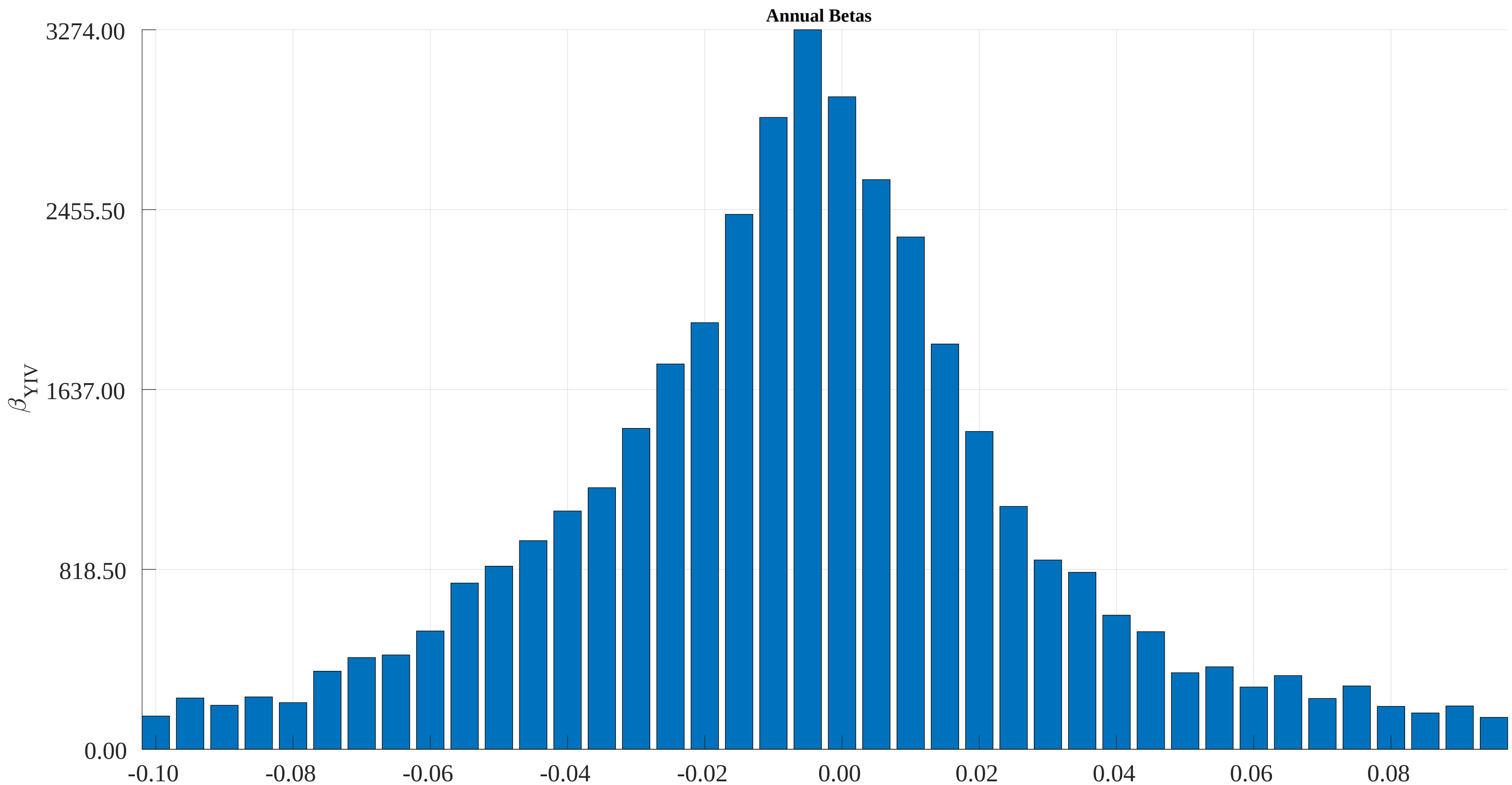


Figure 3. YIV and volatility of bank deposits, credit, and liquid assets.

Notes: This figure plots the YIV and the volatility of the year-on-year growth of deposits, credit, and liquid assets for all domestic banks in the U.S. The blue solid line plots the implied volatility and the red dashed line plots the volatility of deposits, credit, and liquid assets. Months are indicated on the x-axis. The grey shaded regions represent National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Monthly data, 1990 – 2023.



Mean	σ	Min	25^{th}	Median	75^{th}	Max
$-.0040$	0.0691	-1.5484	-0.0256	-0.0029	0.0168	1.1413

Figure 4. Sensitivity of bank stock returns to YIV

Notes: This figure depicts the sensitivity of bank stock returns to YIV. Within each year, we regress daily excess returns (relative to the risk-free rate) for each publicly-listed bank on daily changes in the YIV and daily changes in the yield-to-maturity on the 5-year Treasury note. The figure plots the distribution of coefficients on the daily changes in the YIV from this regression for all domestic banks in the U.S. over all years. Daily data, 1990 - 2023.

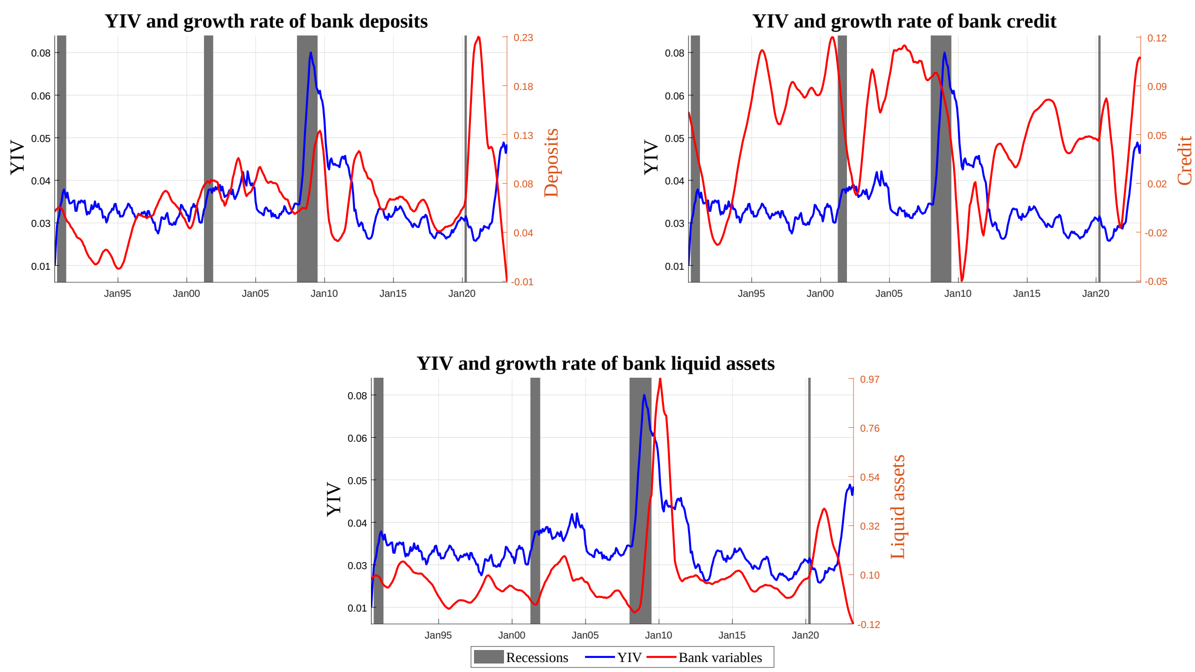


Figure 5. YIV and bank deposits, credit, liquid assets.

Notes: This figure plots YIV and the year-on-year growth of deposits, credit, and liquid assets for all domestic banks in the U.S. The blue solid line plots the implied volatility and the red dashed line plots the year-on-year growth of deposits, credit, and liquid assets. Months are indicated on the x-axis. The grey shaded regions represent National Bureau of Economic Research (NBER) recessions. The NBER recession dates are published by the NBER Business Cycle Dating Committee. Monthly data, 1990 – 2023.

Table 1. Summary statistics.

Notes: This table shows the summary statistics for all variables. The columns report mean, standard deviation, minimum, 25^{th}-percentile, median, 75^{th}-percentile, and maximum values. The last column shows the first-order autocorrelation. YIV is the implied volatility from options on 5-year Treasury notes. Deposits, Credit, and Liquid assets are the year-on-year growth rates of deposits, credit, liquid assets (total of cash, Treasury securities, Agency mortgage-backed securities, Federal funds sold, and Securities Repurchased), and net interest income for all domestic banks in the U.S., respectively. Return and Volatility are the monthly return and volatility on an index of all publicly-traded banks in the U.S. Term spread is the yield spread between the 10-year Treasury note and the 3-month Treasury Bill, Rate is the yield-to-maturity on the 3-month Treasury Bill, Δ Rate is the change in the yield to maturity on the 3-month Treasury Bill, VIX is the CBOE Volatility index, and Credit spread is the option based credit spread from Culp, Nozawa, and Veronesi (2018), respectively. Panel B reports statistics for the aggregate bank sector, while Panel C reports statistics for the cross-section of banks. In panel C, all growth variables are normalized by lagged book value of assets. Monthly or quarterly data, 1990 – 2023.

	Mean	σ	Min	25^{th}	Median	75^{th}	Max	ρ
Panel A: Yield implied volatility								
YIV	0.0326	0.0115	0.0137	0.0257	0.0297	0.0360	0.0921	0.7291
Panel B: Aggregate bank sector variables								
Deposits	0.0610	0.0295	-0.0045	0.0435	0.0620	0.0779	0.1467	0.9561
Credit	0.0601	0.0399	-0.0714	0.0373	0.0652	0.0889	0.1298	0.9708
Liquid assets	0.0910	0.1818	-0.0771	0.0079	0.0556	0.1005	1.2317	0.9473
Return	0.0124	0.0641	-0.2855	-0.0209	0.0167	0.0486	0.2241	0.0317
Volatility	0.0674	0.0567	0.0167	0.0379	0.0511	0.0743	0.4196	0.8195
Panel C: Bank level variables								
Deposits	0.0139	0.0212	-0.0499	0.0003	0.0113	0.0248	0.1877	0.2185
Credit	0.0120	0.0237	-0.0545	-0.0037	0.0082	0.0237	0.2030	0.1023
Liquid assets	0.0030	0.0171	-0.0403	-0.0056	0.0009	0.0083	0.2015	0.4684
Panel D: Control variables								
Term spread	1.7037	1.1295	-0.7000	0.7800	1.6800	2.6400	3.6900	0.9791
Rate	2.6125	2.2377	0.0100	0.1800	2.1700	4.9250	8.0100	0.9867
Δ Rate	-0.0216	0.1902	-1.2400	-0.0550	0.0000	0.0700	0.4900	0.4223
VIX	19.4788	7.7784	10.1255	13.9190	17.4989	23.1713	62.6689	0.8538
Credit spread	1.8816	1.1029	0.4531	1.1150	1.5271	2.3211	8.1086	0.8687

Table 2. Predicting volatility of bank deposits, credit, and liquid assets.

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sigma BANKVAR_{t+H} = \alpha_H + \beta_H YIV_t + Lag + Controls + \epsilon_{t+H}$$

Here, YIV_t is the yield implied volatility measured at time t and $BANKVAR_{t+H}$ is the year-on-year growth of either deposits, credit, or liquid assets for all domestic banks in the U.S. measured over time t - $t+H$. Controls include the lagged volatility of BANKVAR (measured over 12-month lagged windows), Term spread measured by the yield spread between the 10-year Treasury note and the 3-month Treasury Bill, Rate measured by the yield-to-maturity on the 3-month Treasury Bill, Δ Rate measured by the change in the yield to maturity on the 3-month Treasury Bill, VIX measured by the CBOE Volatility index, and Credit spread measured by the option based credit-spread from Culp, Nozawa, and Veronesi (2018), respectively. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, autocorrelation, and overlapping data using the Newey-West correction with up to 12 lags. Monthly data, 1990 – 2023.

$H =$	3	6	9	12
Panel A: Volatility of deposits				
YIV	0.1112*	0.2503***	0.3172***	0.3578***
	(1.70)	(2.96)	(3.60)	(3.96)
Lag volatility	-0.0673***	-0.0835**	-0.1121*	-0.1764***
	(-2.69)	(-2.05)	(-1.62)	(-2.64)
$R^2 - ord$	12.2689	14.6585	18.9562	24.2441
Panel B: Volatility of credit				
YIV	0.1181***	0.1917***	0.2420***	0.3276***
	(2.54)	(2.63)	(3.59)	(6.17)
Lag volatility	0.1186***	0.1990***	0.2258***	0.1760***
	(2.58)	(2.89)	(3.72)	(2.61)
$R^2 - ord$	19.1934	33.5616	43.2735	50.9614
Panel C: Volatility of liquid assets				
YIV	1.0547***	1.5557***	1.7405***	2.0728***
	(3.00)	(3.63)	(3.36)	(2.79)
Lag volatility	0.1854	0.5945	1.0900*	1.6313*
	(0.96)	(1.58)	(1.83)	(1.90)
$R^2 - ord$	21.5491	34.9406	45.5063	48.7457

Table 3. Volatility and cumulative abnormal returns of bank stocks.

Notes: This Table shows the estimated coefficients for the forecasting regression:

$$Y_{t+H} = \alpha_H + \beta_H YIV_t + Lag + Controls + \epsilon_{t+H}$$

Here, YIV_t is the yield implied volatility and Y_t is either the volatility or the abnormal returns (relative to the market) of the value-weighted return on an index of all publicly-listed U.S. domestic banks measured at time t. Controls include the lagged dependent variable, Term spread measured by the yield spread between the 10-year Treasury note and the 3-month Treasury Bill, Rate measured by the yield-to-maturity on the 3-month Treasury Bill, Δ Rate measured by the change in the yield to maturity on the 3-month Treasury Bill, VIX measured by the CBOE Volatility index, and Credit spread measured by the option based credit-spread from Culp, Nozawa, and Veronesi (2018), respectively. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, autocorrelation, and overlapping data using the Newey-West correction with up to 12 Monthly data, 1990 – 2019.

$H =$	3	6	9	12
Panel A: Volatility of bank stock returns				
YIV	0.3579**	0.4572***	0.4700***	0.4338***
	(2.30)	(2.42)	(2.38)	(2.45)
Lag volatility	0.3033*	0.1788	0.1504	0.1295
	(1.72)	(1.06)	(0.93)	(0.93)
$R^2 - ord$	65.8990	58.9600	51.3431	46.4966
Panel B: Cumulative abnormal returns for bank stocks				
YIV	-2.4773	-5.3406**	-5.3170***	-5.2847***
	(-1.59)	(-2.31)	(-2.41)	(-3.45)
Lag returns	-1.2958	-0.7756	0.0423	0.0759
	(-1.10)	(-0.46)	(0.02)	(0.03)
$R^2 - ord$	5.7758	12.7750	13.3232	16.2271

Table 4. What drives YIV-Beta.

Notes: This Table shows the estimated icients for the panel regression:

$$\beta_{YIV,i,t} \quad = \quad \alpha + \beta \mathbf{X} + \epsilon_{t+H}$$

Here, β_{YIV} is the sensitivity of stock returns for bank i to changes in YIV measured at time t. $\mathbf{X}$ consists of a number of bank level income statement and balance sheet variables. In column (1), these include the year-on-year growth of total loans, total deposits, and total liquid assets. In column (2), the explanatory variables include the year-on-year growth of net interest income, interest income, trading income, and non-interest income. In column (3) the explanatory variables are the year-on-year growth of total commercial loans, total real estate loans, and total personal loans. Finally, in column (4) the explanatory variables are the year-on-year growth of notional values of interest rate forwards, interest rate futures, interest rate options bought, interest rate options sold, and interest rate swaps. Since bank size can influence the growth of all our explanatory variables, we normalize all explanatory variables by lagged total book value of assets. We multiply β_{YIV} by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. All regressions include bank fixed effects. Annual data, 1990 – 2023.

	(1)	(2)	(3)	(4)	(5)
Loans	-0.0097				-0.0268
	(-0.83)				(-1.16)
Deposits	0.0224*				0.0229*
	(1.87)				(1.87)
Liquid assets	-0.0215*				-0.0216*
	(-1.88)				(-1.81)
Net interest income		0.0677			0.1334
		(0.17)			(0.31)
Interest income		0.0962			-0.0648
		(0.48)			(-0.28)
Trading income		-0.0689**			-0.0574*
		(-2.12)			(-1.93)
Non interest income		-0.3592***			-0.3311**
		(-2.91)			(-2.49)
Commercial loans			-0.0097		0.0040
			(-0.49)		(0.15)
Real estate loans			0.0120*		0.0238
			(1.76)		(0.98)
Personal loans			0.0274		0.0314
			(0.66)		(0.75)
Forwards				-0.0015	-0.0003
				(-0.52)	(-0.09)
Futures				-0.0037***	-0.0028**
				(-2.72)	(-2.11)
Options bought				-0.0245***	-0.0232***
				(-2.67)	(-2.66)
Options sold				0.0178**	0.0175**
				(1.95)	(2.06)
Swaps				0.0009	0.0014
				(1.10)	(1.62)
Fixed	Yes	Yes	Yes	Yes	Yes
R^2	0.09	0.05	0.03	0.04	0.15
N	9,241	9,241	9,241	9,241	9,241

Table 5. Panel regressions: Volatility.

Notes: This Table shows the estimated coefficients for the panel regression:

$$Y_{i,t+1} \quad = \quad \gamma_{YIV}\Delta YIV_t + \gamma_{YIV-Beta}\beta_{YIV,i,t} + \gamma_{EXP}\beta_{YIV,i,t} \times \Delta YIV_t + Controls + \epsilon_{t+1}$$

Here, ΔYIV is the annual change in yield implied volatility measured at time t. $Y_{i,t}$ is either the volatility of the growth of deposits, credits, or liquid assets for bank i measured at time $t+1$ (i.e., over the next year). All growth variables are normalized by lagged total book value of assets. $beta^{YIV}_{i,t}$ is the sensitivity to interest rate uncertainty measured for bank i at time t. We multiply $beta^{YIV}$ by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. Controls include Capital (the ratio of total book value of equity capital to the book value of total assets) and Assets (the logarithm of book value of total assets). All regressions include bank fixed effects. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. Annual data, 1990 – 2023.

	(Deposits)	(Credit)	(Liquid assets)
ΔYIV	0.0035*	0.0107***	0.0315***
	(1.67)	(5.49)	(10.48)
β_{YIV}	0.0008	0.0010	0.0025*
	(0.97)	(0.92)	(1.65)
$\beta_{YIV} \times \Delta YIV$	0.1060***	0.1047***	0.4078***
	(2.94)	(2.79)	(5.14)
$Capital$	-0.0081***	0.0015	0.0303
	(-2.63)	(0.55)	(5.41)
$Assets$	-0.0008***	-0.0002	0.0001
	(-6.64)	(-1.29)	(0.17)
Bank fixed effects	Yes	Yes	Yes
Lagged volatility	Yes	Yes	Yes
R^2	48.27	47.32	39.57
N	7,890	7,884	7,880

Table 6. Panel regressions: Volatility: Controlling for sensitivity to interest rate changes.

Notes: This Table shows the estimated coefficients for the panel regression:

$$Y_{i,t+H} \quad = \quad \alpha_H + \beta_{YIV} + \beta_{YIV} \times \Delta YIV_t + Controls + \epsilon_{t+H}$$

Here, ΔYIV is the annual change in yield implied volatility measured at time t. $Y_{i,t}$ is either the volatility of the growth of deposits, credits, or liquid assets for bank i measured at time $t+1$ (i.e., over the next year). All growth variables are normalized by lagged total book value of assets. $beta_{i,t}^{YIV}$ is the sensitivity to interest rate uncertainty measured for bank i at time t. We multiply $beta^{YIV}$ by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. Controls include Capital (the ratio of total book value of equity capital to the book value of total assets), Assets (the logarithm of book value of total assets), and $beta^{5YR}$ (the sensitivity to changes in the yield-to-maturity on the 5-year Treasury note). All regressions include bank fixed effects. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. Annual data, 1990 – 2023.

	(Deposits)	(Credit)	(Liquid assets)
ΔYIV	0.0040*	0.0083***	0.0357***
	(1.89)	(4.14)	(11.18)
β_{YIV}	0.0008	0.0008	0.0027*
	(1.02)	(0.72)	(1.78)
$\beta_{YIV} \times \Delta YIV$	0.1102***	0.0834**	0.4485***
	(3.03)	(2.19)	(5.47)
β_{5YR}	-0.0002	0.0001***	-0.0003***
	(-1.12)	(5.81)	(-7.07)
$Capital$	-0.0076**	-0.0014	0.0356***
	(-2.50)	(-0.52)	(5.74)
$Assets$	-0.0007***	-0.0005***	0.0007***
	(-5.16)	(-4.17)	(3.62)
Bank fixed effects	Yes	Yes	Yes
Lagged volatility	Yes	Yes	Yes
R^2	48.28	47.64	40.06
N	7,890	7,884	7,880

Table 7. Panel regressions: Volatility: Controlling for other interest rate risk measures.

Notes: This Table shows the estimated coefficients for the panel regression:

$$Y_{i,t+H} \quad = \quad \alpha_H + \beta_{YIV} + \beta_{YIV} \times YIV_t + Controls + \epsilon_{t+H}$$

Here, ΔYIV is the annual change in yield implied volatility measured at time t. $Y_{i,t}$ is either the volatility of the growth of deposits, credits, or liquid assets for bank i measured at time $t+1$ (i.e., over the next year). All growth variables are normalized by lagged total book value of assets. $beta_{i,t}^{YIV}$ is the sensitivity to interest rate uncertainty measured for bank i at time t. We multiply $beta^{YIV}$ by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. Controls include Capital (the ratio of total book value of equity capital to the book value of total assets), Assets (the logarithm of book value of total assets), $beta^{5YR}$ (the sensitivity to changes in the yield-to-maturity on the 5-year Treasury note), Gap (the income gap measure from Gomez, Landier, Sraer, and Thesmar (2021)), Exposure (the difference between the notional amount of interest rate derivatives used for trading and hedging normalized by book value of assets as in Purnanandam (2007)), and Sensitivity (the difference between the interest sensitive assets and liabilities i.e., assets and liabilities set to be repriced in one year normalized by book value of assets). All regressions include bank fixed effects. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. Annual data, 1990 – 2023.

	(Deposits)	(Credit)	(Liquid assets)
ΔYIV	0.0051***	0.0083***	0.0416***
	(2.13)	(3.55)	(10.28)
β_{YIV}	0.0008	0.0008	0.0024
	(0.94)	(0.70)	(1.44)
$\beta_{YIV} \times \Delta YIV$	0.1091***	0.0861**	0.4396***
	(2.93)	(2.28)	(5.10)
Gap	0.0054	0.0016	-0.0180*
	(1.05)	(0.39)	(-1.91)
$\Delta YIV \times Gap$	0.1155	0.2899*	1.0258***
	(0.44)	(1.76)	(4.38)
$Exposure$	0.0001***	0.0003	0.0001
	(2.87)	(0.70)	(1.32)
$\Delta YIV \times Exposure$	0.0001	-0.0004	-0.0001
	(0.29)	(-1.26)	(-0.12)
$Sensitivity$	0.0056	0.0008	-0.0179*
	(1.10)	(0.18)	(-1.91)
$\Delta YIV \times Sensitivity$	0.1286	0.2900*	1.0867***
	(0.49)	(1.78)	(4.70)
β_{5YR}	0.0004	0.0001***	-0.0003***
	(1.60)	(4.01)	(-7.72)
$Capital$	-0.0072**	-0.0020	0.0361***
	(-2.29)	(-0.71)	(5.74)
$Assets$	-0.0007***	-0.0005***	0.0008***
	(-4.95)	(-4.35)	(3.85)
Bank fixed effects	Yes	Yes	Yes
Lagged volatility	Yes	Yes	Yes
R^2	47.72	45.66	39.67
N	7,772	7,721	7,711

Table 8. Predicting the growth of bank deposits, credit, and liquid assets.

Notes: This Table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + BANKVAR_{t+j})/j = \alpha_H + \beta_H YIV_t + Lag + Controls + \epsilon_{t+H}$$

Here, YIV_t is the yield implied volatility measured at time t and $BANKVAR_{t+j}$ is the year-on-year growth of either deposits, credit, or liquid assets for all domestic banks in the U.S. at time $t+j$. We divide the left-hand-side by j so that the dependent variable in all cases is the average monthly year-on-year growth of total deposits, credit, or liquid assets. Controls include the lagged year-on-year growth of BANKVAR, Term spread measured by the yield spread between the 10-year Treasury note and the 3-month Treasury Bill, Rate measured by the yield-to-maturity on the 3-month Treasury Bill, Δ Rate measured by the change in the yield to maturity on the 3-month Treasury Bill, VIX measured by the CBOE Volatility index, and Credit spread measured by the option based credit-spread from Culp, Nozawa, and Veronesi (2018), respectively. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, autocorrelation, and overlapping data using the Newey-West correction with up to 12 lags. Monthly data, 1990 – 2023.

$H =$	3	6	9	12
	Panel A: Growth rate of deposits			
YIV	-0.0049	0.0035	0.0199	0.0385
	(-0.25)	(0.13)	(0.67)	(1.46)
Lag growth	0.2065***	0.1487***	0.0914***	0.0555*
	(9.55)	(5.11)	(3.19)	(1.79)
$R^2 - ord$	78.1452	67.8574	57.4502	49.9998
	Panel B: Growth rate of credit			
YIV	-0.0490***	-0.0684***	-0.0835***	-0.0953***
	(-2.46)	(-2.58)	(-3.08)	(-3.91)
Lag growth	0.2887***	0.2689***	0.2557***	0.2447***
	(13.25)	(10.04)	(8.80)	(8.04)
$R^2 - ord$	75.9232	69.8035	65.2197	62.1104
	Panel C: Growth rate of liquid assets			
YIV	0.2717**	0.3372***	0.4419***	0.5398***
	(2.02)	(2.97)	(4.10)	(4.96)
Lag growth	0.9875***	0.7799***	0.5516***	0.3629***
	(7.11)	(5.29)	(3.98)	(3.09)
$R^2 - ord$	74.0863	68.8647	66.0613	64.4807

Table 9. Predicting the growth of large bank deposits.

Notes: This Table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + LRGDEP_{t+j})/j = \alpha_H + \beta_H YIV_t + Lag + Controls + \epsilon_{t+H}$$

Here, YIV_t is the yield implied volatility measured at time t and $LRGDEP_{t+j}$ is the year-on-year growth of large deposits (i.e., deposits above \$100,000) for all domestic banks in the U.S. at time $t + j$. We divide the left-hand-side by j so that the dependent variable in all cases is the average monthly year-on-year growth of large deposits. Controls include the lagged year-on-year growth of BANKVAR, Term spread measured by the yield spread between the 10-year Treasury note and the 3-month Treasury Bill, Rate measured by the yield-to-maturity on the 3-month Treasury Bill, Δ Rate measured by the change in the yield to maturity on the 3-month Treasury Bill, VIX measured by the CBOE Volatility index, and Credit spread measured by the option based credit-spread from Culp, Nozawa, and Veronesi (2018), respectively. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, autocorrelation, and overlapping data using the Newey-West correction with up to 12 lags. Monthly data, 2011 – 2023.

$H =$	3	6	9	12
YIV	-0.0822*	-0.1082*	-0.1469**	-0.1864**
	(-1.77)	(-1.78)	(-2.05)	(-2.28)
Lag growth	0.7716***	0.6558***	0.5286***	0.3919***
	(10.01)	(6.01)	(4.45)	(3.55)
Term spread	0.6632***	0.8288***	0.9110***	0.8554***
	(6.82)	(5.40)	(3.93)	(3.25)
Level rate	0.5236***	0.6495***	0.7078***	0.6485***
	(5.74)	(5.03)	(4.13)	(3.42)
Δ rate	0.0435	0.0718	0.0966	0.1595*
	(0.82)	(1.02)	(1.09)	(1.71)
VIX	0.0929	0.0925	0.0902	0.1193
	(1.13)	(0.93)	(0.92)	(1.42)
Credit spread	-0.0150	-0.0156	-0.0136	-0.0077
	(-0.54)	(-0.53)	(-0.44)	(-0.24)
$R^2 - ord$	81.4647	72.5984	61.3383	51.7136

Table 10. Panel regressions: Growth rates.

Notes: This Table shows the estimated coefficients for the panel regression:

$$Y_{i,t+H} \quad = \quad \alpha_H + \beta_{YIV} + \beta_{YIV} \times \Delta YIV_t + Controls + \epsilon_{t+H}$$

Here, ΔYIV is the annual change in yield implied volatility measured at time t. $Y_{i,t}$ is either the growth of deposits, credits, or liquid assets for bank i measured at time $t+1$ (i.e., over the next year). All growth variables are normalized by lagged total book value of assets. $beta_{i,t}^{YIV}$ is the sensitivity to interest rate uncertainty measured for bank i at time t. We multiply $beta^{YIV}$ by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. Controls include Capital (the ratio of total book value of equity capital to the book value of total assets) and Assets (the logarithm of book value of total assets). All regressions include bank fixed effects. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. Annual data, 1990 – 2023.

	(Deposits)	(Credit)	(Liquid assets)
ΔYIV	0.0030**	0.0041***	0.0036***
	(2.07)	(2.90)	(3.66)
β_{YIV}	0.0002	-0.0009	-0.0005
	(0.30)	(-1.09)	(-1.10)
$\beta_{YIV} \times \Delta YIV$	-0.0434	-0.1668***	0.0970***
	(-1.40)	(-4.28)	(4.22)
$Capital$	0.0009	0.0089***	0.0020*
	(0.61)	(5.25)	(1.84)
$Assets$	-0.0002***	-0.0003***	0.0003***
	(-2.86)	(-5.05)	(7.67)
Bank fixed effects	Yes	Yes	Yes
Lagged volatility	Yes	Yes	Yes
R^2	85.03	88.45	73.82
N	7,890	7,884	7,880

Table 11. Panel regressions: Growth rates: Controlling for sensitivity to interest rate changes.

Notes: This Table shows the estimated coefficients for the panel regression:

$$Y_{i,t+H} \quad = \quad \alpha_H + \beta_{YIV} + \beta_{YIV} \times \Delta YIV_t + Controls + \epsilon_{t+H}$$

Here, ΔYIV is the annual change in yield implied volatility measured at time t. $Y_{i,t}$ is either the growth of deposits, credits, or liquid assets for bank i measured at time $t+1$ (i.e., over the next year). All growth variables are normalized by lagged total book value of assets. $beta_{i,t}^{YIV}$ is the sensitivity to interest rate uncertainty measured for bank i at time t. We multiply $beta^{YIV}$ by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. Controls include Capital (the ratio of total book value of equity capital to the book value of total assets), Assets (the logarithm of book value of total assets), and $beta^{5YR}$ (the sensitivity to changes in the yield-to-maturity on the 5-year Treasury note). All regressions include bank fixed effects. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. Annual data, 1990 – 2023.

	(Deposits)	(Credit)	(Liquid assets)
ΔYIV	-0.0002	0.0007	0.0043***
	(-0.02)	(0.47)	(4.35)
β_{YIV}	-0.0001	0.0012	-0.0005
	(-0.02)	(1.45)	(-1.05)
$\beta_{YIV} \times \Delta YIV$	-0.0690**	-0.1963***	0.1036***
	(-2.25)	(-4.92)	(4.43)
β_{5YR}	0.0002***	0.0002***	-0.0004***
	(11.58)	(11.89)	(-3.24)
$Capital$	-0.0023	0.0045***	0.0029**
	(-1.40)	(2.56)	(2.42)
$Assets$	-0.0006***	-0.0008***	0.0004***
	(-8.49)	(-11.15)	(8.36)
Bank fixed effects	Yes	Yes	Yes
Lagged volatility	Yes	Yes	Yes
R^2	85.30	88.71	73.86
N	7,890	7,884	7,880

Table 12. Panel regressions: Growth rates: Controlling for other interest rate risk measures.

Notes: This Table shows the estimated coefficients for the panel regression:

$$Y_{i,t+H} \quad = \quad \alpha_H + \beta_{YIV} + \beta_{YIV} \times YIV_t + Controls + \epsilon_{t+H}$$

Here, ΔYIV is the annual change in yield implied volatility measured at time t. $Y_{i,t}$ is either the growth of deposits, credits, or liquid assets for bank i measured at time $t+1$ (i.e., over the next year). All growth variables are normalized by lagged total book value of assets. $beta^{YIV}_{i,t}$ is the sensitivity to interest rate uncertainty measured for bank i at time t. We multiply $beta^{YIV}$ by (-1) so that higher $beta^{YIV}$s indicate greater exposure to interest rate uncertainty. Controls include Capital (the ratio of total book value of equity capital to the book value of total assets), Assets (the logarithm of book value of total assets), $beta^{5YR}$ (the sensitivity to changes in the yield-to-maturity on the 5-year Treasury note), Gap (the income gap measure from Gomez, Landier, Sraer, and Thesmar (2021)), Exposure (the difference betwwen the notional amount of interest rate derivatives used for trading and hedging normalized by book value of assets as in Purnanandam (2007)), and Sensitivity (the difference between the interest sensitive assets and liabilities i.e., assets and liabilities set to be repriced in one year normalized by book value of assets). All regressions include bank fixed effects. The numbers in parenthesis are the t-statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively using standard errors clustered at the bank level. Annual data, 1990 – 2023.

	(Deposits)	(Credit)	(Liquid assets)
ΔYIV	0.0004	0.0017	0.0026**
	(0.23)	(0.99)	(2.23)
β_{YIV}	0.0004	-0.0003	-0.0011**
	(0.50)	(-0.37)	(-2.26)
$\beta_{YIV} \times \Delta YIV$	-0.0490*	-0.1609***	0.0812***
	(-1.65)	(-4.12)	(3.50)
Gap	0.0031*	-0.0022	-0.0089***
	(0.98)	(-0.74)	(-3.01)
$\Delta YIV \times Gap$	-0.1544	-0.1263	-0.1689**
	(-1.23)	(-0.86)	(-1.97)
Exposure	-0.0001	-0.0002	0.0004**
	(-1.19)	(-1.50)	(2.23)
$\Delta YIV \times Exposure$	0.0002	0.0004*	-0.0003
	(0.70)	(1.87)	(-1.10)
Sensitivity	0.0021*	-0.0036	-0.0092***
	(0.67)	(-1.19)	(-3.10)
$\Delta YIV \times Sensitivity$	-0.1592	-0.1379	-0.1651*
	(-1.29)	(-0.95)	(-1.95)
β_{5YR}	0.0002***	0.0002***	-0.0001***
	(10.97)	(12.35)	(-6.70)
Capital	-0.0032*	0.0030	0.0034***
	(-1.88)	(1.63)	(2.72)
Assets	-0.0006***	-0.0009***	0.0005***
	(-8.70)	(-11.25)	(8.97)
Bank fixed effects	*Yes*	*Yes*	*Yes*
Lagged volatility	*Yes*	*Yes*	*Yes*
R^2	85.30	88.79	72.66
N	7,772	7,721	7,711