Monetary Transmission Through Bank Securities Portfolios

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Abstract

We study the transmission of monetary policy through bank securities portfolios using granular supervisory data on U.S. bank securities, hedging positions, and corporate credit. Banks that experienced larger losses on their securities during the 2022–2023 monetary tightening cycle extended less credit to firms. This spillover effect was stronger for available-for-sale securities, unhedged securities, and banks that must include unrealized gains and losses in their regulatory capital. A structural model, disciplined by our cross-sectional regression estimates, quantifies how interest rate transmission is stronger when more banks are required to adjust their regulatory capital for unrealized value changes of securities.

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1 Introduction

In March 2023, the United States experienced one of the largest bank failures in decades as depositors ran on Silicon Valley Bank (SVB). In the lead-up to its failure, SVB had maintained a large portfolio of long-term securities. As interest rates rose rapidly in 2022, market prices of these securities plummeted, generating unrealized losses that were widely believed to have triggered the run.

These events have put the regulatory treatment of bank securities under the spotlight. Under U.S. regulation, unrealized losses on SVB's securities did not pass through to its regulatory capital, making SVB appear relatively well capitalized from a regulatory perspective despite its fragile position. These considerations have sparked proposals by academics and policymakers to expand the set of securities whose value changes affect regulatory capital.[1] Under such a policy change, banks experiencing market losses on securities would be pressured to improve their capital ratios, for example by raising additional equity, to avoid violating their regulatory capital requirements. In turn, an improved capital position could lower the probability of a subsequent bank run or failure.[2]

At the same time, recognizing unrealized securities losses in regulatory capital could have important consequences for the supply of credit. If banks are reluctant to raise capital, they can instead cut lending to households and firms, thereby reducing risk-weighted assets and improving their capital ratios. If so, the resulting contraction in credit supply may also reduce firm investment and household consumption, affecting overall economic activity. As a result, the accounting treatment of unrealized gains and losses can influence the pass-through from bank securities values to the real economy — a pathway that we denote the *regulatory capital channel*.

In this paper, we explore this channel, studying how the regulatory accounting framework influences transmission from interest rates, through securities values and regulatory capital, into firm credit and investment. Our approach combines granular administrative data with a structural model that allows us to compare policy regimes. For our empirical analysis, we construct a novel data set combining supervisory data on securities portfolios, hedging positions, and corporate credit for large U.S. banks from the Federal Re-

[1] See, for instance, a recent survey conducted by the Kent Clark Center at Chicago Booth: `https://www.kentclarkcenter.org/surveys/banks-business-model/`. A similar debate about marking bank assets to market took place after the 2007–2009 financial crisis, see, e.g., Allen and Carletti (2008), Heaton, Lucas and McDonald (2010), and Laux and Leuz (2010).

[2] For example, such arguments are made in the Review of the Federal Reserve's Supervision and Regulation of Silicon Valley Bank (page 89) and in a recent speech by FDIC Chairman Martin J. Gruenberg, see: `https://www.fdic.gov/news/speeches/2023/spjun2223.html` and `https://www.federalreserve.gov/publications/files/svb-review-20230428.pdf`

serve's Y-14Q data set, which is collected for the purpose of stress-testing. These data give us an unparalleled view of not only bank-firm credit relationships, but also the securities holdings of banks, allowing us to observe the specific securities held, their gains and losses over time, and their associated accounting hedges.

To begin, we document differences in the regulatory treatment of the banks within our data, and their links to banks' securities allocations. The larger banks, denoted AOCI-Capital (AC) banks, must include unrealized gains and losses on their available-for-sale (AFS) securities in their regulatory capital, while the smaller banks in our sample, denoted non-AOCI-Capital (NC) banks, are exempt from this requirement.[3] This differential regulatory treatment appears to influence banks' securities choices. During the period of low interest rates in 2020 and 2021, AC banks increased their securities holdings by much less than NC banks, and sharply raised both the fraction of their securities recorded as held-to-maturity (HTM) and the portion of their AFS securities that were hedged.[4] These results are consistent with AC banks making efforts to avoid exposure of their regulatory capital to security value fluctuations.

In our main set of empirical results, we measure the effect of changes in securities values on bank credit supply, and how this varies with the regulatory treatment of those securities. We focus on the 2022–2023 monetary tightening episode, which featured large declines in the value of securities, and the consequences for bank credit to nonfinancial firms. Using the fixed effects approach of Khwaja and Mian (2008), which allows us to control for firm credit demand, we find that banks that experienced larger value losses on their AFS portfolios extended relatively less credit to firms. The effect is sizable, with a $1 decline in the value of AFS securities leading to a relative credit contraction of around 20 cents. However, we obtain substantially smaller and insignificant results for changes in the value of HTM securities that, unlike for AFS securities, do not affect regulatory capital at any bank.[5] Differentiating AFS securities by whether they are hedged against interest rate risk, we further find that our baseline results are driven by unhedged securities, while changes in the value of hedged securities, which also do not impact regulatory capital, exhibit smaller and insignificant crowding-out effects on firm credit.

Next, to more directly test our regulatory capital mechanism, we exploit the fact that

[3]These regulations have evolved in recent years, and the turmoil around SVB reignited a debate on whether to enlarge the set of banks that need to recognize such unrealized gains and losses in their regulatory capital. See, for example, the Review of the Federal Reserve's Supervision and Regulation of Silicon Valley Bank (page 3) and the proposed reforms to bank capital requirements by Vice Chair for Supervision Michael Barr: `https://www.federalreserve.gov/publications/files/svb-review-20230428.pdf` and `https://www.federalreserve.gov/newsevents/speech/barr20230710a.htm`.

[4]See also related evidence by Fuster and Vickery (2018) and Kim, Kim and Ryan (2019).

[5]Orame, Ramcharan and Robatto (2023) find similar results using European data.

changes in AFS values at AC banks, but not NC banks, pass through into regulatory capital under current regulation. We reestimate our main regressions, allowing for differential responses to gains and losses on AFS securities at AC vs. NC banks. These interacted regressions show crowding out effects that are several times stronger for AC banks, and we cannot reject the hypothesis of zero response by NC banks. Combined, these results point to the regulatory capital channel as the primary conduit through which changes in securities values influence bank lending in our sample.

In a final empirical exercise, we estimate the effects of these changes in bank credit supply at the firm level. We find that small firms whose banks experience larger losses on AFS securities display stronger reductions in total debt from all sources. The magnitude of these responses is similar to the direct reductions in bank lending by affected banks, implying that these firms were unable to substitute into alternative forms of credit. In turn, affected small firms sharply cut investment and reduce their cash holdings.

Inspired by these empirical findings, we develop a structural model, building on Greenwald, Krainer and Paul (2025), to study how the effects of monetary policy are shaped by the regulatory framework of the banking system in general equilibrium. Banks in our model hold long-term securities that are revalued when interest rates change, and lend to smaller, bank-dependent firms, subject to a regulatory capital constraint. When banks face declines in their regulatory capital, they must adjust by cutting lending to firms or cutting payouts to investors, with the degree of financial frictions determining the relative use of each margin. These effects are amplified by an important feedback mechanism, as lower lending following losses to regulatory capital reduces profits, which lowers bank capital further.

Within this framework, we consider the impact of a rise in interest rates under various policy scenarios. To discipline our model exercise, we fit the exact sequence of shocks required to match real yields, long-term inflation expectations, aggregate investment, and aggregate corporate debt. In addition, we calibrate the parameters governing the strength of the regulatory capital channel so that equivalent regressions estimated in the model generate coefficients that exactly match our cross-sectional regression evidence.

Our results show that the partial pass-through of unrealized losses under current regulation contributed substantially to declines in bank lending in the 2022 tightening episode. Compared to a counterfactual economy where regulatory capital ignored unrealized security losses, the current regulatory accounting regime led to additional 10Q declines of 2.9% in bank regulatory capital, 2.8% in term lending, and 3.5% in bank profits. This contraction in credit supply in turn caused bank-dependent firms to contract investment persistently, and by as much as 2.7%.

Turning to policy proposals, we find that an alternative regulatory regime that recognizes unrealized value changes on AFS securities at all banks would display much stronger effects. In this economy, the regulatory capital channel would have reduced bank term lending by 9.9% and bank profits by 12.0% at the 10Q horizon compared to a no-mark-to-market policy, even after we assume that non-AC banks update their securities holdings to match those of current AC banks.

Last, we consider the impact of banks' active management of their regulatory exposure, which was widespread over our sample through reclassifications of AFS to HTM and through the hedging of AFS securities. We find that a counterfactual economy experiencing the same shocks in which AC banks had maintained their 2019–2020 shares of unhedged AFS securities would have experienced relative declines in bank lending, profits, and small firm investment compared to a no-mark-to-market benchmark that are roughly 50% larger than observed under the actual economy. Thus, we find that this active management of regulatory exposure played a key role in mitigating the effects of the regulatory capital channel over this period.

In summary, our results provide evidence for a powerful monetary transmission mechanism, working through bank securities portfolios, that is shaped by the regulatory framework of the banking system. Our findings have implications for current policy debates, showing that the regulatory treatment of securities may have important effects on the dynamics of the macroeconomy outside of its direct financial stability role. If all banks were required to pass through unrealized gains and losses of securities to their regulatory capital, changes in interest rates would have a larger effect on credit supply to all but the largest firms in the economy, with important consequences for aggregate investment.

Related Literature. Our paper connects to the literature on the bank lending channel, which studies the impact of monetary policy actions on the supply of loans by depository institutions (Bernanke and Gertler, 1995). In earlier work, Kashyap and Stein (2000) and Jiménez et al. (2012) find that banks with less liquid balance sheets, measured by the ratio of securities to assets, contract lending more after a monetary tightening. In contrast, we find that banks with *larger* securities holdings respond more to changes in interest rates, all else equal. Our findings likely differ from these existing works for two reasons. First, our Y-14Q sample includes only banks large enough to be subject to stress tests, and therefore excludes the extensive set of smaller banks that are likely more influenced by liquidity channels. Second, we study a period where some banks must include unrealized gains and losses in their regulatory capital, a requirement that was not in place for the periods considered by these earlier papers. Our regulatory capital channel may therefore coexist with the liquidity mechanisms studied previously.

More recently, Drechsler, Savov and Schnabl (2017, 2021) and Gomez et al. (2021) investigate alternative monetary transmission channels through bank balance sheets. Drechsler, Savov and Schnabl (2017, 2021) show that banks widen spreads between the policy rate and rates on liquid deposits after a monetary tightening, leading to deposit outflows and lending contractions, but relatively stable net interest margins. Gomez et al. (2021) find that banks with relatively more assets that reprice or mature in the near term experience higher cash flows after a monetary tightening and cut their lending relatively less. These results are separate from, and complemented by, our findings on the importance of the regulatory capital channel, as we show that our results hold even after directly controlling for changes in bank deposits and net income.

Several other studies have used loan-level data to establish a credit supply effect originating from banks' security exposures.[6] Closest to our work is Orame, Ramcharan and Robatto (2023), who show that the effects of the European Central Bank's quantitative easing programs varied with the accounting treatment of AFS securities. Relative to this literature, we are able to study the transmission from security value changes into credit supply in greater detail, as our data allow us to distinguish securities by their classifications, the extent to which they are hedged, and whether security value changes affect regulatory capital at the banks holding them.[7] Our cross-sectional estimates further enable us to calibrate a macroeconomic model and show how bank regulation shapes interest rate transmission in general equilibrium.

We also provide new empirical evidence on the use and economic importance of derivative contracts for banks, which are particularly challenging to measure. Prior studies on U.S. data find little evidence that banks hedge their interest rate risk exposure.[8] We contribute to these existing studies by using new data on designated accounting hedges, which allow us to determine hedged positions security-by-security. The data confirm prior findings, but also show that a subset of banks—the AC banks that are subject to the distinct regulation we highlight—hedge a larger fraction of their AFS securities. For hedged securities, we find negligible spillover effects from security price changes to

[6] Among others, examples include Bottero, Lenzu and Mezzanotti (2020), Popov and Van Horen (2015), Acharya et al. (2018), De Marco (2019), Rodnyansky and Darmouni (2017), Chakraborty, Goldstein and MacKinlay (2020), and Luck and Zimmermann (2020). Relatedly, Indarte (2023) shows how creditor asset losses affect the transmission of monetary policy.

[7] Abbassi et al. (2016), Peydró, Polo and Sette (2021), Carpinelli and Crosignani (2021), Peydró et al. (2023), and Abbassi et al. (2023) also use security- and loan-level data in combination. However, their focus is on the trade-off that banks face from investing in securities of different risk categories, and vis-á-vis loans.

[8] Examples of such findings can be found in Begenau, Piazzesi and Schneider (2015), Jiang et al. (2023*a*), and McPhail, Schnabl and Tuckman (2023). For European banks, Hoffmann et al. (2019) document a more widespread use of interest rate swaps.

banks' loan portfolios, echoing prior evidence by Purnanandam (2007).

Last, we connect with an evolving literature sparked by the turmoil around SVB. Jiang et al. (2023*b*) compute that the market value of U.S. bank assets was around $2.2 trillion lower than their book value following the 2022 monetary tightening. The combination of these unrealized losses and uninsured depositors posed a run risk for many banks, explored theoretically by Drechsler et al. (2023) and Haddad, Hartman-Glaser and Muir (2023). We show that changing regulatory accounting to address these financial stability concerns may also have important consequences for the transmission of monetary policy.

Overview. The remainder of the paper is organized as follows. Section 2 lays out the institutional setting and U.S. regulatory framework for the banks in our data. Section 3 illustrates balance sheet dynamics following security price changes and develops hypotheses that we aim to test empirically. Section 4 describes the data set, while Section 5 presents some key stylized facts. Section 6 summarizes our main empirical findings. Section 7 constructs the macroeconomic model and presents its implications for alternative regulatory accounting regimes. Section 8 concludes.

2 Institutional Setting

In this section, we provide an overview of the institutional environment, describing how banks can classify their securities, when gains and losses pass through into measured regulatory capital, and how banks hedge interest rate risk on their securities.

Security Classifications. Banks hold debt securities on their balance sheets in the trading book or in the investment portfolio of the banking book, where they can be marked as HTM or as AFS. In this paper, we focus on the investment portfolio, since trading securities constitute only a small fraction of bank assets and we lack disaggregated data on these securities.[9] Classifying a security as HTM or AFS implies a different treatment for the recognition of valuation changes and has distinct implications for bank capital. HTM securities are held at amortized costs, or book value, and are not updated as market prices change. In contrast, AFS securities are held at fair value and are marked to market. While balance sheets are not directly affected by changes in the market prices of HTM

[9]Banks hold securities in the trading book as both trading assets and trading liabilities. On net, the median bank in our data holds around 0.7% of assets in trading securities. Securities inventories associated with market making activity are typically booked in trading.

securities, unrealized gains and losses of AFS securities affect book equity as part of the account “accumulated other comprehensive income” (AOCI).

AOCI and Regulatory Capital. Important for our empirical approach, the treatment of AOCI in the computation of regulatory capital varies with bank size. Prior to 2013, U.S. bank regulators permitted a so-called AOCI filter, which removed AOCI from the calculation of regulatory capital (CET1). Starting in 2013 with the final rule for Basel III, the AOCI filter was removed for larger U.S. banks using the advanced approaches capital framework, as well as any banks that voluntarily opted into the rule change, leading AOCI to be included in CET1 capital for these banks (Fuster and Vickery, 2018).[10] Finally, with the Federal Reserve’s tailoring rule in 2019, the filter was restored for all banks except the global systemically important banks (GSIBs) and the largest non-GSIB banks (Kim, Kim and Ryan, 2023).[11] To provide clarity in the presence of these changing rules, we refer to banks whose regulatory capital includes unrealized gains and losses on AFS securities at a given time as AOCI-Capital (AC) banks, and banks whose regulatory capital is not affected by these unrealized gains and losses as non-AOCI-Capital (NC) banks.

Hedging. To avoid balance sheet and AOCI volatility as interest rates change, banks can hedge their AFS securities. In our sample, the most common hedges used are interest rate swaps, which allow a bank with a long-dated fixed-rate security to pay a fixed rate to the swap counterparty and receive a floating rate instead. If interest rates increase, the expected stream of floating-rate cash flows grows, increasing the value of the bank’s swap position, and offsetting losses on the underlying security.

When interest rate swaps closely track changes in security values, they can qualify as fair value accounting hedges for the associated security. When an AFS security has such a qualified accounting hedge, price fluctuations of the security and the hedging instrument offset each other, negating the direct impact of the price change on banks’ AOCI (and income statements more generally). [12] Our data include both the hedge positions and

[10] Advanced approach banks have assets above $250 billion or foreign exposures above $10 billion. This rule change was phased in at 20% per year until 2018.

[11] That includes non-GSIB banks with at least $700 billion in assets or $75 billion in cross-jurisdictional activity, which implies that advanced approach banks with assets between $250 and $700 billion and foreign exposures below $75 billion were able to reinstate the AOCI filter.

[12] In practice, banks often prefer to use such qualified accounting hedges since valuation changes do not pass through the income statement, in contrast to hedges held in the derivatives book. A hedging arrangement may qualify for fair value hedge accounting treatment if the hedging instrument is judged as “highly effective” in offsetting fluctuations in the value of the security. The rules for hedge accounting are set forth in ASC 815: `https://asc.fasb.org/815/tableOfContent`.

the links to the underlying securities, allowing us to form a precise picture of each bank's exposure to fluctuations in securities prices.

Reclassification. Under certain conditions, banks can reclassify securities between AFS and HTM status. Reclassification from HTM to AFS is more challenging, as it risks "tainting" the entire remaining HTM portfolio and forcing a reclassification of *all* HTM securities into AFS.[13] However, redesignating a security from AFS to HTM does not trigger tainting, and was done extensively over our sample period (Granja, 2023). At the same time, we note that such reclassifications cannot help banks circumvent a fall in the value of an AFS security *after* prices have changed. Instead, when banks reclassify an AFS security as HTM, it is marked at the current market price. Similarly, the associated unrealized loss after a reclassification from AFS to HTM would remain part of AOCI and regulatory capital, to be subsequently amortized against interest income. While banks could hypothetically reclassify securities before expected price declines, this would require banks to have superior information about the path of security prices. Thus, reclassification is primarily a tool for mitigating *future* risk to securities values rather than avoiding losses taken on existing securities.

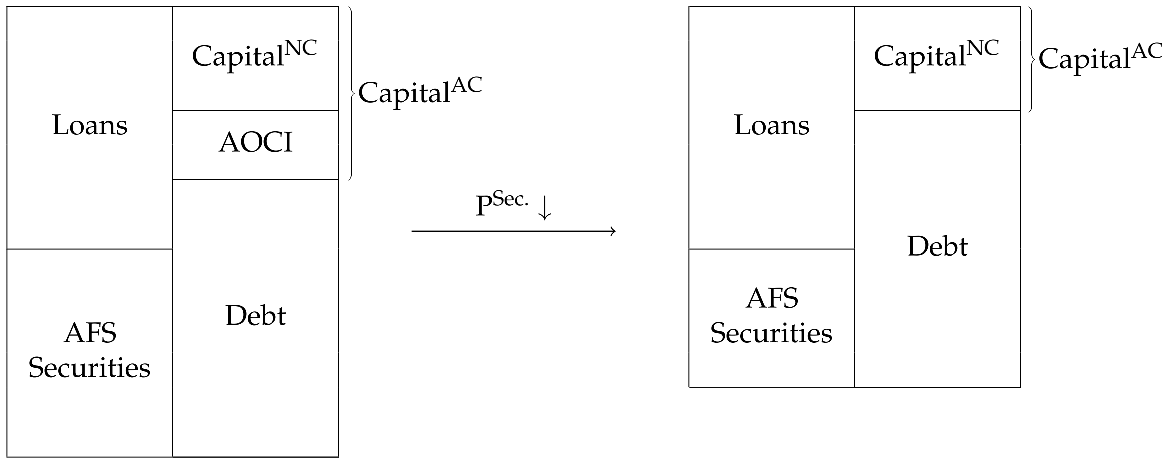
3 Balance Sheet Dynamics

Given this regulatory setting, we now illustrate the impact of security price changes on bank balance sheets. To demonstrate how such mechanisms can work, Figure 3.1 considers a hypothetical balance sheet. Starting with the left-hand side, we consider an AC bank that holds loans and AFS securities. For this example, we assume that the bank has accumulated a positive AOCI account from unrealized gains on its portfolio, but note that AOCI could be zero or negative depending on the past performance of the bank's assets. For an NC bank, AOCI would not be included in regulatory capital, and the bank's regulatory capital would be given by Capital^{NC}. In contrast, AC banks include AOCI in their regulatory capital, which is therefore computed as $\text{Capital}^{AC} = \text{Capital}^{NC} + \text{AOCI}$.

The change from the left-hand side to the right-hand side in Figure 3.1 shows the impact of a fall in the price of securities, holding all else constant. This causes the balance sheet to shrink because AFS securities are marked to market. In this example, we assume for simplicity that the price decline wipes out the previous unrealized capital gains, so that AOCI disappears. As before, this choice is made for illustration, as AOCI could

[13] In certain circumstances a holder can sell HTM securities and avoid tainting (see Appendix C for such instances).

Figure 3.1: Accounting Treatment for AFS Securities.



Notes: The figure shows changes in a hypothetical bank's balance sheet following a decline in the value of its AFS securities.

alternatively shrink but remain positive, or turn negative. Following this price change, an AC bank would suffer a regulatory capital decline, while an NC bank would experience no change in regulatory capital.[14] This could in turn pressure AC banks to reduce their risk-weighted assets by cutting lending, particularly if they are less well capitalized.

Measuring the strength of this regulatory capital channel is not straightforward, however, due to the presence of several confounding channels unrelated to regulatory accounting that could lead securities values to affect bank lending. First, changes in securities values can operate through a net worth channel. Gains and losses on securities, all else equal, influence a bank's net worth (equity), which could affect lending in the presence of financial frictions. Second, changes in securities values could impact credit supply through their role as collateral. Because banks can pledge securities and borrow against them (e.g., in repo markets), a decline in the market value of their securities could reduce their borrowing capacity, potentially affecting their ability to lend.[15] Third, changes in securities values could operate via a liquidity stock channel. Banks hold securities in AFS because they expect to potentially sell them at some future date, for instance to support short-term liquidity needs. A bank may therefore react to securities losses by rebalancing its portfolio from loans to securities to rebuild its buffer stock of liquid securities.

[14]In this example, AC banks are actually better capitalized for a given amount of risk-weighted assets to begin with. In practice, banks would adjust their capital positions to remain relatively close to the required levels of capital. Thus, if AC and NC banks start with the same level of regulatory capital, AC banks would end up with less capital after the price decline.

[15]A similar collateral channel based on a bank's tangible common equity may also be present since certain financial market participants like Federal Home Loan Banks lend according to this ratio.

To identify the independent effect of regulatory capital, our empirical analysis exploits that only a subset of securities at a subset of banks are marked to market in the computation of regulatory capital. This allows us to better isolate the effect of security values on lending via the regulatory channel by comparing "treated" securities whose values may pass through into regulatory capital against "control" securities whose values do not.

Our first approach below compares the effect of changes in the value of AFS securities, which can be marked to market in regulatory capital, against changes in the value of HTM securities, which cannot (see Appendix Figure B.1). This comparison should net out the net worth and collateral channels, which are activated symmetrically by value changes of both types of securities, revealing the combined effect of the regulatory capital and liquidity channels. Similarly, because hedges offset both the net worth and the regulatory capital channels, separately estimating the effects on hedged and unhedged AFS securities will allow us to better isolate the impact of the regulatory capital channel. Last, as the most direct test of the regulatory capital channel, we compare the change in AFS values at AC vs. NC banks. Since AFS value changes at NC banks should trigger the net worth, collateral, and liquidity stock channels, this comparison most cleanly isolates the role of the regulatory capital channel. Equipped with this institutional knowledge and these predictions, we next turn to the data and the empirical analysis.

4 Data

We primarily base our analysis on the FR Y-14Q data, abbreviated as "Y14." These data are collected at the bank holding company (BHC) level for institutions subject to the Dodd-Frank stress tests and are available at a quarterly frequency. We combine data from three different schedules to create a merged data set new to the literature. Of particular interest is the B.1 schedule, which covers the universe of security holdings in the investment portfolio. In this schedule, we observe the current market value of security holdings, the security price, the amortized cost, the accounting intent (AFS or HTM), and an asset class description (e.g., Agency MBS).[16] To measure effective duration, we add security-level information from the Intercontinental Exchange Fixed Income & Data Services.

We match the security-level data with their associated hedging relationships designated under Generally Accepted Accounting Principles (GAAP) from the B.2 schedule. From this schedule, we use information about the hedge type (fair value or cash flow hedge), the hedged risk, the hedge sidedness (offsets in one or multiple directions), and

[16] Amortized cost is defined as the purchase price of a debt security adjusted for amortization of premium or accretion of discount if the debt security was purchased at other than par or face value.

the hedge percentage.[17] For our main empirical analysis, we select only two-sided fair value hedges, which account for around 94% of all hedges.

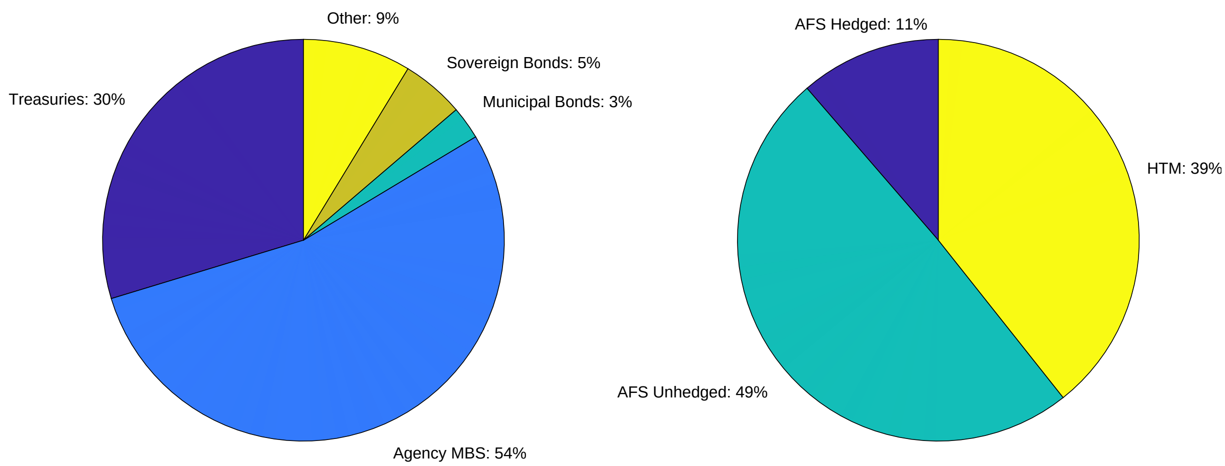
We obtain information on corporate credit relationships and firm financials from the Y14's H.1 schedule. This schedule provides data on all commercial loan facilities with over $1 million committed. In addition to the information on the loan facilities themselves, this schedule also includes detailed data on firm balance sheets and income statements collected by the banks. We refine this information in two ways. First, for publicly traded firms, we replace these fields with data from Standard & Poor's Compustat, which is considered the most reliable source for firm financials. Second, when private firms have multiple loan facilities, and hence multiple reported observations for each financial variable at a given time, we use the median value across all observed BHC loan facilities in that period. This approach helps eliminate reporting errors and increases the number of dates for which we have observations on each firm's financial characteristics. Throughout, we exclude lending to financial and real estate firms.

Finally, we augment the data with BHC-level information from the FR Y-9C. Importantly, the variable BHCAP838 in these data identifies whether a BHC includes AOCI in its regulatory capital, making it an AC bank in our terminology. Appendix Table D.1 lists the resulting classification of AC and NC banks in our data. For our main sample, there were 29 BHCs reporting data in the corporate loan portfolio consecutively, of which 10 were AC banks. Appendix Tables D.2-D.5 summarize all the variables we use from the Y14's B.1, B.2, and H.1 schedules, Compustat, and FR Y-9C, and Appendix E lists a number of sample restrictions and filtering steps that we apply.

For our main empirical analysis, we focus on the monetary tightening cycle of 2022 and include data through 2023:Q1, representing the latest vintage available at the time of our analysis. To include a pre-sample of similar length, we start our sample in 2021:Q1. A benefit of this starting point is that it excludes the period surrounding the COVID-19 outbreak in 2020, which exhibited an unusual pattern of bank-firm lending dominated by credit line draws from large firms (see, e.g., Greenwald, Krainer and Paul, 2025). However, we test the robustness of our findings on a longer sample in Section 6.1.

[17] The "hedge percentage" variable indicates how much of the securities holding is covered by the hedge. Accordingly, we consider a certain percentage of a security's price movement as hedged. Note that more than one hedge can be associated with a security, and we aggregate all the hedges to the security level.

Figure 5.1: Composition of Securities Portfolios.



Notes: Data from FR Y-14Q sampled in 2021:Q4. The charts show the shares of aggregate bank securities by asset class (left panel) and by accounting designation (right panel). Shares are computed as percent of total market value.

5 Stylized Facts

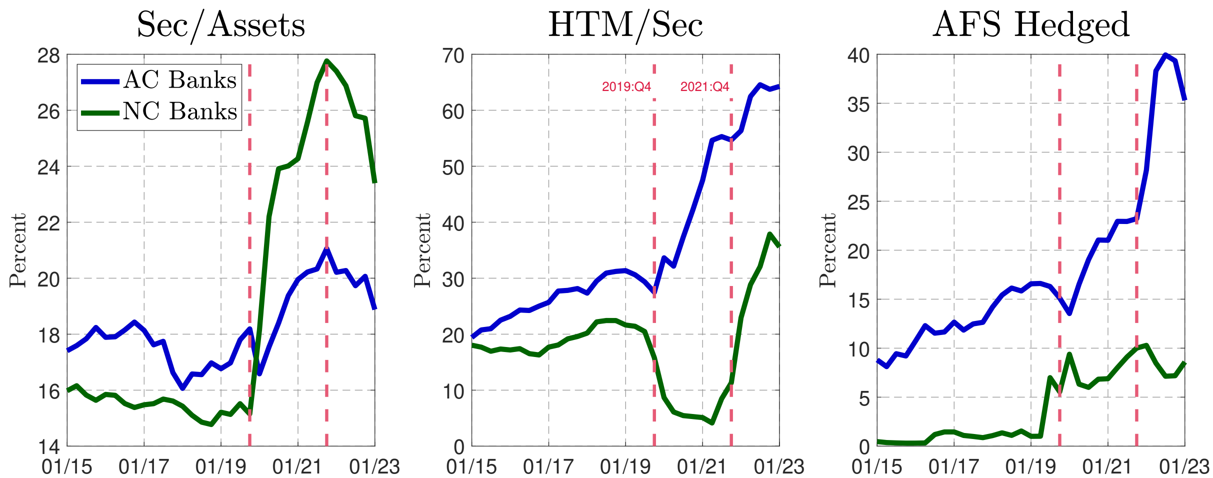
We next summarize key facts about the composition of bank securities portfolios and how these have varied by bank type and time.

Banks' investment securities portfolios are large, accounting for around 23% of aggregate bank assets in 2021:Q4. The left panel of Figure 5.1 displays the composition of securities holdings by asset class. Bank securities are mostly composed of agency MBS and Treasuries, which account for around 85% of the total portfolio at market value. Because these assets are almost exclusively from high-rated issuers or insured by the Government Sponsored Enterprises, credit risk is minimal. Instead, risk exposure on these bank portfolios is dominated by interest rate risk.

The right panel of Figure 5.1 breaks down the securities by their classification in 2021:Q4. Around 60% of all bank securities were held as AFS, with the rest as HTM, while 19% of the AFS portfolio was hedged using some form of accounting hedge. Appendix Figure F.1 shows that banks primarily hedge against interest rate risk, with interest rate swaps accounting for 86% of all contracts.[18]

[18] Appendix Figures F.2 and F.3 decompose these patterns by AC and NC banks, showing that AC banks hold relatively more Treasuries, while NC banks hold relatively more Agency MBS. Hedges effectively shorten the maturity of securities, which we illustrate in Appendix Figure F.4. While the securities in banks' AFS and HTM portfolios have similar effective duration across AC and NC banks, the higher share of hedged AFS securities at AC banks limits their total interest rate exposure.

Figure 5.2: Evolution of Securities Portfolios.



Notes: Data from FR Y-14Q Schedules B.1 and B.2. The figure shows the evolution of bank securities portfolios by bank type (AC vs. NC banks). The left panel depicts securities as a percentage of total assets. The middle panel shows HTM holdings as a percentage of total securities. The right panel shows the share of AFS securities that are hedged. Vertical dashed lines indicate 2019:Q4 and 2021:Q4.

From this baseline, we next analyze changes in bank securities portfolios around our sample period. During the pandemic period, BHCs responded to large inflows of deposits and an environment of heightened uncertainty by dramatically expanding their securities portfolios. This pattern is portrayed in the left panel of Figure 5.2, which shows the fraction of bank assets invested in securities. This surge in securities holdings was particularly pronounced for NC banks, which raised their securities holdings from 15% of total assets to a peak of 28% before partially reversing this increase during the tightening cycle. In contrast, AC banks raised their overall security holdings by substantially less during the period of low interest rates.[19]

The middle panel of Figure 5.2 shows that AC banks hold larger shares of their total securities portfolio in HTM relative to NC banks throughout the sample period. This pattern is also documented in Fuster and Vickery (2018) and Kim, Kim and Ryan (2019) who analyze the years prior to the COVID-19 pandemic. The differences between AC and NC banks become particularly stark during the low interest rate environment in 2020 and 2021, with the HTM share of AC bank securities nearly doubling, while the HTM share for NC banks falls by more than half.[20]

[19]The differential changes in securities holdings may also be partially explained by a larger increase of deposits at NC banks between 2019:Q4 and 2021:Q4, during which NC banks experienced a rise of their deposit-to-asset ratio of around 8pp compared to an increase of around 4pp at AC banks. However, the ratio of securities to deposits also grew substantially more at NC banks (by around 14pp) relative to AC banks (by around 3pp).

[20]Appendix Figure C.1 presents data on the reclassification of existing securities between AFS and HTM

Finally, focusing on fair-value hedges against interest rate risk, the right panel of Figure 5.2 shows that AC banks generally hedge a larger share of their AFS securities compared with NC banks. This hedging gap grew during the period of low interest rates in 2020 and 2021 and accelerated even further when rates started to rise in 2022:Q1.

These trends are all consistent with a regulatory motive for AC banks to avoid exposure to losses on AFS securities that would pass through to their regulatory capital. However, despite these efforts to limit AFS exposure, AC banks experienced securities losses over the 2022–2023 monetary tightening episode that sharply reduced their AOCI positions. Appendix Figure F.5 shows that AOCI at AC banks fell by around 1% of risk-weighted assets due to unrealized losses on AFS securities, directly reducing the regulatory capital positions at these banks by the same amount. At the same time, NC banks experienced an even larger decline of AOCI by around 3% of risk-weighted assets, but faced no resulting change in regulatory capital due to their differential treatment under the regulatory accounting framework.

6 Identifying Credit Supply Effects

In this section, we measure the effect of fluctuations in bank security values on credit supply to nonfinancial firms.

6.1 Effects by Security Classification

To begin, we estimate the overall effect of changes in securities values on bank-firm lending, and decompose this effect by whether securities are classified as AFS or HTM and whether they are hedged. A typical challenge with such an exercise is that the set of firms that borrow from banks with larger securities losses may differ systematically from other firms. In this case, differences in lending could reflect the differential credit demand of these firms, rather than the causal effect of changes in securities values.

To address this, our main regression specifications include firm-time fixed effects, following Khwaja and Mian (2008), which absorb variation in overall firm credit demand. We thus identify credit supply effects from the relative changes in borrowing across mul-

for AC and NC banks, similar to the analysis of Granja (2023). Kim, Kim and Ryan (2023) study reclassifications by the banks that reinstated the AOCI filter with the tailoring rule in 2019 and show that such banks reclassified more securities from HTM to AFS.

tiple lenders by the same firm. For firm i and bank j, we estimate the regression

$$\frac{L_{i,j,t+2} - L_{i,j,t}}{0.5 \cdot (L_{i,j,t+2} + L_{i,j,t})} = \alpha_{i,t} + \beta \cdot \frac{\Delta Value^{SEC}_{j,t+1}}{Assets_{j,t}} + \tau_{AC_j,t} + \gamma X_{j,t} + \kappa_j + u_{i,j,t} \;, \tag{6.1}$$

where $L_{i,j,t}$ is the aggregated amount of term lending between a firm and a bank at time t, and $\alpha_{i,t}$ is a firm-time fixed effect. We focus on term lending and exclude credit lines from our main analysis as the predetermined spreads and commitments on credit lines largely insulate them from shifts in credit supply (Greenwald, Krainer and Paul, 2025), but show that our results are robust to removing this restriction later on. The dependent variable is the symmetric growth rate in $L_{i,j,t}$ over the two quarters from t to $t+2$. Unlike standard growth rates, symmetric growth rates accommodate zeros and are bounded in the range $[-2, 2]$, reducing the potential influence of outliers.

The main regressor of interest is the change in the value of a bank's securities between t and $t+1$ relative to total bank assets, denoted by $\Delta Value^{SEC}_{j,t+1} / Assets_{j,t}$. Since we observe the market value $MV^k_{j,t}$ and the price $P^k_{j,t}$ of each bank security k, we compute a bank's aggregated security value change as

$$\Delta Value^{SEC}_{j,t+1} = \sum_k \left(\frac{P^k_{j,t+1} - P^k_{j,t}}{0.5 \cdot (P^k_{j,t+1} + P^k_{j,t})} \right) \cdot MV^k_{j,t}, \tag{6.2}$$

where we again use the symmetric growth rate to approximate a percentage change in the price. Importantly, our detailed security-level data enable us to compute the total value change of a bank's *pre-existing* securities portfolio aggregated from the individual security value changes. In contrast, a regressor constructed from aggregated bank balance sheet data would confound gains and losses on pre-existing securities with new purchases and sales. Thus, we take a bank's choice of security holdings as given and study how subsequent changes in the value of those securities affect bank credit supply.

The associated coefficient β captures credit supply effects. A positive β would indicate that a bank that experiences a fall in the value of its securities relative to another bank extends less credit to the same firm. Based on the discussions in Sections 3 and 5, a potential concern may be that AC banks have higher true values of β due to their regulatory exposure, but a less negative $\Delta Value^{SEC}_{j,t+1} / Assets_{j,t}$ over our sample period because of their lower securities holdings.[21] If so, this correlation between exposure and response would bias β downward. We therefore include an AC-by-time fixed effect $\tau_{AC_j,t}$, where AC_j is

[21]Specifically, the quarterly average of $\Delta Value^{SEC}_{j,t+1} / Assets_{j,t}$ for AC banks is around -0.35% over our sample, whereas NC banks experienced a larger decline of -0.49%.

Table 6.1: Credit Supply Effects.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value SEC	3.16**					
	(1.33)					
Δ Value AFS		6.08***	6.15***	7.37***		
		(1.85)	(1.78)	(1.89)		
Δ Value HTM			1.93	1.31	1.85	0.71
			(1.47)	(1.23)	(1.38)	(1.44)
Δ Value AFS Unhedged					8.13***	8.68***
					(2.67)	(2.73)
Δ Value AFS Hedged					2.86	3.46
					(4.94)	(5.24)
Fixed Effects						
Firm × Time	✓	✓	✓		✓	
Firm × Time × Purpose				✓		✓
Bank & AC × Time	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Derivatives					✓	✓
R-squared	0.57	0.57	0.57	0.55	0.57	0.55
Observations	13,038	13,038	13,038	11,093	13,027	11,093
Number of Firms	1,289	1,289	1,289	1,105	1,288	1,105
Number of Banks	27	27	27	26	26	26

Notes: Estimation results for regression (6.1). All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (iv) and (vi). Columns (ii)-(iv) distinguish security value changes into AFS and HTM value changes. Columns (v) and (vi) further distinguish AFS value changes into hedged and unhedged value changes. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. Columns (v) and (vi) include controls for derivative contracts from the trading and derivative book (see footnote 24 for details). All specifications include AC-bank-by-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

an indicator that is equal to one if bank j is an AC bank and zero otherwise.[22] This allows us to consider the variation within the set of AC or NC banks at a particular time. Last, to account for possible correlations of our main regressor with bank characteristics, we include a standard set of bank-specific controls $X_{j,t}$ and a bank fixed effect κ_j. Appendix Table G.1 shows summary statistics for the main regressors in (6.1).

The estimation results for regression (6.1) are reported in Table 6.1. Column (i) shows the response to a change in the total value of a bank's securities portfolio. We estimate a

[22] AC_j is time-invariant since banks do not switch types over our sample.

positive β, implying that banks experiencing more negative security value changes extend relatively less credit, and can reject the absence of an effect at the 5% level.

Next, we test whether changes in AFS and HTM values, which are subject to different regulatory treatment, have distinct effects on bank credit supply. Column (ii) reestimates our regression focusing on AFS value changes and excluding changes in HTM values. We find that our estimated coefficient β doubles in size and increases in statistical significance. Column (iii) separately estimates the responses of AFS and HTM, finding a coefficient on AFS value changes close to that of Column (ii), but a coefficient on HTM value changes that is more than three times smaller and cannot be distinguished from zero at standard confidence levels.

A potential identification concern is that banks may specialize in certain types of lending. If the response of firm credit demand differs by loan type in a way correlated with our regressors of interest, then firm-time fixed effects may not be sufficient to control for this variation (Paravisini, Rappoport and Schnabl, 2023). To address this, Column (iv) repeats the analysis using a finer set of firm-time-loan purpose fixed effects and finds even larger differences between our estimated responses to AFS and HTM value changes.[23]

Last, we split changes in AFS security values by whether the security is hedged or unhedged. In our data, banks report the fraction of a security that is hedged against a certain risk. Consistent with our focus on interest rate transmission, we consider fair-value hedges against interest rate risk, which account for 86% of all hedges in our sample.[24] Columns (v) and (vi) of Table 6.1 repeat our analysis, splitting the change in AFS security values into a hedged component and an unhedged component. As in Columns (iii) and (iv), we estimate these responses alongside the response to changes in HTM values, and separately consider regressions using firm-time and firm-time-loan purpose fixed effects. In both cases, we find that changes in the value of unhedged AFS securities have a strong and highly significant effect on bank credit supply that is even larger than the unconditional coefficients on changes in AFS values in Columns (iii) and (iv). In contrast,

[23]Specifically, we consider the categories "Mergers and Acquisitions," "Working Capital (permanent or short-term)," "Real estate investment or acquisition," and "All other purposes" as separate types (see also Appendix Table D.2).

[24]We restrict attention to Treasuries in the hedged component since their values fluctuate only because of interest rate risk, while values of other securities may change due to a number of alternative risk factors (e.g., credit risk, prepayment risk, foreign exchange risk, etc.). To be conservative, we therefore consider value changes of other securities as unhedged, since other risks may remain even if the bank reports that they are fully hedged against interest rate risk. To account for hedges other than those we observe, we add information about bank derivatives from their trading and their derivative books as controls. Specifically, based on the Y-9C filings, we add derivatives with a positive or negative fair value from the trading book (BHCM3543, BHCK3547), as well as notional and fair values for interest rate contracts from the derivative book (BHCKA126, BHCK8733, BHCK8737), all scaled by total assets. See Appendix Table D.5 for details.

the effect of changes in the value of hedged AFS securities is less than half the size and cannot be statistically distinguished from zero.

Overall, our results indicate a strong pass-through from changes in the value of AFS securities to bank-firm lending, particularly for unhedged AFS securities, but a weaker or zero spillover from changes in the value of HTM and hedged AFS securities. These results suggest that the regulatory capital channel, which can explain these relative responses, is quantitatively important, confirming a prediction from Section 3. The weak responses to changes in HTM and hedged AFS values further suggest that the net worth and collateral channels were not as quantitatively important during our sample period.

To measure economic significance, we conduct a back-of-the-envelope calculation. Given the average ratio of term lending to bank assets observed, our estimates imply a lending cut of around 20 cents for each $1 decline in the value of bank AFS portfolios.[25] Moreover, we note that the regulatory capital channel provides incentives to reduce all risk-weighted assets, and is therefore not restricted to firm lending or term loans. As a result, while these measured spillover effects are already substantial, we consider them a lower bound on the total crowding-out effect, which likely extends to other forms of credit not present in our sample such as small business, consumer, and real estate credit.

We perform extensive robustness tests and explore extensions of our baseline results in Columns (ii)-(iv), which are collected in Appendix G. First, we consider alternative regression specifications that (i) replace the firm-time fixed effects by variations of location-, size-, and industry-time fixed effects, (ii) extend the firm-time fixed effects by other contract terms to consider loans of similar types (Ivashina, Laeven and Moral-Benito, 2022), (iii) include credit lines, and (iv) exclude the episode of financial turmoil in 2023:Q1. By and large, our results remain much the same across the various robustness tests.

Second, we extend the sample backwards to include episodes of monetary easing and explore the possibility of asymmetric effects by separating positive and negative AFS value changes. Both extensions yield consistent findings: we obtain smaller effects for positive AFS value changes and samples that cover periods of falling interest rates.

Third, we consider alternative dependent variables in (6.1). We estimate the extensive margin response of creation and termination of credit relationships, finding quantitatively stronger responses compared to our results above. To study dynamic adjustments, we reestimate our regressions at various horizons to form impulse responses. We find that the credit supply effects already show up in the same quarter as the change in security prices, continue to build over time, and peak after three quarters. We also estimate the

[25]This is computed by multiplying the typical ratio of term lending to bank assets across the Y14 banks over our sample (around 3%) with the midpoint of the estimates for β in Table 6.1.

effect on interest rates, and obtain estimates that are consistent but quantitatively weaker compared with the results for credit quantities. Finally, we show that re-estimating our regressions with alternative timing fails to find evidence of pretrends.

6.2 Effects by Bank Type

In the previous section, we compared responses to changes in the value of securities with different classifications or hedging status, finding these credit supply effects were mainly driven by unhedged AFS securities. However, the regulatory treatment of AFS securities is not uniform across banks. Critically, AC banks must pass through changes in AFS values to their regulatory capital, while NC banks do not, providing an ideal comparison.

Before conducting any bank-firm level analysis, we study how C&I lending growth behaved over our sample period at the two types of banks. First, using bank-holding company data, Appendix Figure F.6 presents the evolution of the C&I lending share separately for AC and NC banks, showing that C&I lending grew relatively more at NC than at AC banks over our sample period. Second, Appendix Figure F.7 shows that unrealized losses on AFS securities and C&I lending growth are positively related for NC banks, but negatively related for AC banks. Both patterns are consistent with the influence of the regulatory capital channel.

For a more direct test of our channel, we return to the loan-level data. We explore differences in the response to AFS gains and losses between AC and NC banks. Formally, we estimate the interacted regression

$$\frac{L_{i,j,t+2} - L_{i,j,t}}{0.5 \cdot (L_{i,j,t+2} + L_{i,j,t})} = \alpha_{i,t} + \beta_1 \cdot \frac{\Delta Value^{AFS}_{j,t+1}}{Assets_{j,t}} + \beta_2 \cdot \frac{\Delta Value^{AFS}_{j,t+1}}{Assets_{j,t}} \cdot AC_j + \gamma X_{j,t} + \kappa_j + u_{i,j,t}\,. \quad (6.3)$$

Since the new interaction term directly captures differences in the responses of AC and NC banks, we omit the AC-bank-time fixed effect $\tau_{AC_j,t}$ that was present in (6.1).

Table 6.2 reports our estimates for regression (6.3). As discussed in Section 6.1 above, we address concerns about bank specialization across loan types by reporting our regression results in pairs, with one specification using firm-time fixed effects, and the other using firm-time-loan purpose fixed effects.

Columns (i) and (ii) present our baseline results. We estimate large and significant coefficients β_2, alongside positive estimates for β_1. As before, both coefficients are slightly larger when controlling for the finer firm-time-loan purpose fixed effects. To interpret these estimates, note that the estimated response of an NC bank to a given change in AFS values is β_1, while the estimated response of an AC bank is $\beta_1 + \beta_2$. As a result, our

Table 6.2: Credit Supply Effects, AC vs. NC Banks.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value AFS	4.83**	5.65**	2.45	2.09	-2.08	-2.53
	(2.14)	(2.37)	(2.48)	(2.59)	(4.81)	(4.92)
Δ Value AFS × AC	7.55**	9.26***	10.86*	14.03**	12.95*	15.18**
	(3.50)	(3.14)	(5.81)	(5.23)	(6.94)	(6.39)
Δ Value AFS × Size			-2.11	-3.08*	-3.99	-4.71
			(1.87)	(1.78)	(3.45)	(3.54)
Fixed Effects						
Firm × Time	✓		✓		✓	
Firm × Time × Purpose		✓		✓		✓
Bank	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Bank Controls × Δ Value AFS					✓	✓
R-squared	0.57	0.55	0.57	0.55	0.57	0.55
Observations	13,038	11,093	13,038	11,093	13,038	11,093
Number of Firms	1,289	1,105	1,289	1,105	1,289	1,105
Number of Banks	27	26	27	26	27	26

Notes: Estimation results for regression (6.3). All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii), (iv), and (vi). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. Columns (v) and (vi) include interaction terms between the various demeaned bank controls and $\Delta Value^{AFS}_{j,t+1} / Assets_{j,t}$. All specifications include bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

estimates imply that the response of AC banks is more than 2.5 times larger than that of NC banks, while the statistical significance of the interaction term means that we can reject the hypothesis that AC and NC banks react symmetrically.

An important caveat to these initial results is that assignment of banks to the AC or NC category is not random, but is instead primarily determined by bank size, with the larger banks falling in the AC category. To the extent that large banks react differently to changes in securities values, we could be falsely attributing these differences to variation in regulatory treatment. To address this, we therefore augment our regression (6.3) to include an interaction between the change in AFS values and bank size, measured as the (demeaned) logarithm of assets. This interaction term allows for banks of different size to react to changes in securities values differently in a smooth way, while allowing a discontinuous jump in this reaction at the regulatory size threshold.

Columns (iii) and (iv) display our estimates from the augmented regression. In both specifications, we find that the interaction between changes in AFS values and bank size carries a negative coefficient, implying that larger banks react less to changes in securities values, holding all else equal. Since AC banks are larger, controlling for this trend by size increases our coefficient for β_2. At the same time, our estimated response of NC banks (β_1) is roughly cut in half, and we can no longer reject that the response of an NC bank of average size is zero.

Last, to avoid similar confounding issues with other covariates, Columns (v) and (vi) further extend this regression by interacting the change in AFS values with additional demeaned bank controls. Appendix Table G.1 shows summary statistics of various bank controls for the two types of banks separately. In addition to their larger size, which primarily determines AC status, AC banks have a lower loan share, a lower deposit share, and smaller undrawn credit line commitments. As before, the additional controls absorb smooth variation in the responsiveness of banks to AFS gains and losses by characteristic, so that our main coefficient of interest β_2 more narrowly focuses on variation around the AC classification cutoff. As with our size interaction, allowing for these extra interacted controls increases the interaction coefficients β_2 and decreases the base coefficients β_1.[26]

Combined, these results provide evidence that firm credit supply at AC banks reacts more strongly than at NC banks to the same change in AFS values. This is consistent with our prediction in Section 3, since AFS gains and losses pass through to regulatory capital at AC banks but not NC banks.[27] Our results therefore provide strong evidence that the regulatory capital channel, which is active only at AC banks, is the primary mechanism of transmission from interest rates into bank-firm lending, while alternative channels that should be present for both AC and NC banks, such as the net worth, collateral, or liquidity stock channels, were much weaker or nonexistent for our sample banks and period.

We supplement these findings with additional specifications and robustness checks in Appendix H. First, as in Section 6.1, we rerun regression (6.3), splitting changes in AFS values into hedged and unhedged components. Our estimates show that the effect for AC banks is stronger for changes in unhedged AFS values, though the estimates are less pre-

[26]The additional interaction terms are also meaningful in the sense of Oster (2019). Comparing R-squared measures of the baseline regressions in columns (i) and (ii), the ones with the additional interactions in columns (v) and (vi), and regressions that include bank-time fixed effects, which give the maximum achievable R-squared measures from including bank-level controls, shows that the additional interaction terms close between 6% and 68% of the gap in R-squared measures between the baseline regressions and the maximum R-squared measures.

[27]Appendix Table H.4 shows that these results are not explained by a firm switching between AC and NC banks when borrowing from both, but largely remain and even somewhat intensify when we extend the firm-time fixed effects by the AC-bank indicator AC_j, thus considering samples when a firm only borrows from one type of bank. The pass-through to total firm debt in Section 6.3 provides further evidence against the importance of such a switching effect in our data.

cise for this extended regression. Second, we explore heterogeneity in banks' responses by their capital positions. We find that less-capitalized banks show stronger spillover effects, as predicted in Section 3.

Third, we provide further evidence that our baseline findings are explained by banks' exposure to interest rate risk that leads to fluctuations in the value of their securities portfolios. To this end, we employ an instrumental variable regression, using the interaction between the yield change of the one-year Treasury security and a bank's preexisting AFS portfolio as an instrument for our main regressor. If anything, our results strengthen in magnitude for this alternative specification.

Fourth, we augment our regression to include deposit flows, net income changes, liquid asset holdings, and changes in the quality of loan portfolios at each bank. Incorporating these variables allows us to control for alternative mechanisms centered around liquidity or loan quality following changes in interest rates, such as those highlighted by Drechsler, Savov and Schnabl (2017), Gomez et al. (2021), and Kashyap and Stein (2000). We obtain estimates for the response of credit supply to changes in AFS security values that are similar to and slightly stronger than our baseline results, indicating that our findings are independent from these existing mechanisms.

Last, we test whether our previous results also aggregate up to the bank level. To this end, we sum total firm credit for each bank j and re-estimate variations of regressions (6.1) and (6.3). Appendix Table H.5 collects the results, which confirm that AFS value changes have stronger effects on lending than HTM value changes. As before, these effects are concentrated in changes in the value of unhedged AFS securities, and are much stronger at AC banks than at NC banks.

6.3 Effects at the Firm Level

We conclude our empirical analysis at the firm level, testing whether and how changes in bank securities values transmit into firm balance sheets and investment. We follow an approach similar to Khwaja and Mian (2008), computing each firm's overall exposure to changes in bank AFS values as a weighted average of these changes at each bank lending to that firm, weighted by the share of firm debt obtained from that bank.[28] Formally, we define the exposure of firm i to changes in bank AFS values from time t to $t+1$ as

$$\widetilde{\Delta Value}^{AFS}_{i,t+1} = \sum_j \left(\frac{\Delta Value^{AFS}_{j,t+1}}{Assets_{j,t}} \right) \cdot \left(\frac{L_{i,j,t}}{Debt_{i,t}} \right). \tag{6.4}$$

[28]Consistent with the previous regressions, we restrict the sample to term loans only. Since we do not cover all firm debt positions, we control for the ratio of observed credit to total firm debt.

Using this definition, we estimate the regression

$$\frac{y_{i,t+4} - y_{i,t}}{0.5 \cdot (y_{i,t+4} + y_{i,t})} = \alpha_i + \kappa_t + \beta \cdot \Delta \widetilde{Value}^{AFS}_{i,t+1} + \gamma X_{i,t} + u_{i,t} \ , \tag{6.5}$$

where the dependent variable $y_{i,t}$ is either total liabilities, fixed assets (a proxy for investment), or cash and marketable securities.[29] We again use the symmetric growth rate for the dependent variable to approximate percentage changes, but this time consider a four-quarter horizon since firm financials are updated annually for most private firms.

Because we have one observation per firm in each period, we can no longer include firm-time fixed effects. Instead, we rely on our results in Table G.2 showing that our findings are not dependent on the inclusion of firm-time fixed effects. In their place, we include firm fixed effects (α_i) and time fixed effects (κ_t). We also include a vector of controls $X_{i,t}$ containing both firm-level variables, as well as bank-level variables that are aggregated to the firm level based on the firms' debt shares, as in (6.4). This latter group includes the contemporaneous deposit and net income changes at a firm's lender banks, as in Table H.3, to account for alternative channels highlighted by the existing literature.

The estimation results are reported in Table 6.3. Columns (i), (iii), and (v) show the estimates for total liabilities, fixed assets, and cash holdings. In each case, we find a positive coefficient, implying that all three variables decline at firms whose lender banks experience losses on their AFS securities, and we can reject that each effect is zero at the 5% level. To compare these results to our earlier findings, note that the ratio of our point estimate for total liabilities in Column (i) of Table 6.3 to our point estimates for bank lending in Columns (iii) and (iv) of Table 6.1 is 0.67 and 0.56, respectively. Because the ratio of debt to total liabilities is 0.57 at the average firm in our sample, these results are consistent with complete pass-through, meaning a change in total liabilities (in dollars) that is equal to the change in bank debt from the Y14 banks. These estimates therefore indicate that firms facing contractions of credit supply due to bank securities losses are generally unable to substitute toward credit from other banks or nonbank lenders.

Columns (iii) and (v) show that firm adjustments of investment and cash holdings are also highly economically significant. Since firms in our sample have average ratios of fixed assets to total liabilities of 0.26, and cash to total liabilities of 0.13, these coefficients imply that each dollar of debt crowded out by bank securities losses leads firms to reduce fixed-asset investment and cash holdings by around 33 cents each. Thus, the inability of firms to substitute into other forms of debt has real economic consequences by reducing

[29] We consider total liabilities as opposed to total debt since firms may adjust other non-debt liabilities such as accounts payable in response to a credit supply shock.

Table 6.3: Firm Level Effects.

	Δ Liabilities		Investment		Δ Cash	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value AFS	4.14**		5.30**		10.45**	
	(2.07)		(2.67)		(4.48)	
Δ Value AFS × Small		4.13**		5.35**		10.47**
		(2.07)		(2.67)		(4.49)
Δ Value AFS × Large		5.42		-4.33		7.64
		(6.70)		(9.31)		(18.39)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
Time	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
R-squared	0.78	0.78	0.72	0.72	0.66	0.66
Observations	83,663	83,663	82,473	82,473	81,901	81,901
Number of Firms	22,499	22,499	22,162	22,162	22,116	22,116
Number of Banks	30	30	30	30	30	30

Notes: Estimation results for regression (6.5) where $y_{i,t}$ is either total liabilities in columns (i) and (ii), fixed assets in columns (iii) and (iv), or cash holdings in columns (v) and (vi). All specifications include firm fixed effects and the firm controls: cash holdings, fixed assets, liabilities, net income, sales (all scaled by total assets), firm size (natural logarithm of total assets), the ratio of observed debt to total debt, as well as the set of all bank controls used in previous regressions and deposit and net income changes from Column (iv) of Table H.3 aggregated to the firm level using debt shares across lenders. Standard errors in parentheses are clustered by firm. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

investment and shrinking firms' precautionary cash buffers.

Finally, to explore heterogeneity in transmission, we separately estimate the response of firms by size. We hypothesize that larger firms should be less affected by a contraction of bank credit supply since they have better access to nonbank sources of financing. Columns (ii), (iv), and (vi) repeat the regressions of Columns (i), (iii), and (v), respectively, but use an indicator to split the sample into large firms in the top 10% of our firm size distribution, and small firms in the bottom 90% of our firm size distribution. Our estimates show coefficients on small firms that are significant and highly similar to our overall results. In contrast, our estimates for large firms are imprecise and cannot be statistically distinguished from zero. These findings motivate our construction of the model, which features two types of firms that differ in their access to financing.[30]

[30] Consistent with our model setup, where small firms only have access to term loans, Appendix Table I.1 shows that the results remain if we separate firms according to whether they have any unused credit line capacity in our data. Firms without credit line capacity show a similar pass-through as small firms.

7 Model

To study the effects of changes in security values and their regulatory treatment on interest rate transmission in general equilibrium, we present a structural model building on Greenwald, Krainer and Paul (2025). We briefly summarize the key ingredients of the model, present the detailed structure, calibrate the model, and describe our findings.

7.1 Model Overview

Our model is designed to capture the pathway of transmission from interest rates, through securities values and bank capital requirements, into bank-firm lending and real activity. Banks in our model hold long term securities, which are priced according to long-term interest rate forecasts, and lend to smaller, bank-dependent firms. Banks must also hold capital against their loan portfolio, which may be influenced by gains and losses on their securities, depending on the regulatory regime, and varies endogenously over time with bank profits and payouts. When regulators recognize gains and losses in regulatory capital, an increase in securities prices allows banks to lend more without raising capital, expanding credit supply, while a decline in securities prices has the opposite effect.

We embed this structure into a general equilibrium framework featuring a rich set of quantitatively realistic adjustment frictions, and calibrate the model to directly match our firm-level regressions in Table 6.3. We then expose this model to a sequence of shocks that exactly reproduce the change in real interest rates, inflation, aggregate investment, and aggregate corporate credit over our 2021:Q1–2023:Q1 sample.

7.2 Model Structure

Demographics and Preferences. Our model features four types of households: constrained firm entrepreneurs (denoted C), unconstrained firm entrepreneurs (denoted U), bank entrepreneurs (denoted B), and savers (denoted S). Each type of household is able to trade a complete set of contracts with other households of the same type, but not across types, leading to aggregation to a representative household for each type.

An entrepreneur of type $j \in \{C, U\}$ has exponential utility (constant absolute risk aversion) preferences over consumption $C_{j,t}$ defined by[31]

$$U_{j,t} = E_t \sum_{k=0}^{\infty} \bar{\beta}_j^k \left(\prod_{m=0}^{k} \tilde{\beta}_{t+m} \right) \frac{(1 - \exp(-\zeta_D C_{j,t+k}))}{\zeta_D} \tag{7.1}$$

where $\tilde{\beta}_t$ is a patience shifter used to match variation in real interest rates in our main exercise. To simplify notation, we define $\beta_{j,t} = \bar{\beta}_j \tilde{\beta}_t$. The preferences of the bank entrepreneur (type B) are identical except for an alternative value of absolute risk aversion:

$$U_{j,t} = E_t \sum_{k=0}^{\infty} \bar{\beta}_j^k \left(\prod_{m=0}^{k} \tilde{\beta}_{t+m} \right) \frac{(1 - \exp(-\zeta_B C_{j,t+k}))}{\zeta_B} \tag{7.2}$$

Each entrepreneur owns a firm or bank of the same type and consumes its dividends. As a result, using a concave utility function increases marginal utility when dividends are low, providing incentives for firms to smooth dividends.

Savers have risk-neutral preferences over consumption $C_{S,t}$ and deposit services l_t:

$$U_{S,t} = E_t \sum_{k=0}^{\infty} \bar{\beta}_S^k \left(\prod_{m=0}^{k} \tilde{\beta}_{t+m} \right) (C_{S,t+k} + \eta_{l,t+k} l_{t+k}), \tag{7.3}$$

where $\tilde{\beta}_t$ is the same preference shifter, and $\eta_{l,t}$ is a time-varying utility shifter for deposit services. These risk-neutral preferences ensure that the risk-free rate depends only on the discount factor and expected inflation. We assume the functional form

$$\eta_{l,t} = (1 - \gamma)(1 - R_t^{-1}),$$

which at equilibrium implies partial pass-through of interest rates to deposit rates

$$R_{l,t} = 1 + \gamma(R_t - 1),$$

as has been extensively documented by, e.g., Drechsler, Savov and Schnabl (2017).

Productive Technology and Labor Demand. The production function is

$$Y_{j,t} = Z_t K_{j,t-1}^{\alpha} N_j^{1-\alpha},$$

[31] Using exponential utility rather than power utility (constant relative risk aversion) preferences allows us to avoid taking a stand on whether entrepreneurs also receive consumption from other sources, and is able to accommodate zero or negative dividends (equity issuance), which can occur in practice.

where $j \in \{C, U\}$ denotes the type of the firm, Z_t is exogenous aggregate productivity, $K_{j,t-1}$ is capital, and N_j is labor, which firms use in a fixed quantity at a fixed wage w. Savers inelastically supply N units of labor each period.[32]

Firm Types. Firms take two types: constrained firms (denoted C) and unconstrained firms (denoted U). Each is owned by an entrepreneur of the corresponding type. Types differ in their ability to use financial instruments. While unconstrained firms can borrow using corporate bonds, constrained firms can only borrow using term loans from banks.

Firm Debt Contracts. We model both corporate bonds and term loans as floating rate contracts with fixed spreads, so that at time $t+j$ a firm must make an interest payment on a loan originally issued at time t of $r_{t+j} + s_t$ per dollar of outstanding principal balance, where r_{t+j} is the contemporaneous risk-free rate, and s_t is the initial fixed loan spread. In addition to interest, a fraction ν^B of debt matures and must be repaid each period, while a fraction $1 - \nu^B$ of debt is carried into the following period, so that one-period debt corresponds to $\nu^B = 1$. This structure requires two debt-related state variables per firm: the total principal balance ($B_{j,t}$), and the total amount of promised spread payments in the following period ($S_{j,t}$). These evolve according to

$$\begin{aligned} B_{j,t} &= \underbrace{B^*_{j,t}}_{\text{new loans}} + \underbrace{(1-\nu^B)\pi_t^{-1} B_{j,t-1}}_{\text{existing loans}} \\ S_{j,t} &= \underbrace{s^*_{j,t} B^*_{j,t}}_{\text{new spread payments}} + \underbrace{(1-\nu^B)\pi_t^{-1} S_{j,t-1}}_{\text{existing spread payments}}, \end{aligned}$$

where $B^*_{j,t}$ is new loan issuance, $s^*_{j,t}$ is the average spread per dollar of debt issued, and inflation (π_t) translates from nominal to real terms. The spread on new debt $s^*_{j,t}$ depends on each firm's funding structure: constrained firms borrow using bank loans at spread s_t^{loan}, while unconstrained firms borrow using corporate bonds at spread s_t^{bond}.

At equilibrium, we rebate all spread payments in excess of the steady state spread back to the borrowing firms through lump-sum taxes on banks. To understand why this adjustment is needed, recall that the spread on new debt $s^*_{j,t}$ clears the market for firm debt each period. When credit supply contracts, this spread will rise until firms reduce borrowing sufficiently. Under our calibration, matching the observed decline in debt would require

[32] Assuming labor demand and wages are fixed stands in for unmodeled frictions in the labor market that may prevent wage or hour adjustments at the relatively short time horizons we consider. Assuming that labor is a fixed factor also serves as a simple way to pin down the relative scales of the two types of firms without requiring us to take a stand on the elasticity of substitution the goods they produce.

large increases in spreads. However, our empirical estimates in Appendix Table G.10 find small and statistically insignificant changes in the price of credit following changes in securities values. This reflects a common pattern in empirical corporate finance whereby banks contracting credit supply appear to adjust primarily on quantities (i.e., rationing) rather than prices due to frictions or agency costs.

Applying these lump-sum taxes and rebates is important as it prevents these counterfactually large spreads from generating bank profits so large that banks are able to recapitalize almost immediately — a well-known issue in models of financial intermediation. Our approach therefore allows loan markets to clear through the model's price mechanism while removing these unrealistically large spread payments from bank and firm budget constraints. In this sense, the model can be seen as closer to one with credit rationing, while maintaining the parsimony of a Walrasian market.

Firm Debt Covenants. Firm debt contracts contain debt-to-EBITDA covenants that penalize firms if their total debt exceeds a multiple of smoothed EBITDA ($X_{j,t}$), defined by

$$X_{j,t} = (1-\rho_X)\underbrace{(Y_{j,t} - wN_j)}_{\text{current EBITDA}} + \rho_X \pi_t^{-1} X_{j,t-1}, \tag{7.4}$$

where EBITDA represents output net of the wage bill, and the deflator term π_t^{-1} accounts for the fact that smoothed EBITDA is measured in nominal terms.

Because firms face uncertainty about their future EBITDA, they typically leave a precautionary buffer in their covenant ratios away from the violation threshold. To match this in our framework, we assume that a firm violates its covenant if

$$\pi_t^{-1} B_{j,t-1} > \omega_{i,t} \theta X_{j,t}, \tag{7.5}$$

where $\omega_{i,t}$ are i.i.d. shocks. These shocks induce uncertainty similar to that described above, leading to precautionary behavior. Because firms in our model are not exactly at the covenant violation threshold, they are not literally constrained, and can obtain an additional dollar of debt if they choose to. Instead, the increased probability of covenant violation from maintaining a smaller buffer, combined with the cost of credit, balances against the marginal benefit of debt to create an interior solution.

Rearranging (7.5), a firm of type j violates its covenant if and only if $\omega_{i,t} < \bar{\omega}_{j,t}$, for

$$\bar{\omega}_{j,t} = \frac{\pi_t^{-1} B_{j,t-1}}{\theta X_{j,t}}. \tag{7.6}$$

The probability of violation is $\Gamma_{\omega,j}(\bar{\omega}_{j,t})$, which is increasing in the firm's expected ratio of debt to smoothed EBITDA. We assume that firms that violate their covenants must pay a penalty equal to fraction κ_j of their start-of-period principal balance $\pi_t^{-1}B_{j,t-1}$.

Firm's Problem. The representative firm owned by entrepreneurs of type j chooses dividends $D_{j,t}$, cash holdings $A_{j,t}$, new debt issuance $B^*_{j,t}$, and new capital $K_{j,t}$ to maximize

$$V_{j,t} = D_{j,t} + \eta_{A,j}\frac{A_{j,t}^{1-\zeta_A}}{1-\zeta_A} + E_t\Big[\Lambda_{j,t+1}V_{j,t+1}\Big], \tag{7.7}$$

where the term $\Lambda_{j,t+1}$ is the stochastic discount factor of the type j entrepreneur

$$\Lambda_{j,t+1} = \beta_{j,t}\exp\Big(-\zeta_D(C_{j,t+1} - C_{j,t})\Big), \tag{7.8}$$

which rewards dividend smoothing at equilibrium due to entrepreneurs' concave utility.

The value function (7.7) includes a utility term for holding cash. This stands in for the precautionary or liquidity motives that lead firms to hold cash in reality, allowing our model to reproduce this behavior in a deterministic setting. We allow the utility weight $\eta_{A,j}$ to vary by firm type j to match cash holdings by large and small firms.

The budget constraint for a firm of type j is

$$\begin{aligned} D_{j,t} = {} & \underbrace{(1-\tau)\left(Y_{j,t} - wN_j\right)}_{\text{after-tax profit}} + \underbrace{\Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t}K_{j,t-1}}_{\text{old capital}} + \underbrace{\pi_t^{-1}\Big(1+(1-\tau)r_{t-1}\Big)A_{j,t-1}}_{\text{old cash}} \\ & \underbrace{-\,\pi_t^{-1}\left[\Big((1-\tau)r_{t-1} + \nu^B + \kappa_j\Gamma_{\omega,j}(\bar{\omega}_{j,t})\Big)B_{j,t-1} + (1-\tau)S_{j,t-1}\right]}_{\text{payments on existing debt}} - \underbrace{T_{j,t}}_{\text{lump-sum taxes}} \\ & - \underbrace{Q_{j,t}K_{j,t}}_{\text{new capital}} - \underbrace{A_{j,t}}_{\text{new cash}} + \underbrace{(1-\varphi_t)B^*_{j,t}}_{\text{new debt}}, \end{aligned} \tag{7.9}$$

where $D_{j,t}$ is dividends, $Q_{j,t}$ is the price of new capital, $\bar{Q}_{j,t}$ is the resale price of old capital, $B^*_{j,t}$ is newly issued debt, $T_{j,t}$ is a lump-sum tax (rebate) that returns excess spread payments to firms, r_{t-1} is the risk-free interest rate, τ is the corporate tax rate, δ is the depreciation rate, and φ_t is a time-varying debt issuance cost, rebated lump-sum to firms at equilibrium, used to match the time series of corporate debt below. Both depreciation and interest payments on debt are tax-deductible. Cash is held in short-term government bonds and earns the risk-free rate, with its interest subject to corporate tax. The "payments on existing debt" term consists of base interest rate payments net of the tax shield $(1-\tau)r_{t-1}$, principal payments ν^B, and average violation costs $\kappa_j\Gamma_{\omega,j}(\bar{\omega}_{j,t})$, all per unit of principal balance, in addition to spread payments net of the tax shield $(1-\tau)S_{j,t-1}$.

Bank's Problem. We assume a homogeneous banking sector, owned by a representative bank entrepreneur, in which gains and losses on AFS securities pass through to regulatory capital. Since only a subset of banks (the AC banks) receive this regulatory treatment in reality, we calibrate this homogeneous-bank model carefully in Section 7.4 to match the average effect of mark-to-market regulation across banks in our Y14 data.

Banks in our model lend to firms and hold bonds in fixed quantity b, financed by deposits and equity.[33] The bank's balance sheet from the regulator's perspective is

$$\underbrace{B_t^{loan} + \bar{P}_t b + AOCI_t}_{\text{assets } (a_t)} = \underbrace{l_t + k_t}_{\text{liabilities + net worth}} \tag{7.10}$$

where B_t^{loan} is loans to constrained firms, $\bar{P}_t$ is the book value of each bond, l_t are deposits, and k_t is regulatory capital. For convenience we will define total bank assets as a_t. The term $AOCI_t$ represents unrealized gains and losses on AFS securities, and is defined by

$$AOCI_t = F^{AC} \times F^{AFS} \times (P_t - \bar{P}_t) \times b \tag{7.11}$$

where F^{AFS} is the share of securities held in the AFS category, and F^{AC} is the share of AFS that is held at AC banks and not hedged, since only these securities pass through their gains and losses to regulatory capital under current regulation. This weighting scheme allows our homogeneous bank sector to correctly reproduce the average effect on bank regulatory capital of a change in bond values. The book value of bonds $\bar{P}_t$ is defined by

$$\bar{P}_t = \underbrace{\left(1 - (1-\nu^b)\pi_t^{-1}\right) P_t}_{\text{new bonds}} + \underbrace{(1-\nu^b)\pi_t^{-1}\bar{P}_{t-1}}_{\text{legacy bonds}}, \tag{7.12}$$

which combines the original price of legacy bonds and the current price of new bonds.

Each bank is subject to a risk-based capital requirement of the form:

$$k_t \geq \chi B_t^{loan}. \tag{7.13}$$

This constraint requires that banks hold χ dollars of capital for each dollar of term loans

[33]While banks in reality hold a large amount of other assets besides term loans to firms, our working assumption is that a bank can be modeled as a collection of divisions that perform each type of lending, and each hold a fraction of the bank's securities and deposits proportional to their size. In this case, our banks map to the bank divisions devoted to term lending to firms, assuming that following a contraction in regulatory capital each division of the bank is expected to adjust equally.

B_t^{loan} currently extended to firms. To preview our main mechanism, note from (7.10)–(7.13) that a decrease in bond values will reduce AOCI and hence regulatory capital k_t, tightening the capital requirement (7.13).

The representative bank chooses dividends $D_{B,t}$, bank capital k_t, and new loans to constrained firms $B_t^{loan,*}$ to maximize

$$v_t = \underbrace{D_{B,t}}_{\text{dividends}} + E_t\left[\Lambda_{B,t+1} v_{t+1}\right], \tag{7.14}$$

where

$$\Lambda_{B,t+1} = \beta_{B,t} \exp\Big(-\zeta_B (C_{B,t+1} - C_{B,t})\Big) \tag{7.15}$$

is the stochastic discount factor of the bank entrepreneur. The parameter ζ_B determines the incentive for the bank to smooth its dividends. Since a bank facing declines in regulatory capital must adjust by cutting either lending to firms or payouts to investors, this parameter determines the response of credit supply to changes in the value of securities.

The bank maximizes (7.14) subject to (7.10)–(7.13) and the budget constraint

$$\begin{aligned} D_{B,t} \leq\ & \underbrace{\pi_t^{-1}\left[\left(r_{t-1} + \nu^B - q^{loan}\right) B_{C,t-1}^{loan} + S_{C,t-1}^{loan}\right]}_{\text{payments on existing loans}} - \underbrace{B_{C,t}^{loan,*}}_{\text{new loans}} - \underbrace{T_{B,t}}_{\text{lump-sum tax}} \\ & + \underbrace{\left[\nu^b \pi_t^{-1} - \left(1 - \pi_t^{-1}(1-\nu^b)\right) P_t\right] b}_{\text{LT securities}} + \underbrace{l_t - \pi_t^{-1}(1 + r_{l,t-1}) l_{t-1}}_{\text{net deposit flows}}, \end{aligned} \tag{7.16}$$

which states that bank dividends equal total loan income net of newly issued debt plus net cash flows from long-term securities. The long-term securities cash flow reflects that the bank receives \$1 for each security that matures, but then purchases new securities to replace maturing securities and losses in real value due to inflation at price P_t. The term q^{loan} is a constant cost per dollar of loans paid by the bank that motivates the existence of a spread in steady state, which we rebate lump-sum at equilibrium. The lump-sum tax $T_{B,t}$ taxes excess loan spreads as discussed above, net of the rebates just mentioned.

Entrepreneurs' Problems. Entrepreneurs of type $j \in \{B, C, U\}$ choose consumption $C_{j,t}$ to maximize (7.1) for $j \in \{C, U\}$ or (7.2) for $j = B$, subject to the constraint $C_{j,t} \leq D_{j,t}$.

Government Sector. The monetary authority has a time-varying inflation target π_t that it achieves perfectly. We assume $\pi_t = \bar{\pi} \times \tilde{\pi}_t$, where $\bar{\pi}$ is steady state inflation and $\tilde{\pi}_t$ is a stochastic inflation shifter.

The government provides risk-free one-period bonds (B_t^G) in zero net supply, short-term cash securities ($A_{j,t}$) in the quantity demanded by firms, and long-term securities in positive supply with fixed quantity b.[34] Long-term securities mature with probability ν^b, in which case they pay \$1. The government budget constraint is:

$$
\begin{aligned}
0 = \sum_j & \underbrace{\tau \left[Y_{j,t} - wN_j + \pi_t^{-1} r_{t-1} \left(A_{j,t-1} - B_{j,t-1} \right) - \pi_t^{-1} S_{j,t-1} \right]}_{\text{corporate taxes}} \\
& + \underbrace{B_t^G - (1 + r_{t-1}) \pi_t^{-1} B_{t-1}^G}_{\text{short-term bonds}} + \sum_j \underbrace{\left(A_{j,t} - \pi_t^{-1} (1 + r_{t-1}) A_{j,t-1} \right)}_{\text{cash securities}} \\
& - \underbrace{\left[\nu^b \pi_t^{-1} - \left(1 - \pi_t^{-1} (1 - \nu^b) \right) P_t \right] b}_{\text{long-term securities}} + \underbrace{\sum_{j \in \{B,C,S,U\}} T_{j,t}}_{\text{lump sum taxes}} .
\end{aligned}
\tag{7.17}
$$

The right hand side is equal to corporate tax revenues plus net issuance of cash securities, minus the interest paid on long-term debt, plus a lump sum tax $T_{S,t}$ on the saver (subsidy if negative) that offsets any deficits or surpluses in the government budget.

Saver's Problem. The saver chooses consumption $C_{S,t}$, new corporate bond issuance $B_t^{bond,*}$, new deposits l_t, and new government bonds B_t^G to maximize (7.3) subject to

$$
\begin{aligned}
C_{S,t} \leq \underbrace{wN}_{\text{labor income}} & + \underbrace{\pi_t^{-1} \left[\left(r_{t-1} + \nu^B - q^{bond} \right) B_{t-1}^{bond} + S_{t-1}^{bond} \right]}_{\text{existing corp. bonds}} - \underbrace{B_t^{bond,*}}_{\text{new corp. bonds}} \\
& + \underbrace{(1 + r_{l,t-1}) \pi_t^{-1} l_{t-1} - l_t}_{\text{deposits}} + \underbrace{(1 + r_{t-1}) \pi_t^{-1} B_{t-1}^G - B_t^G}_{\text{government bonds}} - \underbrace{T_{S,t}}_{\text{lump-sum taxes}} ,
\end{aligned}
$$

where at equilibrium we must have $B_t^G = 0$ and $B_t^{bond,*} = B_{U,t}^*$, and where q^{bond} is an exogenous bond holding cost allowing for nonzero bond spreads at equilibrium.[35] Cor-

[34]While bonds B_t^G and short-term cash securities $A_{j,t}$ are effectively identical, we define them separately so that we can impose a zero net supply constraint on the bonds B_t^G, while the quantities of $A_{j,t}$ are determined by firm demand. This constraint is required because the linear preferences of savers imply that their demand for risk-free bonds is indeterminate at equilibrium. In practice, the exact allocation of bonds is arbitrary, since the government budget is balanced by lump sum taxes on savers. Instead, the one-period bonds exist solely to define the equilibrium risk-free rate.

[35]In Appendix A.1, we show that at equilibrium $s_t^{bond} = q^{bond}$, allowing us to consider corporate bond spreads as fixed. This choice is motivated by the relatively stable Baa-Aaa bond spreads over the 2021:Q1 to 2023:Q1 period, which increase by only 20bp (from 78bp to 98bp), substantially less than the contemporaneous increase in long-term risk-free rates.

porate bond principal balance and spread payments evolve according to

$$B_t^{bond} = B_t^{bond,*} + (1 - \nu^B)\pi_t^{-1} B_{t-1}^{bond} \tag{7.18}$$
$$S_t^{bond} = s_t^{bond} B_t^{bond,*} + (1 - \nu^B)\pi_t^{-1} S_{t-1}^{bond}. \tag{7.19}$$

Capital Producers. Capital is created for firm type j using technology

$$K_{j,t} = \exp(\lambda_t)\Phi(i_{j,t})K_{j,t-1} + (1 - \delta)K_{j,t-1},$$

where $i_{j,t} = I_{j,t}/K_{j,t-1}$ is the investment rate in sector j, and λ_t is a time-varying shock to the marginal efficiency of investment, which will be used in Section 7.5 to match the time series of investment. Competitive capital producers buy existing capital at price $\bar{Q}_{j,t}$ and sell new capital at price $Q_{j,t}$, choosing the investment rate $i_{j,t}$ to maximize

$$Q_{j,t}\Big[\exp(\lambda_t)\Phi(i_{j,t})K_{j,t-1} + (1 - \delta)K_{j,t-1}\Big] - i_{j,t}K_{j,t-1} - \bar{Q}_{j,t}(1 - \delta)K_{j,t-1}.$$

Equilibrium. A competitive equilibrium is the allocation that solves the optimization problems of the firms, entrepreneurs, saver, bank, and capital producer, and that clears the markets for output, capital goods, bank loans, corporate bonds, and government bonds. The model's complete set of equilibrium conditions can be found in Appendix A.1.

7.3 Replicating Our Empirical Regressions

To match our empirical estimates in Table 6.3, we need to compute the coefficients from an equivalent regression in the model. We first define our outcome variables as

$$\Delta \text{ Total Liabilities}_{C,t} = \frac{L_{C,t} - L_{C,t-4}}{0.5(L_{C,t} + L_{C,t-4})} \tag{7.20}$$
$$\Delta \text{ Fixed Assets}_{C,t} = \frac{K_{C,t}^{fixed} - K_{C,t-4}^{fixed}}{0.5(K_{C,t}^{fixed} + K_{C,t-4}^{fixed})} \tag{7.21}$$
$$\Delta \text{ Cash}_{C,t} = \frac{A_{C,t} - A_{C,t-4}}{0.5(A_{C,t} + A_{C,t-4})}, \tag{7.22}$$

where $L_{C,t}$ represents total liabilities of the firm and $K_{C,t}^{fixed}$ are firm fixed assets. Since we do not directly model non-debt liabilities, we assume that constrained firms have a constant amount of non-debt liabilities $\bar{L}_C^{other}$ so that $L_{C,t} = B_{C,t} + \bar{L}_C^{other}$, and calibrate $\bar{L}_C^{other}$ to match the ratio of debt to total liabilities among firms in our sample in steady state. Similarly, since we do not distinguish between fixed assets and other assets in the model, we define $K^{fixed}_{C,t} = K_{C,t} - \bar{K}^{other}_{C}$, where $\bar{K}^{other}_{C}$ is chosen to match the observed ratio of fixed to total assets among firms in our sample in steady state. This definition assumes that only a firm's fixed assets respond to the shift in credit supply and can be considered conservative in the sense that it yields the smallest possible response of total firm investment that is consistent with our regression evidence.

We next define the main independent variable from regression (6.5) as

$$\Delta \text{ Value AFS}_t = \frac{(P_{t-3} - P_{t-4}) \times F^{Y14} \times F^{AFS} \times b}{a_{t-4}}, \tag{7.23}$$

where a is total bank assets lagged four quarters, and F^{Y14} is the share of Y14 banks, used to account for the fact that our regression only includes this subset of banks. This timing reproduces that of regression (6.5), where a 1Q change on the right-hand side (here from $t-4$ to $t-3$) drives a subsequent 4Q change on the left-hand side (here $t-4$ to t).

To compute regression coefficients, we need variation in securities gains or losses across banks. To this end, we create new types of constrained firms and banks, which can be thought of as hypothetical or as actually existing with infinitesimal size. In particular, we assume that firms of type $C(+)$ borrow from banks of type $(+)$ that hold a slightly larger share of AFS securities ($F^{AFS} + \epsilon$). This implies the AOCI values

$$AOCI_t(+) = F^{AC} \times \left(F^{AFS} + \epsilon\right) \times (P_t - \bar{P}_t) \times b,$$

where we use $\epsilon = 10^{-4}$ in our calculations. When P_t fluctuates, this leads to differences in security gains and losses, AOCI, and therefore credit supply adjustments, across the type C banks and type $C(+)$, providing the variation required for our model regressions.

With these definitions in hand, we estimate the model regressions

$$\begin{aligned} &\Delta \text{ Total Liabilities}_{C,t}(+) - \Delta \text{ Total Liabilities}_{C,t} \\ &\quad = \beta_{liabilities} \left(\Delta \text{ Value AFS}_t(+) - \Delta \text{ Value AFS}_t\right) + \varepsilon^{liabilities}_t \end{aligned} \tag{7.24}$$

$$\begin{aligned} &\Delta \text{ Fixed Assets}_{C,t}(+) - \Delta \text{ Fixed Assets}_{C,t} \\ &\quad = \beta_{assets} \left(\Delta \text{ Value AFS}_t(+) - \Delta \text{ Value AFS}_t\right) + \varepsilon^{assets}_t \end{aligned} \tag{7.25}$$

$$\begin{aligned} &\Delta \text{ Cash}_{C,t}(+) - \Delta \text{ Cash}_{C,t} \\ &\quad = \beta_{cash} \left(\Delta \text{ Value AFS}_t(+) - \Delta \text{ Value AFS}_t\right) + \varepsilon^{cash}_t. \end{aligned} \tag{7.26}$$

These regressions of the differences between the corresponding variables for the "+" firms or banks and the baseline firms or banks are equivalent to the non-differenced regression on the combined sample including both types, after removing a time fixed effect.

7.4 Calibration

We calibrate the model at quarterly frequency, with parameter values displayed in Table 7.1. For consistency with our empirical findings in Table 6.3, we match unconstrained moments to those for the top 10% of the firm size distribution and constrained firm moments to those for the bottom 90% of the size distribution. Unless otherwise mentioned, our calibration is designed to match steady-state values to corresponding values in the data for the period from 2012:Q3 to 2019:Q4, the most recent extended "normal" period for which we have Y14 data.

Adjustment Frictions. The frictions on the various margins available to banks and firms are governed by the family of ζ parameters. These are differentiated by their subscripts, which denote the main variable they influence. These correspond to the firms' margins for cash (ζ_A), dividends (ζ_D), investment (ζ_K), and to the bank's cost of adjusting payouts, which determines the response of debt (ζ_B). Since these parameters are the most central to the model's dynamics, we calibrate them to directly match our estimates in Table 6.3.

Because it is the relative rather than the absolute degree of frictions that determines how heavily these margins are used following a shock, we need to first pin down one of the parameters externally, after which we can calibrate the remaining ζ parameters to match our regression evidence. Following our previous work (Greenwald, Krainer and Paul, 2025), we externally calibrate the investment friction to a standard value $\zeta_K = 0.250$, but show that our results are robust to alternative values in Appendix A.3.

With this parameter pinned down, we calibrate the remaining frictions to align our implied regression coefficients in equations (7.24) - (7.26) to match the regression results in Table 6.3. First, on the bank side, the curvature of bank entrepreneur utility (ζ_B) determines how much changes in the value of securities pass through into spreads and ultimately borrowing by constrained firms. We set $\zeta_B = 34.506$ so that $\beta_{liabilities}$ in our model, measured four quarters after a shock to interest rates, is exactly equal to our small firm coefficient in Column (ii) of Table 6.3. We similarly set the dividend adjustment friction to $\zeta_D = 0.525$ and the cash adjustment friction to $\zeta_A = 6.281$ so that β_{assets} and β_{cash} in our model match our small firm coefficients in columns (iv) and (vi) of Table 6.3, respectively.

Table 7.1: Parameter Values: Baseline Calibration (Quarterly)

Parameter	Name	Value	Internal	Target/Source
		Adjustment Frictions		
Capital Adjustment (Curvature)	ζ_K	0.250	N	Standard
Cash Utility (Curvature)	ζ_A	6.281	Y	β_{cash}
Banker ARA	ζ_B	34.506	Y	$\beta_{liabilities}$
Entrepreneur ARA	ζ_D	0.525	Y	β_{assets}
		Preferences		
Saver Discount Factor	$\bar{\beta}_S$	0.995	N	Standard
Entrepreneur Discount Factor (U)	$\bar{\beta}_U$	0.990	N	Standard
Entrepreneur Discount Factor (C)	$\bar{\beta}_C$	0.990	N	Standard
Entrepreneur Discount Factor (B)	$\bar{\beta}_B$	0.990	N	Standard
		Long-Term Securities		
Frac. Securities Maturing	ν^b	0.053	N	4Y Duration
Face Value of Securities	b	2.746	Y	Securities-loans ratio
Frac. AFS	F^{AFS}	0.541	Y	AFS / Assets
Frac. AC	F^{AC}	0.412	N	See text
Frac. Y14	F^{Y14}	0.700	N	See text
		Debt Contracts		
Frac. Debt Maturing	ν^B	1.000	N	1Q Maturity
Bond Holding Cost	q^{bond}	0.625%	N	250bp Spread (Ann.)
Debt-to-EBITDA Limit	θ	15.000	N	Dealscan
Covenant Smoothing	ρ_X	0.750	N	4Q smoothing
Covenant Violation Fee (U)	κ_U	0.003	N	Leverage, violation rate
Covenant Violation Fee (C)	κ_C	0.003	N	Leverage, violation rate
Idio. EBITDA Vol. (U)	$\sigma_{\omega,U}$	0.712	N	Leverage, violation rate
Idio. EBITDA Vol. (C)	$\sigma_{\omega,C}$	0.664	N	Leverage, violation rate
		Financial		
Cash Utility (Level, C)	$\eta_{A,C}$	0.307	Y	$\bar{A}/\bar{K} = 9.6\%$
Cash Utility (Level, U)	$\eta_{A,U}$	0.302	Y	$\bar{A}/\bar{K} = 7.4\%$
Loan Risk Weight	χ	0.120	N	See text
Deposit Pass Through	γ	0.881	Y	See text
Bank Loan Issuance Cost	q^{loan}	0.625%	Y	250bp Spread (Ann.)
Non-Debt Liabilities	$\bar{L}_C^{other}$	6.366	Y	Total liabilities to debt
Non-Fixed Assets	$\bar{K}_C^{other}$	22.125	Y	Debt to fixed assets
		Technology and Government		
Capital Share	α	0.330	N	Standard
Unconstrained Labor Demand	N_U	0.860	N	Asset shares
Productivity	$\bar{Z}$	1.000	Y	$Y = 1$
Corporate Tax Rate	τ	0.210	N	Standard
Inflation Rate	$\bar{\pi}$	1.005	N	2% inflation

Preferences. We set the saver discount factor to $\bar{\beta}_S = 0.995$, implying a steady state real annualized interest rate of 2%. We set the entrepreneur discount factors to $\bar{\beta}_C = \bar{\beta}_U = \bar{\beta}_B = 0.990$, which delivers a reasonable capital-output ratio of 2.2.

Bank Securities. For the long-term AFS securities held by banks, we set ν^b so that these securities have a cash flow duration of 4 years (16 quarters), which is typical in our data. Given the security's perpetuity structure, this requires choosing ν^b to satisfy

$$\frac{1+r}{r+\nu^b} = 16,$$

which implies $\nu^b = 0.053$. We set the total amount of securities held by banks to $b = 2.746$ so that the aggregate ratio of total securities value ($P \times b$) to bank assets (a) matches the corresponding ratio for Y14 banks over our sample period. We set the fraction of securities held as AFS to $F^{AFS} = 0.541$, so that the steady state ratio of AFS securities ($F^{AFS} \times \bar{P} \times b$) to bank assets ($a_t$) is equal to 0.116, consistent with the average share in our Y14 sample over the 2021:Q1–2023:Q1 period. We set the fraction of securities held by AC banks to $F^{AC} = 0.412$ so that the $F^{AC} \times F^{AFS}$ matches the share of securities held as unhedged AFS at AC banks over the same sample period. Last, we set $F^{Y14} = 0.700$, which roughly matches the asset share of Y14 banks in the total banking sector.

Debt Contracts. We assume a one-period maturity ($\nu^B = 1$), but show in Appendix A.3 that we obtain nearly identical results using a five year (20Q) debt maturity ($\nu^B = 0.05$).

We set the (constant) spread on corporate bonds to $\bar{s}^{bond} = 0.625\%$, consistent with evidence by Schwert (2020). Following the evidence in Greenwald (2019), we choose a debt-to-EBITDA limit of $\theta = 15.000$, which corresponds to an annual debt-to-EBITDA limit of 3.75. For the smoothing parameter, we choose $\rho_X = 0.750$, which approximates the typical practice of averaging EBITDA over four quarters when evaluating covenant compliance. We parameterize the $\omega_{i,t}$ distribution as lognormal, with

$$\log \omega_{i,t} \sim N\left(-\frac{1}{2}\sigma^2_{\omega,j}, \sigma^2_{\omega,j}\right)$$

for a firm of type j. We choose the violation costs κ_C and κ_U and the volatilities $\sigma_{\omega,C}$ and $\sigma_{\omega,U}$ to jointly match four targets: the ratio of debt to capital (leverage) for $j \in \{C, U\}$, equal to 28% and 32% respectively, and the rate at which firms exceed the model debt-to-EBITDA threshold for $j \in \{C, U\}$, equal to 32% and 34%, respectively.

Financial. We choose scale parameters for the utility of cash at each type of firm ($\eta_{A,C}$ and $\eta_{A,U}$) to match the ratios of cash to assets of 9.6% at small (constrained) firms and 7.4% at large (unconstrained) firms, respectively, measured in our Y14 data.

We set the required capital ratio to $\chi = 0.120$, corresponding to the statutory 8% minimum plus a typical 4% buffer. For the pass-through from interest rates to deposits, our goal is to target a stable net interest income stream, as documented by Drechsler, Savov and Schnabl (2021). To this end, we set $\gamma = 0.881$ to match the share of bank assets in the form of loans. Since loans are floating rate, while banks' remaining assets (securities) are fixed-rate, this allows us to roughly match the pass-through from interest rates to the rates of return on both sides of the balance sheet. We set the loan issuance cost to $q^{loan} = 0.625\%$ to ensure a steady state annual term loan spread of 250bp, equal to that on corporate bonds.

We set the amount of non-debt liabilities to $\bar{L}_C^{other} = 6.366$ to reproduce a ratio of debt to total liabilities of 0.57, while the amount of non-fixed assets is $\bar{K}_C^{other} = 22.125$ to match a ratio of debt to fixed assets of 1.5.[36]

Technology and Government. For the capital share, we use a standard value of $\alpha = 0.330$. We set $\bar{Z} = 1.000$ so that $Y_t = 1$ in steady state. For the investment adjustment cost, we choose the functional form

$$\Phi(i_{j,t}) = \phi_0 + \phi_1 \frac{i_{j,t}^{1-\zeta_K}}{1-\zeta_K}.$$

We calibrate $\zeta_K = 0.250$, as discussed above, and choose values of ϕ_0 and ϕ_1 so that $\Phi(i) = i$ and $\Phi'(i) = 1$ in steady state. For the labor supply quantities, we normalize $N = 1$, and set $N_U = 0.860$ and $N_C = N - N_U$ to target a steady state share of capital held by unconstrained firms of 0.860, which is the share of assets held by firms in the top 10% of the size distribution in the Y14 data. Turning to the government sector, we calibrate the corporate tax rate to $\tau = 0.210$ to match its typical value in the U.S., and set the average level of inflation to $\bar{\pi} = 1.005$ to match an annual inflation rate of 2%.

7.5 Model Results

Having constructed the model, we now investigate its quantitative implications.

[36] We choose this ratio as the ratio of debt to fixed assets translates our regression coefficients into a marginal propensity to invest. However, because we are also matching the steady state ratio of debt to total assets, this can also be thought of as matching the steady state ratio of total assets to fixed assets.

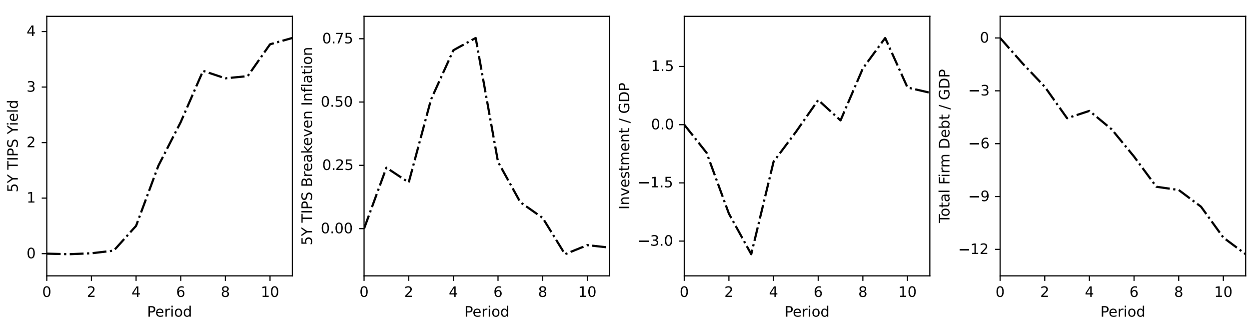
The Experiment. Our empirical analysis uses a sample that covers the tightening cycle from 2021:Q1 to 2023:Q1. To reproduce the cycle exactly, we parameterize our shocks as

$$\begin{aligned}
\log \tilde{\beta}_t &= \rho_\beta \log \tilde{\beta}_{t-1} + \varepsilon_{\beta,t} \\
\log \tilde{\pi}_t &= \rho_\pi \log \tilde{\pi}_{t-1} + \varepsilon_{\pi,t} \\
\lambda_t &= \rho_\lambda \lambda_{t-1} + \varepsilon_{\lambda,t} \\
\varphi_t &= \rho_\varphi \varphi_{t-1} + \varepsilon_{\varphi,t}.
\end{aligned}$$

Since our shock system is just identified, with each observable pinning down one shock innovation, the persistence parameters do not influence the estimation of the shocks, and so we set $\rho_\beta = \rho_\pi = \rho_\lambda = \rho_\varphi = 0.99$. We next linearize the model and use the Kalman smoother to fit a sequence of shocks $\{\varepsilon_{\beta,t}, \varepsilon_{\pi,t}, \varepsilon_{\lambda,t}, \varepsilon_{\varphi,t}\}$ to exactly match four observable series, with full details on our shock fitting procedure and macroeconomic data construction available in Appendix A.2.

For our observable time series, we choose the 5-year real TIPS yield, the 5-year TIPS breakeven inflation, the ratio of investment to GDP, and the ratio of corporate debt to GDP, which are displayed in log deviations from their 2021:Q1 values in Figure 7.1. These first two series are required to reproduce the sources of changes in interest rates and bond values, while the third corrects for a well-known issue that investment does not respond as strongly to changes in real discount rates as predicted by models with a simple investment technology such as this one, and the last allows the model to match the downward post-pandemic trend in firm credit.

Figure 7.1: Observable Time Series, 2022 Tightening Cycle



Notes: This plot displays the observable series that form the targets for our shock-fitting exercise. All series are expressed in percent deviations from 2021:Q1. Full definitions and details on data construction can be found in Appendix A.2.

To emphasize the impact of bank regulatory policy, we compare a "Baseline" economy, corresponding to the model described above, against two counterfactual economies: (i) a

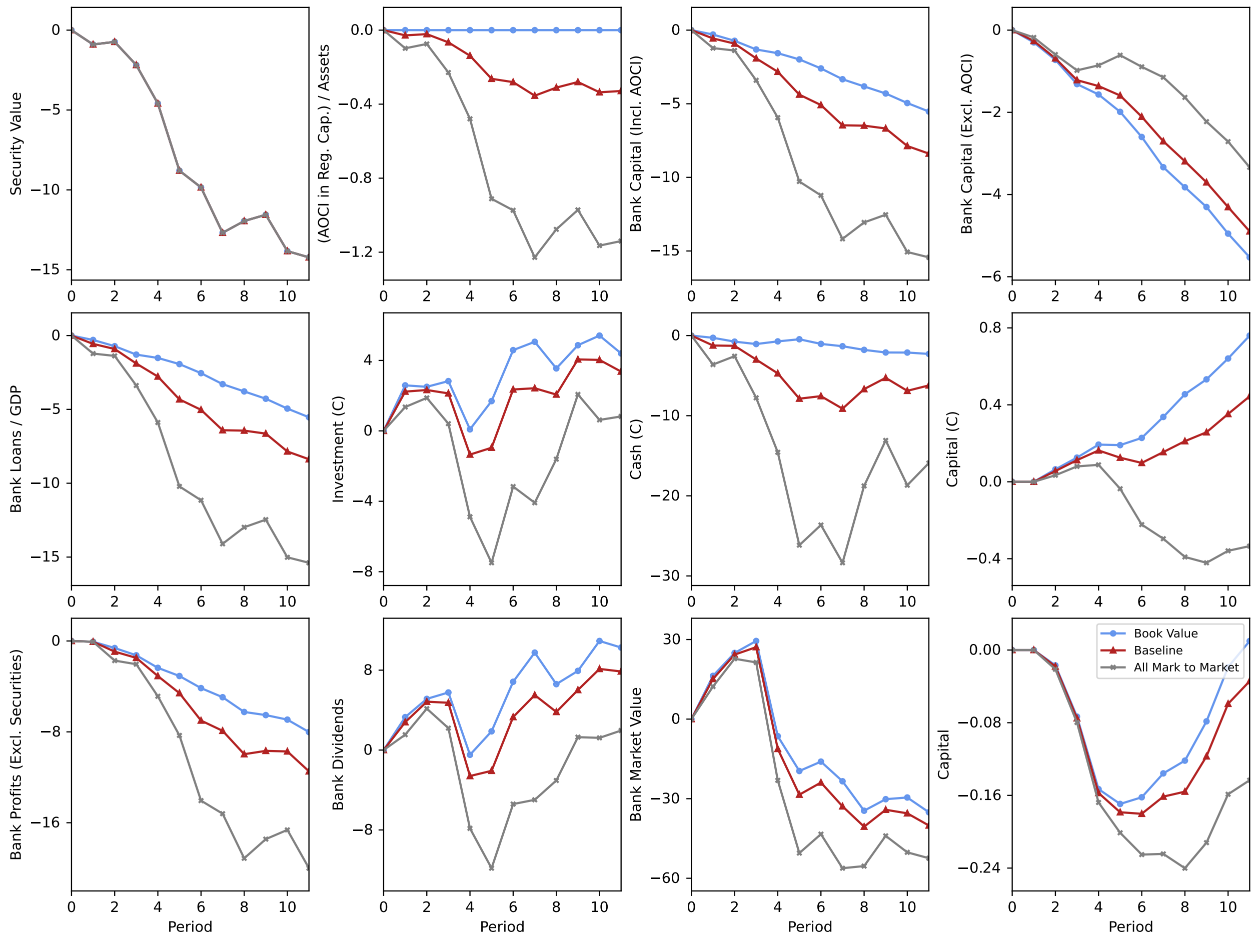
"Book Value" economy, in which bank regulatory capital is computed using book value ($P_t = \bar{P}_t$), so that $AOCI_t = 0$ in the computation of regulatory capital; and (ii) an "All Mark to Market" economy, in which AFS securities are marked to market by regulators at all banks. For this second counterfactual, we assume that although non-AC banks currently hold large amounts of AFS, they would reduce their AFS allocations to have the same ratio of AFS to assets as AC banks in our sample, who are currently subject to this regulatory treatment. As a result, the effects of this counterfactual policy are conservative relative to alternatives in which non-AC banks continue to hold their current AFS allocations, or where unrealized gains and losses on both AFS and HTM securities would pass through to regulatory capital, as has been mentioned in some proposals. Still, because AC banks account for only 31% of the market over our sample, extending mark to market treatment of AFS in regulatory capital to all banks corresponds to a roughly three-fold increase in the exposure of bank regulatory capital to securities values.[37]

Results. Figure 7.2 displays the responses to the implied paths of shocks in the various models. The top row displays the impact of the shock on bond values and bank capital. The left-most panel shows that rising interest rates cause a decrease in the value of the long-term securities by around 15%. These bond values depend only on the exogenous paths of $\tilde{\beta}_t$ and π_t, and hence are identical across models.

Moving to the right, we observe the response of AOCI as a component of regulatory capital, normalized by bank assets, representing the direct impact of unrealized bond losses on regulatory capital. Although the declines in bond values are equal across the three economies, the impact on regulatory capital is sharply different due to the different regulatory accounting regimes. In the Book Value economy, no unrealized losses are counted toward regulatory capital, leading to a null response. In contrast, regulators in the Baseline economy count a fraction of unrealized losses (those on AFS at AC banks) toward regulatory capital, ultimately reducing regulatory capital by 0.3% of bank assets. The All Mark to Market economy, where regulators count a much larger share of unrealized losses toward regulatory capital, displays a similar pattern but a much larger magnitude, contributing to a reduction in bank capital nearly four times as large (1.1%).

[37]In Appendix A.5, we develop a simple static model that solves for optimal bank securities holdings. Our calibration of this model exploits the fact that AC banks are currently required to mark AFS securities to market in their regulatory capital, while NC banks are not. Comparing the securities holdings of the two types of banks can therefore pin down the cost to banks of having all their securities marked to market by regulators, and thus how their securities holdings would change under alternative regulation. We find that if all securities were marked to market by regulators, banks would hold a ratio of securities to assets of 0.127, much lower than the average ratios of 0.241 and 0.206 held by NC and AC banks over our sample, and only slightly higher than the ratio of AFS securities to assets at AC banks of 0.116 used in our current All Mark to Market experiment.

Figure 7.2: Model Responses, 2022 Tightening Cycle



Notes: This figure plots the economy's response to the combined set of shocks $\{\varepsilon_{\beta,t}, \varepsilon_{\pi,t}, \varepsilon_{\lambda,t}, \varepsilon_{\varphi,t}\}$ described above. Variable definitions are as follows: Security Value (P_t), (AOCI in Reg. Cap.) / Assets ($AOCI_t/a_t$), Bank Capital (Incl. AOCI) (k_t/a_t), Bank Capital (Excl. AOCI) ($(k_t - AOCI_t)/a_t$), Bank Loans / GDP ($B_t^{loan}/\bar{Y}$), Investment (C) ($i_{C,t}K_{C,t-1}$), Cash (C) ($A_{C,t}$), Capital (C) ($K_{C,t}$), Bank Profits (Excl. Securities) ($(r_{t-1}B_{C,t-1}^{loan} + S_{C,t-1}^{loan} - r_{l,t-1}l_{t-1})/\pi_t$), Bank Dividends ($d_t$), Bank Market Value ($v_t$), and Capital ($K_t$). Aggregate variables (firm variables without a type subscript) are computed as sums over constrained and unconstrained firms. All variables are displayed in percent changes from steady state with the exception of (AOCI in Reg. Cap.) / Assets, which is displayed in percentage point changes in levels.

The third panel of the top row displays the response of total regulatory capital. This variable is generally falling due to the overall decrease in firm credit at this time. More important for this paper, however, is the difference across accounting regimes. Relative to the Book Value economy, banks in the Baseline and All Mark to Market economies experience larger decreases in regulatory capital. Quantitatively, these gaps peak at 3.1% and 10.8%, respectively.

The right-most plot on the top row displays the non-AOCI component of bank regulatory capital. This figure shows that banks in the Baseline and All Mark to Market economies partially respond to their losses of regulatory capital by endogenously accumulating book equity. However, due to the concave preferences of their investors, who prefer a smooth dividend stream, these banks do not adjust fully through this margin. Instead, they compensate by shrinking their balance sheets, contracting credit supply substantially in order to meet their regulatory requirements.

The middle row of Figure 7.2 displays the responses of the constrained (bank-dependent) firms.[38] The left-most panel shows the ratio of these firms' bank loans to GDP, which Appendix Figure A.10 shows provides a good match to the data in the Baseline economy. More important, we observe large differences in credit quantities across the regulatory accounting regimes. At the end of our sample, bank lending as a fraction of GDP is 2.8% lower in the Baseline economy relative to the Book Value economy, and 9.9% lower in the All Mark to Market economy, due to the additional pressure on bank balance sheets.

The remaining panels of the middle row show that firms respond to these larger reductions in credit when bond losses pass through to regulatory capital by cutting investment, spending down cash holdings, and shrinking dividends to their shareholders. Appendix Figure A.9 shows that these differences in investment peak at 2.7% and 9.2% relative to the Book Value economy for the Baseline and All Mark to Market economies respectively, while differences in cash holdings peak at 7.8% and 27.0%, respectively. To show the long-term effects on real activity, the right-most panel displays the path of capital at constrained firms. This figure reveals a large and growing gap between the three economies, reaching 0.3% between the Book Value and Baseline economies, and 1.1% between the Book Value and All Mark to Market economies at the end of the sample.

The bottom row displays the implications for the banking sector and the macroeconomy. The left panel shows the path of bank "franchise" profits, defined as $(r_{t-1}B^{loan}_{C,t-1} + S^{loan}_{C,t-1} - r_{l,t-1}l_{t-1})/\pi_t$, comprising interest and spread income on loans net of interest paid on deposits. Importantly, this measure excludes both capital gains and income on securities. While bank profits fall in all three economies due to the overall decline in bank lending, we observe larger declines in the Baseline and All Mark to Market economies due to the regulatory capital channel, with the gaps reaching 3.5% and 12.0%, respectively, at the end of the sample. These differences represent an important amplification mechanism, as reductions in regulatory capital lead banks to forego profitable lending opportunities, which reduces their profits and causes further falls in bank equity.

The second panel from the left displays the effect on bank dividends. For this variable, the gaps between models peak earlier, at 4.3% and 14.7% for the Baseline and All Mark to

[38]The responses of the unconstrained firms, which do not depend on bank term lending, are unaffected by the regulatory accounting regime, and thus omitted from the plot.

Market economies, respectively, as banks facing losses of regulatory capital cut payouts sharply in an effort to accumulate equity. By the end of the sample, the gaps shrink to 2.4% and 8.3%, respectively, in line with the long-term decline in profits.

The third panel shows the paths of bank market value, defined as v_t in equation (7.14). Bank value declines in all economies due to the increase in discount rates. However, it declines by substantially more in the Baseline and All Mark to Market economies due to the declines in profits and payouts just documented. These differences peak at 9.5% and 32.8%, respectively, before ending the sample at 5.0% and 17.3%. To the extent that low bank valuations can lead to distress, this implies that the regulatory capital channel may potentially lead to additional strain on the banking sector.

Last, the right-most panel displays the total impact on capital. While "constrained" (bank-dependent) firms only account for a minority of output and capital, and the unconstrained firms are not affected by the regulatory accounting regime, we observe that the regulatory capital channel has an economically significant impact on the overall capital stock. In particular, we observe gaps opening relative to the Book Value economy of 0.04% and 0.15% at the end of our sample, indicating a nontrivial and long-lasting impact of regulatory accounting on economic output.[39]

Combined, these results point to an economically important role for the regulatory capital channel in driving bank lending following a change in interest rates. These results transmit strongly to investment and cash holdings at bank-dependent firms, and are amplified by the loss of bank profits following a tightening cycle, which leads to further declines in bank equity and regulatory capital.

Robustness. In Appendix A.3, we explore the robustness of our model results to alternative assumptions. To begin, recall that because our regression coefficients only pin down the relative strength of the frictions on firm adjustment of investment, cash, and dividend payments, we normalized the friction on investment to a standard value of $\zeta_K = 0.25$. In Appendix Figures A.1 and A.2, we compare our benchmark results in Figure 7.2 to alternative calibrations that either double or halve the value of ζ_K. In Appendix Figure A.3, we similarly compare our benchmark results to an alternative calibration in which loans have a 5-year average maturity ($\nu^B = 0.05$). In all cases, we find results that are extremely close to the benchmark results, due to the tight discipline that our regression-matching and shock-fitting procedures place on the model.

[39]We anticipate that models with additional margins of long-term investment beyond physical capital, such as sticky labor relationships or investment in technology, would find even larger persistent impacts.

Time Varying AFS Shares. Our results above are computed using the average share of securities whose gains and losses are counted toward regulatory capital (unhedged AFS at AC banks) over our sample. However, as shown in Figure 5.2, an important feature of the tightening period is a large decrease in this share, as AC banks booked more securities as HTM and hedged a larger fraction of AFS. While, as discussed above, reclassification of securities does not undo the effect of unrealized losses on regulatory capital, it can reduce banks' future regulatory exposure to additional securities losses. Thus, a question of clear policy relevance is to what degree these precautionary reallocations of securities influenced the transmission of the monetary tightening through the banking sector.

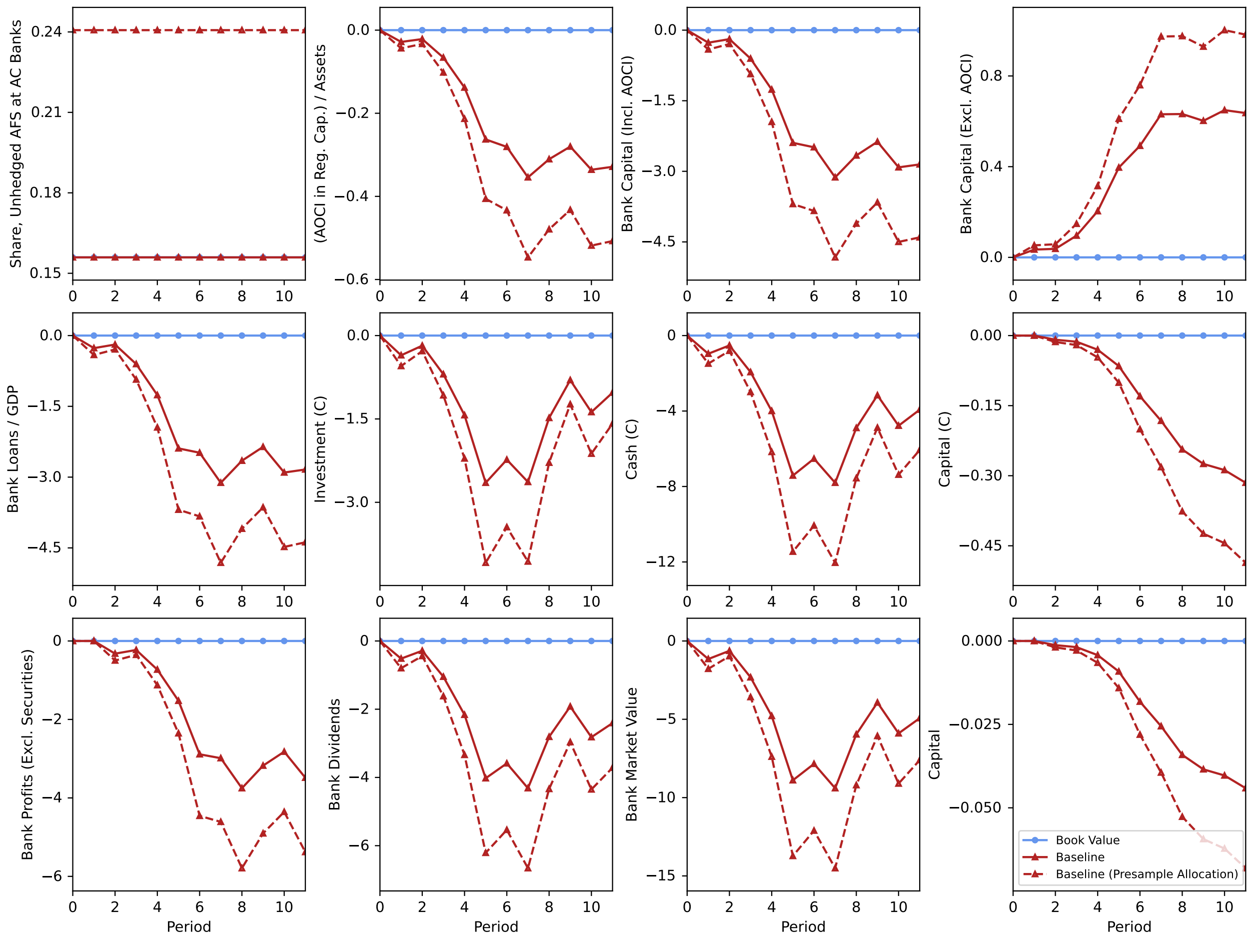
To study the effects of this change, Figure 7.3 compares the Baseline path described earlier against an alternative version, labeled as "Baseline (Presample Allocation)", in which AC banks instead hold their average share of unhedged AFS securities from the 2019–2020 pre-period. The top-left panel, expressed in levels, shows the shares of total securities held as unhedged AFS at AC banks, showing that this share is around 50% larger when using the pre-sample allocations.

The remaining panels in Figure 7.3 display the same variables as in Figure 7.2. To isolate the role of the regulatory capital channel, we express these series in deviations from the corresponding series in the Book Value economy. These plots show that the strength of the regulatory capital channel is substantially larger in the alternative Presample Allocation economy, implying that the increase in HTM shares and hedging of AFS by AC banks observed in the data did nontrivially dampen the impact of unrealized securities losses on regulatory capital via AOCI. We find that without this dampening effect, the final gap for bank capital relative to the Book Value economy would have been roughly 50% larger (4.4% vs. 2.9%). In response, banks would have increased non-AOCI capital by more relative to the Book Value economy over our sample (1.0% vs. 0.6%), and seen larger peak gaps in franchise profits relative to the Book Value economy (5.8% vs. 3.7%).

In summary, while increasing the share of AC bank securities held in HTM or hedged by derivatives cannot eliminate past unrealized losses from AOCI, it can insulate banks from future rate increases. In this case, the consequences were economically significant, as the impact of the regulatory capital channel on the paths of most variables would have been around 50% larger in a world where AC banks had continued to hold their 2019–2020 share of unhedged AFS securities, rather than performing a large precautionary reallocation to non-exposed or hedged classifications.

Alternative Capital Requirements. For our final experiment, we study how a higher capital requirement would influence the strength of the regulatory capital channel. The

Figure 7.3: Effect of Security Reallocations



Notes: All panels except for the top-left plot displaying "Share, Unhedged AFS at AC Banks" are plotted in deviations, obtained by subtracting the corresponding path from the Book Value economy. This figure plots the economy's response to the combined set of shocks $\{\varepsilon_{\beta,t}, \varepsilon_{\pi,t}, \varepsilon_{\lambda,t}, \varepsilon_{\varphi,t}\}$ described above. Variable definitions are as follows: Security Value (P_t), (AOCI in Reg. Cap.) / Assets ($AOCI_t/a_t$), Bank Capital (Incl. AOCI) (k_t/a_t), Bank Capital (Excl. AOCI) ($(k_t - AOCI_t)/a_t$), Bank Loans / GDP ($B_t^{loan}/\bar{Y}$), Investment (C) ($i_{C,t}K_{C,t-1}$), Cash (C) ($A_{C,t}$), Capital (C) ($K_{C,t}$), Bank Profits (Excl. Securities) ($(r_{t-1}B_{C,t-1}^{loan} + S_{C,t-1}^{loan} - r_{l,t-1}l_{t-1})/\pi_t$), Bank Dividends ($d_t$), Bank Market Value ($v_t$), and Capital ($K_t$). Aggregate variables (firm variables without a type subscript) are computed as sums over constrained and unconstrained firms. All variables are displayed in percent changes from steady state with the exception of (AOCI in Reg. Cap.) / Assets, which is displayed in percentage point changes in levels.

results, plotted in Appendix Figure A.4, and described in detail in Appendix A.3, show that doubling the capital charge to $\chi = 0.24$ would reduce the impact of the same change in securities values on bank lending and profits. This finding is due to a leverage effect: the lower the ratio of assets to capital, the less banks must shrink their balance sheets to restore their capital ratios following a loss to capital.

8 Conclusion

Bank regulation and monetary policy are often considered separately. In this paper, we provide evidence that the two are inherently linked. By changing interest rates, monetary policy affects market prices of debt securities that account for close to one quarter of bank assets. We show that such value changes lead to adjustments of banks' credit supply to nonfinancial firms and translate to changes of real firm outcomes like investment.

The strength of this monetary transmission channel through bank balance sheets is determined by the regulatory treatment of securities. In the United States, larger banks must adapt their regulatory capital when the value of their securities that are marked to market changes. Our empirical evidence shows that this regulatory capital channel is the primary factor driving the response of bank lending to securities values in our sample.

We study the quantitative importance of this transmission channel within a general equilibrium model that is tightly calibrated to our cross-sectional regression evidence. We find that even current policy that recognizes securities losses in regulatory capital at a subset of banks substantially amplified the economic consequences of the 2022 tightening episode, while alternative policies that would impose this regulatory treatment at all banks would increase these effects several-fold.

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Internet Appendix

A Model Appendix

A.1 Model Optimality Conditions

This section derives the optimality conditions that must hold at equilibrium.

Firms. Define expected violation costs per dollar of debt to be

$$\xi_{j,t} = \kappa_j \Gamma_{\omega,j}(\bar{\omega}_{j,t}),$$

which is equal to the product of the cost and probability of violation. The optimality condition for capital for a firm of type j is

$$Q_{j,t} = E_t \Bigg\{ \Lambda_{j,t+1} \Bigg[(1-\tau) \underbrace{\frac{\partial Y_{j,t+1}}{\partial K_{j,t}}}_{\text{MPK}} + \underbrace{\Big(1-(1-\tau)\delta\Big)\bar{Q}_{j,t+1}}_{\text{remaining capital}} + \underbrace{\Psi_{j,t+1}\frac{\partial X^*_{j,t+1}}{\partial K_{j,t}}}_{\text{violation costs}} \Bigg] \Bigg\},$$

which equates the cost of a new unit of capital to the discounted value of the marginal income it will provide next period, the marginal sale value of the remaining capital next period, and the effect of that capital on expected violation costs. To this end, the term $\Psi_{j,t}$ represents the marginal benefit of reducing the firm's violation costs by increasing smoothed EBITDA, both today and in the future, and is equal to

$$\Psi_{j,t} = -\pi_t^{-1} \frac{\partial \xi_{j,t}}{\partial X_{j,t}} B_{j,t-1} + E_t \left\{ \Lambda_{j,t+1} \Psi_{j,t+1} \frac{\partial X^*_{j,t+1}}{\partial X_{j,t}} \right\}.$$

The optimality condition for debt is

$$1 - \varphi_t = \Omega^B_{j,t} + \Omega^S_{j,t} s_{j,t},$$

which sets the benefit of debt (\$1 today net of φ_t issuance cost) against the marginal cost of carrying an additional \$1 of debt into the next period and promising an additional $s_{j,t}$ in spread payments. The marginal continuation costs of principal balances $\Omega^B_{j,t}$ and spread payments $\Omega^S_{j,t}$ are

$$\Omega^B_{j,t} = E_t\Big\{\Lambda_{j,t+1}\pi^{-1}_{t+1}\Big[\Big((1-\tau)r_t + \nu^B + \xi_{j,t+1}\Big) + \frac{\partial \xi_{j,t+1}}{\partial B_t} + (1-\nu^B)\Omega^B_{j,t+1}\Big]\Big\}$$
$$\Omega^S_{j,t} = E_t\Big\{\Lambda_{j,t+1}\pi^{-1}_{t+1}\Big[(1-\tau) + (1-\nu^B)\Omega^S_{j,t+1}\Big]\Big\}.$$

The optimality condition for cash is

$$1 = \eta_{A,j}A^{-\zeta_A}_{j,t} + (1+r_t)E_t\Big[\Lambda_{j,t+1}\pi^{-1}_{t+1}\Big],$$

which sets the cost of acquiring \$1 of cash equal to the utility benefit to the firm from the liquidity services as well as the continuation value of \$1 of cash next period, net of discounting and inflation. Last, the derivative terms used above can be evaluated as

$$\frac{\partial Y_{j,t+1}}{\partial K_{j,t}} = \alpha\frac{Y_{j,t+1}}{K_{j,t}} \qquad \frac{\partial X^*_{j,t+1}}{\partial K_{j,t}} = (1-\rho_X)\frac{\partial Y_{j,t+1}}{\partial K_{j,t}} \qquad \frac{\partial X^*_{j,t+1}}{\partial X_{j,t}} = \rho_X\pi^{-1}_{t+1}$$

$$\frac{\partial \xi_{j,t}}{\partial X_{j,t}} = -\kappa_j f_{\omega,j}(\bar{\omega}_{j,t})\frac{\bar{\omega}_{j,t}}{X_{j,t}} \qquad \frac{\partial \xi_{j,t+1}}{\partial B_{j,t}} = \kappa_j f_{\omega,j}(\bar{\omega}_{j,t+1})\frac{\bar{\omega}_{j,t+1}}{B_{j,t}}.$$

Saver. The saver's optimality condition for risk-free short-term government debt is

$$1 = \beta_{S,t}(1+r_t)E_t[\pi^{-1}_{t+1}].$$

The saver's optimality condition for the long-term bond is

$$P_t = E_t\left\{\beta_{S,t}\pi^{-1}_{t+1}\Big[\nu^b + (1-\nu^b)P_{t+1}\Big]\right\}.$$

The saver's optimality condition for corporate bonds is

$$1 = \Omega^B_{S,t} + \Omega^S_{S,t}(s^{bond}_t - q^{bond}), \tag{A.1}$$

which sets the cost of buying \$1 of corporate bonds today equal to the marginal benefit of \$1 of corporate bond balances and the marginal benefit of an extra s^{bond}_t of corporate bond spread payments going forward, net of the holding cost q^{bond}. These marginal continuation values are equal to

$$\Omega^B_{S,t} = E_t\left\{\beta_{S,t}\pi^{-1}_{t+1}\left[r_t + \nu^B + (1-\nu^B)\Omega^B_{S,t+1}\right]\right\} \tag{A.2}$$

$$\Omega^S_{S,t} = E_t\left\{\beta_{S,t}\pi^{-1}_{t+1}\left[1 + (1-\nu^B)\Omega^S_{S,t+1}\right]\right\}. \tag{A.3}$$

Since $1 + r_t = \beta^{-1}_{S,t}E_t[\pi^{-1}_{t+1}]$, we can guess and verify $\Omega^B_{S,t} = 1$, in which case (A.1) implies

$$0 = \Omega^S_{S,t}(s^{bond}_t - q^{bond}).$$

Since it is straightforward to show that $\Omega^S_{S,t} > 0$, this implies $s^{bond}_t - q^{bond} = 0$, or that $s^{bond}_t = q^{bond}$, so that the corporate bond spread is effectively fixed. The saver's optimality condition for deposits is

$$1 = R_{l,t}E_t\left\{\beta_{S,t}\pi_{t+1}\right\} + \eta_{l,t}.$$

Substituting from the first order condition for government debt, we obtain

$$1 = \frac{R_{l,t}}{R_t} + \eta_{l,t}$$

and so

$$R_{l,t} = (1-\eta_{l,t})R_t.$$

Substituting in $\eta_{l,t} = (1-\gamma)(1-R^{-1}_t)$, we obtain

$$R_{l,t} = 1 + \gamma(R_t - 1),$$

which is the desired deposit pass-through.

Bank. The optimality condition for the bank with respect to lending becomes

$$1 = \Omega_{B,t} + s^{loan}_{C,t}\Omega_{S,t} + \mu_t(1-\chi)$$

where

$$\Omega_{B,t} = E_t\left\{\pi^{-1}_{t+1}\Lambda_{b,t+1}\left[r_t + q^{loan} + \nu^B + (1-\nu^B)\Big((1-\chi)\mu_{t+1} + \Omega_{B,t+1}\Big)\right]\right\}$$
$$\Omega_{S,t} = E_t\left\{\pi^{-1}_{t+1}\Lambda_{b,t+1}\left[1 + (1-\nu^B)\Omega_{S,t+1}\right]\right\}$$

and μ_t is the multiplier on the capital requirement.

At equilibrium, we have

$$T_{B,t} = \pi_t^{-1}(S_{C,t-1}^{loan} - \bar{s}^{loan} B_{C,t-1}^{loan}) - q^{loan} B_{C,t}^{loan,*}, \tag{A.4}$$

which removes excess spreads and allows banks to earn their debt issuance wedge.

Capital Producer. The optimality condition for a capital producer of type j is

$$\begin{aligned} Q_{j,t} &= \Phi'(i_{j,t})^{-1} \\ \bar{Q}_{j,t} &= Q_{j,t} + \frac{Q_{j,t}\Phi(i_{j,t}) - i_{j,t}}{1-\delta} \end{aligned}$$

where $i_{j,t} \equiv I_{j,t}/K_{j,t-1}$. The difference between $Q_{j,t}$ and $\bar{Q}_{j,t}$ is second order and would disappear in a linearized solution.

A.2 Matching the Observable Data

This section provides additional detail on our shock-fitting exercise, used to obtain the values of the shocks $\{\varepsilon_{\beta,t}, \varepsilon_{\pi,t}, \varepsilon_{\lambda,t}, \varepsilon_{\varphi,t}\}$. We first describe the data series used, then turn to the Kalman smoothing procedure used to obtain the values of the shocks.

Macroeconomic Data. Our shock-fitting exercise matches four observable series: the 5-year real TIPS yield, 5-year TIPS inflation expectations, the ratio of investment to GDP, and the ratio of total firm debt to GDP.

Our data series are obtained as follows. We begin by obtaining several series from the Federal Reserve Economic Data (FRED) portal, with the FRED code and source in parentheses: the 5-year nominal yield (GS5, Federal Reserve Board of Governors), the 5-year TIPS yield (FII5, Federal Reserve Board of Governors), private nonresidential fixed investment (PNFI, Bureau of Economic Analysis), and gross domestic product (GDP, Bureau of Economic Analysis). We supplement these with measures from the Federal Reserve's Financial Accounts of the United States of debt securities and loans for the corporate nonfinancial sector, and sum these to obtain a total measure of corporate debt.

From these initial data, we create our four data series as follows. The 5-year real yield is the FII5 series, converted from an annual percentage rate to a quarterly continuously compounded rate as $(0.25 \times \log(1 + \text{FII5}/100))$. Five-year inflation compensation is constructed from the nominal and real 5-year yields as the log difference between their gross returns, $(0.25 \times [\log(1 + \text{GS5}/100) - \log(1 + \text{FII5}/100)])$. The log investment-to-GDP ratio is the log of private nonresidential fixed investment divided by GDP, and the log corporate-debt-to-GDP ratio is the log of total corporate debt divided by GDP. Finally, all four series are expressed as deviations from their 2021:Q1 values, matching the model's use of deviations from steady state in the time-series fitting exercise.

Kalman Smoothing. To obtain the values of the shocks required to match the observable data, we use the Kalman filter and smoother. To begin, we map our model objects to the observable series described above as follows. We construct the model's 5-year real yield in logs as

$$\begin{aligned}
\log R_t^{5Y,real} &= -\log \beta_S - \frac{1}{20}\sum_{j=0}^{19} E_t \log \tilde{\beta}_{t+j} \\
&= -\log \bar{\beta}_S - \frac{1}{20}\sum_{j=0}^{19} \rho_\beta^j \log \tilde{\beta}_t \\
&= -\log \bar{\beta}_S - \frac{1}{20}\left(\frac{1-\rho_\beta^{20}}{1-\rho_\beta}\right)\log \tilde{\beta}_t.
\end{aligned}$$

Measured in deviations from steady state, this becomes

$$\log R_t^{5Y,real} - \log R_{steady}^{5Y,real} = -\frac{1}{20}\left(\frac{1-\rho_\beta^{20}}{1-\rho_\beta}\right)\log \tilde{\beta}_t.$$

We similarly construct the model's 5-year log inflation expectations as

$$\begin{aligned}
\log \pi_t^{5Y} &= \log \bar{\pi} + \frac{1}{20}\sum_{j=1}^{20} E_t(\log \pi_{t+j} - \log \bar{\pi}) \\
&= \log \bar{\pi} + \frac{1}{20}\sum_{j=1}^{20} \rho_\pi^j(\log \pi_t - \log \bar{\pi}) \\
&= \log \bar{\pi} + \frac{1}{20}\rho_\pi\left(\frac{1-\rho_\pi^{20}}{1-\rho_\pi}\right)(\log \pi_t - \log \bar{\pi}).
\end{aligned}$$

Measured in deviations from steady state, this becomes

$$\log \pi_t^{5Y} - \log \pi_{steady}^{5Y} = \frac{1}{20}\rho_\pi\left(\frac{1-\rho_\pi^{20}}{1-\rho_\pi}\right)(\log \pi_t - \log \bar{\pi}).$$

We compute the log ratio of investment to GDP as $\log(I_t/Y_t)$, where $I_t = i_{U,t}K_{U,t-1} + i_{C,t}K_{C,t-1}$, and compute the log ratio of total debt to GDP as $\log((B^{bond}_{U,t} + B^{loan}_{C,t})/Y_t)$.

A.3 Model Robustness

In this section we evaluate the model's robustness to various assumptions.

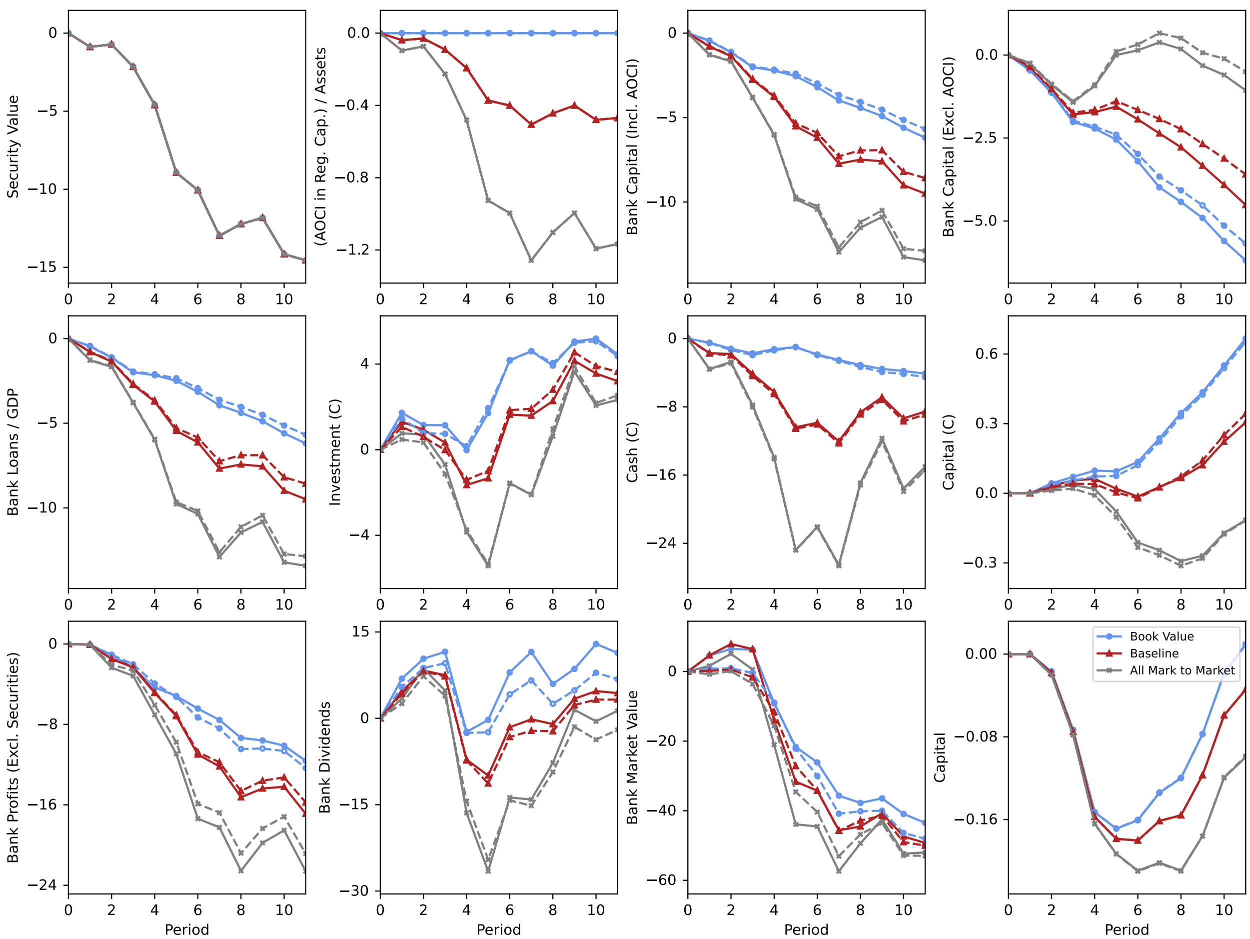
Investment Elasticity. As explained in Section 7.4, because our regressions pin down the relative frictions across margins, we first calibrate the absolute friction for one firm margin (the investment friction ζ_K), and then calibrate the remaining friction (ζ) parameters to match our regression coefficients. To study the influence of our choice of ζ_K on our results, Figures A.1 and A.2 display versions of our main model results in Figures 7.2 that vary this parameter. In particular, Figure A.1 imposes a value of $\zeta_K = 0.125$ that is half that of our baseline calibration, while Figure A.2 imposes a value of $\zeta_K = 0.5$ that is twice that of our baseline calibration. In each case, we recalibrate the remaining parameters, including recalibrating the other ζ parameters to match our empirical regressions.

Figures A.1 and A.2 show at most modest differences between the paths using our benchmark value for $\zeta_K = 0.25$ and the alternative versions with higher or lower investment frictions. Even investment at constrained firms is barely affected by this difference. This strong robustness of the results is due to two features of our experiment. First, because we have recalibrated the remaining frictions in the model (via ζ_B, ζ_D, and ζ_A) to match our empirical regressions, we ensure that the effect of the regulatory capital channel on firm investment is identical in both sets of models. Second, we re-estimate the set of $\{\lambda_t\}$ shocks to fit the time series of investment, ensuring that aggregate investment is identical across models. Combined, these tight mappings between model and empirics ensure that our results do not depend on this parameter.

Long-Term Debt. In our baseline model, we assume that debt is one-quarter debt ($\nu^B = 1$). In practice, most debt to firms has substantially longer maturity than a single quarter, potentially dampening the effect of shifts in credit supply on constrained firm borrowing. To show that our results are robust to the maturity of debt, Figure A.3 displays results after recalibrating our model under an average debt maturity of five years or 20 quarters ($\nu^B = 0.05$). As before, we then compute the response to our tightening cycle experiment under the same set of regulatory accounting policies (Baseline, Book Value, All Mark to Market).

Perhaps surprisingly, extending the maturity of debt barely changes our results. The

Figure A.1: Model Responses, Low Investment Frictions

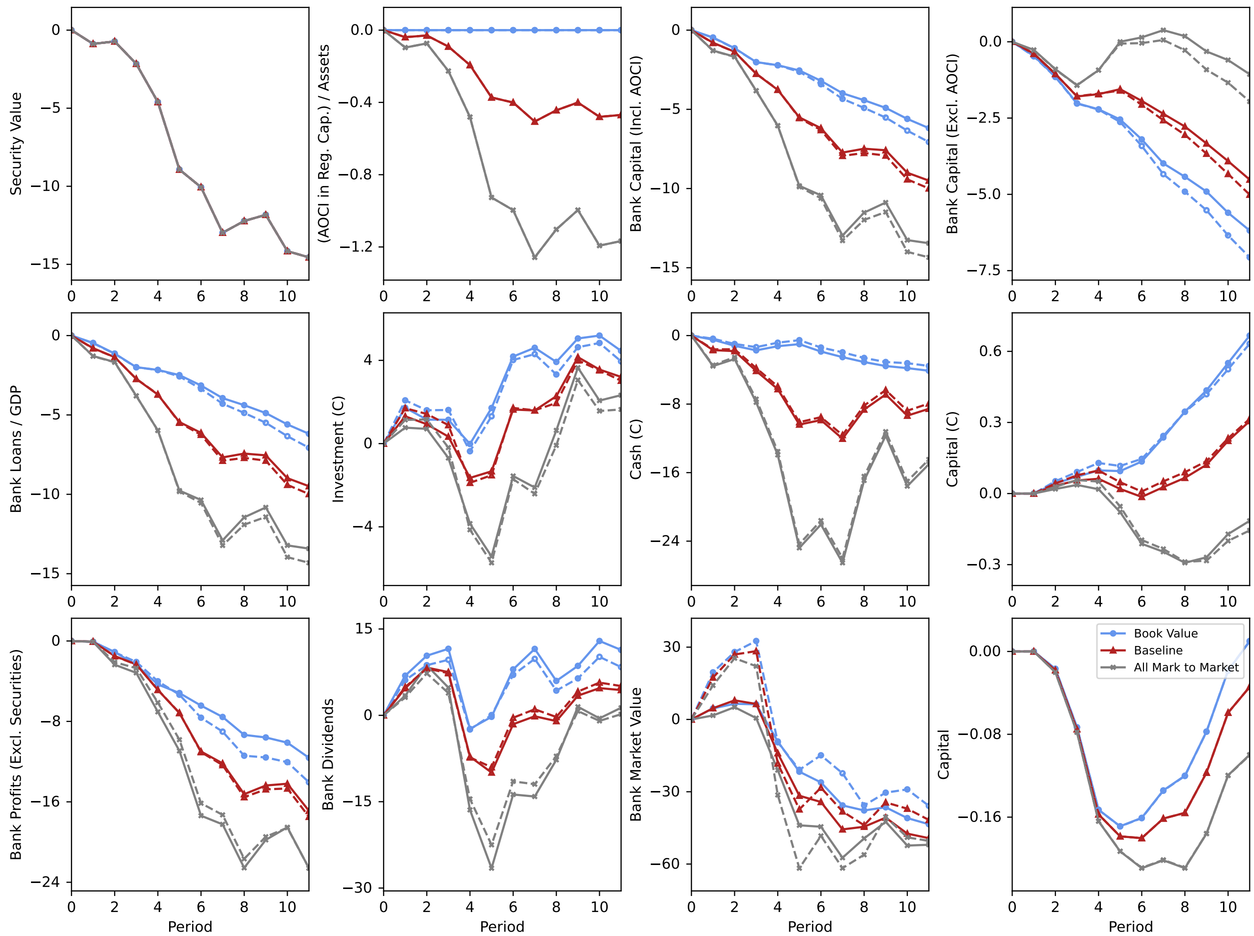


Notes: This figure reproduces Figure 7.2 for a set of alternative models with lower investment frictions ($\zeta_K = 0.125$). Solid lines indicate the original paths from Figure 7.2, while dashed lines indicate the new paths under the alternative calibration. See notes to Figure 7.2 for additional details.

only variable that reacts very differently is bank market value, due to a change in duration of bank assets. However, if we were to recalibrate our deposit pass-through to target a stable net interest margin under this alternative duration of assets, this disparity would likely be greatly reduced. Otherwise, while there are some small deviations relative to the short-term debt benchmark, the paths, and in particular the relative differences between the paths, which display the strength of the regulatory capital channel, are very close to those in our original experiment.

The reason for this robustness is once again our calibration procedure. Holding all other parameters fixed, extending the maturity of debt would decrease the responsiveness of credit growth to a change in spreads, because only a fraction of that debt is turning over and therefore exposed to changing spreads, while spreads on non-maturity debt are

Figure A.2: Model Responses, High Investment Frictions



Notes: This figure reproduces Figure 7.2 for a set of alternative models with higher investment frictions ($\zeta_K = 0.5$). Solid lines indicate the original paths from Figure 7.2, while dashed lines indicate the new paths under the alternative calibration. See notes to Figure 7.2 for additional details.

unaffected by the change in spreads. All else equal, this would weaken the regulatory capital channel we have highlighted in this paper. However, holding other parameters fixed, this weaker response of debt to a change in bank securities values would also cause us to seriously understate the magnitude of firm credit responses, as measured by our implied regression coefficients. To restore the model's ability to match our estimated regression coefficients, the recalibration step will strengthen the curvature of bank entrepreneur utility, leading to a larger change in spreads. This larger change in spreads in turn causes a larger proportional change in the issuance of *new* debt, until the proportional response of total debt is similar to that in the short-term debt model.

In summary, recalibrating our model causes it to offset this weakening effect of long-term debt on the mechanism with a strengthening of the quantitative pass-through from

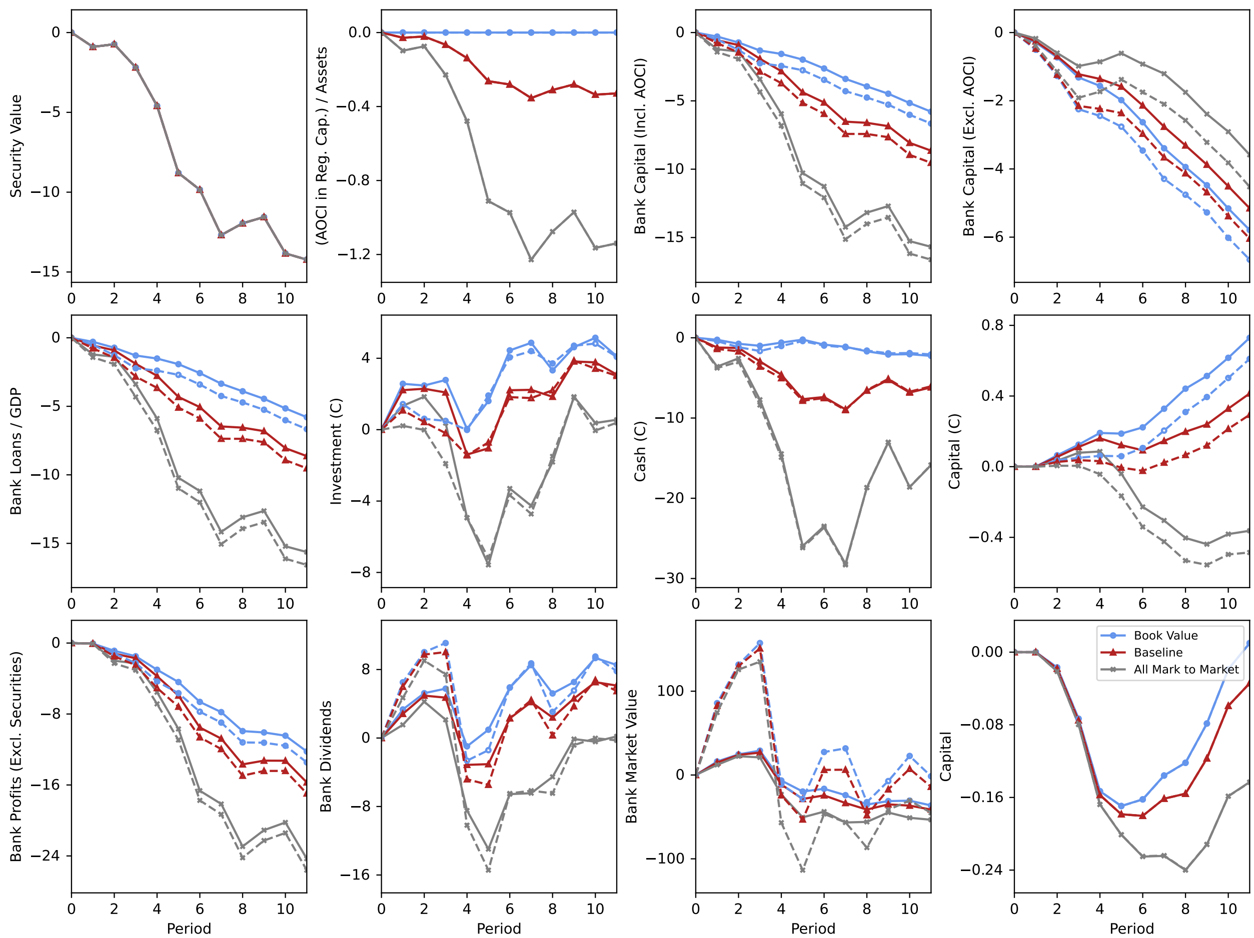


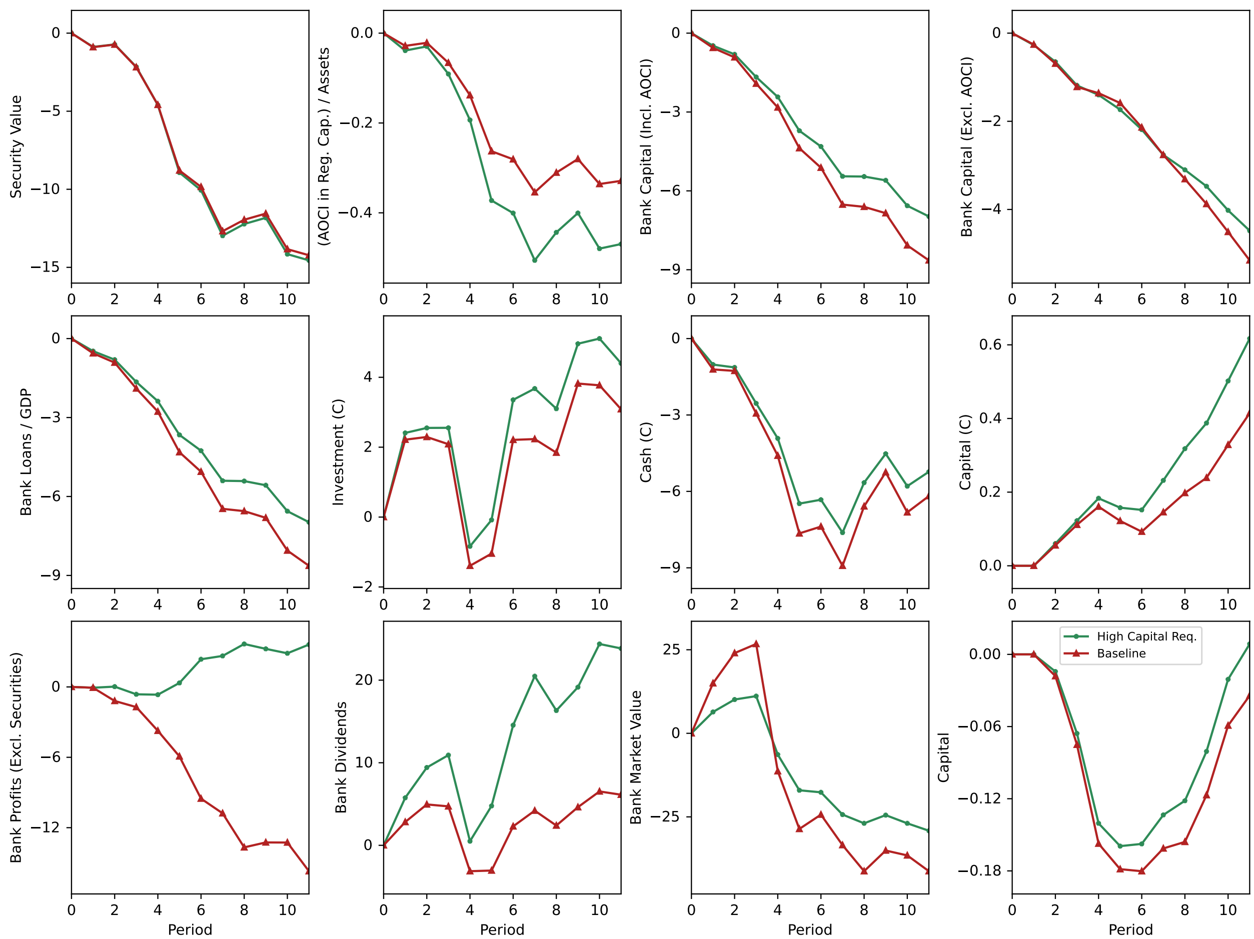
Figure A.3: Model Responses, Long-Term Debt

Notes: This figure reproduces Figure 7.2 for a set of alternative models with long-term bank loans ($\nu^B = 0.05$). Solid lines indicate the original paths from Figure 7.2, while dashed lines indicate the new paths under the alternative calibration. See notes to Figure 7.2 for additional details.

securities values to spreads, until we match our regression coefficients, yielding results extremely similar to our baseline results.

Higher Capital Requirement. Our results on the regulatory capital channel raise the important question of how alternative levels of the capital requirement χ might affect its strength. To investigate this, Figure A.4 displays results for a counterfactual economy in which the capital requirement is doubled from $\chi = 0.12$ to $\chi = 0.24$, denoted the "High Capital Req." economy. Perhaps surprisingly, although regulatory capital requirements are more restrictive in this alternative economy, the effect of the shocks on bank lending, firm investment, and bank profit and value fundamentals, are smaller under higher regulatory requirements.

Figure A.4: Extension, Higher Capital Requirement



Notes: This plot compares the Baseline economy paths from Figure 7.2 to an alternative set of paths under higher capital requirements ($\chi = 0.24$). See notes to Figure 7.2 for further details.

To understand this result, recall that our baseline calibration implies that regulatory capital must be equal to 12% of risk weighted assets, which represents the regulatory minimum of 8%, plus a constant buffer of 4%, since our model lacks the idiosyncratic volatility that would generate the precautionary buffer of similar size that we observe in practice. This means that bank loans are equal to $1/0.12 \simeq 8$ times bank capital. Now imagine that banks lose \$1 of regulatory capital through securities losses, and that they do not reduce payouts to offset it. In this case, banks will need to cut lending by \$8 to meet their capital requirements.

In the alternative economy, which requires banks to hold capital equal to 24% of risk weighted assets, the ratio of loans to bank capital would be approximately 4 rather than 8. In this case, if the bank loses \$1 on securities, it must cut lending by only \$4, or half as much. As a result, the impact on bank lending is inversely proportional to the required capital ratio, through what is effectively a leverage mechanism.

This rule of thumb does not hold exactly in the alternative model, which features the full set of mechanisms and potential adjustments on other margins described in Section 7. However, a comparison of the two paths in Figure A.4 shows that higher capital requirements do indeed attenuate the effects of the regulatory capital channel. Thus, higher capital requirements might nontrivially reduce the effect of mark-to-market regulatory accounting policies on bank and firm outcomes following changes in interest rates.

A.4 Impulse Responses to Individual Shocks

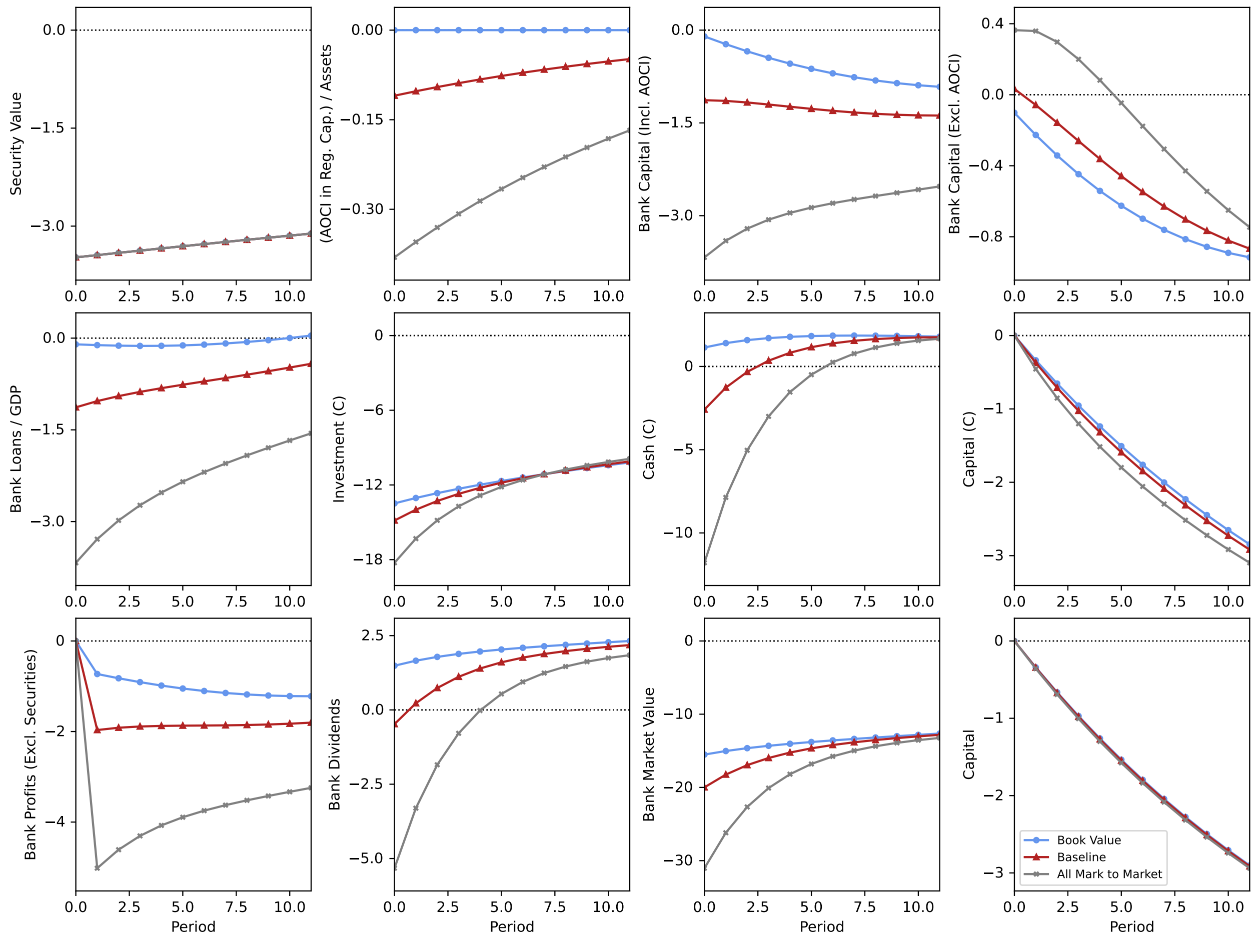
While our main results in Section 7.5 provide a close match for the actual paths observed during the tightening cycle, this fit requires a combination of different structural shocks arriving at different times. In this section, we provide intuition for the underlying dynamics using separate impulse responses for each of our shocks.

Real Discount Rate Shock. To begin, Figure A.5 shows the responses to a discount rate shock (ε_β). The figure shows the response to a 25bp decrease in the quarterly discount factor, corresponding to a 100bp annual increase in the real discount rate. The top row shows that this shock leads to a drop in securities values, activating the regulatory capital channel. In particular, the Baseline and All Mark to Market economies see declines in regulatory capital due to negative AOCI. The middle row shows that this in turn leads to a contraction in credit supply to constrained firms, and ultimately lower investment and cash holdings in the economies that recognize more losses in regulatory capital. The bottom row shows that this channel translates into lower bank profits, payouts, and market values in the economies recognizing more losses, as well as lower cumulated investment (capital).

At the same time, this shock in isolation has some aggregate properties unrelated to the regulatory capital channel that do not match empirical patterns observed during the tightening cycle. Most important, investment drops massively in all three economies, and by a counterfactual amount. This occurs because firms in our model effectively attempt to align the marginal product of capital with the real discount rate. As a result, movements in the real discount rate can require very large movements in the capital stock in order to change the marginal product of capital sufficiently.

To address this well-known issue, we employ offsetting shocks to investment demand to match the actual path of investment observed in the data, which do not display this large decline. However, we note that an alternative model in which firms' effective dis-

Figure A.5: Impulse Responses, Shock to Discount Rate

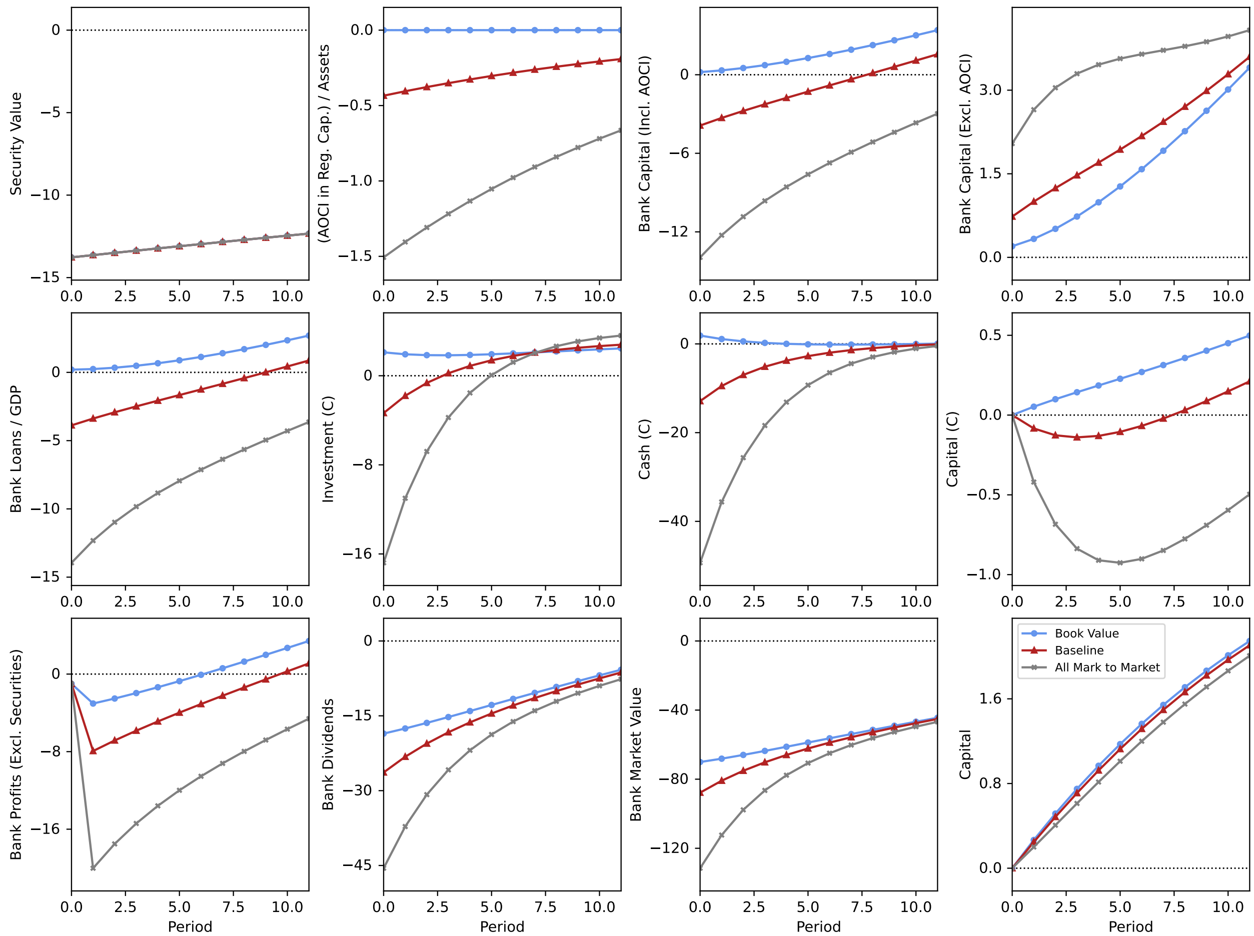


Notes: This figure displays impulse responses to a shock to the discount rate (ε_β). See notes to Figure 7.2 for additional details.

count rates are not affected by market-wide real interest rates, supported by the new evidence in Gormsen and Huber (2025), would allow shocks to real discount rates to generate variation in bond prices without this counterfactual change in investment. In practice, moving to this alternative model would affect the mix of shocks used to fit the data (in particular the size of the required investment efficiency shocks), but not the impact of the regulatory capital channel we focus on here.

Inflation Shock. Next, Figure A.6 displays the response to an inflation shock (ε_π) of 25bp quarterly, corresponding to a 100bp initial increase in nominal interest rates. As with the real discount rate shock, this shock leads to a decline in securities prices, activating the regulatory capital channel, and leading to relative responses across the three economies similar to those in Figure A.5.

Figure A.6: Impulse Responses, Shock to Inflation

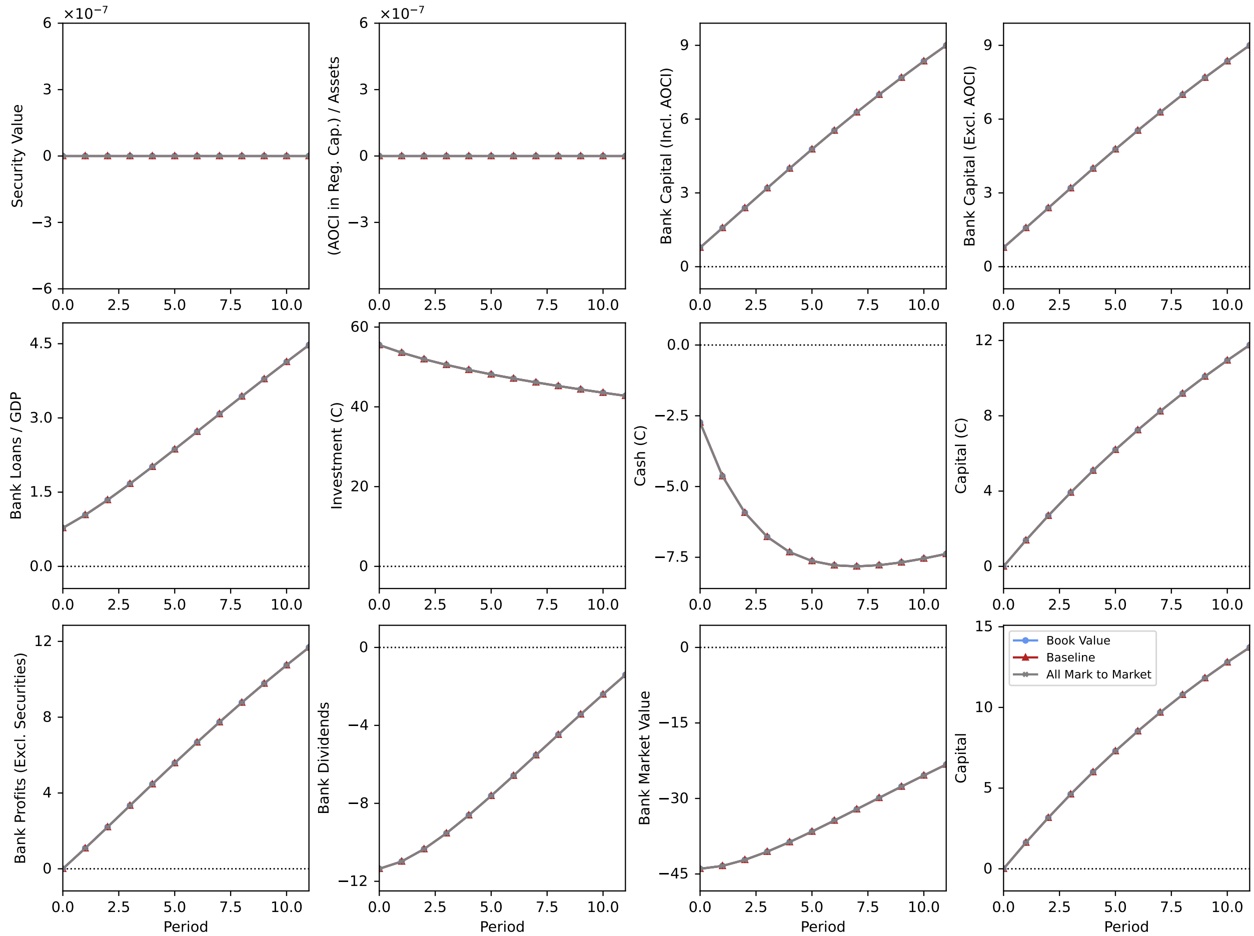


Notes: This figure displays impulse responses to a shock to the inflation rate (ε_π). See notes to Figure 7.2 for additional details.

In terms of the level responses, the most notable feature is that the inflation shock increases bank debt and investment in the long run. There are two reasons for this. First, inflation reduces the real value of firms' legacy debt, leading to an effective increase in firm resources. Second, inflation increases the value of the tax shield on debt, encouraging firms to borrow and invest using the additional funds. These forces will be balanced against the investment efficiency and credit demand shocks at equilibrium to match the observed paths of investment and total firm debt.

Investment Efficiency Shock. Figure A.7 displays the response to an investment efficiency shock ($\varepsilon_{\lambda,t}$) of size 1%. Because savers are risk-neutral, this shock has no impact on the nominal interest rate or securities values, and hence does not activate the regulatory capital channel, leading to identical responses across economies. In levels, this shock un-

Figure A.7: Impulse Responses, Shock to Investment

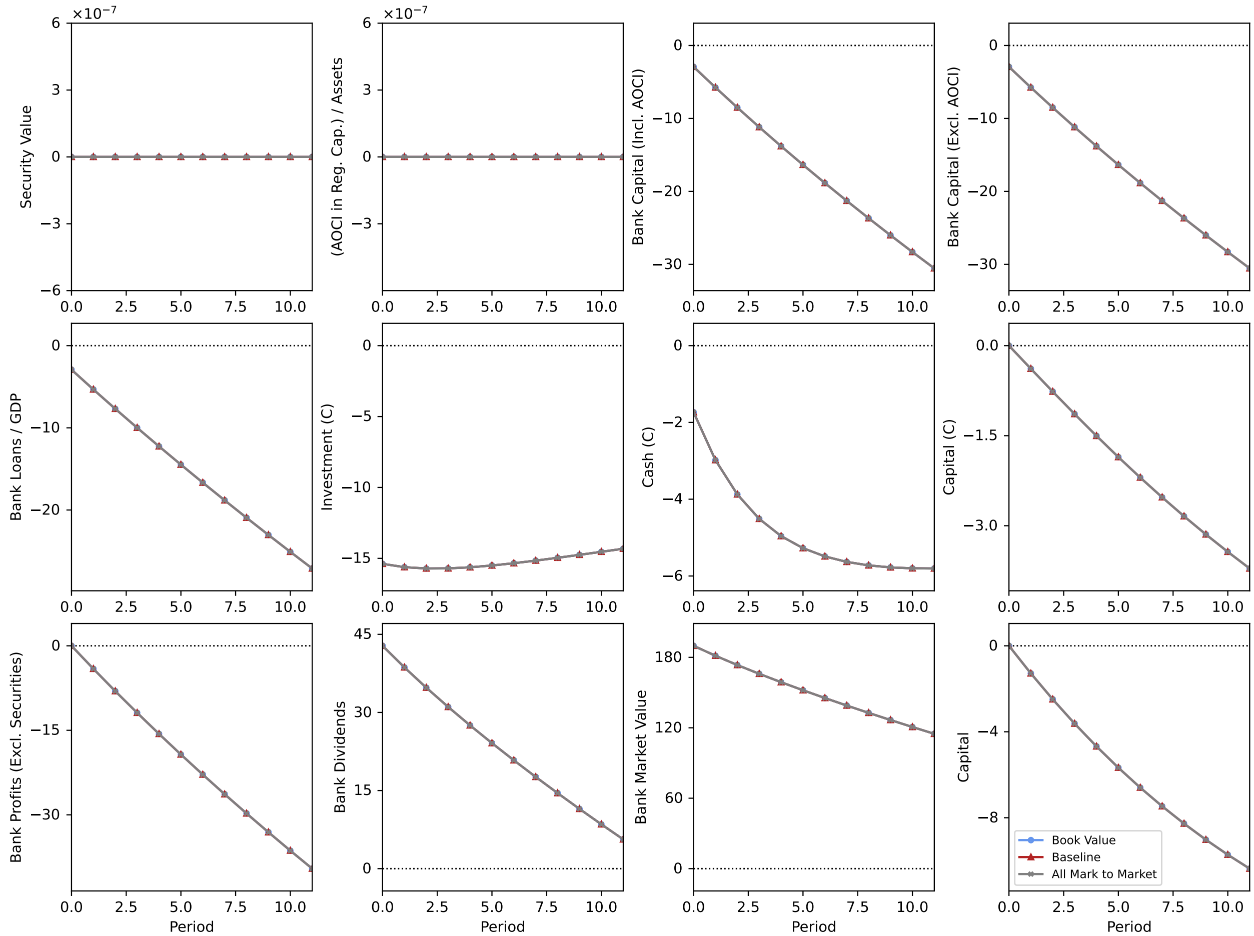


Notes: This figure displays impulse responses to a shock to the marginal efficiency of investment (ε_λ). See notes to Figure 7.2 for additional details.

surprisingly leads to a large increase in investment. This leads to a large increase in credit demand, with lending and bank capital gradually rising as banks slowly accumulate the required equity to do so.

Credit Demand Shock. Last, Figure A.8 displays the response to a credit demand shock (ε_φ) that increases the cost of credit issuance for firms by 100bp. As with the investment efficiency shock, this shock has no impact on the nominal interest rate when savers are risk-neutral, and thus does not activate the regulatory capital channel. However, it heavily reduces bank lending to firms over time, leading to a decline in investment. While this shock has similar qualitative implications for firm debt and investment as the investment efficiency shock, its effects are quantitatively much more tilted toward firm debt, allowing us to separately match changes in aggregate investment and firm debt over this period.

Figure A.8: Impulse Responses, Shock to Credit Demand



Notes: This figure displays impulse responses to a shock to firm credit demand (ε_{φ}). See notes to Figure 7.2 for additional details.

A.5 Endogenizing Bank Securities Holdings

Let b denote total bank securities holdings scaled by bank assets, and let A denote bank AFS securities holdings scaled by bank assets. To provide a motive for banks to hold securities, we assume that banks have an optimal quantity of securities holdings $\bar{b}$, and face a quadratic cost from deviating from this

$$c(b) = \frac{\varpi}{2}(b - \bar{b})^2, \tag{A.5}$$

where without loss of generality we can set $\varpi = 1$. We assume that an exogenous fraction w of securities must be held as AFS securities, so that $b^{AFS} = wb$.

Banks also face a cost of holding securities that are marked to market by the regulator. For AC banks in the baseline environment, this cost is $c^{AFS}(b^{AFS})$, while for NC banks in the baseline environment, this cost is $c^{AFS}(0)$. We can parameterize the cost function as

$$c^{AFS}(b^{AFS}) = \frac{\phi}{2}(b^{AFS})^2, \tag{A.6}$$

where the choice of a quadratic cost is consistent with experiencing disutility proportional to the variance of the value of AFS securities.

In this setting, an AC bank minimizes

$$c(b_{AC}) + c^{AFS}(w_{AC}b_{AC}), \tag{A.7}$$

while an NC bank minimizes

$$c(b_{NC}) + c^{AFS}(0). \tag{A.8}$$

The first order conditions are

$$0 = c'(b_{AC}) + c'(w_{AC}b_{AC})w_{AC} \tag{A.9}$$

$$0 = c'(b_{NC}). \tag{A.10}$$

Substituting in the parametric forms of these functions and rearranging yields

$$\bar{b} - b_{AC} = \phi(w_{AC}b_{AC})w_{AC} \tag{A.11}$$

$$\bar{b} - b_{NC} = 0. \tag{A.12}$$

In this setting, an AC bank chooses b_{AC} to minimize

$$\frac{1}{2}(b_{AC} - \bar{b})^2 + \frac{\phi}{2}(wb_{AC})^2, \tag{A.13}$$

while an NC bank minimizes

$$\frac{1}{2}(b_{NC} - \bar{b})^2. \tag{A.14}$$

The first order conditions are

$$0 = b_{AC} - \bar{b} + \phi w^2 b_{AC}$$

$$0 = b_{NC} - \bar{b}.$$

which can be rearranged to yield

$$b_{AC} = \frac{\bar{b}}{1 + \phi w^2} \tag{A.15}$$

$$b_{NC} = \bar{b}. \tag{A.16}$$

Equation (A.16) implies that we can use the NC banks, who are unaffected by the constraint, to pin down the optimal (unconstrained) level of bank security holdings. Computing the average ratio of securities to assets among NC banks over the period 2021:Q1 to 2023:Q1, we obtain a value of $b_{NC} = 0.241$.

Given our value for $\bar{b}$, we can now recover the parameter ϕ from (A.15). Averaging the ratios of securities to assets and AFS securities to total securities for AC banks over the period 2021:Q1–2023:Q1, we obtain values $w = 0.433$ and $b_{AC} = 0.206$. Substituting and solving for ϕ now yields

$$\phi = \frac{1}{w^2}\left(\frac{\bar{b}}{b_{AC}} - 1\right) = \frac{1}{0.433^2}\left(\frac{0.241}{0.206} - 1\right) = 0.899. \tag{A.17}$$

Intuitively, the greater the disutility from being exposed to volatility in regulatory capital, the less securities an AC bank will hold, holding the AFS share w fixed. This allows us to use the lower securities holdings of AC banks to infer the disutility of regulatory risk *phi*.

Given this estimate, we can now solve for optimal bank securities holdings in a counterfactual economy in which all securities are marked to market. This can be modeled in our simple framework by setting $w = 1$. In this case, banks would choose counterfactual securities holdings $\hat{b}$ to minimize

$$\frac{1}{2}(\hat{b} - \bar{b})^2 + \frac{\phi}{2}\hat{b}^2, \tag{A.18}$$

yielding the optimality condition

$$0 = \hat{b} - \bar{b} + \phi\hat{b}. \tag{A.19}$$

Solving for $\hat{b}$ we obtain

$$\hat{b} = \frac{\bar{b}}{1+\phi} = \frac{0.241}{1+0.899} = 0.127. \tag{A.20}$$

This calculation implies that in a world where all securities are marked to market, we would observe a ratio of securities to assets of 0.127. This dramatic decline compared to bank securities holdings in the current equilibrium for both AC and NC banks shows the importance of allowing banks to endogenously choose their portfolios.

Last, we can compute the change in the effect of securities values on regulatory capital between the Baseline and the All Mark to Market economies. To do this, we compute the ratio of marked-to-market securities between the two economies as

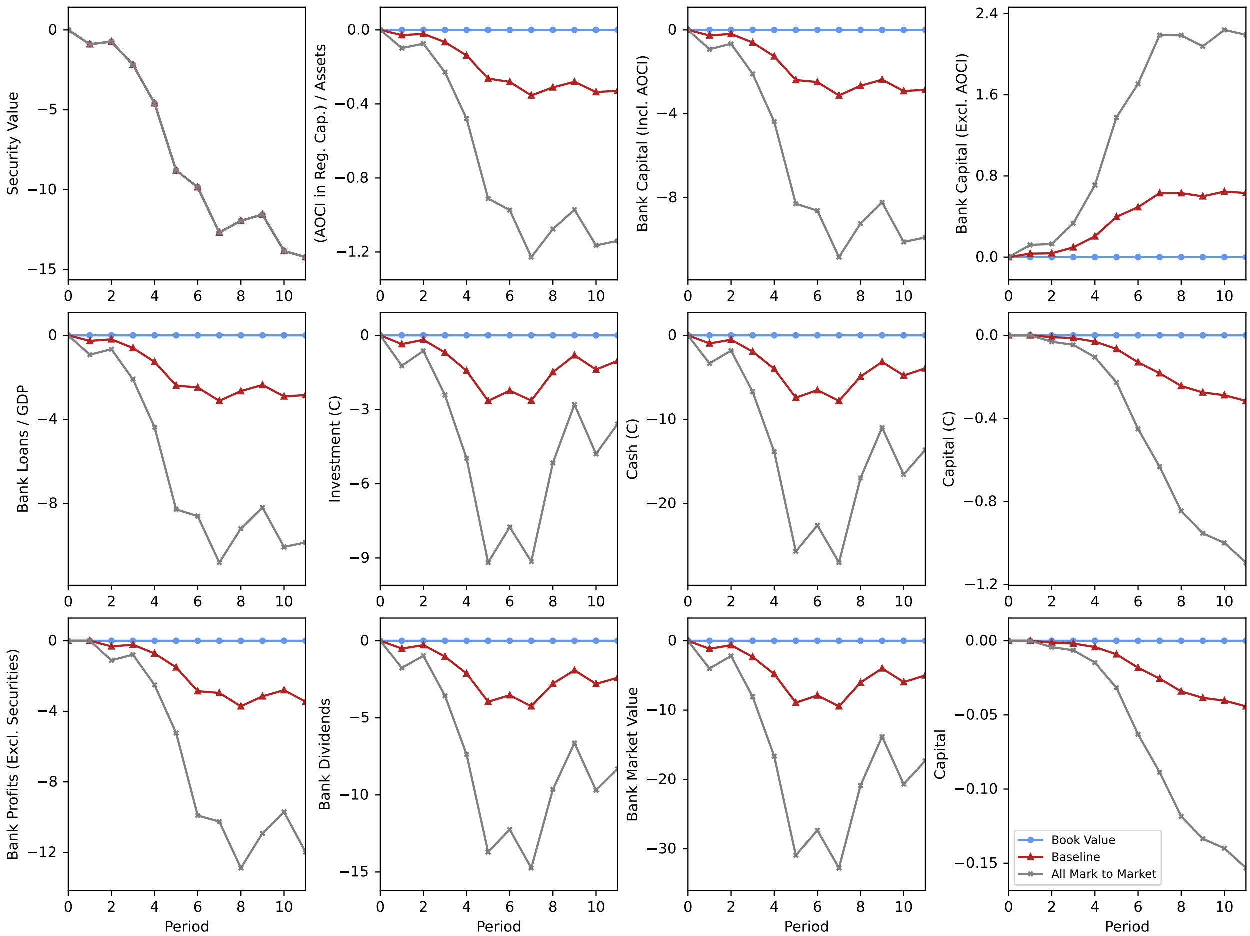
$$\frac{1.0}{0.44 \times 0.70} \times \frac{0.127}{0.116} = 3.55. \tag{A.21}$$

The first term on the left hand side of (A.21) adjusts for the share of banks that have their securities marked to market by regulators. In the All Mark to Market economy, this is all banks, represented by the 1.0 term in the numerator. In the Baseline economy, this only reflects AC banks, who are responsible for 44% of lending to firms in the Y14 sample, which itself represents 70% of the overall banking market. The second term accounts for differences in the amount of marked-to-market securities at each affected bank. According to (A.20) above, each bank holds securities equal to 0.127 of assets in the All Mark to Market counterfactual, compared to an average ratio of marked-to-market (AFS) securities to assets at Y14 banks of 0.116 in our 2021:Q1–2023:Q1 sample.

A.6 Additional Model Results

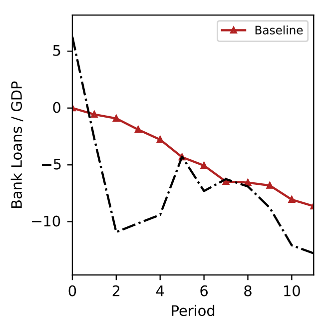
This section displays additional model results. Figure A.9 reproduces the same paths as in Figure 7.2, but expressed as deviations from the Book Value economy. Figure A.10 displays the path of Bank Loans / GDP against the actual path observed in the data. Because of the large temporary draws on credit lines documented in Greenwald, Krainer and Paul (2025), firm credit in 2021:Q1 is somewhat anomalous. As a result, we instead normalize this data series so that it equals zero in 2019:Q1, matching the latest pre-pandemic observation with the same seasonality.

Figure A.9: Deviations from Book Value Economy, 2022 Tightening Cycle



Notes: This plot displays the paths from Figure 7.2 presented as deviations, obtained by subtracting the corresponding paths from the Book Value economy. See notes to Figure 7.2 for further details.

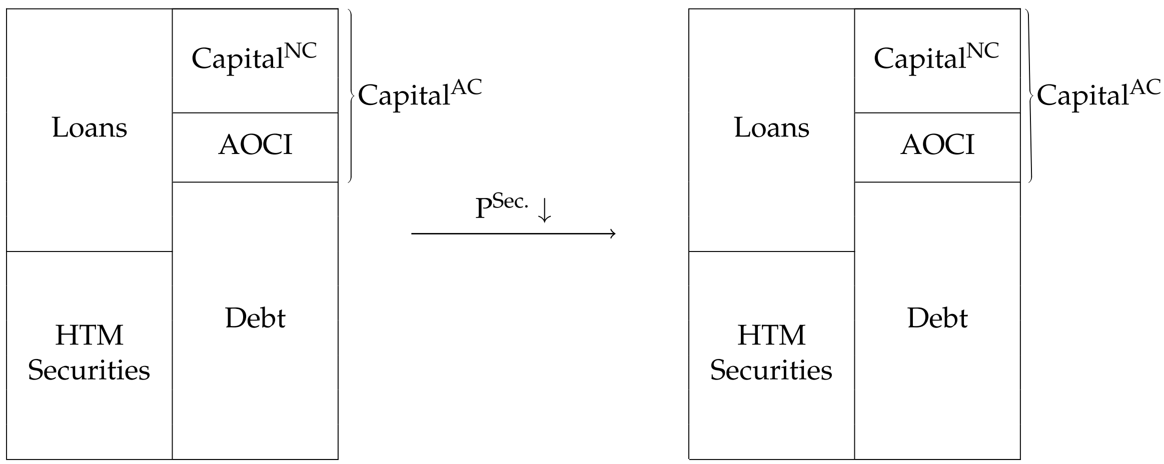
Figure A.10: Bank Lending to GDP, Model vs. Data



Notes: This plot displays the paths of Bank Loans / GDP from Figure 7.2 compared to the corresponding path in the data. The data series is normalized to equal zero in 2019:Q1. See notes to Figure 7.2 for further details.

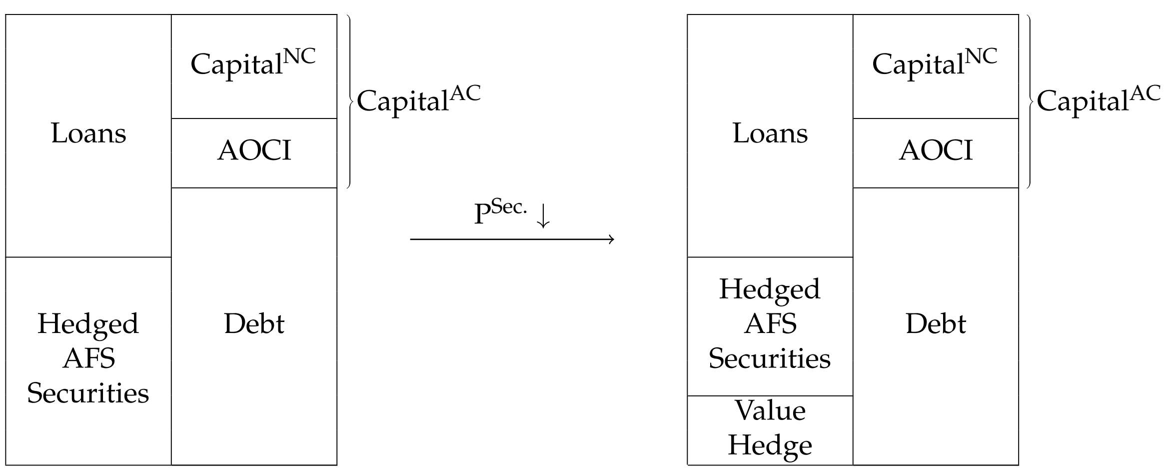
B Balance Sheet Dynamics

Figure B.1: Accounting treatment for HTM Securities.



Notes: The figure shows changes in a hypothetical bank's balance sheet following a decline in security prices where securities are booked in HTM.

Figure B.2: Accounting treatment for hedged AFS Securities.



Notes: The figure shows changes in a hypothetical bank's balance sheet following a decline in security prices where securities are booked in AFS and matched with a qualified fair value hedge.

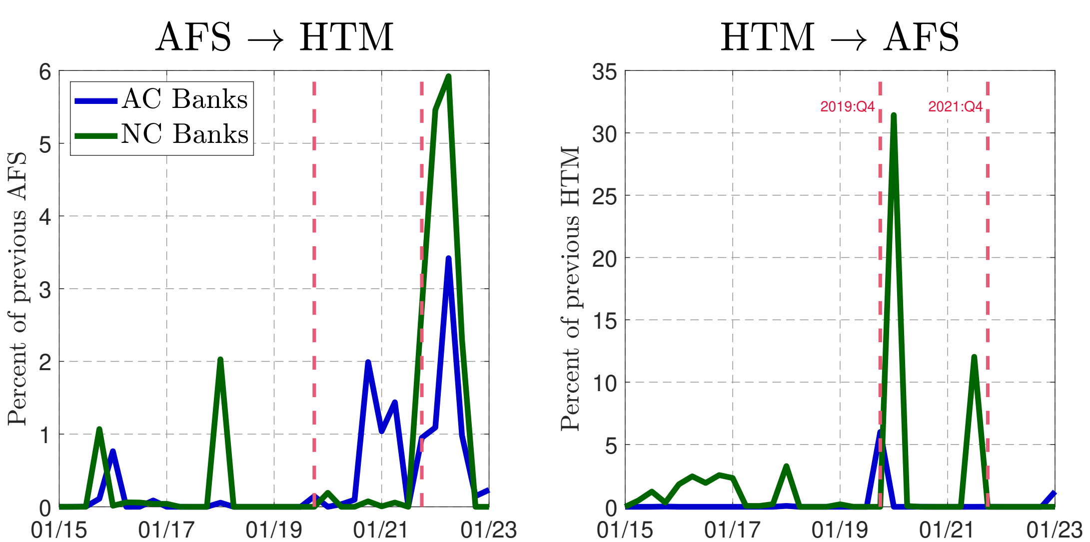
C Security Reclassifications

Accounting reclassifications are intended to be rare, but permissible under certain circumstances. Conditions under which a security holder can reclassify from HTM to AFS include (see ASC 320-10-25-6):

- Evidence of significant deterioration in security issuer's creditworthiness
- A change in tax law that eliminates or reduces the tax-exempt status of interest of the debt security
- A major business combination or major disposition that necessitates the sale or transfer of held-to-maturity securities to maintain the entity's interest rate risk position or credit risk policy
- A change in statutory or regulatory requirements significantly modifying either what constitutes a permissible investment or the maximum level of investments in certain kinds of securities, thereby causing an entity to dispose a held-to-maturity security
- A significant increase in the industry's capital requirements by the regulator that causes the entity to downsize by selling held-to-maturity securities
- A significant increase in the risk weights of debt securities used for regulatory risk-based capital purposes

Also relevant for security reclassifications is that holders are allowed a one-time election to sell and/or transfer debt securities classified as held-to-maturity that reference a rate expected to be discontinued (e.g., LIBOR), see ASC 848-10-35-1.

Figure C.1: Accounting designation changes



Notes: Data from FR Y-14 Schedule B.1. The chart shows the fraction of securities transferred between AFS and HTM accounting designations relative to total AFS or HTM securities in the previous quarter. Vertical dashed lines indicate 2019:Q4 and 2021:Q4.

D Data

Table D.1: AC and NC Banks.

AC BHCs	NC BHCs
JPMORGAN CHASE & CO	CHARLES SCHWAB CORP
BANK OF AMER CORP	M&T BK CORP
STATE STREET CORP	KEYCORP
WELLS FARGO & CO	HUNTINGTON BSHRS
NORTHERN TR CORP	PNC FNCL SVC GROUP
CITIGROUP	FIFTH THIRD BC
MORGAN STANLEY	TRUIST FC
GOLDMAN SACHS GROUP THE	U.S. BANCORP
DB USA CORP	CITIZENS FNCL GRP
BANK OF NY MELLON CORP	BMO FNCL CORP
	MUFG AMERS HOLDS CORP
	ALLY FNCL
	CAPITAL ONE FC
	HSBC N AMER HOLDS
	REGIONS FC
	TD GRP US HOLDS LLC
	SANTANDER HOLDS USA
	UBS AMERS HOLD LLC
	RBC US GRP HOLDS LLC

Notes: This table lists the AC and NC banks in our data for our main sample 2021:Q1–2023:Q1. Banks are identified to be one of the two categories according to the variable BHCAP838 from the Y-9C filings.

Table D.2: FR Y-14Q H.1 Variable Definitions.

Variable Name	**Description / Use in main analysis**	**Field No.**
Zip code	Zip code of headquarters	7
Industry	Derived 2-Digit NAICS Code	8
TIN	Taxpayer Identification Number	11
Internal Credit Facility ID	Used together with BHC and previous facility ID to construct loan histories	15
Previous Internal Credit Facility ID	Used together with BHC and facility ID to construct loan histories	16
Term Loan	Loan facility type reported as Term Loan, includes Term Loan A-C, Bridge Loans, Asset-Based, and Debtor in Possession.	20
Credit Line	Loan facility type reported as revolving or non-revolving line of credit, standby letter of credit, fronting exposure, or commitment to commit.	20
Purpose	Credit facility purpose	22
Committed Credit	Committed credit exposure	24
Used Credit	Utilized credit exposure	25
Line Reported on Y-9C	Line number reported in HC-C schedule of FR Y-9C	26
Participation Flag	Used to determine whether a loan is syndicated	34
Variable Rate	Interest rate variability reported as “Floating” or “Mixed”	37
Interest Rate	Current interest rate	38
Date Financials	Financial statement date used to match firm financials to Y-14 date	52
Net Sales Current	Firm sales over trailing 12-month period	54
Net Income	Current net income for trailing 12-months used to construct return on assets	59, 60
Cash	Cash & Marketable Securities	61
Fixed Assets	Fixed assets	69
Total Assets	Total assets, current year and prior year	70
Short Term Debt	Used in calculating total debt	74
Long Term Debt	Used in calculating total debt	78
Total Liabilities	Firm Total Liabilities	80
Syndicated Loan	Syndicated loan flag	100

Notes: Nominal series are converted into real series using the consumer price index for all items taken from St. Louis Fed’s FRED database. The corresponding “Field No.” can be found in the data dictionary (Schedule H.1, pp. 162–217): https://www.federalreserve.gov/reportforms/forms/FR_Y-14Q20200331_i.pdf

Table D.3: FR Y-14Q B.1 & B.2 and Vendor Data Variable Definitions.

Variable Name	Description / Use	Schedule / Field No.
Unique Identifier	Unique ID used by BHC to identify each record over time	B.1/B.2
Identifier Value	ID, corresponds to a CUSIP, ISIN, or SEDOL identifier, if it exists	B.1
Security description	Reported asset class of security	B.1
Market value	Fair value of security holding in $USD	B.1
Price	Price of security in $USD.	B.1
Amortized cost	Purchase price of debt security in $USD adjusted for amortization/accretion of discounts/premia and adjusted for hedge gains and losses	B.1
Accounting intent	Available-for-sale, held-to-maturity.	B.1
Hedge type	Use only fair value hedges.	B.2/6
Hedged risk	Use only hedges linked to interest rate risk.	B.2/7
Hedge percentage	Portion of the asset holding being hedged, 0%–100%.	B.2/9
Hedge sidedness	Use only two-sided hedges.	B.2/12
Security duration	Effective rate duration at security level.	ICE

Notes: Variables and further descriptions for FR Y-14Q schedules B.1 and B.2 may be found in data dictionary: https://www.federalreserve.gov/reportforms/forms/FR_Y-14Q20200331_i.pdf

Table D.4: Compustat Variable Definitions.

Variable Name	Description	Compustat Name
Total Assets	Total firm assets	atq
Employer Identification Number	Used to match to TIN in Y14	ein
Total Liabilities	Total firm liabilities	ltq
Net Income	Firm net income (converted to 12-month trailing series)	niq
Total Debt	Debt in current liabilities + long-term debt	dlcq + dlttq
Sales	Total firm sales	saleq
Fixed Assets	Net property, plant, and equipment	ppentq
Cash	Cash & Marketable securities	cheq

Notes: All data obtained from the Wharton Research Data Services. Nominal series deflated using the consumer price index for all items taken from St. Louis Fed's FRED database.

Table D.5: Variables from Y-9C filings.

Variable Code	**Variable Label**
BHCK2170	Total Assets
BHCK2948	Total Liabilities
BHCK4340	Net Income
BHCK3197	Earning assets that reprice or mature within one year
BHCK3296	Interest-bearing deposit liabilities that reprice or mature within one year
BHCK3298	Long-term debt that reprices within one year
BHCK3408	Variable-rate preferred stock
BHCK3409	Long-term debt that matures within one year
BHDM6631	Domestic offices: noninterest-bearing deposits
BHDM6636	Domestic offices: interest-bearing deposits
BHFN6631	Foreign offices: noninterest-bearing deposits
BHFN6636	Foreign offices: interest-bearing deposits
BHCAP793	CET 1 Capital Ratio
BHCA7206	Tier 1 Capital Ratio
BHCA7205	Total Capital Ratio
BHCKB529	Loans and Leases held for investment
BHCK5369	Loans and Leases held for sale
BHCM3543	Trading Assets: Derivatives positive fair value
BHCK3547	Trading Liabilities: Derivatives with a negative fair value
BHCKA126	Derivatives, Interest Rate Contracts: Total gross notional amount of derivative contracts held for trading
BHCK8733	Derivatives, Interest Rate Contracts: Contracts held for trading: Gross positive fair value
BHCK8737	Derivatives, Interest Rate Contracts: Contracts held for trading: Gross negative fair value
BHCAP838	AOCI opt-out election
BHCM3531, BHCM3532, BHCM3533	Trading book: Government securities
BHCKG379, BHCKG380, BHCKG381, BHCKK197, BHCKK198	Trading book: Mortgage-backed securities
BHCKHT62, BHCKG386	Trading book: Other debt securities
BHCKG210	Trading book: Short position for debt securities
BHCKJJ33	Provision for loan and lease losses
BHCAB530	AOCI
BHCAA223	Risk-weighted Assets

Notes: The table lists variables that are collected from the Consolidated Financial Statements or FR Y-9C filings for Bank-Holding Companies from the Board of Governors' National Information Center database. The one-year income gap is defined as $(\text{BHCK}\,3197 - (\text{BHCK}\,3296 + \text{BHCK}\,3298 + \text{BHCK}\,3408 + \text{BHCK}\,3409))\,/\text{BHCK}\,2170$. Total deposits are given by $(\text{BHDM}\,6631 + \text{BHDM}\,6636 + \text{BHFN}\,6631 + \text{BHFN}\,6636)$. Nominal series are deflated using the consumer price index for all items taken from St. Louis Fed's FRED database.

E Sample Restrictions and Filtering Steps

We apply the following filtering steps to the H.1 schedule:

1. We constrain the sample to loan facilities with line reported on the HC-C schedule in the FR Y9-C filings as commercial and industrial loans, "other" loans, "other" leases, and owner-occupied commercial real estate (corresponding to Field No. 26 in the H.1 schedule of the Y14 to be equal to 4, 8, 9, or 10; see Table D.2). In addition, we drop all observations with NAICS codes 52 and 53 (loans to financial firms and real estate firms).

2. Observations with negative or zero values for committed exposure, negative values for utilized exposure, with committed exposure less than utilized exposure, and gaps in their loan histories are excluded.

3. When aggregating loans at the firm level, we exclude observations for which the firm identifier "TIN" is missing. To preserve some of these missing values, we fill in missing TINs from a history where the non-missing TIN observations are all the same over a unique facility ID.

4. When using information on firms' financials in the analysis, we apply a set of filters to ensure that the reported information is sensible. We exclude observations (i) if total assets, total liabilities, short-term debt, long-term debt, cash assets, tangible assets, or interest expenses are negative, (ii) if tangible assets, cash assets, or total liabilities are greater than total assets, and (iii) if total debt (short term + long term) is greater than total liabilities.

5. When using the interest rate on loans in our calculations, we exclude observations with interest rates below 0.5% or above 50% to minimize the influence of data entry errors.

We apply the following filtering steps to the B.1 and B.2 schedules:

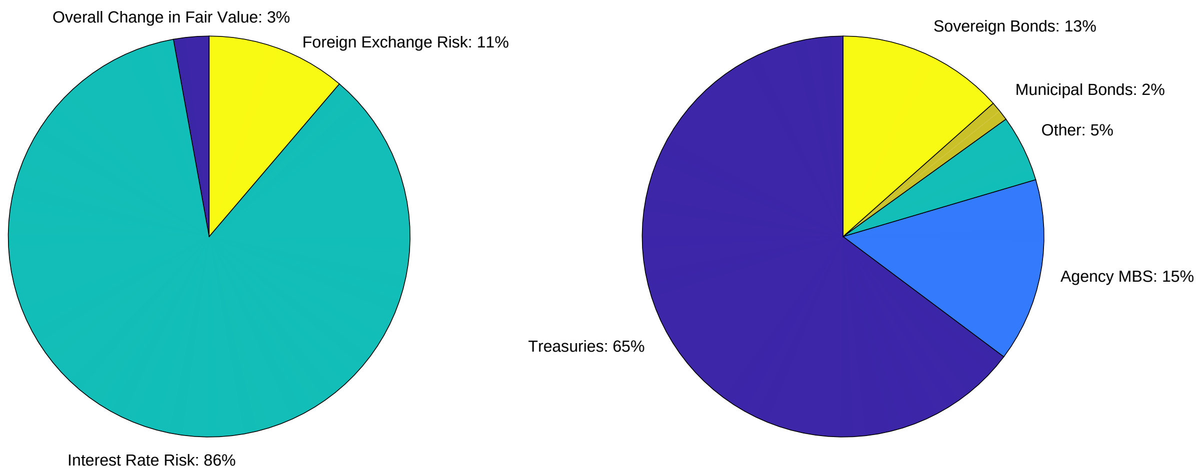
1. We exclude hedges with hedge horizons past the observation date.

2. We exclude observations with negative market values, amortized costs, or prices.

3. If the pricing date differs from the observation date, we refill the price variable one year backwards or forward, so that pricing date and observation date align.

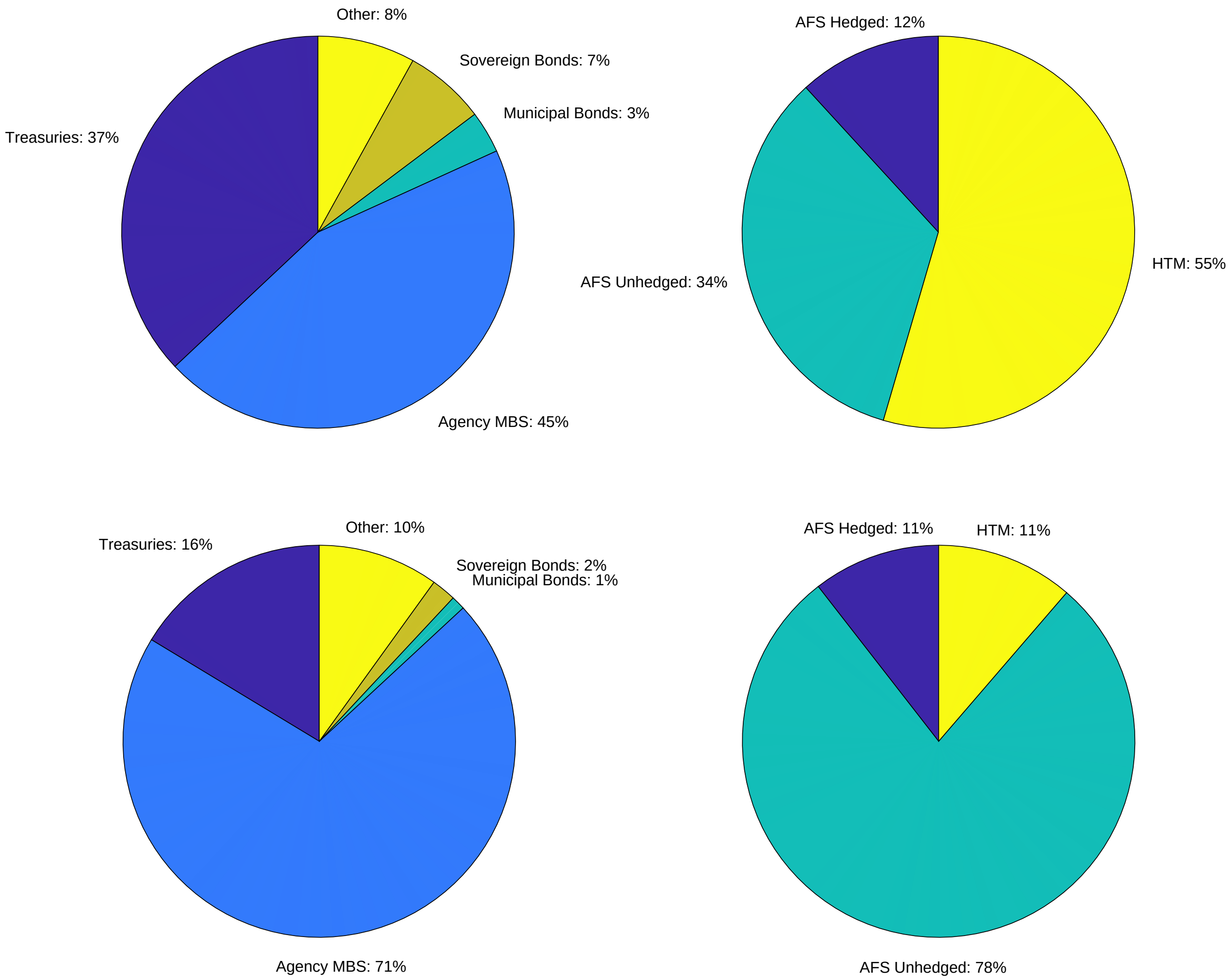
F Stylized Facts

Figure F.1: Composition of Accounting Hedges.



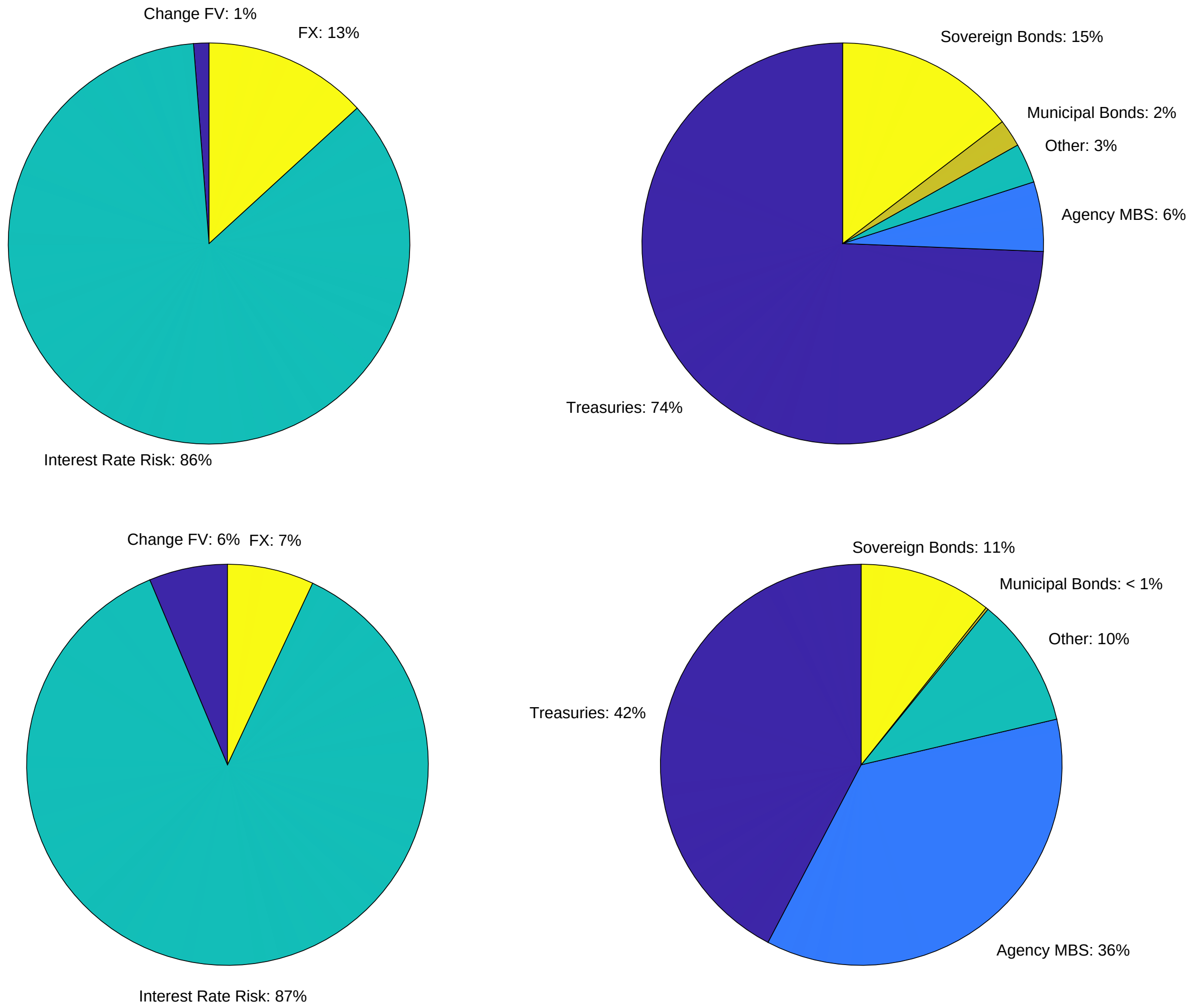
Notes: Data from FR Y-14Q sampled in 2021:Q4. The charts show the allocation shares of qualified accounting hedges by hedge type (left panel) and by hedged item or asset class (right panel). Shares are computed as percent of total market value hedged.

Figure F.2: Securities Portfolios for AC banks (top) and NC Banks (bottom).



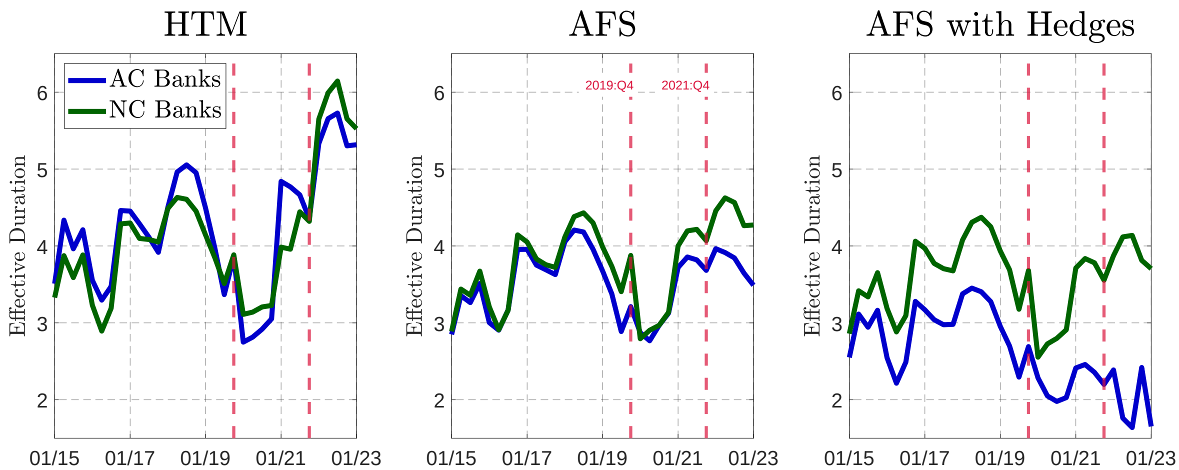
Notes: Data from FR Y-14Q sampled in 2021:Q4. The charts show the allocation shares of aggregate securities portfolio by asset class (left panels) and by accounting designation (right panels), separately for AC banks (top) and NC banks (bottom). Shares are computed as percent of total market value.

Figure F.3: Accounting Hedges for AC banks (top) and NC Banks (bottom).



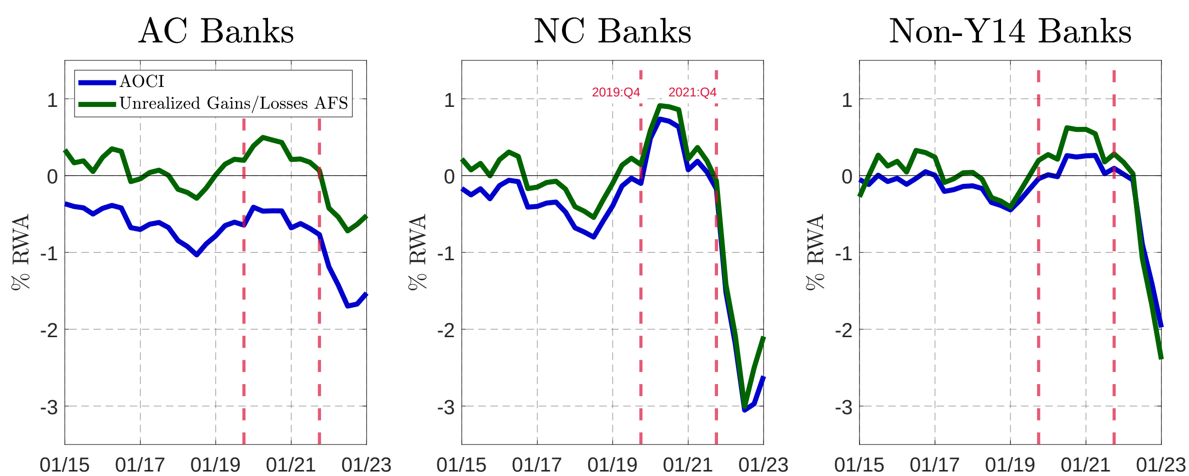
Notes: Data from FR Y-14Q sampled in 2021:Q4. The charts show the allocation shares of qualified accounting hedges by hedge type (left panels) and by hedged item or asset class (right panels), separately for AC banks (top) and NC banks (bottom). Shares are computed as percent of total market value hedged.

Figure F.4: Duration of Securities Portfolios.



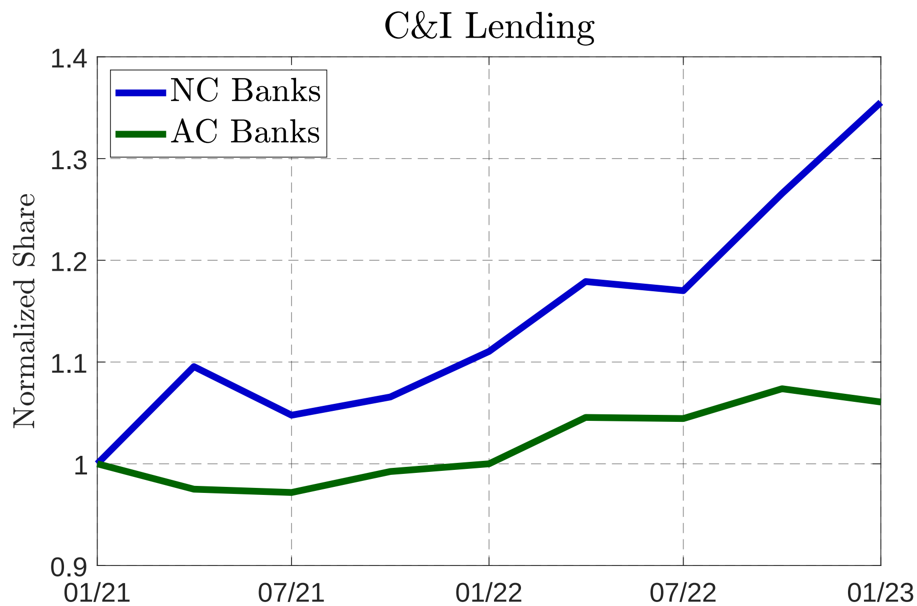
Notes: The graph shows the evolution of the effective duration of banks' HTM and AFS securities portfolios weighted by the market value of securities. The right panel takes into account that hedges shorten the maturity of AFS securities (i.e. a security that is fully hedged has a zero maturity).

Figure F.5: AOCI and Unrealized Gains/Losses AFS.



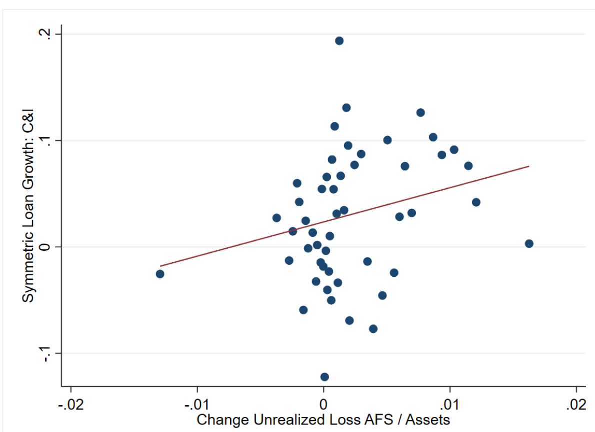
Notes: The graph shows the evolution of AOCI and unrealized gains/losses on AFS securities (both relative to risk-weighted assets) for AC banks (left panel), NC banks (middle), and non-Y14 banks (right). Source: Y-9C data.

Figure F.6: C&I Lending—AC and NC Banks.

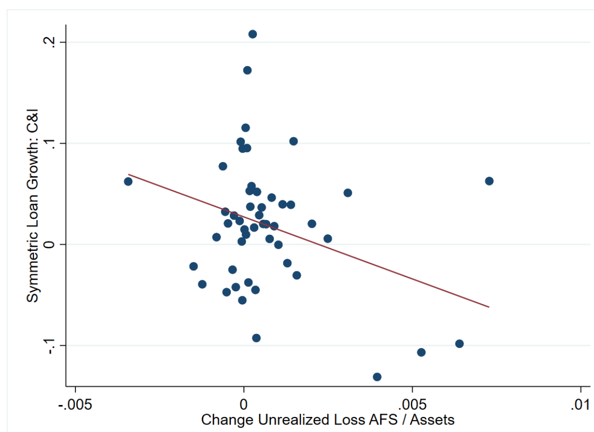


Notes: C&I lending share at AC and NC banks relative to the level in 2021:Q1.

Figure F.7: Unrealized Losses AFS and Lending Growth.



(a) NC Banks



(b) AC Banks

Notes: The figure displays a binscatter plot of the change in unrealized losses on AFS securities between t and $t+1$ (relative to total assets at t) against the C&I lending growth between t and $t+2$ computed using the symmetric growth rate. Panel (a) displays results for NC banks, while Panel (b) displays results for AC banks. The data are obtained from FR Y-9C over 2021:Q1-2023:Q1 for banks that are part of the Y-14 sample.

G Credit Supply Effects

In this appendix, we explore extensions and test the robustness of our empirical findings in Section 6.

First, we consider alternative fixed effects specifications. Table G.2 omits the firm-time fixed effects and replaces those by variations of location-, size-, and industry-time fixed effects, which extends the sample to include firms that borrow from a single lender.

Second, loans differ by contract terms such as maturity, whether they are adjustable- or fixed-rate loans, and whether a loan is syndicated. To ensure that we compare loans with similar contract terms, we extend the firm-time fixed effects with such characteristics. Table G.3 shows the updated estimation results. For both extensions, our results are similar to our baseline estimates.

Third, we extend the sample to include bank-firm observations that also cover credit lines. Columns (i) and (ii) of Table G.4 show that our results vanish when we consider used credit amounts. This finding can be explained by the fact that banks have less control over restricting the usage of credit lines which are strongly demand-driven. However, banks may adjust committed credit amounts. We therefore consider regressions with changes in committed credit as a dependent variable in columns (iii) and (iv) of Table G.4. Despite this change, we still find that our baseline results are substantially weaker, which may be explained by the fact that many firms have substantial room between their committed and used credit lines and adjusting the committed amounts may not change the used amounts substantially. However, once we restrict the unused amount to be below 10% of the total committed amount in columns (v) and (vi) of Table G.4, our initial results reappear. Thus, our findings are robust to including credit lines into the analysis if those do not have substantial unused credit.

Fourth, a potential concern may be that firms reduce their credit demand at banks with larger value losses of securities, as opposed to banks restricting credit supply, since firms might be worried about overall bank health. We view such a concern to be less applicable to the set of relatively large banks in our data over most of the sample when the stability of the U.S. financial system was not being questioned. However, in 2023:Q1, financial stability concerns may have played a role with the turmoil around SVB. We therefore rerun our regressions on a sample that ends in 2022:Q4. The results are shown in Table G.5. The findings for value changes of AFS securities remain the same for this new sample. We also find positive and marginally significant results for value changes of HTM securities. These results can be explained by the collateral channel or the net worth channel discussed in Section 3.

Fifth, we extend the sample backwards as far as possible to include periods of monetary easings. Table G.6 shows the updated results for the period 2016:Q4–2023:Q1. While our key findings remain, the coefficients reduce somewhat in magnitude. This comparison indicates that the effects are larger following a sharp unexpected monetary tightening as it occurred in 2022. To further explore the possibility of asymmetric effects, we separate positive and negative AFS value changes in Table G.7. We find larger and statistically significant effects for negative AFS value changes, though we cannot reject that the estimates are different from the ones of positive AFS value changes at standard confidence levels.

Sixth, in addition to the intensive margin responses, we further analyze extensive margin adjustments. That is, the dependent variable in our baseline regression (6.1) includes all bank-firm observations in t and $t+2$ that show an existing lending relationship for both periods and are non-zero in at least one of the periods. However, non-existing relationships in either t or $t+2$ are not part of the sample. We incorporate such new lending relationships or the end of old relationships by including zero-observations for $L_{i,j,t}$ or $L_{i,j,t+2}$ in such instances. The updated results are shown in Table G.8. The estimated coefficients β increase in magnitude and are even more precisely estimated, showing that such extensive margin adjustments further strengthen our findings.[40]

Seventh, we reestimate regression (6.1) for various horizons to portray the dynamic response of credit. Table G.9 shows the results. The crowding out effect is already sizable and significant within the same quarter during which securities change value. Hence, the transmission of monetary policy through bank securities portfolios operates at a high frequency since asset prices change instantly and lead to quick credit adjustments. The response builds up over time and becomes strongest at the three-quarter horizon.

Eighth, we test whether the identified supply effects apply not only to credit quantities but also to interest rates charged on loans. Table G.10 shows the results for regressions that use changes in interest rates as a dependent variable in (6.1), again portraying the dynamic response for various horizons. We find negative coefficients for β that indicate the identification of supply adjustments. At the three-quarter horizon, the responses are statistically different from zero at the 5% confidence level. However, compared with the credit responses, the statistical significance is weaker overall.[41]

[40] However, we do not measure the exact strength of the spillover effect in dollar terms based on these estimates, since the symmetric growth rate that we use as a dependent variable in regression (6.1) approximates all new relationships or the ending of old relationships as either -2 or 2.

[41] We note that although this evidence supports a rise in interest rates, it is not strictly necessary since our model mechanism ultimately works through quantities, as constrained firms adjust other margins such as investment to offset credit lost due to crowding out. While crowding out occurs via credit spread increases in our model, it could also occur via credit rationing as in e.g., Stiglitz and Weiss (1981), with a smaller increase or no increase in spreads, due to information frictions not present in our model.

And, finally, we test for a pretrend by re-estimating (6.1) using $(L_{i,j,t} - L_{i,j,t-2})/(0.5 \cdot (L_{i,j,t} + L_{i,j,t-2}))$ as the dependent variable. Table G.11 shows that our findings vanish for this alternative setup.

Table G.1: Summary Statistics.

Variable	Obs.	Mean	Std.	P10	Median	P90	AC	NC
Main Regressors								
Δ Value SEC/Assets	183	-.44	.61	-1.26	-.16	.10	-.35	-.49
Δ Value AFS/Assets	183	-.28	.39	-.91	-.11	.06	-0.13	-0.36
Δ Value HTM/Assets	183	-.16	.40	-.55	-.012	.02	-.22	-0.13
Bank Controls								
ROA	183	.62	.42	.22	.55	1.11	0.53	0.64
Income Gap	183	37.30	11.74	28.50	38.85	49.23	36.89	37.50
Leverage	183	90.23	1.81	87.93	90.40	92.47	91.60	89.50
Ln(Total Assets)	183	19.67	1.01	18.73	19.22	21.39	20.65	19.16
Deposit Share	183	69.50	16.06	50.79	75.23	84.51	68.75	74.03
Loan Share	183	42.40	17.27	15.41	45.25	63.85	24.79	51.63
Unused Credit/Assets	183	8.13	5.37	2.23	6.63	16.98	3.72	10.44

Notes: Summary statistics for the regressors in regression (6.1) at the bank level. All variables are multiplied by 100, except for Ln(Total Assets). The AC and NC columns represent averages for the corresponding bank type. Sample: 2021:Q1–2023:Q1.

Table G.2: Omitting Firm-Time Fixed Effects.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS	4.59**	6.09**	3.47**	5.46**
	(1.91)	(2.31)	(1.51)	(2.33)
Δ Value HTM			-4.59**	-3.15
			(2.04)	(2.04)
Fixed Effects				
Location × Size × Time	✓		✓	
Location × Size × Time × Industry		✓		✓
Bank & AC × Time	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
R-squared	0.25	0.46	0.26	0.46
Observations	51,242	25,906	51,242	25,906
Number of Firms	12,544	7,719	12,544	7,719
Number of Banks	28	28	28	28

Notes: Estimation results for regression (6.1). Columns (i) and (iii) include location-size-time fixed effects based on U.S. states and percentiles of the total asset distribution and columns (ii) and (iv) include location-size-time-industry fixed effects, which additionally use 2-digit NAICS codes. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.3: Firm-Time Fixed Effects Extensions.

	(i)	(ii)	(iii)	(iv)	(v)
Δ Value AFS	6.08***	5.65***	5.49***	5.33***	5.63**
	(1.85)	(1.94)	(1.56)	(1.65)	(2.08)
Fixed Effects					
Firm $\times$ Time	✓				
Firm $\times$ Time $\times$ Syn.		✓			
Firm $\times$ Time $\times$ Mat.			✓		
Firm $\times$ Time $\times$ Float.				✓	
Firm $\times$ Time $\times$ All					✓
Bank & AC $\times$ Time	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
R-squared	0.57	0.53	0.54	0.54	0.53
Observations	13,038	11,606	12,523	11,376	10,277
Number of Firms	1,289	1,165	1,242	1,142	1,035
Number of Banks	27	27	27	27	25

Notes: Estimation results for regression (6.1). Column (i) shows the baseline estimate using firm-time fixed effects, Column (ii) extends the fixed effects by whether the loan is syndicated, Column (iii) by the loan's maturity based on three bins (less than one quarter, less than one year, and more than one year), Column (iv) by whether the loan carries an adjustable or a floating rate, and Column (v) uses all three additional characteristics. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.4: Credit Lines.

	Used		Committed		Committed Res.	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value AFS	3.07	2.46	1.32	2.10**	5.70**	7.00***
	(1.99)	(2.70)	(1.01)	(0.90)	(2.19)	(1.92)
Δ Value HTM	0.66	-0.30	0.93	0.60	2.93**	2.93*
	(1.06)	(0.94)	(0.88)	(0.76)	(1.33)	(1.48)
Fixed Effects						
Firm × Time	✓		✓		✓	
Firm × Time × Purpose		✓		✓		✓
Bank & AC × Time	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
R-squared	0.69	0.71	0.47	0.5	0.53	0.53
Observations	84,241	66,960	84,241	66,960	23,575	18,525
Number of Firms	5,622	4,581	5,622	4,581	2,371	1,899
Number of Banks	28	28	28	28	28	28

Notes: Estimation results for regression (6.1) which extends the sample to include bank-firm observations that also cover credit lines. Columns (i) and (ii) employ used credit for the dependent variable, while the remaining columns use committed credit instead. Columns (v) and (vi) restrict unused credit to be below 10% of total committed credit. All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii) and (iv). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.5: Excluding 2023:Q1.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS	8.16***	9.95***	8.44***	10.26***
	(2.70)	(2.66)	(2.40)	(2.43)
Δ Value HTM			3.20*	2.52*
			(1.58)	(1.36)
Fixed Effects				
Firm × Time	✓		✓	
Firm × Time × Purpose		✓		✓
Bank & AC × Time	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
R-squared	0.59	0.56	0.59	0.56
Observations	11,020	9,365	11,020	9,365
Number of Firms	1,243	1,065	1,243	1,065
Number of Banks	27	26	27	26

Notes: Estimation results for regression (6.1). All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii) and (iv). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2022:Q4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.6: Extended Sample.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS	3.17**	4.87***	3.23**	4.91***
	(1.49)	(1.77)	(1.53)	(1.79)
Δ Value HTM			1.24	0.60
			(0.94)	(0.91)
Fixed Effects				
Firm × Time	✓		✓	
Firm × Time × Purpose		✓		✓
Bank & AC × Time	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
R-squared	0.56	0.55	0.56	0.55
Observations	41,541	33,269	41,541	33,269
Number of Firms	2,301	1,896	2,301	1,896
Number of Banks	34	34	34	34

Notes: Estimation results for regression (6.1). All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii) and (iv). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2016:Q4–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.7: Asymmetric Effects.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value AFS (-)	3.38**	5.62***			3.24**	5.50***
	(1.49)	(1.63)			(1.48)	(1.60)
Δ Value AFS (+)			3.66	3.77	3.07	2.80
			(4.06)	(5.18)	(4.00)	(5.04)
Fixed Effects						
Firm $\times$ Time	✓		✓		✓	
Firm $\times$ Time $\times$ Purpose		✓		✓		✓
Bank & AC $\times$ Time	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
R-squared	0.56	0.55	0.56	0.55	0.56	0.55
Observations	41,561	33,290	41,561	33,290	41,561	33,290
Number of Firms	2,303	1,897	2,303	1,897	2,303	1,897
Number of Banks	35	35	35	35	35	35

Notes: Estimation results for regression (6.1), separating positive and negative AFS value changes. All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii), (iv), and (vi). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2016:Q4–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.8: Extensive Margin.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS	48.38***	43.47***	47.48***	43.70***
	(14.23)	(11.57)	(13.48)	(11.26)
Δ Value HTM			-7.61	1.89
			(11.82)	(9.14)
Fixed Effects				
Firm × Time	✓		✓	
Firm × Time × Purpose		✓		✓
Bank & AC × Time	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
R-squared	0.69	0.71	0.69	0.71
Observations	23,200	19,744	23,200	19,744
Number of Firms	2,781	2,385	2,781	2,385
Number of Banks	30	28	30	28

Notes: Estimation results for regression (6.1) that incorporates new lending relationships and the ending of old relationships. All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii) and (iv). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.9: Dynamic Response.

	h=1	h=2	h=3	h=4	h=5
Δ Value AFS	6.82**	11.80***	12.56***	9.91*	6.03
	(3.18)	(3.80)	(4.11)	(5.17)	(4.04)
Fixed Effects					
Firm × Time	✓	✓	✓	✓	✓
Bank & AC × Time	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
R-squared	0.59	0.57	0.57	0.57	0.58
Observations	5,087	5,087	5,087	5,087	5,087
Number of Firms	771	771	771	771	771
Number of Banks	27	27	27	27	27

Notes: Estimation results for regression (6.1) that uses $2 \cdot (L_{i,j,t+h} - L_{i,j,t})/(L_{i,j,t+h} + L_{i,j,t})$ as a dependent variable for $h = 1, 2, \ldots$. All specifications are estimated for a balanced sample, include firm-time fixed effects, as well as various bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.10: Interest Rates.

	h=1	h=2	h=3	h=4	h=5
Δ Value AFS	-0.02	-0.09	-0.16**	-0.13	-0.10
	(0.03)	(0.05)	(0.06)	(0.11)	(0.13)
Fixed Effects					
Firm × Time	✓	✓	✓	✓	✓
Bank & AC × Time	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓
R-squared	0.6	0.81	0.89	0.91	0.92
Observations	5,017	5,017	5,017	5,017	5,017
Number of Firms	765	765	765	765	765
Number of Banks	27	27	27	27	27

Notes: Estimation results for regression (6.1) that uses changes in interest rates $r_{i,j,t+h} - r_{i,j,t}$ as a dependent variable for $h = 1, 2, \ldots$. All specifications are estimated for a balanced sample, include firm-time fixed effects, as well as various bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table G.11: Placebo Regression.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS	-0.33	-0.08	-0.26	-0.06
	(1.98)	(1.84)	(1.97)	(1.84)
Δ Value HTM			0.44	0.08
			(0.57)	(0.72)
Fixed Effects				
Firm × Time	✓		✓	
Firm × Time × Purpose		✓		✓
Bank & AC × Time	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
R-squared	0.58	0.56	0.58	0.56
Observations	16,570	14,082	16,570	14,082
Number of Firms	1,423	1,215	1,423	1,215
Number of Banks	29	28	29	28

Notes: Estimation results for regression (6.1) which uses $2 \cdot (L_{i,j,t} - L_{i,j,t-2})/(L_{i,j,t} + L_{i,j,t-2})$ as a dependent variable. All specifications include firm-time fixed effects that additionally vary by the loan purpose in columns (ii) and (iv). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include AC-banks-time fixed effects and bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

H Mechanism

In this section, we further explore the mechanisms explaining our results and contrast them with alternative channels.

AC Banks - Hedged vs. Unhedged Securities. We rerun regression (6.3) but additionally distinguish AFS value changes into hedged and unhedged ones. The results—reported in Table H.1—show that the coefficient related to unhedged security value changes interacted with the AC-banks indicator is statistically different from zero when we use the finer firm-time-loan purpose fixed effects. In contrast, we do not find such differential effects for hedged securities. These findings are consistent with the regulatory capital channel, which operates for unhedged securities at AC banks.

Bank Capital. We investigate differences across banks depending on their capital positions. To this end, we consider the regression

$$\frac{L_{i,j,t+2} - L_{i,j,t}}{0.5 \cdot (L_{i,j,t+2} + L_{i,j,t})} = \beta_1 \cdot \frac{\Delta Value^{AFS}_{j,t+1}}{Assets_{j,t}} + \beta_2 \cdot \frac{\Delta Value^{AFS}_{j,t+1}}{Assets_{j,t}} \cdot Cap_{j,t} + \gamma X_{j,t} + \kappa_j + u_{i,j,t} \,, \tag{H.1}$$

where $\Delta Value^{AFS}_{j,t+1} / Assets_{j,t}$ is now interacted with a measure of bank capital $Cap_{j,t}$. For bank capital positions, we consider CET1, Tier 1, and total bank capital, and use the difference between the ratio and the requirement for each.

The estimation results for regressions (H.1) are reported in Table H.2. Across the various capital measures, β_2 is negative and statistically different from zero at standard confidence levels. That is, banks that are less capitalized show stronger spillover effects, confirming a prediction from Section 3. For the reported estimation results, we control for interaction terms between $\Delta Value^{AFS}_{j,t+1} / Assets_{j,t}$ and various other bank controls, ensuring that we are not picking up an alternative channel based on correlations between bank observables.

Interest Rate Risk Channel. We provide further evidence that our baseline findings are explained by banks' exposure to interest rate risk that leads to fluctuations in the value of their securities portfolios, as opposed to other simultaneous reactions to changes in interest rates. To this end, we consider three extensions of regression (6.1) that are summarized in Table H.3 where Column (i) shows our baseline results.

First, Kashyap and Stein (2000) show that the effect of monetary policy on lending is stronger for banks with less liquid balance sheets, that is, with lower security holdings relative to assets. Intuitively, as monetary policy tightens, these banks have less liquid assets to sell and therefore need to contract lending. In contrast, we find that banks with larger value changes of securities relative to assets show a stronger lending response (which tend to be banks with more ex-ante securities relative to assets). To account for the channel by Kashyap and Stein (2000), we further control for banks' ex-ante AFS and HTM holdings, as well as their trading securities (distinguishing government, mortgage-backed, and other debt securities, as well as short positions for debt securities, see Appendix Table D.5 for details). The estimation results with these additional controls are shown in Column (ii) of Table H.3. If anything, our findings slightly strengthen in magnitude and statistical significance.

Second, we employ an instrumental variable regression. As discussed above, value changes of a bank's AFS portfolio can be the result of a number of risk factors and we aim to isolate the channel working through unexpected changes in interest rates. As an instrument for $\Delta Value^{AFS}_{j,t+1}/Assets_{j,t}$, we therefore use the interaction between the yield change of the one-year treasury security from t to $t+1$, which captures changes in the stance of monetary policy, and a bank's AFS portfolio valued at market prices relative total assets at time t.

The first-stage regression yields a negative coefficient with respect to our instrument which is statistically different from zero at the 1% confidence level with an F-statistic of 45. Intuitively, an unexpected increase in interest rates leads to a more negative response of the value of a bank's AFS portfolio the larger the initial value of that portfolio. Table H.3 reports the second-stage results in Column (iii). The coefficient associated with $\Delta Value^{AFS}_{j,t+1}/Assets_{j,t}$ remains positive and statistically significant at the 5% confidence level for the instrumental variable regression, providing additional evidence for the interest rate risk channel. The estimated coefficient is also larger than our baseline estimate, indicating that unexpected value changes of securities may yield even stronger spillover effects.

Third, we directly control for other simultaneous responses to interest rate movements. Specifically, changes in interest rates affect the interest rate gap between deposit rates and short-term market rates, resulting in deposit fluctuations (Drechsler, Savov and Schnabl, 2017). In turn, banks may alter their credit supply schedule to firms. Moreover, changes in the stance of monetary policy can affect banks differently depending on the maturity structure of their balance sheets. For example, banks that hold more adjustable-rate loans may obtain relatively more interest income in the short-run when monetary policy tightens (Gomez et al., 2021).

While our baseline controls—in particular banks' deposit shares and their income gap—partly account for such simultaneous deposit flows and cash flow effects, we directly control for them by including changes in bank deposits and net income from t to $t+1$ (both relative to total assets at time t) as separate regressors into our baseline regression (6.1).[42]

Moreover, a potential alternative explanation for our results is that banks with larger value losses of securities also experienced a stronger decline in the expected profitability of their legacy loans, leading to a contraction in lending that is not caused by the value losses of securities but by the poor performance of the loan portfolio. To address this concern, we directly control for the change in the quality of a bank's existing term loan portfolio using banks' reported probabilities of default and provision for loan losses from

[42] We use banks' net income change as opposed to changes in the net interest margin to account for other non-interest income changes. However, the results are unaffected by this choice. They equally hold when controlling for changes of net interest margins instead.

banks' income statements from t to $t+1$.[43]

Column (iv) of Table H.3 reports the new estimation results. While the coefficients on the added regressors are not statistically different from zero, the size and significance of the coefficient with respect to $\Delta Value^{AFS}_{j,t+1} / Assets_{j,t}$ remain largely unchanged, providing further evidence that our initial results are not driven by such simultaneous developments but by responses to security price changes.

Bank Level. To test whether our findings aggregate up to the bank level, we estimate variations of the regression

$$\frac{L_{j,t+2} - L_{j,t}}{0.5 \cdot (L_{j,t+2} + L_{j,t})} = \beta \cdot \frac{\Delta Value^{SEC}_{j,t+1}}{Assets_{j,t}} + \tau_{AC_j,t} + \gamma X_{j,t} + \kappa_j + u_{j,t} \,, \tag{H.2}$$

where $L_{j,t}$ is the aggregated amount of credit at the bank level. Table H.5 reports estimation results similar to the ones in Tables 6.1 and 6.2. In accordance with our main findings, columns (ii) and (iii) show that AFS value changes lead to credit adjustments at the bank level, while HTM value changes do not have such an effect. Relative to Table 6.1, the size and statistical significance slightly change, given the aggregation and the fact that we cannot control for firm credit demand in the same way. Column (iv) further shows that these results are driven by unhedged AFS value changes. Moreover, column (v) replicates the finding from Table 6.2 that AC-banks show stronger lending adjustments. Overall, these results at the bank level are therefore consistent with our earlier findings.

[43] Specifically, we compute changes in banks' reported probabilities of default on their total term loan portfolio weighted by used credit amounts and omitting the observation associated with the dependent variable (leave-one-out). Provision for loan losses are measured using item BHCKJJ33 from the Y-9C filings (see Appendix Table D.5 for details).

Table H.1: AC Banks - Hedged vs. Unhedged.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS Unhedged	-1.16	-1.41	-1.73	-1.62
	(4.77)	(5.29)	(4.98)	(4.94)
Δ Value AFS Unhedged $\times$ AC	6.85	14.44	14.70	24.21**
	(9.00)	(9.34)	(9.49)	(10.19)
Δ Value AFS Hedged			19.61	18.93
			(21.11)	(32.31)
Δ Value AFS Hedged $\times$ AC			-49.57	-49.16
			(40.62)	(57.78)
Fixed Effects				
Firm $\times$ Time	✓		✓	
Firm $\times$ Time $\times$ Purpose		✓		✓
Bank	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Derivatives	✓	✓	✓	✓
Bank Controls $\times$ Δ Value AFS Unhedged	✓	✓	✓	✓
Bank Controls $\times$ Δ Value AFS Hedged			✓	✓
R-squared	0.57	0.55	0.57	0.55
Observations	13,027	11,093	13,027	11,093
Number of Firms	1,288	1,105	1,288	1,105
Number of Banks	26	26	26	26

Notes: Estimation results for regression (6.3). All specifications include firm-time and bank fixed effects. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. All specifications include controls for derivative contracts from the trading and derivative book (see footnote 24 for details) and $\Delta Value^{HTM}_{j,t+1} / Assets_{j,t}$. Interaction terms between the various demeaned bank controls and $\Delta Value^{AFS}_{j,t+1} / Assets_{j,t}$ are included for hedged securities in columns (iii) and (iv) and for unhedged securities in all specifications. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.2: Bank Capital Positions.

	(i)	(ii)	(iii)
Δ Value AFS	5.82	6.00	7.42
	(4.50)	(4.89)	(5.12)
Δ Value AFS × CET1	-1.06*		
	(0.57)		
Δ Value AFS × Tier1		-1.17*	
		(0.66)	
Δ Value AFS × Total			-1.50**
			(0.69)
Firm × Time FE; Bank FE	✓	✓	✓
Bank Controls	✓	✓	✓
Bank Controls × Δ Value AFS	✓	✓	✓
R-squared	0.57	0.57	0.57
Observations	13,038	13,038	13,038
Number of Firms	1,289	1,289	1,289
Number of Banks	27	27	27

Notes: Estimation results for regression (H.1). All specifications include firm-time and bank fixed effects. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, the ratio of unused credit lines to assets, and each respective capital buffer. All specifications include interaction terms between the various demeaned bank controls and $\Delta Value^{AFS}_{j,t+1}/Assets_{j,t}$, apart from bank leverage which is highly correlated with the other capital measures. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.3: Interest Rate Risk Channel.

	(i)	(ii)	(iii)	(iv)
Δ Value AFS	6.08***	7.71***	14.07**	6.58***
	(1.85)	(1.47)	(6.12)	(2.07)
Δ Net Income				0.64
				(2.83)
Δ Deposits				-0.06
				(0.20)
Δ Probability Default				31.79
				(45.21)
Δ Provision Losses				5.91
				(6.43)
Firm × Time FE	✓	✓	✓	✓
Bank FE; AC × Time FE	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓
Banking Book Securities		✓	✓	
Trading Book Securities		✓		
Estimator	OLS	OLS	IV	OLS
First Stage F-Stat.			45	
R-squared	0.57	0.57	0.57	0.57
Observations	13,038	13,027	13,038	13,038
Number of Firms	1,289	1,288	1,289	1,289
Number of Banks	27	26	27	27

Notes: Estimation results for regression (6.1). All specifications include firm-time fixed effects, AC-banks time fixed effects, and bank fixed effects. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. Columns (ii) and (iii) include AFS securities at market value as well as HTM securities at book value, both relative to assets. Column (ii) includes banks' securities from the trading portfolio at time t: government, mortgage-backed, and other debt securities, as well as short positions on debt securities (all relative to assets). Column (iii) considers an instrumental variable regression using the interaction between the yield change of the one-year treasury security from t to $t+1$ and a bank's AFS portfolio valued at market prices relative total assets at time t as an instrument. Column (iv) includes changes in net income, deposits, probabilities of default of banks term loan portfolios (weighted by used credit amounts), and provision for loan losses from t to $t+1$ (all relative to assets). Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.4: AC Banks - Firm-time FE Extension.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value AFS	4.11*	5.60*	2.11	1.79	-3.70	-6.45
	(2.21)	(3.22)	(4.22)	(5.51)	(6.76)	(7.68)
Δ Value AFS × AC	29.24	34.40*	30.96	37.66*	29.27	35.76**
	(18.23)	(16.92)	(19.59)	(19.05)	(17.59)	(17.16)
Δ Value AFS × Size			-2.09	-3.82	-2.74	-4.59
			(2.79)	(3.43)	(4.96)	(5.87)
Fixed Effects						
Firm × Time × AC	✓		✓		✓	
Firm × Time × AC × Purpose		✓		✓		✓
Bank	✓	✓	✓	✓	✓	✓
Bank Controls	✓	✓	✓	✓	✓	✓
Bank Controls × Δ Value AFS					✓	✓
R-squared	0.61	0.6	0.61	0.6	0.61	0.6
Observations	7,115	5,738	7,115	5,738	7,115	5,738
Number of Firms	758	628	758	628	758	628
Number of Banks	27	25	27	25	27	25

Notes: Estimation results for regression (6.3). All specifications include firm-time-AC-bank fixed effects that additionally vary by the loan purpose in columns (ii), (iv), and (vi). Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. Columns (v) and (vi) include interaction terms between the various demeaned bank controls and $\Delta Value^{AFS}_{j,t+1}/Assets_{j,t}$. All specifications include bank fixed effects. Standard errors in parentheses are clustered by bank. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table H.5: Credit Supply Effects, Bank-Level.

	(i)	(ii)	(iii)	(iv)	(v)
Δ Value SEC	4.23				
	(4.38)				
Δ Value AFS		10.48	10.88*		0.67
		(6.16)	(6.30)		(5.26)
Δ Value HTM			1.71	3.44	
			(5.15)	(4.31)	
Δ Value AFS Unhedged				14.88**	
				(6.14)	
Δ Value AFS Hedged				-22.36	
				(15.91)	
Δ Value AFS × AC					23.82**
					(8.81)
Fixed Effects					
Bank	✓	✓	✓	✓	✓
AC × Time	✓	✓	✓	✓	
Time					✓
Bank Controls	✓	✓	✓	✓	✓
Bank Controls × Δ Value AFS					✓
R-squared	0.38	0.39	0.39	0.4	0.37
Observations	183	183	183	183	183
Number of Banks	27	27	27	27	27

Notes: Estimation results for variations of regression (H.2). All specifications include bank fixed effects. Columns (i)-(iv) include AC-bank-time fixed effects and column (v) includes time fixed effects. Bank controls: bank size (natural log of assets), return on assets (net income/assets), deposit share (total deposits/assets), loan share (loans/assets), leverage (liabilities/assets), banks' income gap, and the ratio of unused credit lines to assets. Standard errors in parentheses are clustered by bank. Column (v) includes interactions between these bank controls and AFS value changes. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

I Effects at the Firm Level

Table I.1: Firm Level Effects - Credit Line Access.

	Δ Liabilities		Investment		Δ Cash	
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Δ Value AFS	4.14**		5.30**		10.45**	
	(2.07)		(2.67)		(4.48)	
Δ Value AFS × No CL		5.23**		6.68**		10.84**
		(2.05)		(2.65)		(4.54)
Δ Value AFS × CL		-13.06**		-16.50**		4.39
		(6.16)		(7.23)		(10.41)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
Time	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
R-squared	0.78	0.78	0.72	0.72	0.66	0.66
Observations	83,663	83,663	82,473	82,473	81,901	81,901
Number of Firms	22,499	22,499	22,162	22,162	22,116	22,116
Number of Banks	29	29	29	29	29	29

Notes: Estimation results for regression (6.5) where $y_{i,t}$ is either total liabilities in columns (i) and (ii), fixed assets in columns (iii) and (iv), or cash holdings in columns (v) and (vi). All specifications include firm fixed effects and the firm controls: cash holdings, fixed assets, liabilities, net income, sales (all scaled by total assets), firm size (natural logarithm of total assets), the ratio of observed debt to total debt, as well as the set of all bank controls used in previous regressions and deposit and net income changes from Column (iv) of Table H.3 aggregated to the firm level using debt shares across lenders. Columns (ii), (iv), and (vi) separate firms as to whether they have any unused credit line capacity in our data ("CL") or not ("No CL"). Standard errors in parentheses are clustered by firm. Sample: 2021:Q1–2023:Q1. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.