Do Higher Interest Rates Make The Banking System Safer? Evidence From Bank Leverage

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Abstract

A vast theoretical literature claims that increasing interest rates reduce bank leverage, making banks safer. Validating this empirically is key to understanding monetary policy transmission and its impact on financial stability. I show that raising interest rates *increases* bank leverage. This rise in leverage is consequential as it is accompanied by a meaningful increase in bank failure rates. I propose and validate the *loan-loss mechanism* which explains the entire increase in leverage: contractionary shocks increase loan losses, reduce profits and equity, thus raising leverage. I document why existing models cannot account for this and develop a model of bank risk transformation in which floating-rate loans convert interest rate risk to credit risk, leading to loan losses. Empirical evidence from microdata is consistent with the model's predictions.

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1 Introduction

As early as 1945, one of the most influential economists of the twentieth century, Paul Samuelson, proclaimed that in response to an increase in interest rates, the banking system is "tremendously better off" (Samuelson (1945)).[1] Close to seventy years later, former Federal Reserve Chair Janet Yellen echoed a similar sentiment in an influential speech on monetary policy and financial stability, explaining that higher interest rates reduce financial sector vulnerabilities through reducing their leverage (i.e., ratio of assets to equity).[2] The empirical validity of these claims is critical to improving our understanding of monetary policy transmission through banks in addition to informing the ongoing debate on whether monetary policy should support financial stability. In this paper, I address this first-order question: do contractionary monetary policy shocks make banks safer by reducing their leverage?

The answer to this question, from much of the theoretical literature, is yes. Woodford (2012) argues using a typical New Keynesian model with credit frictions that we should "use monetary policy to 'lean against' a credit boom" which in his model implies higher interest rates reduce leverage. Angeloni and Faia (2013) build a macroeconomic model featuring banks to similarly conclude that an "increase in interest rate activates the risk taking channel: bank leverage and risk decline." Dell'Ariccia et al. (2014) develop a model of financial intermediation where banks engage in costly monitoring to reduce credit risk. Despite their different modelling approach, they also find that: "a reduction in risk-free interest rates leads banks to increase their leverage." Drechsler et al. (2018b) take yet another approach by developing a dynamic asset pricing model in which monetary policy affects the risk premium component of the cost of capital. Nonetheless, their analysis leads to the same claim: "Lower nominal rates make liquidity cheaper and raise leverage." Martinez-Miera and Repullo (2019) also show that "[monetary] tightening reduces aggregate investment…and reduces bank leverage." Finally, Martin et al. (2021) highlight that the framework of Van der Ghote (2021), which consists of a general equilibrium economy with boom-bust cycles, also supports leaning against a boom. Martin et al. (2021) subsequently summarise the theoretical literature by concluding "this is true in most models…By tightening ex ante, monetary policy contributes to reducing credit and, more specifically, leverage."

Given such strong and consistent claims across much of the theoretical literature and a plethora of modelling approaches, one might expect considerable empirical support.

[1] Samuelson (1945) argues that rate hikes improves bank profitability and stability.

[2] https://www.federalreserve.gov/newsevents/speech/yellen20140702a.htm

However, as Boyarchenko et al. (2022) highlight in their review paper, there is a dearth of empirical evidence on the causal impact of monetary policy on leverage and the potential underlying mechanisms. In this paper, I focus specifically on bank leverage rather than economy-wide leverage, as it is substantially higher, constitutes a significant component of economy wide-leverage, and is tightly linked to systemic risk amplification.[3] Despite the central role of intermediary leverage in many macro-financial models (e.g., Brunnermeier and Sannikov (2014)), the causal impact of monetary policy on bank leverage remains largely unexamined.[4]

The first contribution of this paper is to directly estimate the causal impact of monetary policy on bank leverage. My empirical strategy relies on existing measures of exogenous monetary policy shocks which capture unexpected changes in the Fed Funds Rate (FFR). Using quarterly data from the Federal Deposit Insurance Corporation between 1984 and 2007, I estimate lag-augmented local projections of aggregate bank leverage with these exogenous shocks. Contrary to much of the theoretical literature, I find that a contractionary monetary shock that induces a one percentage point rise in the FFR leads to a five to ten percent *increase* in bank leverage. This finding is robust to different definitions of leverage, time-periods, lag lengths, and monetary policy shock series. Importantly, I also show that these same contractionary monetary policy shocks increase the rate of bank failures, indicating that the rise in leverage is not merely a mechanical accounting response but instead reflects real financial fragility which reinforces the economic significance of the main result.[5]

My second contribution is to document a mechanism that explains why leverage increases in response to contractionary monetary policy shocks which also sheds light on how banks respond to and are affected by monetary policy. The literature has traditionally focused on the bank lending channel of monetary policy as a key way in which banks interact with monetary policy (e.g., Bernanke and Gertler (1995)). However, there has been a resurgence of research on monetary policy transmission through the financial system, largely driven by empirical evidence that monetary policy has meaningful consequences on banks in ways not captured by the workhorse New Keynesian models

[3] According to the Flow of Funds data as of end-2024, household leverage (the ratio of assets to net worth) was around 1.1, non-financial corporate leverage was around 1.9, while banking sector leverage was over 10.

[4] Empirical papers related to this question include Miranda-Agrippino and Rey (2020), Wieland and Yang (2020), and Li (2022). However, the primary focus of these papers is not the estimation of a causal domestic bank leverage response to domestic monetary policy.

[5] This is consistent with recent work showing that bank failures are often triggered by equity losses and deteriorating asset quality (e.g., Baron et al. (2021) and Correia et al. (2024)), but shows that monetary policy can be a direct driver of such fragility.

(Drechsler et al. (2018a)). I show that while raising interest rates does indeed reduce bank borrowing (as per the bank lending channel), it also increases the proportion of loans that are delinquent and so increases loan losses. Unexpectedly higher loan losses decrease bank profits which subsequently reduce bank equity. The drop in equity increases leverage more than the drop in borrowing decreases it, so bank leverage increases overall. I term this the *loan-loss mechanism*. I show that the loan-loss mechanism explains almost all the variation in bank leverage in response to contractionary monetary policy shocks. Finally, I provide suggestive evidence, at the macro level, that shows that the rise in loan losses is linked to the direct impact of a higher FFR rather than the recessionary impact of tight monetary policy. This highlights a potential role for floating-rate loans in generating the loan-loss mechanism.[6]

My next contribution is to dissect the theoretical literature in order to show how such different models generate empirically inconsistent leverage responses. Investigating the literature in this way is important not only to provide an empirically-grounded theoretical answer to whether contractionary monetary policy reduces bank leverage, but also because bank leverage, per se, plays a vital role in macroeconomic models with financial sectors. As highlighted in Adrian et al. (2014), in many models, such as Fostel and Geanakoplos (2008), when a bank's own funds are fixed, leverage is the key state variable and lending is determined solely by leverage. This directly connects leverage to the bank lending channel of monetary policy. Furthermore, as commented in Ajello et al. (2022), leverage is core to the financial accelerator models (e.g., Bernanke et al. (1999)), and both amplifies and propagates the response of the economy to shocks, thus generating aggregate fluctuations.

The empirical inconsistency of the literature appears to derive from three broad, though not necessarily mutually exclusive, modelling decisions. First are models such as Angeloni and Faia (2013) and Drechsler et al. (2018b) that rely on some form of direct price effect as the dominant mechanism whereby higher interest rates raise the cost of bank funding and thus reduce bank leverage. Second are models such as Woodford (2012) and Rannenberg (2016) that rely on the observed procyclical behaviour of leverage in order to conclude that leverage declines in response to monetary policy tightening. Finally, models such as Gertler and Kiyotaki (2010) and Gertler and Karadi (2011), while able to generate an increase in leverage in response to contractionary monetary policy shocks, attribute this rise to an increase in expected profitability. Despite an empirically consistent

[6] While rising interest rates can generate losses due to mark-to-market accounting as shown by Jiang et al. (2024), my mechanism does not rely on mark-to-market accounting but rather direct losses due to defaults.

leverage response, the proposed mechanism is inconsistent with the observed evidence that profitability falls rather than rises in response to a monetary contraction.[7] Moreover, this class of models typically generates an increase in leverage in response to any contractionary shock which is inconsistent with the empirical response of leverage to other (non-monetary) contractionary shocks, such as oil shocks. This underscores the importance of the loan-loss mechanism which is specific to monetary policy shocks.

The empirical inconsistencies across models typically arise in the the banking block rather than the general equilibrium structure of the model. Indeed, some banking-specific models generate more empirically consistent dynamics as they feature both a fall in profits and a rise in leverage in response to contractionary monetary policy shocks.[8] However, such models still do not capture a loan-loss mechanism which features a role for floating-rate loans. Therefore, I develop a banking model that emphasises the role of floating-rate loans and credit risk. In my model, banks optimise by choosing the floating share of their loan portfolio. While floating-rate loans hedge against interest rate risk, they do so by passing this risk onto borrowers which generates credit risk for the bank. As such, a key insight of the model is that banks are doing risk transformation, and that this implies a trade-off between managing interest rate risk and credit risk. The model generates testable implications that depend on the share of a bank's loans that is floating rate. Specifically, the model predicts that banks with a higher share of floating-rate loans will see greater loan losses in response to a contractionary monetary policy shock.

Finally, I use microdata (bank-level variation in the share of floating-rate loans) in a panel local projection framework to show that, consistent with the model, banks with higher floating shares experience higher net interest income but also higher loan losses in response to contractionary monetary policy shocks. The effect on profits is more negative for those with higher shares which worsens bank stability. This provides supporting evidence that floating-rate loans contribute to the loan-loss mechanism and has implications for regions more exposed to floating-rate loans.[9]

Overall, my findings that monetary policy tightening can worsen financial stability are consistent with recent work by Grimm et al. (2023) and Jiménez et al. (2024). While these papers do not directly examine the impact of monetary policy on bank leverage, they show that periods of accommodative policy followed by tightening can increase the likelihood of crises. By contrast, I document a much simpler and more direct mechanism: a

[7] English et al. (2018) also find that contractionary monetary policy reduces bank profits while Altavilla et al. (2018) find that long periods of low rates reduce loan losses which raise profits.

[8] See for example Van den Heuvel (2009) and Corbae and Levine (2023).

[9] One can think of these defaults for floating-rate borrowers as being the bank balance sheet perspective of the floating-rate channel documented by Ippolito et al. (2018)

monetary policy hike alone, without requiring a preceding cut or prolonged accommodative period, is sufficient to weaken bank balance sheets through loan losses, especially when the share of floating-rate loans is high, and raise both bank leverage and bank failure rates. In doing so, my findings document a novel way in which the financial accelerator mechanism can operate: a monetary policy hike itself can act as the triggering shock that deteriorates bank balance sheets, raising leverage and amplifying financial fragility. This provides an empirical foundation for concerns in the "leaning against the wind" debate — namely, that attempts to reduce risk ex ante may unintentionally increase fragility ex post. Therefore, the overall contributions of this paper lend support to the conclusions of Svensson (2017), Svensson (2018), and former Federal Reserve Chair Ben Bernanke that monetary policy may not be effective at targeting financial stability.[10] Indeed, my findings would suggest that if the goal is reduce bank leverage to improve financial stability, a more targeted macroprudential approach may better address balance sheet vulnerabilities without interfering with the primary objectives of monetary policy.[11]

2 Data

This paper brings together both aggregate and individual bank-level data, ensuring that the individual bank-level data matches the aggregate data, and combines it with different measures of monetary policy shocks. All data is either already at quarterly frequency or has been transformed to be at quarterly frequency. Data coverage for my baseline analysis is from the first quarter of 1984 up until the last quarter of 2006.[12] For the purpose of documenting external validity, I show my main results hold when using data until 2019 (see Figure 13).

2.1 Aggregate Banking Sector Time-Series Data

The aggregate banking sector time-series data is from the Federal Deposit Insurance Corporation (FDIC). Specifically, I obtain aggregated balance sheet and income statement data for all FDIC-insured institutions for each quarter starting in 1984 using the FDIC's Quarterly Banking Profile data. This provides me with accounting-based measures of dif-

[10] https://www.brookings.edu/articles/should-monetary-policy-take-into-account-risks-to-financial-stability/

[11] Macroprudential policy uses primarily regulatory measures (e.g., bank leverage caps) to limit crisis risk. See for example Galati and Moessner (2018) and Gourio et al. (2018).

[12] Given that the 2007-08 global financial crisis (GFC) resulted in such substantive changes to the regulatory architecture, my analysis will mostly focus on the period prior to the crisis

ferent variables. I also obtain market-based measures of leverage from He et al. (2017).[13] Finally, I obtain a time series of bank failure rates from the FDIC.

From the aggregate balance sheet, I collect time-series data on four key variables. The first variable is total banking sector assets. While useful in its own right, the measure of total assets is mostly used to normalise all remaining variables so that they are interpreted as a share of total assets. Second, I collect data on loans that are 30-89 days past due as a measure of delinquency. The final two variables capture different measures of equity. The first is total equity (sometimes referred to as net worth). Using this measure of equity, I define the simple leverage of a bank as total assets divided by total equity. This is easily comparable across time, space, and banks. As such, when referring to leverage, I will be referencing simple leverage. The second variable is regulatory equity which is also known as Tier 1 capital. This variable is a stricter definition of equity as it excludes several components from total equity such as revaluation reserves and hybrid capital instruments. The regulatory community argues that the Tier 1 Leverage Ratio (i.e., regulatory equity divided by average assets over the quarter) is a more accurate measure of the losses a bank can withstand in response to a shock. Therefore, I also use a measure of regulatory leverage (i.e., total assets divided by regulatory equity) for robustness.[14]

From aggregate income statements, I have four main variables. First, I collect data on aggregate profits as measured by net income from the income statements. Second, I collect data on dividends. The last two variables represent loan losses and are loan-loss provisions and net charge-offs. The former captures a bank's expectation of future loan losses, while the latter are recorded when a bank decides to finally write off a loan. If loan-loss provisions were perfectly estimated by banks, they would be exactly equal to net charge-offs over the long run. In the 10 years prior to the financial crisis, loan-loss provisions averaged around 110% of net charge-offs, which is consistent with regulatory examiners pushing for conservative estimates of expected losses.[15] Therefore, while loan-loss provisions might be slightly conservatively estimated, my analysis utilises provisions instead of net charge-offs for two reasons. First, provisions are recognised in a timelier fashion than charge-offs. Indeed, as soon as a shock occurs, banks will update their estimate of expected loss in accordance with accounting standards. Second, provisions directly impact bank profits and subsequently bank equity so there is a direct accounting-identity

[13] See Appendix B for a discussion on using book (accounting) versus market leverage. Figure C.8 shows the response of market leverage which is qualitatively similar to that of book leverage.

[14] While the regulatory measure uses average assets over the quarter, my data only allows for total assets at the end of the quarter.

[15] https://fraser.stlouisfed.org/title/economic-trends-federal-reserve-bank-cleveland-3952/economic-trends-november-5-2015-529746/loan-loss-provisioning-517772

link between provisions and bank leverage, which will be important for my empirical work.[16] Nonetheless, the underlying mechanism in my empirical analysis remains the same whether one uses provisions or net charge-offs as both respond similarly to a contractionary monetary policy shock (see Figure C.2 in Appendix C).

2.2 Bank-Level Panel Data

I use the bank-level series of Drechsler et al. (2017) which is a merger adjusted consistent time series. I use the same variables used in the aggregate data in addition to the share of loans that is effectively floating-rate which is available from 1997.

2.3 Monetary Policy Data

The monetary policy data has two components. The first is simply the Fed Funds Rate (FFR) which is directly from FRED. The second consists of a number of different estimates of exogenous changes in monetary policy (i.e., monetary policy shocks). There is a large literature on constructing monetary policy shocks and a number of papers that compare and contrast the different shocks (e.g., Ramey (2016)). This paper does not seek to evaluate the effectiveness of a given monetary policy shock. Instead, it focuses on how bank leverage responds to a given exogenous monetary policy shock. A benchmark monetary policy shock used in the literature is the series by Romer and Romer (2004) (the RR shock). Their identification strategy combines narrative methods with the Federal Reserve's (the Fed) own internal forecasts. I use the updated RR shock series from Wieland and Yang (2020) which gives me a quarterly shock from 1984 to 2006. Given its prominence in the literature, the RR shock is the monetary shock used in my baseline specification.

To ensure my empirical results are not dependent on one specific measure of monetary policy shocks, I repeat my analysis with two additional monetary policy shock series. I choose shock series that are estimated using different identification strategies. While the RR shock relies on narrative identification, Gertler and Karadi (2015) (GK shock) rely on high frequency identification, and Bu et al. (2021) (BRW shock) utilise a heteroskedasticity-based partial least squares approach, combined with Fama-MacBeth style cross-sectional regressions.[17] However, unlike the RR shock series which covers my entire sample, the GK shock series starts in 1990 and the BRW shock series does not start until 1994. See Figure C.1 for a time series of each monetary policy shock.

[16] Concerns that banks manipulate the timing of loan-loss provisions for tax advantages were largely addressed by the 1969 and 1986 Tax Reform Acts (Walter (1991)).

[17] Bu et al. (2021) also show their shock contains no significant information effect.

2.4 Non-Monetary Shocks Data

To better understand the loan-loss mechanism, I utilise two additional series. While a contractionary monetary policy shock features a rise in the FFR and a decline in GDP, the two additional series have different economic implications which allows me to disentangle the drivers of loan losses.

The first series is an oil shock series. Oil shocks behave as a 'cost-push' shock and so typically do not feature a meaningful rise in the FFR but still result in a decline in GDP. The oil shock series I use is from Känzig (2021). He exploits the institutional features of the Organization of the Petroleum Exporting Countries (OPEC) and high-frequency variation in oil futures prices around OPEC announcements to identify an oil supply news shock. The time period of the shock series is sufficient to span my empirical exercise (i.e., 1984-2007).

The second series is not a shock per se but rather a measure of risk perceptions. While analysis utilising this measure is predictive rather than causal, it still provides important insights. I use the measure of perceived risk from Pflueger et al. (2020) who define it as the price of volatile stocks (PVS_t) which is the difference between the average book-to-market ratio of low-volatility stocks and high-volatility stocks. When PVS_t is high, agents are optimistic about the economy (e.g., banks are loosening lending standards). Intuitively, one can think of an increase in PVS_t as acting like a positive demand shock and so should result in a rise in the FFR and GDP. I choose this measure of risk perceptions as Pflueger et al. (2020) introduce it to explicitly evaluate risk-centric theories of business cycles (e.g., Caballero and Simsek (2020b)). Such theories explore the interactions between monetary policy and financial stability and have been used to show that tightening monetary policy can have financial stability benefits (see Caballero and Simsek (2020a)).[18]

3 Time-Series Evidence

My empirical approach uses existing measures of exogenous monetary policy shocks in the Jordà (2005) local projection method to estimate impulse responses using data from 1984 until the end of 2006 (unless otherwise specified). This is sometimes referred to as the LP-IV approach (see for example Stock and Watson (2018)). Specifically, I estimate the

[18] In a recent paper, Goldberg and López-Salido (2023) extend the framework of Caballero and Simsek (2020b) and show that leaning against the wind may worsen financial stability.

following for each variable z at each horizon $h = 0, \ldots, 16$:

$$z_{t+h} = \alpha_h + \sum_{l=0}^{L} \beta_{h,l} Shock_{t-l} + \sum_{m=1}^{M} \gamma_{h,m} z_{t-m} + \sum_{q=2}^{4} \delta_q Quarter_{qt} + \epsilon_{t+h}, \tag{1}$$

where z refers to the outcome variable of interest, *Shock* refers to the exogenous monetary policy shock measure, and *Quarter* represents quarterly dummies.[19] The impulse response function is the sequence $\{\beta_{h,0}\}_{h=0}^{H}$ which captures the response of z at time $t+h$ to the shock at time t. In my baseline specification, the lag length is $L = M = 16$ quarters. Finally, I use heteroskedasticity-robust standard errors.[20]

The lead-lag exogeneity condition is an important requirement for my specification, and indeed LP-IV approaches more broadly. Stock and Watson (2018) highlight that the main concern with LP-IV is that the shock at time t is correlated with past values of the outcome variable. They suggest a simple test: the shock should be unforecastable in a regression of the shock at time t on the lags of the outcome variable. Therefore, I regress the RR shock on 16 lags of leverage and find little evidence of predictability. Specifically, each lag is individually statistically insignificant as is the F-statistic when jointly testing all lags.

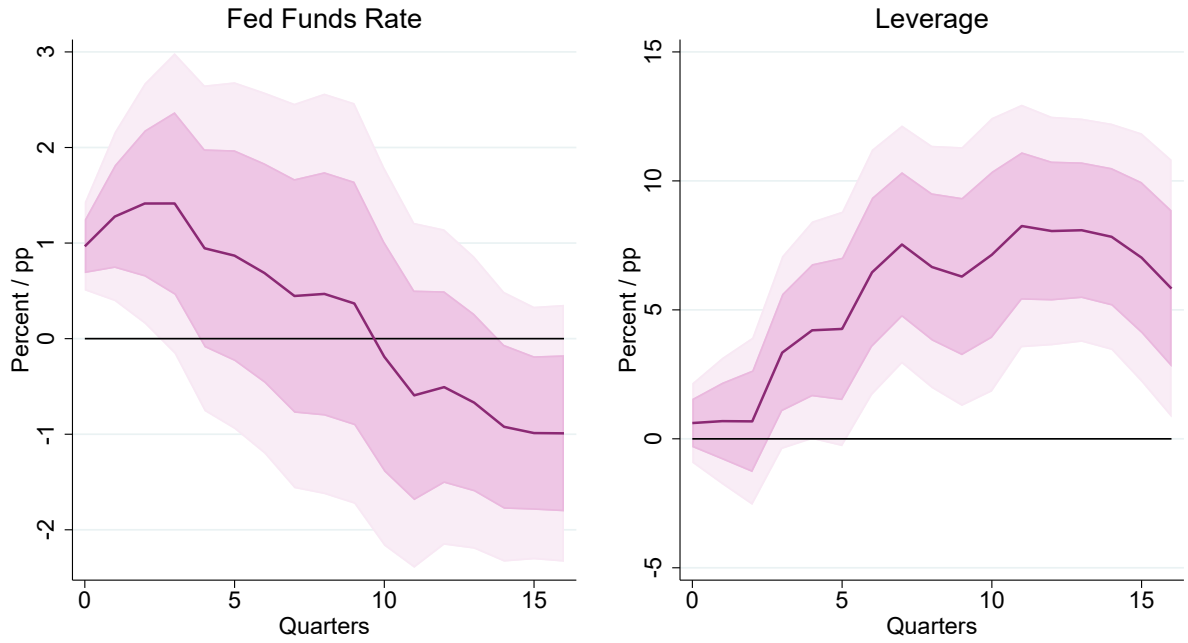
3.1 Leverage Response to Monetary Policy Shocks

My baseline specification is to estimate (1) using data from the first quarter of 1984 until the last quarter of 2006 with 16 lags and the RR shock series. Figure 1 below depicts the impulse responses of the FFR and leverage.

[19] While using the shock directly in the regression is common in the literature (see Ramey (2016)), one can also instrument for the policy rate using the shock in a two-stage regression. As one would expect, estimating this two-stage specification yields very similar results.

[20] Montiel Olea and Plagborg-Møller (2021) recommend using heteroskedasticity-robust standard errors instead of Newey-West with lag-augmented local projections (i.e., where lags of the outcome variable are included as regressors). They further explain that using the same number of lags as the projection horizon implies that local projections and VARs estimate the same impulse response function. As such, my baseline specification has 16 lags.

Figure 1: Impulse Response of Leverage to Contractionary Monetary Shock



68% and 90% confidence bands displayed

The result above shows that a contractionary monetary policy shock that induces an increase in the FFR of one percentage point significantly increases bank leverage by about 5 percent within a year, which then hovers around 8 percent higher for the remaining three years. This is a meaningful response, both in size and persistence, and is in strong contrast to the claims from much of the theoretical literature.

Given the result goes against much of the predictions in the literature, it is important to test the robustness of this finding. First, the result in Figure 1 uses the simple definition of leverage (i.e., total assets divided by total equity). In Figure C.3, I show the same analysis when using regulatory leverage (i.e., total assets divided by regulatory equity). The results do not change in a meaningful way. Moreover, in Figure C.4, I repeat the analysis with the risk-based capital ratio (i.e., total equity divided by risk-weighted assets) which shows a result consistent with the impact on leverage. This confirms that the deterioration in bank balance sheets after contractionary monetary shocks is not an artifact of simple leverage measures. Next, in Figure C.5, I re-estimate (1) using different time periods: 1987-2006, 1990-2006, and 1993-2006. While the period 1989-92 contained a number of regulatory changes relating to bank leverage, the result is remarkably consistent before and after this period. The result is also robust to changing the lag structure (Figure C.6).

My final, and perhaps strictest, robustness test is to use different shock series, each with a distinct identification strategy. To ensure comparability, I use the largest overlap-

ping period (1994-2007). Given the smaller sample, I use 4 lags, otherwise the specification is as in (1). Figure C.7 shows the results from using the Romer and Romer (2004), Gertler and Karadi (2015), and Bu et al. (2021) shock series. Remarkably, the result remains consistent despite using different shocks. Given potential concerns that the results reflect an accounting artifact, I also repeat this exercise with the measure of market leverage from He et al. (2017)) and confirm the response is qualitatively similar and quantitatively larger (Figure C.8). While throughout all the specifications, leverage consistently rises in response to the monetary policy shock, a common feature is that it does so with a reasonable lag which suggests the underlying mechanism is likely to be slow-moving.

3.2 The Loan-Loss Mechanism

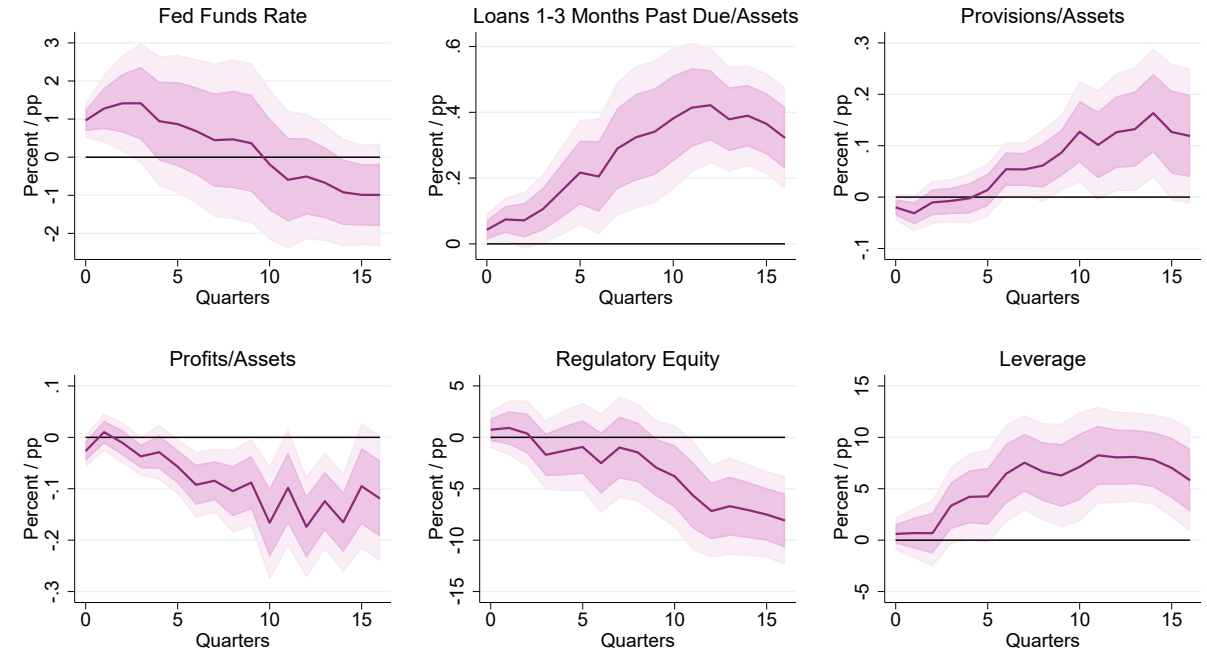
The literature highlights several different mechanisms that might cause an increase in interest rates to decrease leverage. One of the more intuitive reasons is that higher interest rates make debt financing relatively more expensive. Given banks decrease their balance sheets in response to contractionary shocks, the decrease in total liabilities must be driven more by a fall in debt than equity. This direct price effect therefore predicts that higher interest rates reduce bank leverage.

For leverage to rise overall, it must be that the fall in equity is more consequential. As such, I posit an additional mechanism, which I term the *loan-loss mechanism*, that might be driving the overall response in leverage (and offsetting the direct price effect). The mechanism is simple and intuitive and is best described in three key steps. First, a rise in interest rates leads to greater difficulty for borrowers to repay loans. This should result in *(i) an increasing proportion of loans past due* and *(ii) a delayed but increasing proportion of loan-loss provisions*. The latter rises as banks raise their estimates of expected losses due to the unexpected growth in missed loan repayments. Second, greater loan losses overall, as measured by (ii), should result in *(iii) decreasing profits*. Finally, all else equal, decreasing profits should lead to *(iv) decreasing bank equity* and if the overall fall in equity is more important than the fall in assets, then we would expect *(v) increasing leverage*.

To test my mechanism, I estimate my benchmark specification (i.e., (1) with the RR shock, 16 lags, and data from 1984-2006) separately for each of the five variables emphasised in the paragraph above (Figure 2). The first panel (top-left) simply reproduces the impulse response function of the FFR and so the remaining analysis can be interpreted as responding to a monetary policy shock that induces the FFR to increase by around one percentage point on impact. The second panel (top-middle) shows that loans that are up to three months past due increase by nearly 0.5 percentage points as a proportion of total

assets at their peak. This is a significant rise as the average share of loans past due during 1984-2006 is around 0.8%. This confirms (i). The third panel (top-right) shows that provisions as a proportion of total assets also increase, albeit at a slower pace, which confirms (ii). The greater than 0.1 percentage point rise in provisions is also significant as it is roughly double its average by the end of the projection horizon. The fourth panel (bottom-left) shows that profits as a proportion of total assets decrease by around 0.15 percentage points from an average of around 0.22% at around the same time as when provisions rise which confirms (iii). The fifth panel (bottom-middle) shows equity falls by nearly five percent within two years and continues to fall to nearly a ten percent decline by the end of the horizon which confirms (iv). Finally, the sixth panel (bottom-right) simply reproduces the main finding in Figure (1) (i.e., that leverage rises) and thus confirms (v).

Figure 2: Mechanism Underlying Leverage Response



3.3 Importance of the Loan-Loss Mechanism

Despite the evidence supporting my mechanism, it is possible that other mechanisms might be more important in driving the increase in leverage. One approach to deal with such concerns is to rule out alternative mechanisms. However, such an approach is not exhaustive as it is difficult to know all possible alternative mechanisms; the best we can usually do is to rule out the most likely contenders. Therefore, instead of ruling out alternative mechanisms, I show empirically the importance of my mechanism directly by

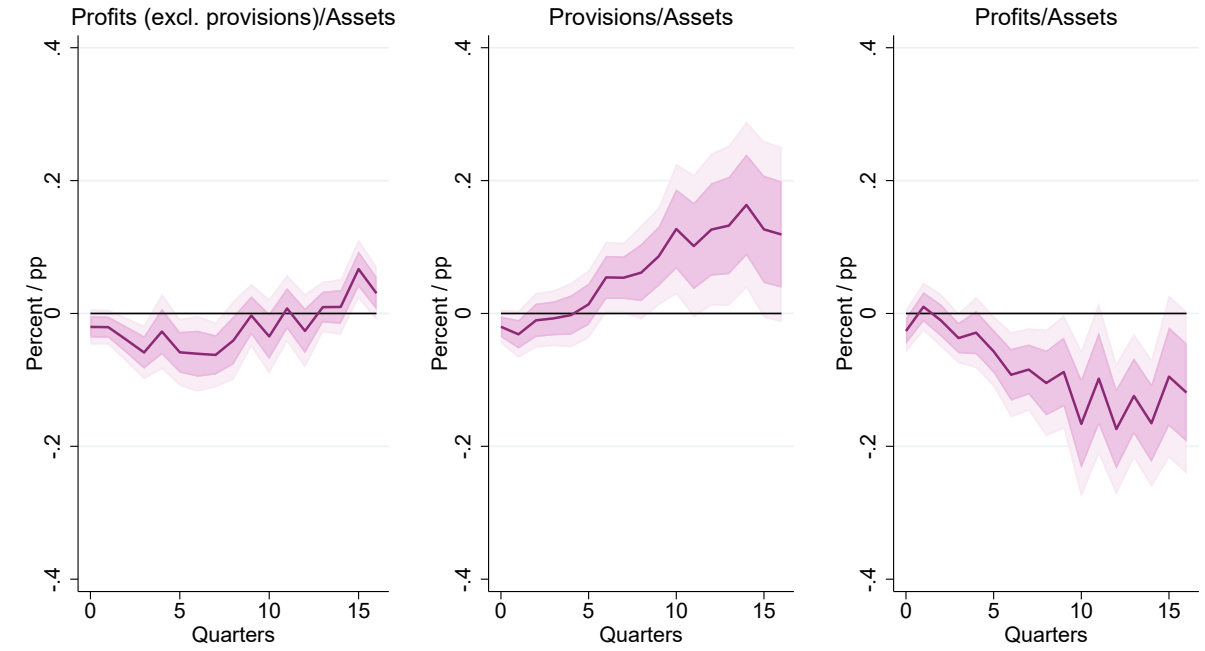
taking advantage of accounting identities.

For my mechanism to be driving the overall response, I need to document two steps. First, that the increase in loan losses, as measured by provisions, in response to contractionary monetary policy shocks (top-right panel of Figure 2) is *causing* most, if not all, of the decrease in profits (bottom-left panel of Figure 2). Profits can be decomposed into several components on a bank income statement:

$$\frac{\text{Profits (excluding provisions)}_t}{\text{Assets}_t} - \frac{\text{Provisions}_t}{\text{Assets}_t} = \frac{\text{Profits}_t}{\text{Assets}_t} \tag{2}$$

where the first term is constructed by adding together net interest income, net noninterest income, net gains on securities, and subtracting taxes. Therefore, if my mechanism is important, it should be the case that the variation in profits is driven by the variation in provisions rather than the other income terms. Figure 3 below shows the impulse responses of each term in (2) which are obtained by estimating (1) with each of those terms as the outcome variable.

Figure 3: Decomposing the Profit Decline



The variation in overall profits is driven almost entirely by the variation in provisions with the remaining variation (captured by profits excluding provisions) being relatively immaterial. This is consistent with findings in the literature that document the stability of bank net interest income (e.g., Drechsler et al. (2021)). Thus my mechanism appears

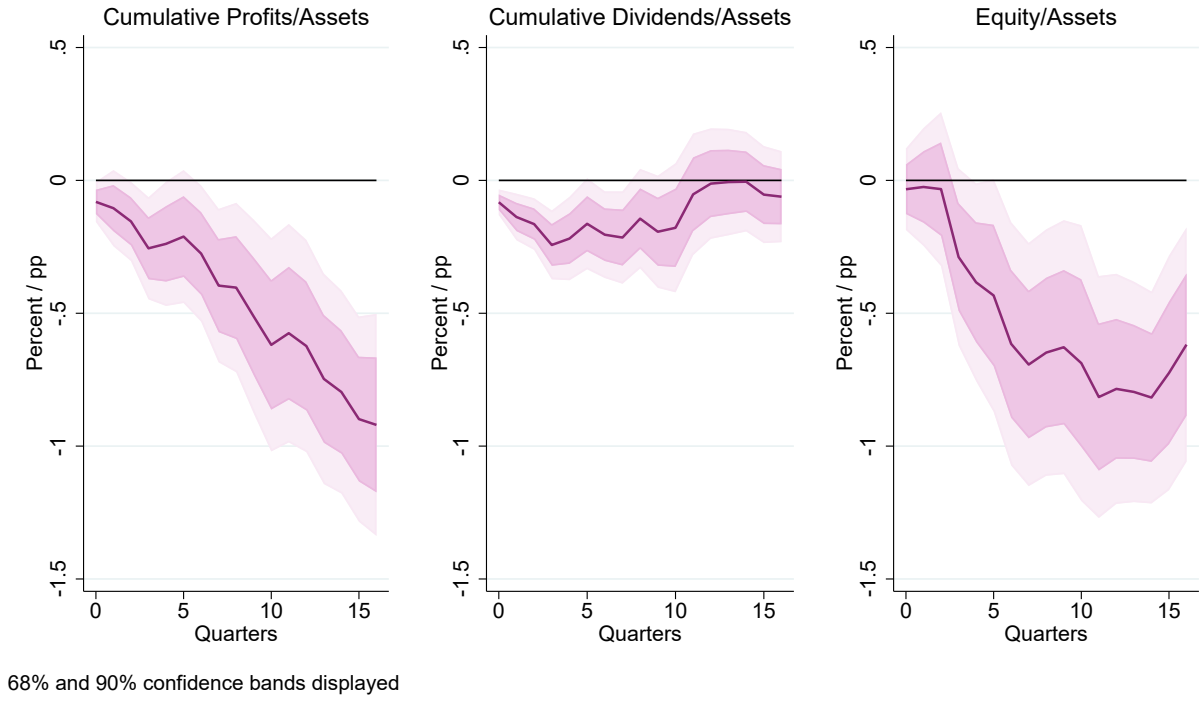
to be the key driving force behind the fall in profits.

The second step I need to document is that the fall in profits (bottom-left panel of Figure 2) is *causing* most, if not all, of the increase in leverage (bottom-right panel of Figure 2). Combining information from both the income statement and balance sheet, I utilise the following identity for a balance sheet item at time t:

$$\frac{\text{Cumulative Profits}_t}{\text{Assets}_t} - \frac{\text{Cumulative Dividends}_t}{\text{Assets}_t} \approx \frac{\text{Equity}_t}{\text{Assets}_t} = \frac{1}{\text{Leverage}_t} \tag{3}$$

Note that (3) shows we need a measure of cumulative profits to transform an income statement measure (a flow) to a balance sheet measure (a stock). Equity at time t is constructed by adding all profits earned before t to the starting equity then subtracting all dividends paid before t and finally making some accounting adjustments (e.g., revaluations) at horizon t. While I do not have a direct measure of the accounting adjustments, I can construct the two cumulative measures: cumulative profits and cumulative dividends (accumulated from 1984 to 1984 + t). If my proposed mechanism is important, the variation in leverage should be driven by the variation in profits. Figure 4 shows the impulse response of the first, second, and final term of (3) which are obtained by estimating (1) with each of those terms.

Figure 4: Decomposing the Leverage Increase



As can be seen, the variation in overall leverage (or more precisely the inverse of lever-

age) is largely driven by the variation in cumulative profits. As one might expect due to the potential penalties associated with reducing dividend payments (Guttman et al. (2010)), the response of cumulative dividends is muted. Moreover, while not shown, there is little unexplained variation after accounting for cumulative profits and dividends which implies that accounting adjustments would not be driving the overall response. Therefore, I have shown that my mechanism is driving the overall response in leverage as the decrease in profits is largely driven by the increase in loan losses and the increase in leverage is largely driven by the decrease in profits.[21]

One take-away thus far is that the macro-banking models used to understand monetary policy and its interaction with financial stability should allow for contractionary interest rates to raise bank leverage, given the robustness of the empirical moment. Furthermore, understanding what specifically drives loan losses will be key to determining the features that might be important when developing such models.

3.4 Drivers of Loan Losses

While loan losses drive the variation in bank leverage in response to monetary policy shocks, it is not clear why loan losses respond in the first place. Intuitively, contractionary monetary policy can cause unexpected loan losses for two reasons. First, a higher FFR may directly raise the loan-servicing cost on floating-rate loans (or short maturity fixed-rate loans) which reduces a borrower's ability to repay and hence raises loan losses. Second, a higher FFR may reduce incomes due to its recessionary impact which also reduces a borrower's ability to repay and hence raises loan losses. However, contractionary monetary policy both increases loan-servicing costs by directly raising the FFR and reduces borrower income by reducing GDP; it is unclear whether a higher FFR or lower GDP is driving loan losses.

One way to assess whether a higher FFR or lower GDP is driving loan losses is to consider variation that only affects one of the two factors. Cost-push shocks provide such variation as despite their recessionary impact, central banks are less likely to react by raising interest rates. Oil shocks are a classic example of cost-push variation. Indeed, in response to an oil shock, we would expect a fall in GDP with little reaction of the FFR. This leads to the following empirical test: if loan losses are driven by the direct impact of the FFR on loan-servicing costs, then we expect loan-loss provisions to respond to a monetary shock but not to an oil shock.

[21] While bank assets and bank borrowings also fall which puts downward pressure on leverage, the reduction in equity is far more important empirically in driving the variation in leverage.

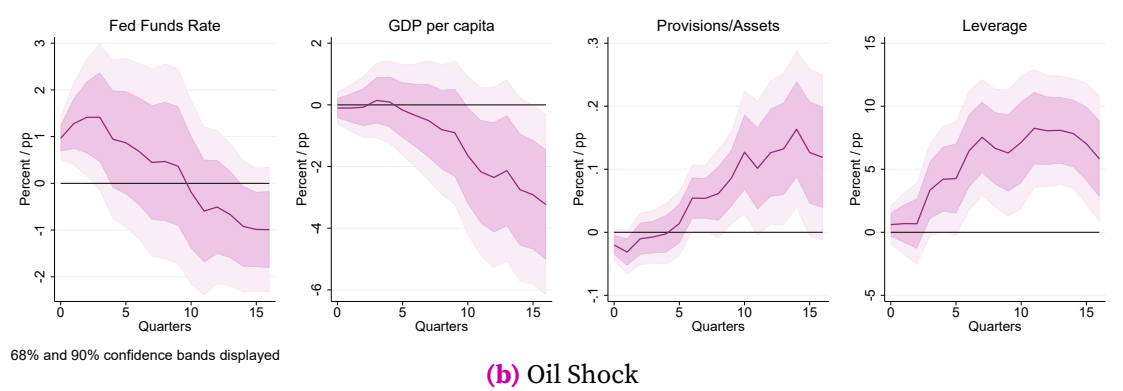
Figure 5 presents the results of the empirical test. 5a shows the effect of a contractionary monetary policy shock on the FFR, GDP, loan-loss provisions and bank leverage while 5b shows the effect of an oil shock on these same variables.[22] As expected, both shocks decrease GDP, while only the monetary shock features a rise in the FFR. Loan-loss provisions rise in response to the contractionary monetary policy shock but not in response to the oil shock which suggests the direct impact of the FFR on loan-servicing costs is important in generating loan losses. Moreover, leverage only rises in the case of the monetary shock which is further validation of the importance of the loan-loss mechanism in driving variation in leverage. However, this is only suggestive evidence as cost-push shocks also result in greater inflation (see Figure C.9) and higher than expected inflation can decrease the real value of debt of borrowers, making default less likely (Gomes et al. (2016)).

Therefore, as additional corroborating evidence, Figure 5 extends the empirical test with the risk perception series mentioned in Section 2.4. A rise in PVS (the measure of risk perception) can be thought of as a decline in risk and an increase in optimism by agents in the economy. Therefore, it behaves similarly to a positive aggregate demand shock (indeed both GDP and inflation rise as can be seen in Figure C.10). Figure 5c shows both the FFR and GDP rise, as is typically the case with positive demand shocks. Loan-loss provisions rise despite the improvement in GDP (which can improve borrower cash flow) and higher than expected inflation (which can decrease the real value of debt of borrowers) which suggests that the direct impact on loan-servicing costs due to the increasing FFR is especially important.

[22] Each figure is estimated as a separate local projection following the specification in (1).

Figure 5: Disentangling the Drivers of Loan Losses

(a) Monetary Policy Shock



(b) Oil Shock

(c) Risk Perception (PVS)

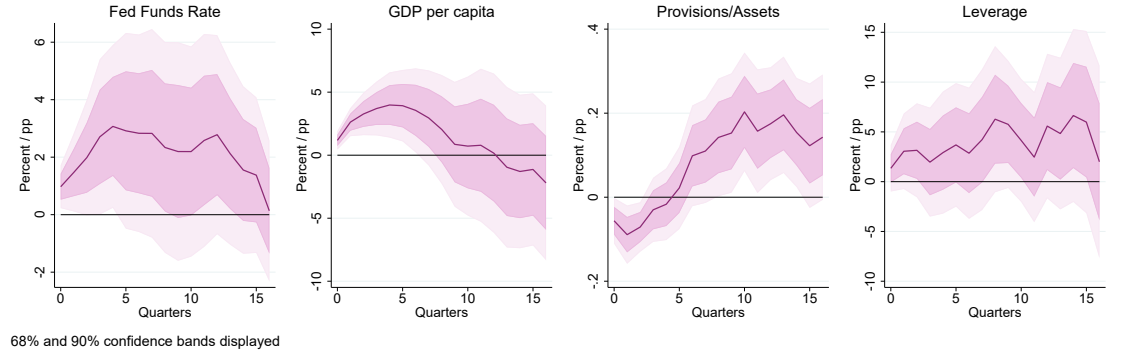


Figure 5 lends support to the idea that loan losses are driven by floating-rate loans where higher interest rates directly increase loan-servicing costs, but it is only suggestive evidence. In Section 5, I formalise the role of floating-rate loans in a simple banking model and test its implications using microdata in Section 6.

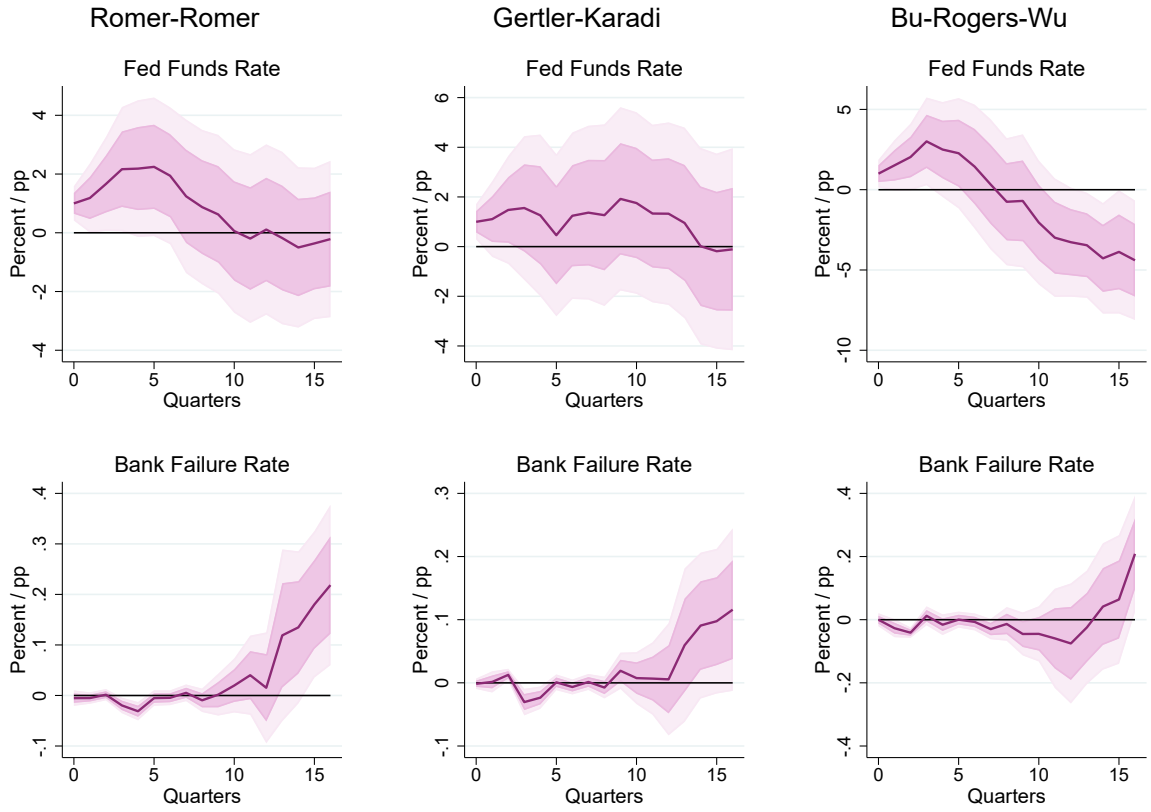
3.5 Bank Failures and Monetary Policy Shocks

While the preceding analysis shows that contractionary monetary policy shocks increase bank leverage by increasing loan losses and reducing profits, a natural question arises:

do these same monetary policy shocks also translate into real financial fragility? While financial fragility could have numerous definitions, I focus on a simple measure: the failure rate of banks. As such, I estimate the response of the bank failure rate using the same specification as in previous sections across three different shocks.

Figure 6 shows that across all the different shocks, a one percentage point hike in the FFR leads to a statistically significant increase in the bank failure rate towards the end of the projection horizon. This is an economically meaningful increase as it is more than double the average failure rate over the sample period. These results suggest that the rise in leverage documented earlier is not a mechanical accounting artifact, but instead reflects a meaningful deterioration in the stability of the banking sector.

Figure 6: The Response of the Bank Failure Rate to Different Monetary Policy Shocks



68% and 90% confidence bands displayed

The above findings are consistent with Baron et al. (2021) and Correia et al. (2024) who document that bank failures are typically the result of equity losses and asset deterioration. However, my findings additionally highlight that these deteriorations can be a direct result of monetary policy. This has important implications for the interaction of monetary policy and financial stability. For example, the risk-taking channel of monetary policy posits that contractionary monetary policy supports financial stability through

a reduction in bank risk-taking. While the reduction in bank risk-taking has been documented empirically, the focus is on risk-taking on new loans.[23] Given the bank failure rate increases, it would appear that the reduction in risk on new loans is not sufficient to offset the increased risk of existing loans when the interest rate increases over my projection horizon.[24] This suggests that unexpected monetary contractions can instead lead to financial instability in the near term.

Given such a clear mechanism in the data, and the fact that, contrary to the conventional wisdom, monetary policy increases both bank leverage and bank failure rates, it is important to first examine precisely where the theory and empirics diverge as this yields important modelling implications.

4 Why do so many models generate a counterfactual leverage response?

The divergence of the literature from the empirical evidence appears to derive from three broad, though not necessarily mutually exclusive, modelling choices: relying on a direct price effect; relying on procyclical leverage; and, relying on a profitability channel. In Appendix D, I explain in detail how each of these modelling choices leads the model to generate empirically inconsistent leverage predictions as well as highlighting the typical models in each category. In this section, I briefly describe the underlying mechanisms of each type of model.

Models that rely on the direct price effect require that an increase in interest rates raises the relative cost of debt financing for banks in some form and so banks substitute away from debt financing which is equivalent to a reduction in leverage. The overarching message of these models is summarised in the review paper by Ajello et al. (2022): "Accommodative monetary policy reduces the cost of funding for banks, and thus may increase reliance on debt by banks." The direct price effect is the underlying mechanism across a variety of models (see Appendix D.1). While debt financing does fall in response to higher interest rates in my data (see Figure D.1), the empirically dominant mechanism is the loan-loss mechanism which not only offsets the effect on leverage from falling debt liabilities, but actually leads to a reversal in sign such that contractionary monetary policy shocks increase leverage.

[23] See for example Jiménez et al. (2014), Dell'Ariccia et al. (2017), Bonfim and Soares (2018) among many others.

[24] It is of still possible that the economy reaches a new steady state eventually where risk is lower.

Models relying on leverage procyclicality highlight that this procyclicality is widely documented in the literature (e.g., Adrian and Shin (2010), Laux and Rauter (2017), and Adrian et al. (2019)). However, the procyclicality between leverage and output is correlational, not structural. In Figure D.2 of Appendix D.2, I confirm that this procyclicality is also true in my data. Models using this feature of the data typically have some form of the following mechanism embedded in the model: a contractionary monetary shock reduces output and because leverage is procyclical, it also reduces leverage. This leads to the conclusion that monetary policy should 'lean against the wind' by tightening in response to increasing leverage. Indeed, Woodford (2012) embeds this mechanism in a workhorse NK model to also support leaning against the wind (see Appendix D.2 for details). However, one cannot match conditional moments in a model to unconditional moments in the data. Moreover, as Galí (1999) points out, evaluating models based on their ability to match unconditional moments in the data can be misleading as the model may perform well according to that criterion despite providing a very distorted image of the economy's response to different types of shocks. Therefore, a conditional leverage moment, as I have documented, serves as a much sharper test of the model, and one that directly provides insight on the role of monetary policy through banks.

Models that rely on a profitability channel build on the canonical models of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) which are some of the most influential macroeconomic models featuring a banking sector. The defining feature of this class is that they use a Gertler-Karadi-Kiyotaki-type constraint (i.e., an incentive-compatibility leverage constraint) to model banks which generates the profitability channel.[25] In Appendix D.3, I follow a stylised model of Gertler and Karadi (2011) to precisely depict the mechanisms in these models. In this section, I highlight the two key features that generate the empirical inconsistencies.

First, while these models correctly show that leverage increases in response to a contractionary monetary policy shock, they have leverage increasing alongside an increase in profitability (which I term the profitability channel). The incentive-compatibility constraint in these models means banks have an incentive to cheat depositors (which forces the bank to close) if the return from doing so is higher than the return from staying in business. Therefore, if banks expect greater profits, then the return from staying in business is higher and so they have less incentive to cheat depositors. As such, depositors are more willing to lend to banks which raises bank leverage. In the model, contractionary monetary policy raises future bank profits and thus bank leverage. This link between

[25] This modelling approach is widely used in the literature (e.g., Gertler and Kiyotaki (2015), Maggiori (2017), Gertler et al. (2020), Van der Ghote (2021), Sims and Wu (2021)).

higher bank profits and higher leverage is derived solely from the bank problem and incentive constraint (see equation (27) in D.3)) and is at odds with the empirical evidence that the increase in leverage following a contractionary monetary policy shock *is caused by* a decrease in profits. The Gertler and Karadi (2015) series itself generates a negative profit response which is inconsistent with the Gertler and Karadi (2011) model (see Figure D.3).

Despite the empirical inconsistency regarding the mechanism, one could argue that it is sufficient that Gertler and Karadi (2011) and similar models are able to predict that leverage rises following contractionary monetary policy shocks. This leads to the second key feature in these models: given equity frictions, *any* negative shock increases bank profitability and leverage (see equation 30 in D.3).[26] This feature allows such models to correctly predict that leverage rises in response to contractionary monetary policy shocks, but it also means that all other negative shocks would yield a rise in leverage which is a much stronger claim. I have already provided one counterexample to the claim that any negative shock will increase bank leverage as negative oil shocks decrease leverage (Figure 5b). Therefore, the type of shock matters empirically not just in terms of magnitude but also direction. While both an oil shock and monetary policy shock cause a decline in GDP, only the latter increases loan losses, which also highlights the role of floating-rate loans. This again underscores the importance of the underlying loan-loss mechanism; a component missing from Gertler and Karadi (2011). Ensuring the mechanism is modelled appropriately ensures that the predictions are made in the right context.

One important aside is that in the theoretical literature there are typically two types of analyses when considering monetary policy and financial stability. One that considers exogenous monetary policy shocks (e.g., Gertler and Karadi (2011) and Drechsler et al. (2018b)) and another that derives a monetary policy *rule* that suggests leaning against the wind (e.g. Woodford (2012) and Van der Ghote (2021)). Therefore, one may argue that the analysis in this paper is only pertinent to the papers considering exogenous shocks. However, Wolf and McKay (2023) show that analyses using exogenous shocks and analyses considering alternate policy rules can be equivalent under certain conditions. Specifically, if policy affects behaviour only through the current and future expected path of the policy instrument (the case in most models), then a prevailing non-leaning-against-the-wind monetary policy rule subject to a particular sequence of contractionary interest rate shocks is identical to some counterfactual leaning-against-the-wind policy rule. Put

[26] A negative shock increases the marginal value of net worth because it causes an on-impact decrease in the price of capital, Q. This reduces bank net worth as bank assets are now worth less. A fall in net worth means banks are less able to lend which decreases total loans. A fall in total lending raises the expected profitability of lending which raises the marginal value of net worth.

simply, the private sector is not able to distinguish between a contractionary shock and a change in the monetary policy rule that would generate the same contractionary shock. As such, my empirical findings are relevant for analyses involving both exogenous shocks and modified policy rules, albeit more directly for the former.[27]

5 An Empirically Consistent Theoretical Model

The models presented thus far capture a wide variety of the results in the literature as they are some of the most foundational models. However, they do not capture the empirical dynamics that I have documented. One interesting exception is Di Tella and Kurlat (2021) who show that due to bank risk aversion, higher interest rates lead to losses for banks. Nonetheless, a missing component across the models is the loan-loss mechanism.[28] Moreover, while many of the models explored in the previous section are GE models (as is typically the case when modelling monetary policy), we did not need to examine the whole GE structure as the empirical inconsistencies arise primarily from how the banking system is modelled (e.g., from the bank problem in Gertler and Karadi (2011) or the bank leverage law of motion in Woodford (2012)).

Partial equilibrium banking models, such as Van den Heuvel (2009) and Corbae and Levine (2023), appear better able to generate consistent empirical dynamics. Van den Heuvel (2009) develops the bank capital channel of monetary policy which sees profits fall and leverage rise following contractionary monetary policy. The underlying mechanism of the model is through maturity transformation rather than loan losses. However, he also shows how an exogenous default shock, unrelated to monetary policy, works in the model and generates dynamics similar to the loan-loss mechanism. Nonetheless, there is still no explicit role for floating-rate loans which appear to be an important feature in the data (see Section 6). Corbae and Levine (2023) take a different approach but also see profits fall and leverage rise in response to contractionary monetary policy. The mechanism is also different to the loan-loss mechanism as higher rates raise the marginal cost of financing for banks which induces greater risk-taking and a fall in profits. While such models get fairly close to matching the empirical dynamics, the mechanism underpinning the fall in profits in these models is different to loan losses and does not feature a role for floating-rate loans, both of which appear important for the empirical mechanism.

[27] Wolf and McKay (2023) note that their result is less suited to study policies that alter the steady state (e.g., changes in the inflation target). However, many analyses of optimal rules compare different cyclical stabilisation policies such as augmented Taylor rules, where the results of Wolf and McKay (2023) apply.

[28] Di Tella and Kurlat (2021) argue that banks sustain mark-to-market losses rather than credit losses in response to contractionary monetary policy.

Therefore, from examining theories that are unable to match the empirical dynamics as well as those that match them better, one can surmise the following. First, the general equilibrium structure does not appear to be especially important in generating the dynamics of leverage in response to shocks. This means one can focus on partial equilibrium banking models in order to illuminate the mechanism more clearly. Second, a common missing ingredient across most models is loan losses that are increasing in contractionary monetary policy shocks which drive the fall in bank profits in response to such shocks. Third, there needs to be a potential role for floating-rate loans in generating loan losses. For these reasons, I develop a parsimonious model with these three components. The goal of the model is not to fully characterise general equilibrium interactions, but to provide a minimal partial equilibrium framework that isolates the key mechanism: risk transformation through floating-rate lending and thus generate implications which can be tested using microdata.

By focusing only on floating-rate loan issuance and interest rate risk on deposits, my model illuminates a novel *risk transformation* function of banks which works as follows. Banks are exposed to interest rate risk because their deposits are floating-rate liabilities (i.e., when interest rates rise, deposits become more costly). To hedge the interest rate risk and alleviate the cash flow mismatch on their balance sheets, banks issue floating-rate loans. So when interest rates unexpectedly rise, while banks have to pay more to depositors, they also receive more income from floating-rate borrowers. However, this hedge transfers the risk from banks to borrowers. Unlike banks, borrowers cannot hedge against unexpected interest rate changes.[29] As such, in response to contractionary monetary policy shocks, borrowers are less able to repay their loans which leads to loan losses for banks. Such losses represent a credit risk for the bank. Therefore, through issuing floating-rate loans, banks are conducting risk transformation as they are hedging interest rate risk at the expense of greater credit risk. In order to remain parsimonious and specifically highlight the potential role for floating rate loans for loan losses, the model abstracts away from alternative interest rate risk hedges such as derivatives or short-term treasuries.

My model builds on Kirti (2020) but incorporates credit risk via loan losses. Consider a one-period model with the following timeline. First, banks make loans funded by deposits and internal net worth. Second, the realization of the monetary shock takes place. Finally, repayment occurs. Banks are exogenously endowed with deposits D and a loan portfolio

[29] There is an important distinction between unexpected and expected changes in interest rates. Expected interest rate changes are procyclical, so borrowers are naturally hedged as their loan-servicing costs rise and they receive greater cash flows. See Figure 12 and the associated discussion.

of size L, as such, internal net worth is $N = L - D$. The key choice for banks is the share of floating-rate loans f_L in their loan portfolio. The deposits are floating-rate liabilities. However, as shown by Drechsler et al. (2017), there is not perfect pass-through of the central bank interest rate to deposit rates. In the model, the pass-through coefficient, known as the deposit-beta (β^{dep}), is exogenous but one can microfound this by following Drechsler et al. (2017). The interest rate is a random variable $r = \bar{r} + \varepsilon$ where $\varepsilon \sim \mathcal{N}(0, \sigma^2)$. Therefore, $\mathbb{E}[r] = \bar{r}$, $Var[r] = \sigma^2$. Note that ε is the monetary policy shock.

The one-period nature of the model implies leverage moves in lockstep with profits (i.e., if profits fall, leverage rises). I choose this approach because, as in most models, banks have limited scope to adjust dividends or raise equity. Therefore, the interesting variation comes from the response of profitability. As such, the testable implications of the model focus on profits and its components rather than leverage. The goal is to understand whether in response to contractionary monetary policy shocks, bank profits differentially respond based on the share of floating-rate loans.

I model banks as having mean-variance preferences for simplicity.[30] Banks maximise value V by choosing the share of its loan portfolio that is floating rate:

$$\max_{f_L} V = \mathbb{E}[\pi] - \frac{\gamma}{2} Var[\pi]$$

where π is bank profits and γ captures risk-aversion. Solving this yields an expression for f_L^* in terms of μ which is solved in equilibrium with the firm problem (see Appendix A for the full model and an analytical expression for f_L^*). However, the core insight from the model comes from the following thought experiment: given the optimal choice f_L^*, what is a bank's profits?

$$\pi = \overbrace{\underbrace{L(1-f_L^*)(\bar{r}+\mu^*(f_L^*))}_{\text{fixed-rate income}} + \underbrace{Lf_L^*(\bar{r}+\varepsilon+\mu^*(f_L^*))}_{\text{floating-rate income}} - \underbrace{D(\bar{r}+\beta^{dep}\varepsilon)}_{\text{cost of deposits}}}^{\text{Net Interest Income}} - \overbrace{Lf_L^*\theta(\varepsilon)}^{\text{Loan Losses}} \tag{4}$$

μ^* is the equilibrium loan spread between the lending rate charged to firms and the central bank interest rate.[31] One key point in (4) is that net interest income is not the same as profits. Indeed, as seen in the aggregate data, loan losses drive the vast majority of the variation in bank profits in response to a monetary policy shock. The model only features loan losses on floating-rate loans. $\theta(\varepsilon)$ is the loan-loss rate where $\theta'(\varepsilon) > 0$ and $\theta'(\varepsilon)$ is lin-

[30] The assumption that banks have risk-averse preferences is not uncommon in the literature. See discussion in Di Tella and Kurlat (2021).

[31] μ^* is decreasing in the floating share of loans as banks have to accept a lower spread because firms are risk-averse and will also want to avoid bearing interest rate risk.

ear in ε. This is intended to capture in a reduced-form way that loan losses are increasing in the size of the monetary policy shock. There are no unexpected loan losses on fixed-rate loans as a change in the central bank interest rate does not impact the loan-servicing cost of the fixed-rate borrower. While recessions may also induce defaults, the model rules out any recessionary channel of defaults as the purpose is to specifically highlight the role of floating-rate loans in order to explain that in the aggregate data we see loan losses rise with contractionary monetary policy shocks but not for other contractionary shocks.

I define deviations from expected profits (as measured by return on assets) as

$$\begin{aligned} \Delta &= \frac{\pi}{L} - \frac{\mathbb{E}[\pi]}{L} \\ \implies \Delta &= \underbrace{f_L^* \varepsilon - \frac{D}{L}\beta^{dep}\varepsilon}_{\text{interest rate risk}} \underbrace{- f_L^* \left(\theta(\varepsilon) - \mathbb{E}[\theta(\varepsilon)]\right)}_{\text{credit risk}} \end{aligned} \tag{5}$$

Equation (5) represents a key insight of the model. The bank is exposed to interest rate risk because a contractionary monetary policy shock makes deposits more expensive. Floating-rate loans generate more revenue for the bank when interest rates increase and therefore banks issue floating-rate loans as a way to hedge interest rate risk. This is consistent with Kirti (2020) who shows empirically that banks that have a higher deposit pass-through (higher β^{dep}) issue more floating-rate loans. However, the core insight of (5) is that this interest rate risk hedge comes at the expense of credit risk. Specifically, the bank hedges the interest rate risk by passing that risk onto the borrower. If a borrower cannot hedge this risk, it generates loan losses for the bank. In the model, this is captured by $\theta(\varepsilon)$. A simple example can illustrate this more clearly. Consider a bank that issues a floating-rate loan that exactly tracks the central bank rate. If the central bank raises the interest rate, the borrower now has to pay more on the loan which raises the probability of default of the borrower. The bank has merely traded interest rate risk for credit risk. While in many models, banks do maturity transformation, my model highlights a different function that banks carry out: *risk transformation*. In the model, the bank has a single choice variable to manage two risks and is unable to mitigate both simultaneously. Therefore, it specifically highlights the potential for floating-rate loans to generate loan losses in response to contractionary monetary policy shocks.[32]

By differentiating equation (5) with respect to the monetary shock (ε), I construct the

[32] See Hellwig (1994) for a similar argument about the trade-off between interest rate risk and credit risk in relation to the Basel I regulatory framework.

model counterparts to the empirical impulse response functions:

$$\underbrace{\frac{\partial \Delta}{\partial \varepsilon}}_{\text{Profits IRF}} = \underbrace{f_L^* - \frac{D}{L}\beta^{dep}}_{\text{Net Interest Income IRF}} - \underbrace{f_L^* \theta'(\varepsilon)}_{\text{Provisions IRF}} \tag{6}$$

Equation (6) simply states that the impulse response function of profits with respect to an interest rate shock is equal to the difference between the impulse response functions of net interest income and loan-loss provisions.[33]

Importantly, equation (6) yields specific implications for the role of floating-rate loans. First, looking at the impulse response function of loan-loss provisions (the final term in (6)), we can see that it is increasing in the share of floating-rate loans. This tells us that loan losses will increase by more in response to a contractionary shock for banks with a higher floating share. Second, the impulse response function for net interest income is also increasing in the floating share which tells us that net interest income will respond more positively in response to a contractionary shock for banks with a higher floating share.[34] This captures the trade-off between interest rate risk and credit risk. The model suggests that in response to a contractionary shock, banks with a higher floating share should experience a larger increase in net interest income but also a larger increase in loan-loss provisions.

The overall impact on bank profits will depend on the impact on net interest income relative to that on loan losses. However, we know from the aggregate data that profits fall, so one would expect that the impact of loan losses will dominate.

Before testing the model implications with microdata, it is worth highlighting a few limitations of the model. First, in the model, banks can only manage risk through issuing floating-rate loans. This is a simplifying assumption as banks have many alternative methods to manage risk. As mentioned earlier, banks can utilise interest rate derivatives, purchase short-term assets (such as US treasuries), or simply rely on the deposit franchise, to hedge interest rate risk. If these alternative forms of hedging are especially important, one might expect that the predictions of the model regarding floating-rate loans will not be consistent with the data. Banks can also manage risk by lending to less risky borrowers, i.e., the risk-taking channel of monetary policy. This channel is well documented in literature both theoretically and empirically (e.g., Dell'Ariccia et al. (2014) and Dell'Ariccia et al. (2017)). However, my model predicts that a higher share of floating-rate

[33] I abstract away from other components of bank income such as fee income or salary expenses as these components are not core to understanding the loan-loss mechanism.

[34] Strictly speaking, it will also depend on the correlation between the share of floating-rate loans and the product of the deposit-loan ratio and deposit beta.

loans prior to a monetary contraction would result in higher loan losses and potentially worse profits due to the existing stock of loans. This is a different mechanism to the risk-taking channel which typically finds that a contractionary monetary policy shock lowers risk-taking and therefore would predict fewer losses on the flow of new loans. Indeed, at the aggregate level, I have shown in Section 3.3 that loan losses explain the decline in bank profits in response to a contractionary shock so even if risk-taking decreases on the flow of new loans, the losses on the stock is quantitatively more meaningful for at least sixteen quarters.

Second, the model is partial equilibrium by construction. While general equilibrium feedback is certainly important for understanding the broader macroeconomic effects of monetary policy, the purpose of the model here is deliberately narrower in order to yield a clean mapping to the empirical evidence of the mechanism. Nonetheless, extending this framework into a full general equilibrium setting would be an interesting avenue for future work. Not only would this provide useful quantification, but it would enable one to capture the feedback between the bank's problem and loan demand, deposit supply, and loan performance, capturing richer macroeconomic feedbacks between monetary policy, bank balance sheets, and financial stability.

6 Microdata Evidence

First, I aggregate the bank-level data to ensure it is close to the aggregate data series from the FDIC. The main variables that I am interested in exploring in this section are net interest income, provisions, and profits (all normalised by assets) as these are the core components of the model. In Figure 7, I show both the aggregate data from the FDIC and aggregated microdata from Drechsler et al. (2017).

Figure 7: Comparing Aggregate Data to Aggregated Microdata

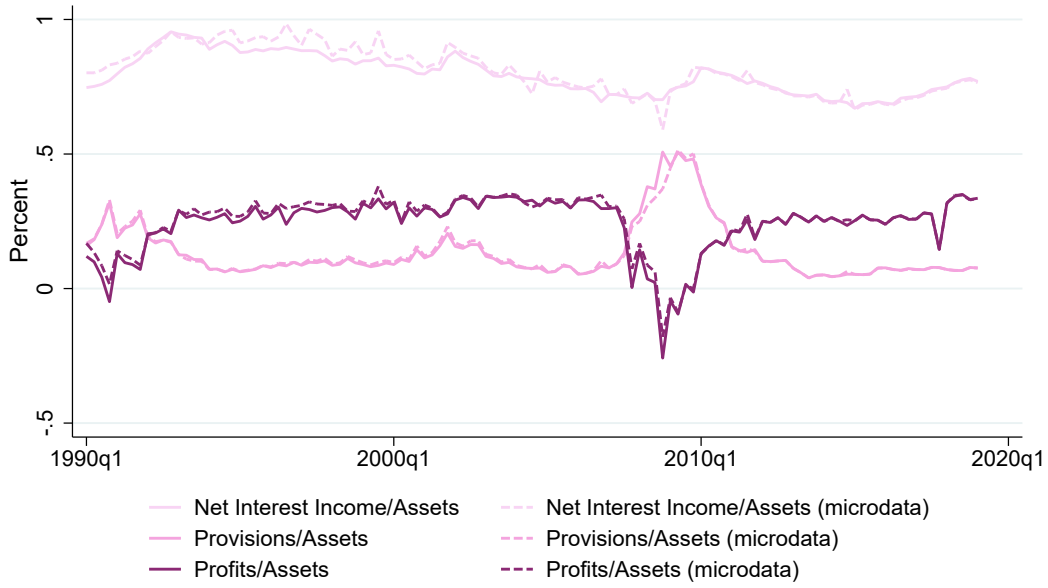


Figure 7 shows the microdata matches the macro data very well. While there are some deviations in the mid-1990s and during the global financial crisis, both of these are not in my estimation sample. The former is excluded as data on the share of floating-rate loans begins in the late-1990s, while the latter is excluded to be consistent with my earlier empirical analysis. I define the floating share as follows:

$$f_L = \frac{\text{loans with repricing maturity of less than three months}}{\text{total loans}} \tag{7}$$

In the data, the numerator is a single variable and consists of two loan types: floating-rate loans where the interest rate resets (at least) every three months and fixed-rate loans with a remaining maturity of three months or less. While the latter is not technically floating-rate, it is considered as such for the purposes of my analysis given the data available and given fixed-rate loans with short maturity effectively act as floating-rate loans in terms of interest rate pass through.[35]

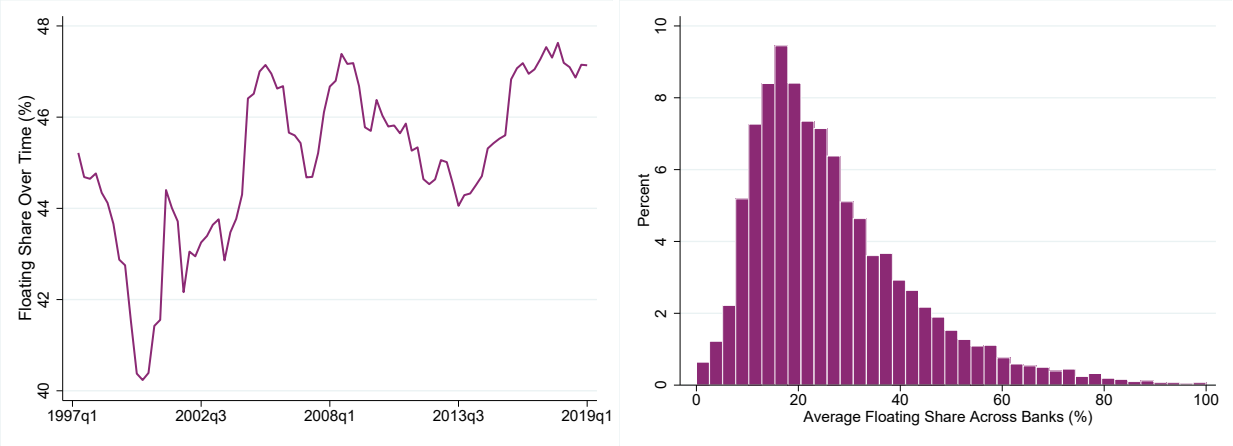
In Figure 8 below, I show the share of floating-rate loans in the time series and cross section. Figure 8a shows the time-series variation in the floating share for the aggregated banking sector. The aggregate floating share varies between 40% and 48%. Figure 8b takes the average floating share per bank over time and plots a histogram. As can be seen, there is considerable cross-sectional variation. While close to ten percent of banks have just under 20% of their loan portfolio composed of floating-rate loans, the distribution is

[35] The main difference occurs where a borrower cannot refinance a fixed-rate loan of short maturity due to a high likelihood of default, but would have been forced to default on a floating-rate loan with longer maturity. As such, my measure is likely to understate potential defaults.

clearly right-skewed.

Figure 8: Variation in the Share of Floating Rate Loans

(a) Time-Series Variation **(b)** Cross-Sectional Variation



While determining the specific causes of the floating share empirically is beyond the scope of this paper, it is worth documenting some of the average characteristics of banks with a lower average floating share relative to those with a higher average floating share within my estimation window (1999-2006). Specifically, I find that the average bank above the median floating share, relative to below the median, is similarly profitable as measured by return assets (0.247% versus 0.250%), has a higher share of commercial and industrial loans (20% versus 13%), has a slightly lower share of real estate-backed loans (62% versus 67%), has a lower share of personal loans (9% versus 14%), and is over five times larger larger.

Having explored the floating-rate data, it is worth revisiting the model from Section 5. The model predicted that in response to a contractionary monetary policy shock, banks with a higher floating share should experience higher net interest income but also higher loan-loss provisions, and that the impact on profits depends on the relative changes of the two components. I will test these implications using bank-level variation in the floating share. More precisely, I will estimate a panel local projection (a panel version of (1)) using data from 1999 to 2006 where the shock is interacted with the bank-specific floating share in the second quarter of 1997 (when the data is first available). By using this initial share, I ensure that the variation in the floating share is not driven by the shocks in the estimation period.[36] As in English et al. (2018), I also include horizon-specific bank fixed effects. Otherwise, the specification is consistent with (1) as it includes lags of the dependent variable and a quarter dummy. Therefore, I estimate the following specification for

[36] The initial share is highly correlated with the average share of floating-rate loans between 1997 and 2006 with a correlation coefficient of over 70%. As robustness, I also estimate an alternative specification where I use the average floating share per bank from 1999 to 2006 which gives similar results.

$h = 0 \dots 16$:

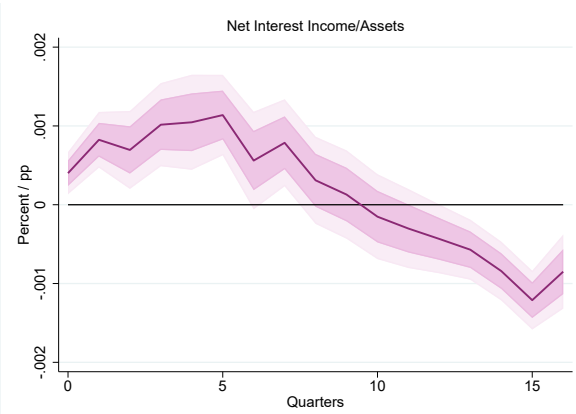
$$z_{i,t+h} = \alpha_{i,h} + \sum_{m=1}^{M} \gamma_{h,m} z_{t-m} + \sum_{l=0}^{L} \beta_{h,l}^{(1)} Shock_{t-l} + \beta_{h}^{(2)} FloatShare_{i,1997Q2} + \sum_{l=0}^{L} \beta_{h,l}^{(3)} Shock_{t-l} \cdot FloatShare_{i,1997Q2} + \sum_{q=2}^{4} \delta_q Quarter_{qt} + \epsilon_{i,t+h} \quad (8)$$

Given the relatively short time series, I use four lags. Standard errors are clustered by bank and quarter. The main object of interest is the *interaction effect* $\{\beta_{h,0}^{(3)}\}_{h=0}^{H}$ for $h = 0 \dots 16$. A positive value of $\beta_{h,0}^{(3)}$ at horizon h implies that a higher floating share increases the response of $z_{i,t+h}$ to a monetary policy shock at time t. To ease interpretation and to document the magnitude, I also show the *total effect* which is given by $\{\beta_{h,0}^{(1)} + \beta_{h,0}^{(3)} \cdot FloatShare_{i,1997Q2}\}_{h=0}^{H}$ for $h = 0 \dots 16$. The total effect measures the response of $z_{i,t+h}$ to a monetary policy shock at time t for specific values of the floating share. For illustrative purposes, I will show the 10th percentile and 90th percentile. However, these are only to aid interpretation as the interaction effect directly captures the significance of the floating share.

Figure 9 shows the response of net interest income to a contractionary monetary policy shock. The interaction effect in Figure 9a is mostly increasing in the floating share, albeit turning negative towards the end of the projection horizon. Figures 9b and 9c capture banks with a low and high floating share, respectively. Consistent with the model, banks with a low share are more negatively impacted by the shock. Specifically, banks with a low floating share see a persistent fall in their net interest income. Intuitively, one can think of such banks as issuing largely fixed-rate loans and seeing the cost of their funding rise with interest rates. As such, their net interest income will fall. On the other hand, banks with a high floating share see their net interest income rise on impact and remain elevated for over two years as they generate more revenue on their loans, despite the higher cost of funding. However, because these banks have passed on the interest rate risk to borrowers, borrowers eventually default which reduces loan repayments over time such that net interest income becomes negative, even for these high floating share banks. Overall, banks with a low floating share see a significantly larger cumulative fall in their net interest income than banks with a high floating share. As the model suggests, banks with a high floating share are better hedged against interest rate risk.

Figure 9: Net Interest Income Response To Contractionary MP Shock By Floating Share

(a) Interaction Effect



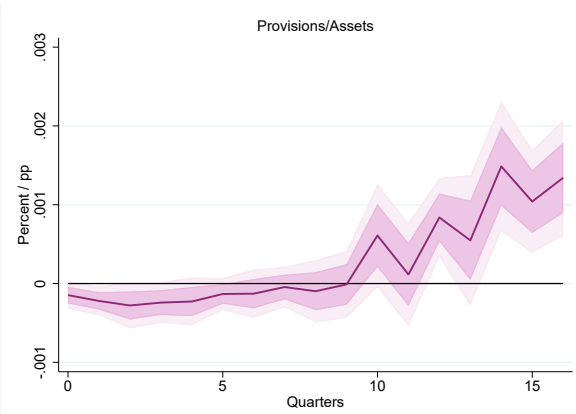
(b) Low Floating Share

(c) High Floating Share

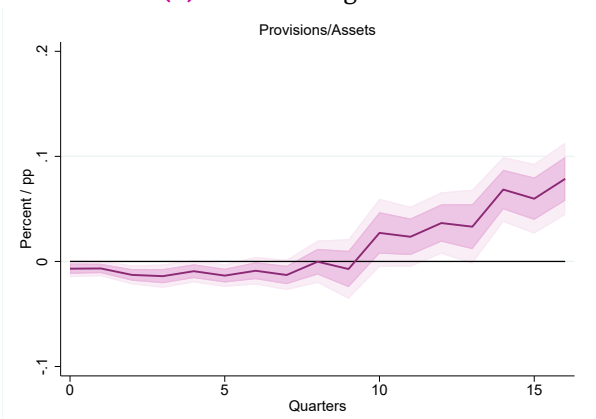
In Figure 10, I repeat the analysis with loan-loss provisions instead of net interest income. Recall that the model predicts that loan losses should rise more for banks with a higher floating share than those with a lower floating share. Figure 10a plots the interaction effect which confirms this prediction of the model. Moreover, given the low floating share banks see a negative impact on their net interest income, one would expect minimal loan losses for this group as these banks do not appear to pass on their interest rate risk to their borrowers and so should not experience much loss from credit risk. Figure 10b shows precisely that low floating share banks see minimal loan losses. On the other hand, Figure 10c shows that loan losses rise significantly for banks with a high floating share, around twice as much as those with a low floating share. Indeed, this is specifically the trade-off emphasised by the model: banks are transforming (near-term) interest rate risk into (longer-term) credit risk.

Figure 10: Loan-Loss Provision Response To Contractionary MP Shock By Floating Share

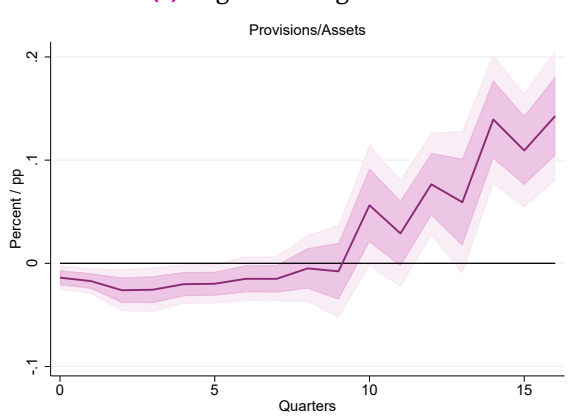
(a) Interaction Effect



(b) Low Floating Share



(c) High Floating Share

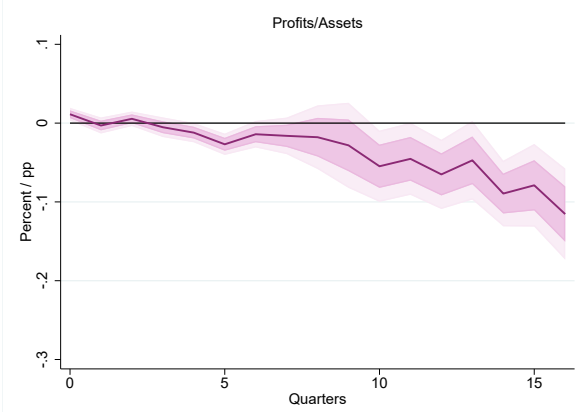


Finally, Figure 11 shows the same analysis but with overall bank profits. While the theoretical model in the previous section does not generate a directional prediction on overall profits, it does tell us that the impact on profits will be the difference between impulse response of net interest income and the impulse response of loan-loss provisions. One can see this immediately in Figure 11. For the low floating share banks (Figure 11b), profits are broadly flat, with a relatively small decline driven by the smaller increase in loan losses at the the end of the projection horizon. The high floating share banks (Figure 11c) initially see profits rise, driven by higher income on floating rate loans, but this hedged interest rate risk eventually becomes a crystallised credit risk. This results in a substantial rise in loan losses which leads to a significant overall decline in profits. Moreover, consistent with findings in the literature on the stability of net interest income (Drechsler et al. (2021)), most of the variation in profits is due to loan losses rather than net interest income.

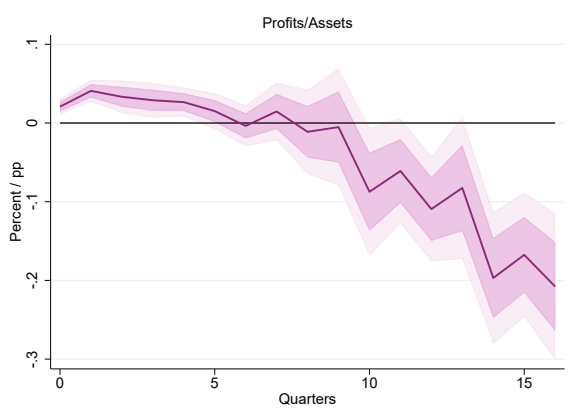
Figure 11: Profit Response To Contractionary MP Shock By Floating Share

(a) Interaction Effect

(b) Low Floating Share



(c) High Floating Share



Taken together, Figures 9, 10, and 11 present evidence consistent with an important role for floating-rate loans in generating defaults, as in the model developed in Section 5. Put simply, the following story emerges. Banks are exposed to interest rate risk so they issue floating-rate loans to hedge this risk. Given differential exposure to interest rate risk (e.g., through different deposit betas), banks issue different proportions of floating-rate loans. These floating-rate loans hedge the interest rate risk by passing it onto the borrower which becomes a credit risk for the bank. Ultimately, the credit risk component dominates as loan losses eventually offset the initial gain in net interest income, leading to lower profits for banks with high floating shares.

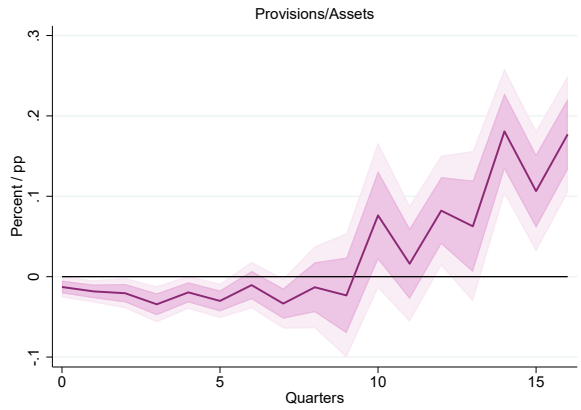
One might ask why banks issue floating-rate loans if it reduces profits. First, banks are not maximising value in order to only reduce the impact of interest rate shocks on profits. Second, floating-rate loans are likely to see more benefit from expected interest rate changes rather than unexpected interest rate changes. While not explicitly modelled as my focus is on the causal impact of monetary policy, a simple way to understand this point is the following. Higher interest rates lead to more income from floating-rate loans for banks. However, higher unexpected rates also result in less income for banks

due to defaults. These defaults occur as borrowers are not well hedged against unexpected interest rate rises. The difference with higher expected interest rates is that they are not exogenous, they typically coincide with booms. As such, when interest rates rise, floating-rate borrowers experience higher income due to the economic boom, but also higher loan-servicing costs. This type of natural hedge is more pronounced with expected interest rate changes which are more procyclical than interest rate shocks. Therefore, while floating-rate loans may result in lower profits in response to contractionary monetary policy shocks, they are a better hedge against typical interest changes.

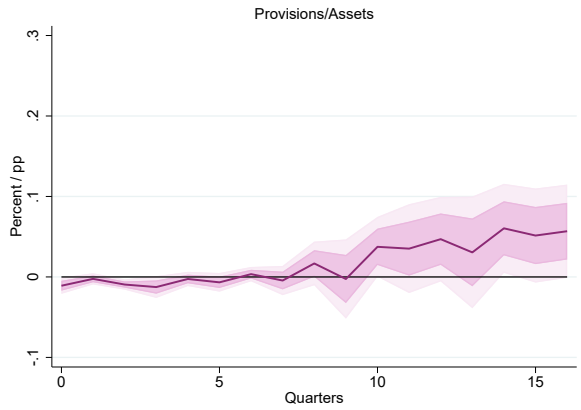
Figure 12 compares the response of loan-loss provisions to a contractionary monetary policy shock (12a) and to changes in the FFR (12b) where both result in a one percentage point rise in FFR.[37] I compare banks with high floating shares as they experience the largest increase in loan losses. The figures confirms that loan losses are substantially lower, and barely significant, in response to FFR changes.

Figure 12: Loan Loss Response for High Floating Share Banks

(a) Contractionary Monetary Policy Shock



(b) Higher Fed Funds Rate



The fact that floating-rate loans, due to interest rate pass-through, generates an additional channel of defaults has been documented in different forms in the literature (see Campbell and Cocco (2015) for evidence in the US and Gaudêncio et al. (2019) for evidence in Europe). Moreover, one can think of my results as being the bank side, rather than the firm side, of the floating-rate channel documented by Ippolito et al. (2018). They find that firms with more unhedged loans (i.e., more floating-rate loans) display a stronger sensitivity of their stock price, cash holdings, inventory, and fixed capital investment to monetary policy. They also show that this floating-rate channel works through the stock of existing loans and is at least as important as the bank lending channel operating through new loans.

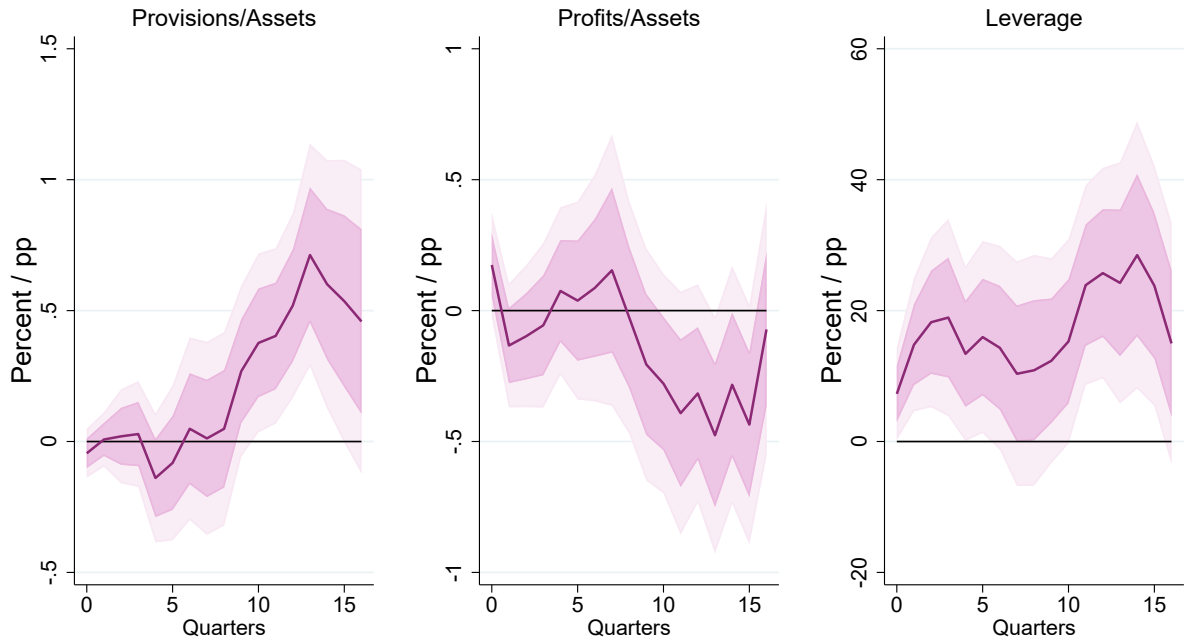
[37] Changes in the FFR are mostly expected changes but will include both expected and unexpected changes. As such, it should be considered an upper bound on the impact on loan losses.

More broadly, the implication of my analysis in this section is that the unintended consequences of higher interest rates on the stability of the banking sector are potentially more severe when the share of floating-rate loans is higher.

7 External Validity

In terms of external validity, my baseline analysis stops before the GFC in 2007. A natural question is whether my findings are still relevant. In Figure 13, I use the BRW monetary policy shock to show that, at the aggregate level, my main finding regarding leverage as well as the key steps in the mechanism regarding loan losses and profits all provide similar results when using data from 1994 to 2019. One caveat with this analysis is that it goes through the financial crisis, where there were important regulatory changes, in particular to bank capital and leverage. However, the results regarding bank loan losses and profits are nonetheless instructive.

Figure 13: Impulse Response to Contractionary Monetary Shock, 1994-2019



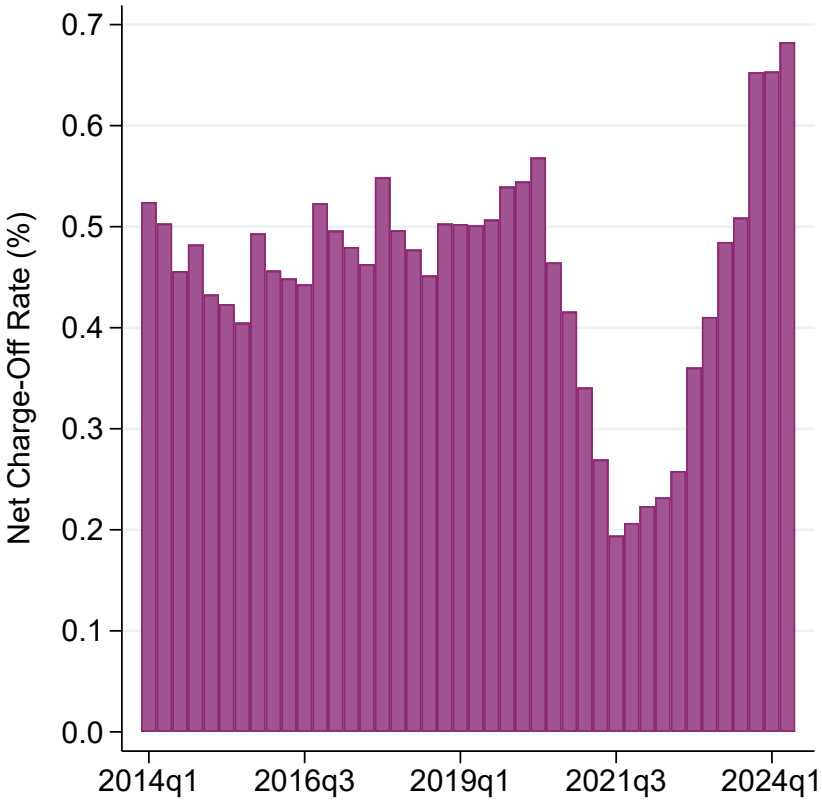
68% and 90% confidence bands displayed

One might also expect that given the loan-loss mechanism, the Fed's 2022 hiking cycle should have led to more defaults. The financial press noted rising defaults, in particular on floating-rate loans.[38] One can also see that the net charge-off rate (a measure of loan

[38] https://www.ft.com/content/6b28d31c-1a69-4309-9752-a96d7455d0e9

delinquencies available from the FDIC's aggregate loan performance data) is, as of the second quarter of 2024, the highest it has been in over a decade, despite robust economic growth (Figure 14). The data also shows that the largest contributors to the higher charge-offs were credit card loans and commercial and industrial loans, both of which are more likely to be floating rate.[39] Similarly, one would potentially expect more significant loan losses in Europe where the share of floating-rate loans is higher. In the UK, the Bank of England itself projected that its rate hikes will lead to rising interest payments which will make it difficult for many companies to repay their debt.[40] While all of the above is only suggestive evidence, together they support the external validity of the findings in this paper.

Figure 14: Net Charge-Off Rate, 2014Q1-2024Q2



[39] https://www.fdic.gov/system/files/2024-08/loan-performance.xlsx

[40] https://www.bankofengland.co.uk/bank-overground/2023/how-vulnerable-are-uk-companies-to-higher-interest-rates

8 Conclusion

In this paper, I explore the following question: do contractionary monetary policy shocks make banks safer through reducing their leverage? While a vast theoretical literature claims the answer is yes, I show empirically that the answer is actually no. Not only is raising interest rates ineffective in reducing bank leverage, it is actively counterproductive as it increases leverage instead and additionally increases bank failure rates. I show this result is robust to varying specifications and using different measures of monetary policy shocks.

Next, I show empirically why leverage rises in response to contractionary monetary policy shocks. Higher interest rates increase loan losses for banks. This reduces bank profits overall which subsequently reduces bank equity. The fall in equity drives an increase in bank leverage. I term this mechanism the loan-loss mechanism. Moreover, I show empirically that the loan-loss mechanism can explain nearly all the variation in bank leverage in response to monetary policy shocks. Finally, I show that while loan losses and leverage increase in response to monetary policy shocks (where the FFR rises), loan losses do not rise and leverage falls in response to contractionary oil shocks (where the FFR does not rise). This analysis provides suggestive evidence, at the aggregate level, of the importance of the rise in the FFR specifically and hence floating-rate loans. This highlights the importance of understanding bank balance sheets, and in particular the structure of the loan portfolio, in order to understand the transmission of monetary policy.

I show that the divergence between the theoretical claims and empirical evidence is largely a result of three broad modelling choices and that there is one important factor that can help rectify this. The first modelling choice relates to models that rely on profitability rising in response to a contractionary monetary policy shock which is inconsistent with the empirical evidence. The second relates to models that incorrectly rely on the procyclicality of bank leverage and so erroneously conclude that leverage declines in response to rising interest rates. The third relates to models that rely on the direct price effect through which higher rates reduce bank leverage which is inconsistent with the observed evidence. The crucial missing factor in this eclectic mix of models is a loan-loss mechanism that is connected to the share of floating-rate loans issued by a bank.

I develop a banking model that emphasises the role of floating-rate loans and credit risk. Banks optimise by choosing the floating share of their loan portfolio which acts as a hedge against interest rate risk, but generates credit risk for the bank as the interest rate risk is now held by borrowers. A key insight of the model is that banks are doing risk transformation, and that this implies a trade-off between managing interest rate risk and

credit risk. The model predicts that banks with a higher share of floating-rate loans will see greater loan losses in response to a contractionary monetary policy shock. I confirm this prediction using microdata, specifically, bank-level variation in the floating share.

My results have important implications for using monetary policy for financial stability purposes. First, one reason to support a monetary policy strategy that targets financial stability (i.e., "leaning against the wind") is the claim that higher rates reduce bank leverage. In this paper, I have shown this claim to be empirically false. Indeed, I show directly that contractionary monetary policy shocks raise both bank leverage and bank failure rates. Therefore, this paper lends support to the conclusions of Bernanke and Svensson (2017) that issues of financial stability, such as bank leverage, may best be dealt with targeted macroprudential policy which would not require interfering with the primary objectives of monetary policy.[41] However, my results also suggest that floating-rate loans are one specific way through which monetary policy creates unintended vulnerabilities in the banking sector. This is particularly pertinent in economies with a greater share of floating-rate loans (e.g., Europe). Future research could consider this novel trade-off for monetary policy: a higher share of floating-rate loans can increase the potency of monetary policy (e.g., Auclert (2019)) but at the cost of a more vulnerable financial sector, as documented in this paper.

References

Adrian, T., Boyarchenko, N., and Shin, H. (2019). On the Scale of Financial Intermediaries. *Federal Reserve Bank of New York Staff Reports*, 56(10):25–27.

Adrian, T., Moench, E., and Shin, H. S. (2014). Dynamic leverage asset pricing. *Federal Reserve Bank of New York Staff Reports*, (625).

Adrian, T. and Shin, H. S. (2010). Liquidity and leverage. *Journal of financial intermediation*, 19(3):418–437.

Ajello, A., Boyarchenko, N., Gourio, F., and Tambalotti, A. (2022). Financial stability considerations for monetary policy: Theoretical mechanisms. *FRB of New York Staff Report*, (1002).

Altavilla, C., Boucinha, M., and Peydró, J.-L. (2018). Monetary policy and bank profitability in a low interest rate environment. *Economic Policy*, 33(96):531–586.

Angeloni, I. and Faia, E. (2013). Capital regulation and monetary policy with fragile banks. *Journal of Monetary Economics*, 60(3):311–324.

[41] https://www.brookings.edu/articles/should-monetary-policy-take-into-account-risks-to-financial-stability/

Auclert, A. (2019). Monetary policy and the redistribution channel. *American Economic Review*, 109(6):2333–2367.

Baron, M., Verner, E., and Xiong, W. (2021). Banking crises without panics. *The Quarterly Journal of Economics*, 136(1):51–113.

Begenau, J. and Landvoigt, T. (2021). Financial regulation in a quantitative model of the modern banking system. *National Bureau of Economic Research Working Paper Series*, No. 28501.

Bernanke, B. S. and Gertler, M. (1995). Inside the black box: the credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4):27–48.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of Macroeconomics*, 1:1341–1393.

Bonfim, D. and Soares, C. (2018). The risk-taking channel of monetary policy: Exploring all avenues. *Journal of Money, Credit and Banking*, 50(7):1507–1541.

Boyarchenko, N., Favara, G., and Schularick, M. (2022). Financial Stability Considerations for Monetary Policy: Empirical Evidence and Challenges. *Federal Reserve Bank of New York Staff Reports*, No. 1003.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

Bu, C., Rogers, J., and Wu, W. (2021). A unified measure of fed monetary policy shocks. *Journal of Monetary Economics*, 118:331–349.

Caballero, R. J. and Simsek, A. (2020a). Prudential monetary policy. *National Bureau of Economic Research Working Paper Series*, No. 25977.

Caballero, R. J. and Simsek, A. (2020b). A risk-centric model of demand recessions and speculation. *The Quarterly Journal of Economics*, 135(3):1493–1566.

Campbell, J. Y. and Cocco, J. F. (2015). A model of mortgage default. *The Journal of Finance*, 70(4):1495–1554.

Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy*, 113(1):1–45.

Corbae, D. and Levine, R. (2023). Competition, Stability, and Efficiency in the Banking Industry. *Unpublished Manuscript*.

Correia, S. A., Luck, S., and Verner, E. (2024). Failing banks. *National Bureau of Economic Research Working Paper Series*, No. 32907.

Dell'Ariccia, G., Laeven, L., and Marquez, R. (2014). Real interest rates, leverage, and bank risk-taking. *Journal of Economic Theory*, 149(1):65–99.

Dell'Ariccia, G., Laeven, L., and Suarez, G. A. (2017). Bank leverage and monetary policy's risk-taking channel: evidence from the united states. *the Journal of Finance*, 72(2):613–654.

Di Tella, S. and Kurlat, P. (2021). Why Are Banks Exposed to Monetary Policy? *American Economic Journal: Macroeconomics*, 13(4):295–340.

Drechsler, I., Savov, A., and Schnabl, P. (2017). The Deposits Channel of Monetary Policy. *Quarterly Journal of Economics*, 132(4):1819–1876.

Drechsler, I., Savov, A., and Schnabl, P. (2018a). Liquidity, Risk Premia, and the Financial Transmission of Monetary Policy. *Annual Review of Financial Economics*, 10:309–328.

Drechsler, I., Savov, A., and Schnabl, P. (2018b). A model of monetary policy and risk premia. *The Journal of Finance*, 73(1):317–373.

Drechsler, I., Savov, A., and Schnabl, P. (2021). Banking on deposits: Maturity transformation without interest rate risk. *The Journal of Finance*, 76(3):1091–1143.

English, W. B., Van den Heuvel, S. J., and Zakrajšek, E. (2018). Interest rate risk and bank equity valuations. *Journal of Monetary Economics*, 98:80–97.

Fostel, A. and Geanakoplos, J. (2008). Leverage cycles and the anxious economy. *American Economic Review*, 98(4):1211–44.

Galati, G. and Moessner, R. (2018). What Do We Know About the Effects of Macroprudential Policy? *Economica*, 85:735–770.

Galí, J. (1999). Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations? *American economic review*, 89(1):249–271.

Gaudêncio, J., Mazany, A., and Schwarz, C. (2019). The impact of lending standards on default rates of residential real-estate loans. *ECB Occasional Paper*, (220).

Gertler, M. and Karadi, P. (2011). A model of unconventional monetary policy. *Journal of monetary Economics*, 58(1):17–34.

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Gertler, M. and Kiyotaki, N. (2010). Financial intermediation and credit policy in business cycle analysis. In *Handbook of Monetary Economics*, volume 3, pages 547–599. Elsevier.

Gertler, M. and Kiyotaki, N. (2015). Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review*, 105(7):2011–2043.

Gertler, M., Kiyotaki, N., and Prestipino, A. (2020). A macroeconomic model with financial panics. *The Review of Economic Studies*, 87(1):240–288.

Goldberg, J. and López-Salido, D. (2023). "Sowing the Wind" Monetary Policy. *Unpublished Manuscript*.

Gomes, J., Jermann, U., and Schmid, L. (2016). Sticky leverage. *American Economic Review*, 106(12):3800–3828.

Gourio, F., Kashyap, A. K., and Sim, J. W. (2018). The Trade offs in Leaning Against the Wind. *IMF Economic Review*, 66.

Grimm, M., Jordà, Ò., Schularick, M., and Taylor, A. M. (2023). Loose monetary policy and financial instability. *National Bureau of Economic Research Working Paper Series*, No. 30958.

Guttman, I., Kadan, O., and Kandel, E. (2010). Dividend stickiness and strategic pooling. *The Review of Financial Studies*, 23(12):4455–4495.

He, Z., Kelly, B., and Manela, A. (2017). Intermediary asset pricing: New evidence from many asset classes. *Journal of Financial Economics*, 126(1):1–35.

Hellwig, M. (1994). Liquidity provision, banking, and the allocation of interest rate risk. *European Economic Review*, 38(7):1363–1389.

Ippolito, F., Ozdagli, A. K., and Perez-Orive, A. (2018). The transmission of monetary policy through bank lending: The floating rate channel. *Journal of Monetary Economics*, 95:49–71.

Jiang, E. X., Matvos, G., Piskorski, T., and Seru, A. (2024). Monetary tightening and us bank fragility in 2023: Mark-to-market losses and uninsured depositor runs? *Journal of Financial Economics*, 159:103899.

Jiménez, G., Kuvshinov, D., Peydró, J.-L., and Richter, B. (2024). Monetary policy, inflation, and crises: evidence from history and administrative data. *Unpublished Manuscript*.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica*, 82(2):463–505.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, 95(1):161–182.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, 111(4):1092–1125.

Kirti, D. (2020). Why do bank-dependent firms bear interest-rate risk? *Journal of Financial Intermediation*, 41:100823.

Laux, C. and Rauter, T. (2017). Procyclicality of us bank leverage. *Journal of Accounting Research*, 55(2):237–273.

Li, Z. (2022). Financial intermediary leverage and monetary policy transmission. *European Economic Review*, 144:104080.

Maggiori, M. (2017). Financial intermediation, international risk sharing, and reserve currencies. *American Economic Review*, 107(10):3038–3071.

Martin, A., Mendicino, C., and Van der Ghote, A. (2021). On the interaction between monetary and macroprudential policies. *ECB Working Paper Series*, No. 2527(2527).

Martinez-Miera, D. and Repullo, R. (2019). Monetary Policy, Macroprudential Policy, and Financial Stability. *Annual Review of Economics*, 11:809–832.

Miranda-Agrippino, S. and Rey, H. (2020). US monetary policy and the global financial cycle. *The Review of Economic Studies*, 87(6):2754–2776.

Montiel Olea, J. L. and Plagborg-Møller, M. (2021). Local projection inference is simpler and more robust than you think. *Econometrica*, 89(4):1789–1823.

Nuño, G. and Thomas, C. (2017). Bank leverage cycles. *American Economic Journal: Macroeconomics*, 9(2):32–72.

Ottonello, P. and Song, W. (2022). Financial Intermediaries and the Macroeconomy: Evidence from a High-Frequency Identification. *National Bureau of Economic Research Working Paper Series*, No. 29638.

Pflueger, C., Siriwardane, E., and Sunderam, A. (2020). Financial market risk perceptions and the macroeconomy. *The Quarterly Journal of Economics*, 135(3):1443–1491.

Ramey, V. (2016). Macroeconomic Shocks and Their Propagation. volume 2 of *Handbook of Macroeconomics*, chapter 2, pages 71–162. Elsevier.

Rannenberg, A. (2016). Bank leverage cycles and the external finance premium. *Journal of Money, Credit and Banking*, 48(8):1569–1612.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Samuelson, P. A. (1945). The effect of interest rate increases on the banking system. *The American economic review*, 35(1):16–27.

Sims, E. and Wu, J. C. (2021). Evaluating central banks' tool kit: Past, present, and future. *Journal of Monetary Economics*, 118:135–160.

Smets, F. and Wouters, R. (2007). Shocks and frictions in us business cycles: A bayesian dsge approach. *American economic review*, 97(3):586–606.

Stock, J. H. and Watson, M. W. (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal*, 128(610):917–948.

Svensson, L. E. (2018). Monetary policy and macroprudential policy: Different and separate? *Canadian Journal of Economics*, 51(3):802–827.

Svensson, L. E. O. (2017). Cost-benefit analysis of leaning against the wind. *Journal of Monetary Economics*, 90:193–213.

Van den Heuvel, S. (2009). The bank capital channel of monetary policy. *Unpublished Manuscript*.

Van der Ghote, A. (2021). Interactions between monetary and macroprudential policy. *American Economic Journal: Macroeconomics*, 13(1):1–34.

Walter, J. R. (1991). Loan loss reserves. *FRB Richmond Economic Review*, July/August:20–30.

Wieland, J. F. and Yang, M.-J. (2020). Financial Dampening. *Journal of Money, Credit and Banking*, 52(1):79–113.

Wolf, C. K. and McKay, A. (2023). What Can Time-Series Regressions Tell Us About Policy Counterfactuals? *Econometrica*, 91(5).

Woodford, M. (2012). Inflation Targeting and Financial Stability. *National Bureau of Economic Research Working Paper Series*, No. 17967.

Appendix A Theoretical Model

A.1 Bank Problem

The bank has the following objective

$$\max_{f_L} V_b = \mathbb{E}[\pi_b] - \frac{\gamma}{2} Var[\pi_b] \tag{9}$$

where profits are given by the following

$$\pi_b = L(1-f_L)(\bar{r} + \mu(f_L)) + Lf_L(\bar{r} + \varepsilon + \mu(f_L)) - D(\bar{r} + \beta\varepsilon) - Lf_L\theta(\varepsilon) \tag{10}$$

Therefore, we can rewrite V_b as

$$\begin{aligned} V_b = {} & L(1-f_L)\bar{r} + Lf_L\bar{r} + L\mu(f_L) - D\bar{r} - Lf_L\overline{\theta(\varepsilon)} - \frac{\gamma L^2 f_L^2 \sigma_\varepsilon^2}{2} - \frac{\gamma D^2 \beta^2 \sigma_\varepsilon^2}{2} - \frac{\gamma L^2 f_L^2 \sigma_\theta^2}{2} \\ & + \gamma L f_L D\beta\sigma_\varepsilon^2 + \gamma L^2 f_L^2 \rho_{\varepsilon\theta} - \gamma D\beta L f_L \rho_{\varepsilon\theta} \end{aligned} \tag{11}$$

where $\sigma_\varepsilon^2 = Var[\varepsilon]$, $\sigma_\theta^2 = Var[\theta(\varepsilon)]$, $\mathbb{E}[\theta(\varepsilon)] = \overline{\theta(\varepsilon)}$, and $Cov(\varepsilon, \theta(\varepsilon)) = \rho_{\varepsilon\theta}$. Note that I assume the following: $\sigma_\varepsilon^2 > \sigma_\theta^2$ and $\rho_{\varepsilon\theta} > 0$ where the latter captures that the loan-loss rate increases in the size of the monetary policy shock. Taking the first-order condition with respect to f_L and simplifying yields the following expression for f_L^*

$$f_L^* = \frac{\frac{\partial \mu(f_L)}{\partial f_L} - \overline{\theta(\varepsilon)}}{\gamma L\left(\sigma_\varepsilon^2 + \sigma_\theta^2 - 2\rho_{\varepsilon\theta}\right)} + \frac{D\beta\left(\sigma_\varepsilon^2 - \rho_{\varepsilon\theta}\right)}{L\left(\sigma_\varepsilon^2 + \sigma_\theta^2 - 2\rho_{\varepsilon\theta}\right)} \tag{12}$$

The term in parentheses in the denominator is positive as it is the variance of the difference between the monetary policy shock and the loan-loss rate. Therefore, the denominator is also positive. The numerator in the second term is positive as $\sigma_\varepsilon^2 + \sigma_\theta^2 - 2\rho_{\varepsilon\theta} > 0$ and $\sigma_\varepsilon^2 > \sigma_\theta^2$, so $\sigma_\varepsilon^2 > \rho_{\varepsilon\theta}$. All else equal, a bank would choose a higher floating share if it is more exposed to interest expense on its deposits (e.g., through a higher deposit-loan ratio or a higher deposit beta). This is because the floating share would act as a hedge. However, the bank will choose a lower floating share if it more exposed to credit risk from monetary policy shocks (e.g., through a higher $\overline{\theta(\varepsilon)}$). This is because the hedge comes at the cost of credit risk. The functional form of $\theta(\varepsilon)$ and its covariance with the shock determines the sensitivity of these effects.

A.2 Firm Problem

The firm has a similar objective function (with the same risk-aversion coefficient), except that it is choosing how much invest, I, which it can only do through borrowing. So the

firm objective function is

$$\max_I V_f = \mathbb{E}[\pi_f] - \frac{\gamma}{2} Var[\pi_f] \tag{13}$$

where firm profits are given by the following

$$\pi_f = AI - I - I(1 - f_L)(\bar{r} + \mu(f_L)) - If_L(\bar{r} + \varepsilon + \mu(f_L)) - If_L\theta(\varepsilon) \tag{14}$$

Note that $If_L\theta(\varepsilon)$ captures in, a reduced form way, that the firm cannot repay some of its floating-rate debt if there is a contractionary monetary policy shock. We can now rewrite V_f as the following

$$V_f = AI - I - I\bar{r} - I\mu(f_L) - If_L\overline{\theta(\varepsilon)} - \frac{\gamma}{2}\left(I^2 f_L^2 \sigma_\varepsilon^2 + I^2 f_L^2 \sigma_\theta^2 + 2If_L\rho_{\varepsilon\theta}\right) \tag{15}$$

Taking the first-order condition with respect to I and simplifying yields the following expression for $\mu(f_L)$

$$\mu(f_L) = A - 1 - \bar{r} - f_L\overline{\theta(\varepsilon)} - \gamma If_L^2\sigma_\varepsilon^2 - \gamma If_L^2\sigma_\theta^2 - \gamma f_L\rho_{\varepsilon\theta} \tag{16}$$

A.3 Equilibrium

In equilibrium, we will have a loan spread, μ^* that will equate firm credit demand, I, with bank loan size, L. So, using $I = L$ and plugging the derivative of (16) with respect to f_L into (12) yields the equilibrium f_L^*

$$f_L^* = \frac{D\beta\gamma\left(\sigma_\varepsilon^2 - \rho_{\varepsilon\theta}\right) - \gamma\rho_{\varepsilon\theta} - 2\overline{\theta(\varepsilon)}}{\gamma L\left(3\sigma_\varepsilon^2 + 3\sigma_\theta^2 - 2\rho_{\varepsilon\theta}\right)} \tag{17}$$

Note that the denominator of (17) is positive because γ, L, and $3\sigma_\varepsilon^2 + 3\sigma_\theta^2 - 2\rho_{\varepsilon\theta}$ are all positive.[42] Moreover, given that D and β are positive, and that $\sigma_\varepsilon^2 > \rho_{\varepsilon\theta}$, then we have $\frac{\partial f_L}{\partial\beta} > 0$, which is consistent with banks using floating-rate loans as a hedge against interest rate risk. One can also show that f_L^* is positive as $\frac{\rho_{\varepsilon\theta}}{D\beta} \approx 0$, $\frac{2\overline{\theta(\varepsilon)}}{D\beta\gamma} \approx 0$, and $\sigma_\varepsilon^2 > \rho_{\varepsilon\theta}$.[43]

[42] $3\sigma_\varepsilon^2 + 3\sigma_\theta^2 - 2\rho_{\varepsilon\theta}$ is positive because $3\sigma_\varepsilon^2 + 3\sigma_\theta^2 - 2\rho_{\varepsilon\theta} > \sigma_\varepsilon^2 + \sigma_\theta^2 - 2\rho_{\varepsilon\theta} \equiv Var(\varepsilon - \theta) > 0$

[43] Note this requires that σ_ε^2 has to be sufficiently large relative to $\rho_{\varepsilon\theta}$.

Appendix B Book Leverage versus Market Leverage (online)

In this paper, I use accounting-based measures of leverage (i.e., book leverage). An alternative approach would be to use market-based measures of leverage. Each measure has its own advantages and disadvantages. The definition of book leverage is the ratio of total assets to book equity while the definition of market leverage is the ratio of enterprise value (i.e., the sum of total liabilities and market equity) to market equity where market equity captures the market value of equity. I use book leverage for several reasons.

The first reason is consistency with the overall policy framework. When considering financial stability, macroprudential regulations focus on book leverage rather than market leverage. As such, from a policy consistency perspective, one would expect that monetary policy that targets financial stability would also do so through book leverage.

The second reason relates to bank decision-making. Banks themselves present their targets for return on equity at book value and report the evolution of leverage at book value. Indeed, Adrian et al. (2019) documents empirically that banks base their balance sheet management around book equity and book leverage and as such actively manage book leverage. While they mention market leverage also plays a role, they conclude that it is secondary to book leverage determined primarily by market forces. Similarly, Li (2022) highlight that it is book leverage that matters for bank lending decisions. Nuño and Thomas (2017) also highlight that book equity is the appropriate notion of equity when interested in the bank lending while market equity would be more appropriate if interested in new share issuance or mergers and acquisitions decisions. Given the role of book leverage in lending decisions, it clearly interacts more directly with the bank lending channel of monetary policy and would therefore constitute the appropriate measure of leverage for my analysis.

The third reason relates to explicit modelling choices. While many papers do not explicitly model book leverage or market leverage, they often implicitly consider book leverage. For example, models that rely on procyclicality of leverage are considering book leverage as market leverage is countercyclical. Ottonello and Song (2022) show analytically that in their model there is a tight link between book leverage and market leverage. More recently, Begenau and Landvoigt (2021) construct a rich model where delayed loss recognition can explain why book values differ from fundamental values.

The final reason is a question of data. Book leverage captures the entirety of the banking system as this data is available for all banks. Including the entire system is important in order to most accurately evaluate aggregate macroeconomic effects. Market leverage is only available for listed banks and so would significantly narrow the scope of the analysis.

Despite its limited scope, I repeat my analysis using market leverage. Figure C.8 shows that the results are qualitatively similar, albeit noisier and larger in magnitude for market

leverage. The measure of market leverage I use is from He et al. (2017). They construct it as follows:

$$\text{Market Leverage}_t = \frac{\sum_i (\text{Market Equity}_{i,t} + \text{Book Debt}_{i,t})}{\sum_i \text{Market Equity}_{i,t}} \tag{18}$$

A few reasons for the different response in terms of magnitude are that the measure is only for the bank-holding companies of primary dealers. My data for book leverage is at the commercial bank level. Therefore, the samples are not strictly comparable. However, it is not especially surprising that they yield similar qualitative results as He et al. (2017) highlight that book and market leverage exhibit a strong positive correlation for the primary dealers in their sample.

Appendix C Robustness Checks (online)

Figure C.1: Time Series of Monetary Policy Shocks

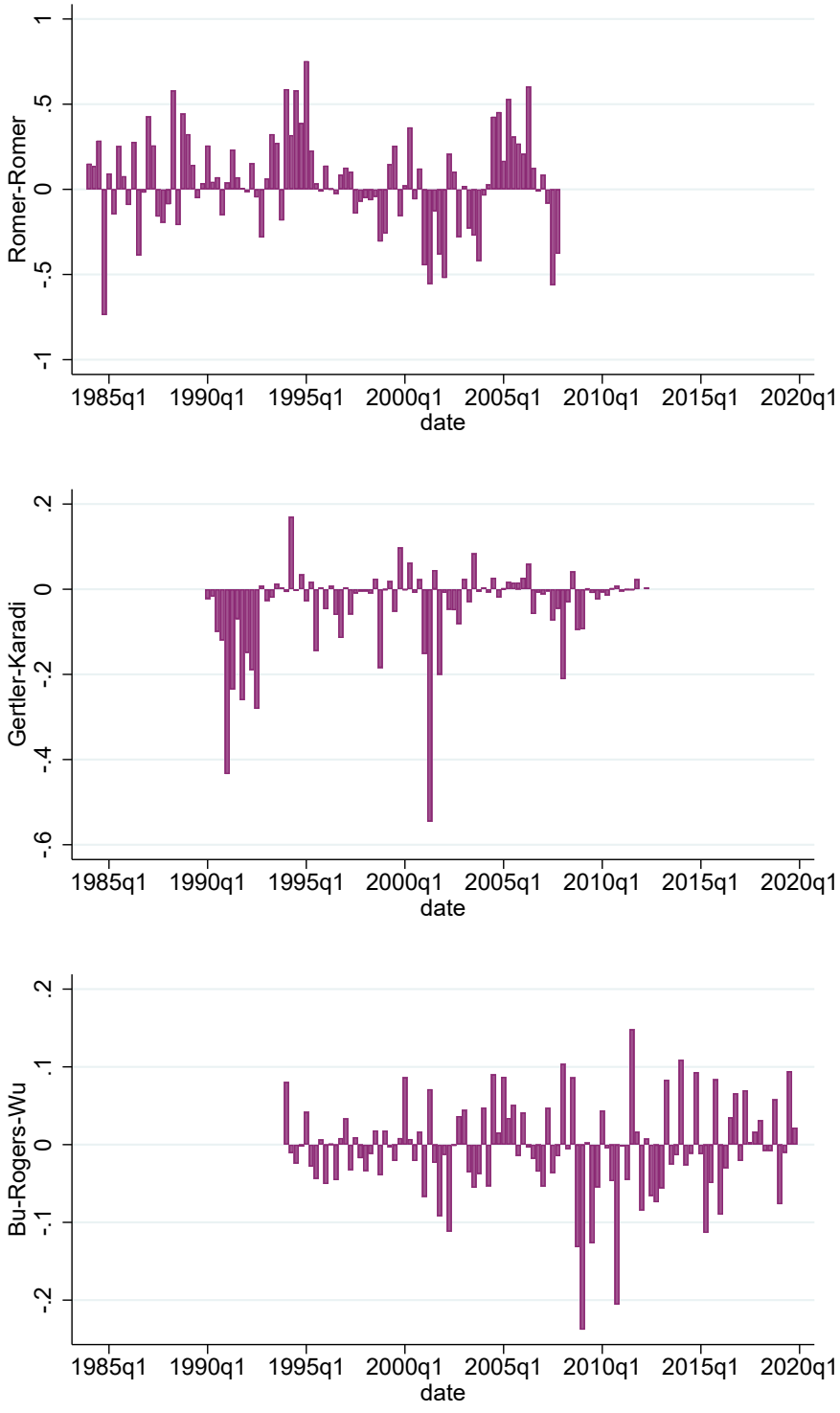


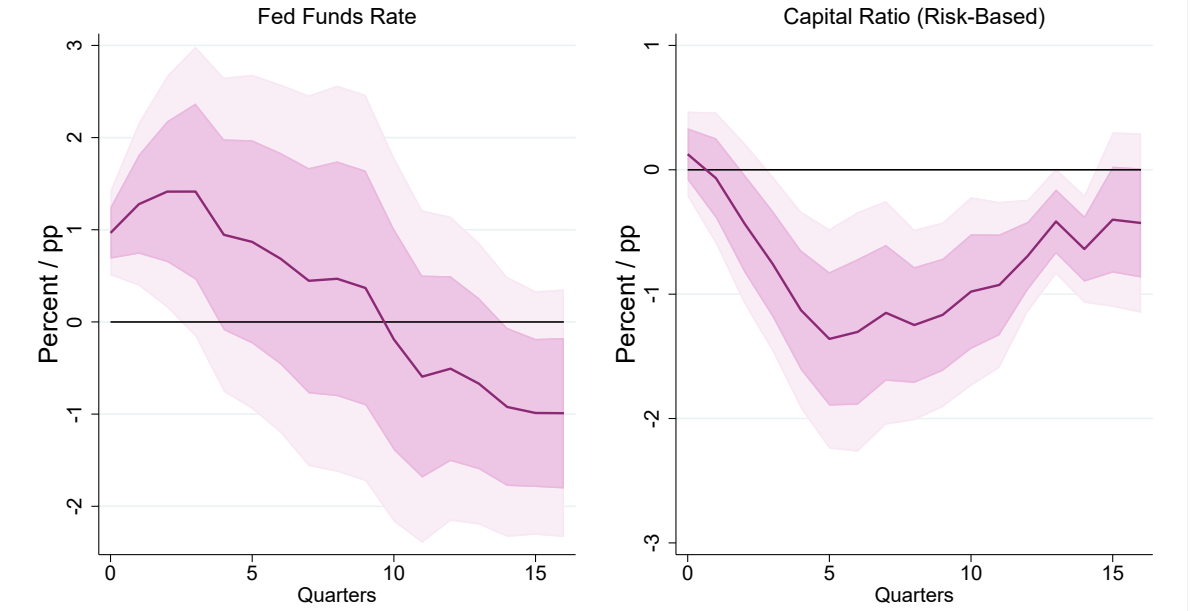
Figure C.2: Impulse Response of Provisions and Write-Offs

68% and 90% confidence bands displayed

Figure C.3: Impulse Response of Regulatory Leverage to Contractionary Monetary Shock

68% and 90% confidence bands displayed

Figure C.4: Impulse Response of Risk-Based Capital Ratio to Contractionary Monetary Shock



68% and 90% confidence bands displayed

Figure C.5: Different Time Periods

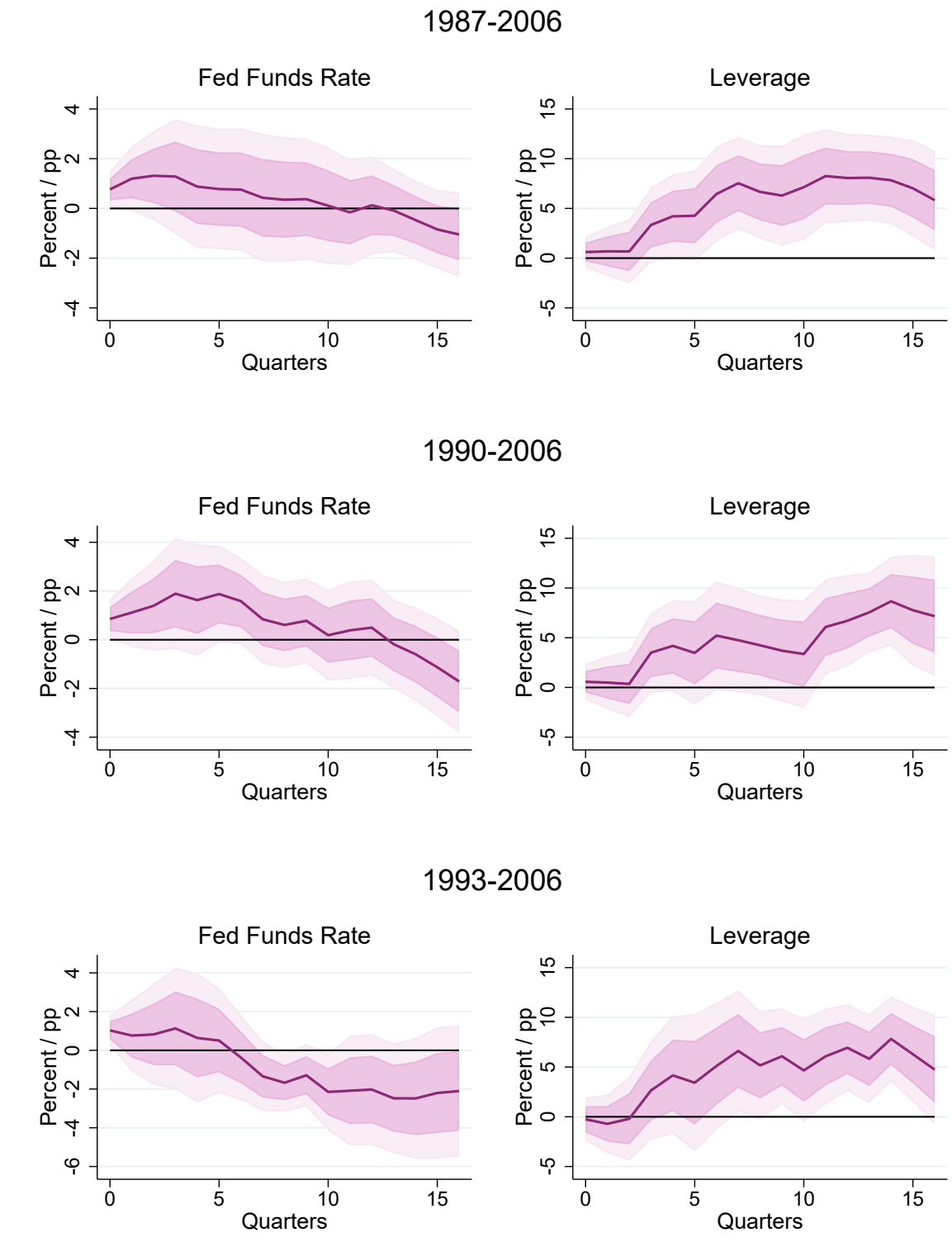
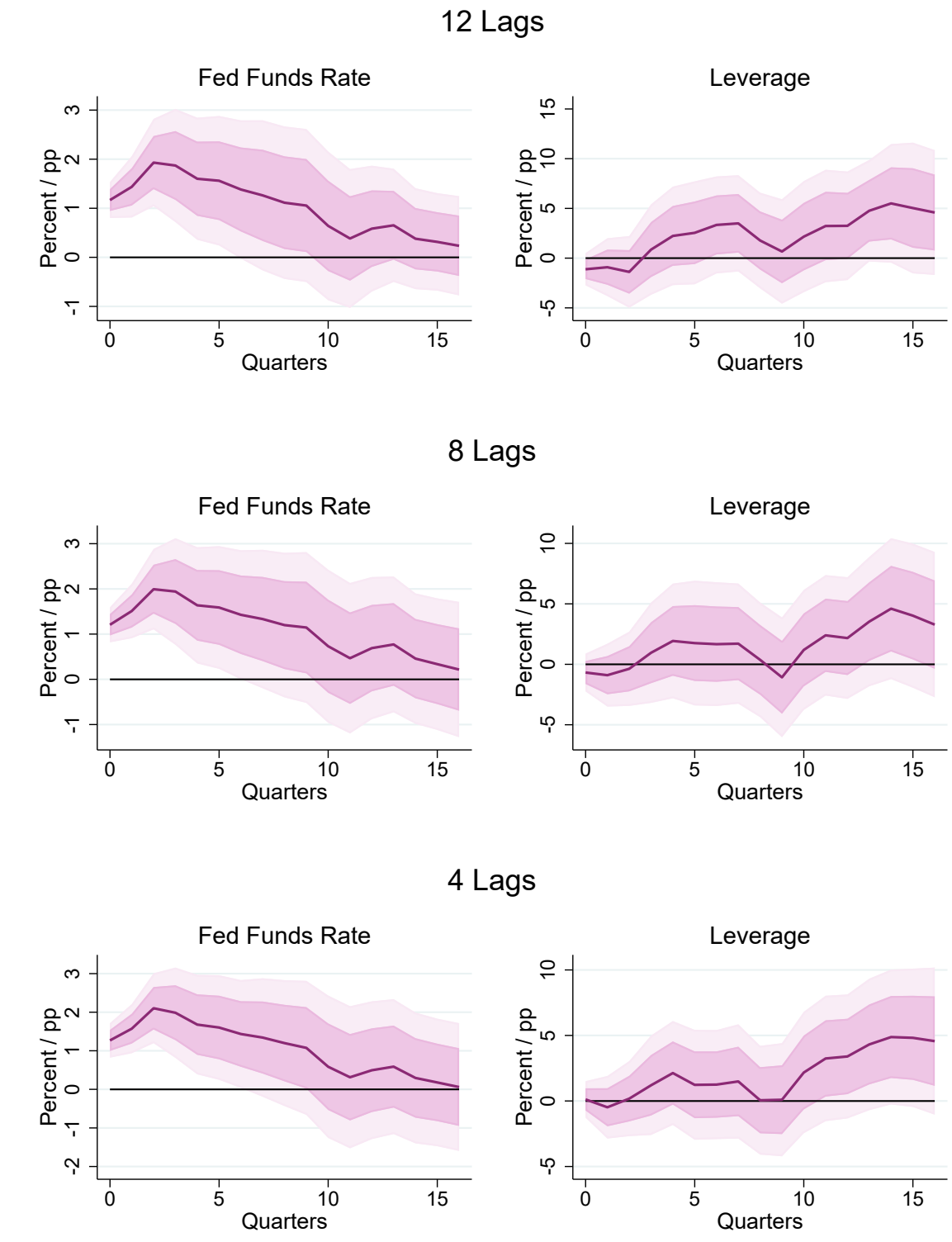
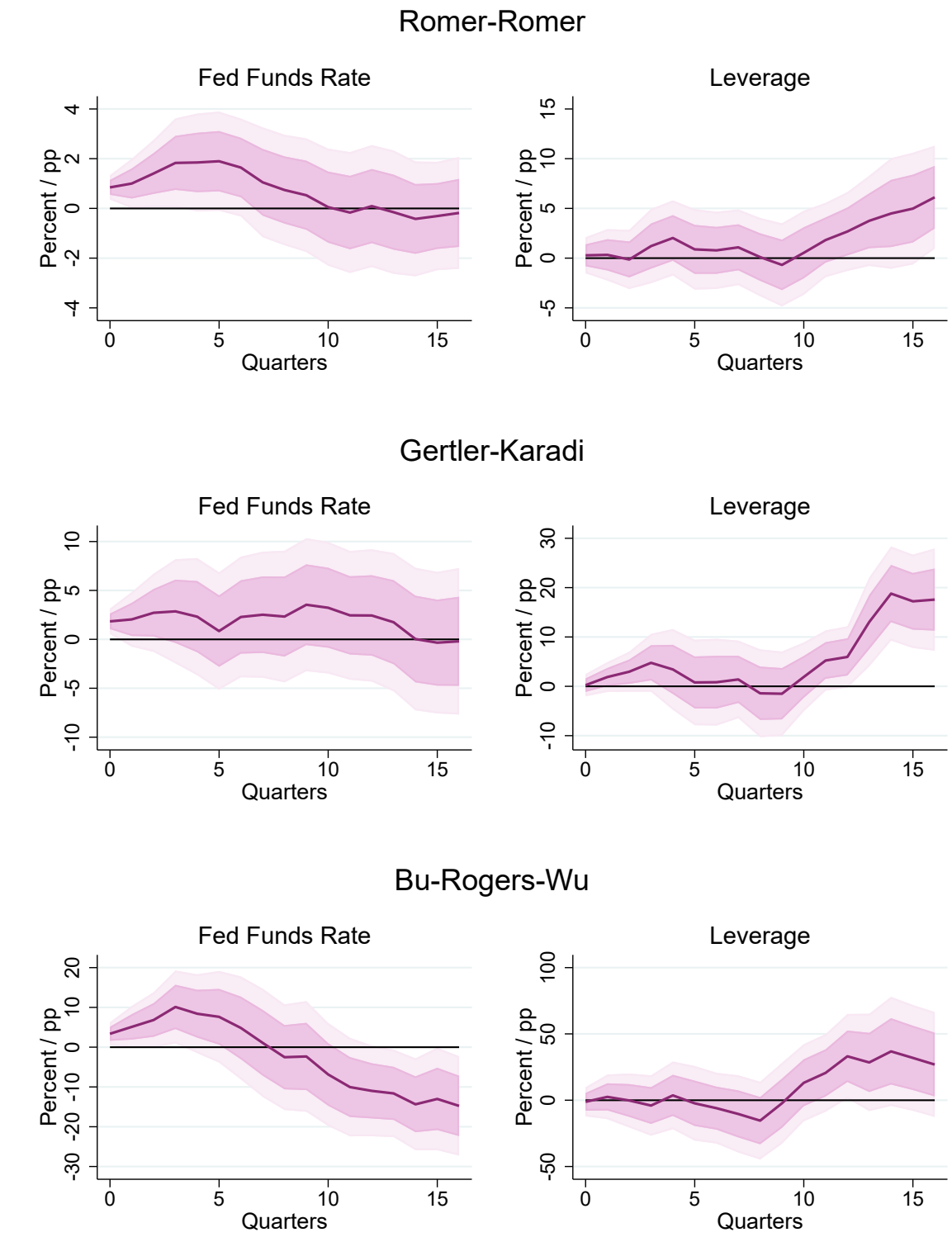


Figure C.6: Different Number of Lags



68% and 90% confidence bands displayed

Figure C.7: Book Leverage Response to different Monetary Policy Shock Series



68% and 90% confidence bands displayed

Figure C.8: Market Leverage Response to different Monetary Policy Shock Series

68% and 90% confidence bands displayed

Figure C.9: Impulse Response of GDP and Inflation to Oil Shock ('supply shock')

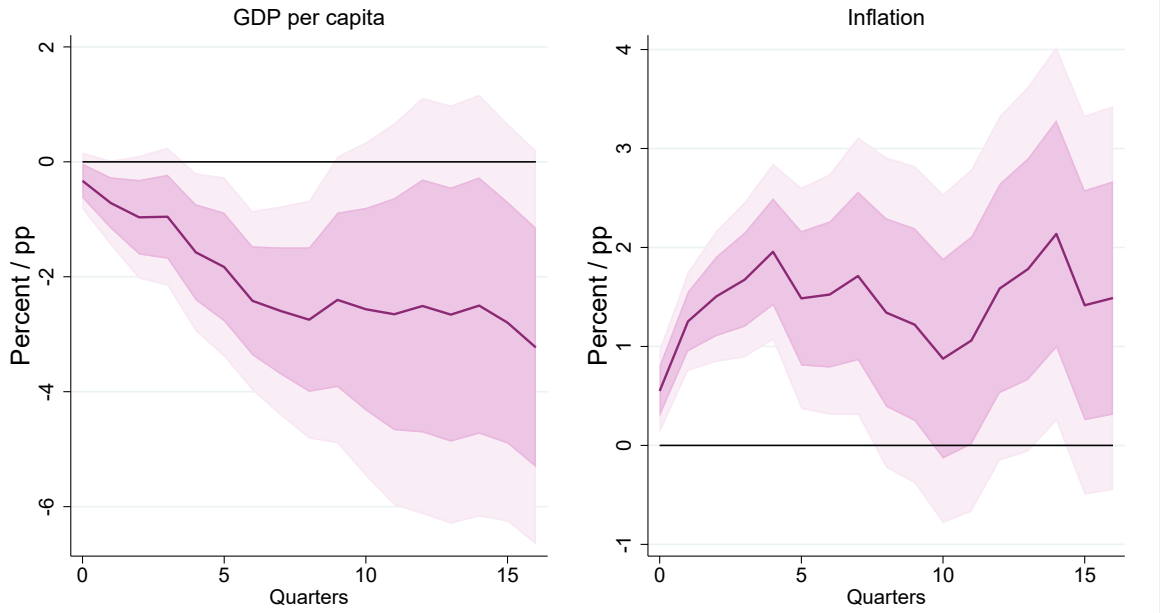
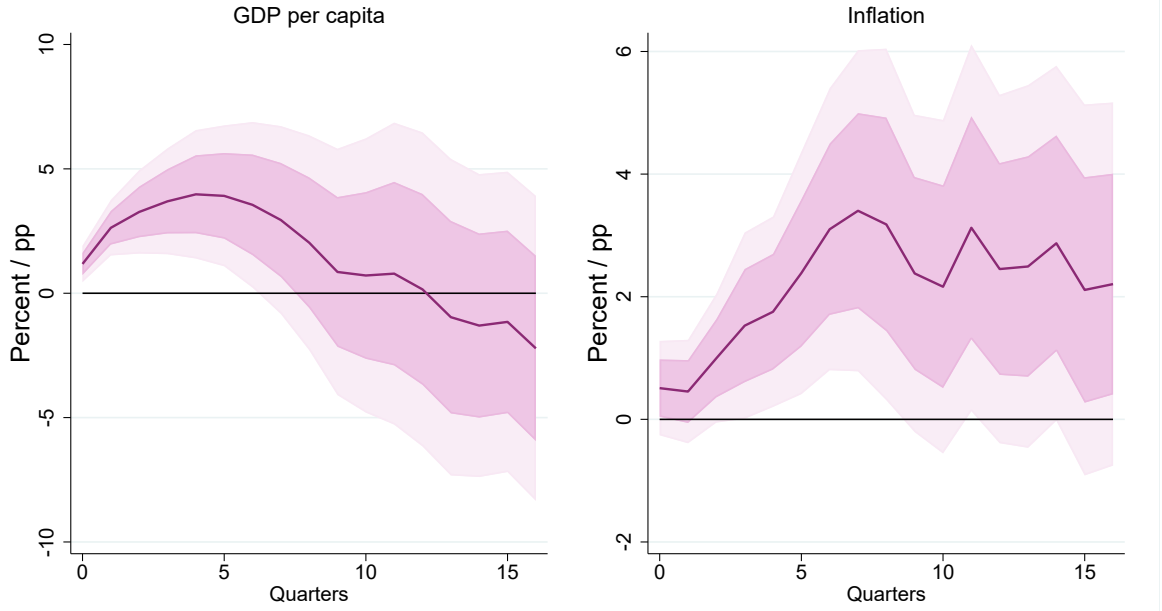


Figure C.10: Impulse Response of GDP and Inflation to Risk Perception ('demand shock')



Appendix D Inspecting Model Mechanisms (online)

D.1 Models that rely on a direct price effect

The direct price effect is perhaps the most intuitive and simple mechanism that generates a counterfactual response of leverage to contractionary monetary policy shocks. Specifically, the direct price effect implies that an increase in the interest rate raises the relative cost of debt financing for banks and so banks substitute away from debt financing. A reduction in the reliance on debt financing is equivalent to a reduction in leverage. All else equal, this implies that higher rates reduce bank leverage, a claim I have shown to be empirically inaccurate.

Given the relative simplicity of the direct price effect, I will not go into the details of any particular model; rather I will briefly highlight some examples.

This type of mechanism is common across the literature. For example, Angeloni and Faia (2013) introduce banks to a conventional DSGE model with nominal rigidities. Banks exist in the model because they can extract more liquidation value from projects. Banks are financed with deposits and equity and they are also subject to the risk of a run. The return on a project is equal to the expected value plus a random shock. Moreover, a run occurs if the outcome of a project is too low to repay depositors. If there is a contractionary monetary policy shock, the deposit rate increases which directly raises the price of deposits for the bank and reduces the bank's ability to repay its depositors. This increases the probability of a run and so the bank reduces its deposits which decreases its leverage. Indeed, this mechanism is essentially a direct price effect that is induced by an endogenous run probability.

Another, albeit very different, example is the model by Drechsler et al. (2018b). They develop a dynamic asset pricing model in which monetary policy affects the risk premium component of the cost of capital. Risk-tolerant agents (banks) borrow from risk-averse agents by taking deposits to fund levered investments. Leverage exposes banks to funding shocks. As such, banks hold liquidity buffers composed of safe assets (e.g., US Treasuries) to insure against such funding shocks. If the central bank raises interest rates, it directly raises the price of holding liquid securities which raises the liquidity premium. This increase in the price of funding shock insurance means banks will reduce their liquidity buffers. Therefore, with lower insurance, banks reduce their exposure to funding shocks by reducing deposits. Again, this is essentially a direct price effect but in this model it is induced by the dynamics of liquidity insurance.

For the direct price effect to increase leverage in response to a contractionary monetary policy shock, the following must be true: (i) debt liabilities fall; and (ii) the fall in debt liabilities is greater than the fall in equity. In Figure D.1 below, I show that debt liabilities do fall in my data, consistent with (i). However, the more important contribution of my empirical analysis is that (ii) does not hold in the data. As I show in Section 3, the empirically dominant mechanism is the loan-loss mechanism which not only offsets the effect on leverage from falling debt liabilities, but actually leads to a reversal in sign such that contractionary monetary policy shocks increase leverage.

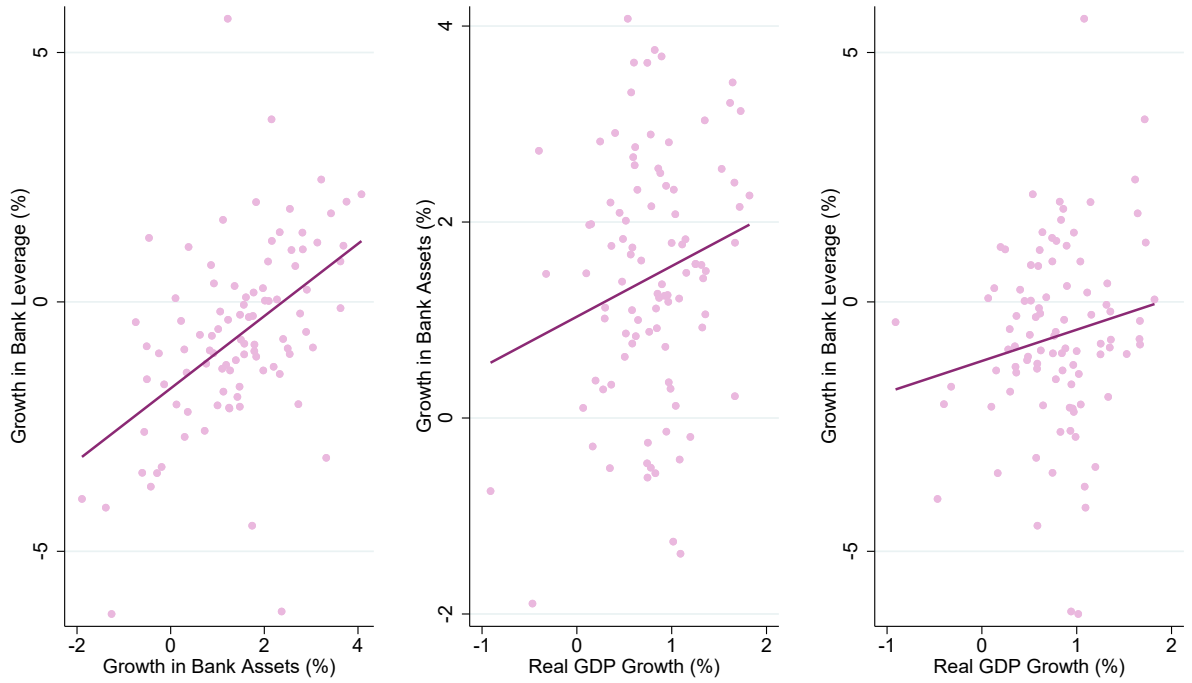
Figure D.1: Impulse Response of Debt Liabilities to Contractionary Monetary Shock

D.2 Models that rely on leverage procyclicality

Like models based on the direct price effect, this class of models are similarly eclectic in their underlying structures, but have the common feature that the results are driven by the procyclicality of bank leverage. This procyclicality has been widely documented in the literature (e.g., Adrian and Shin (2010), Laux and Rauter (2017), and Adrian et al. (2019)). Such studies typically document this procyclicality by showing a positive relation between the growth of bank leverage and the growth of bank assets. The latter is considered procyclical as bank lending grows during a boom and shrinks during a bust. Figure D.2 shows that leverage is indeed procyclical in my data. Specifically, it shows the positive correlation between the growth in bank leverage and the growth in bank assets as well as growth in bank leverage and GDP growth directly.[44]

[44] One can also do a simple regression of the growth in leverage on GDP growth which would yield a positive coefficient with a t-statistic of 1.87.

Figure D.2: Procyclicality of Bank Leverage



In these models, a contractionary monetary shock will reduce output and because leverage is procyclical, it will also reduce leverage. Such models rely on leverage procyclicality in different ways. Some use procyclicality of leverage as a target or a measure of success of the model. For example, Rannenberg (2016) points out that by introducing a firm sector in the spirit of Bernanke et al. (1999) to the model of Gertler and Karadi (2011) (he terms this combined model the "full model"), he is able to generate procyclical leverage. Specifically, he concludes that "in the full model, bank leverage declines in response to contractionary monetary policy and productivity shocks, which allows the full model to match the procyclicality of bank leverage in U.S. data. By contrast, bank leverage in the Gertler–Karadi-type model is strongly countercyclical."

However, as explained in Section 4 one cannot match conditional moments in a model to unconditional moments in the data as these are two entirely different measures. Like Rannenberg (2016), many papers do not distinguish between the procyclicality of leverage in the data (an unconditional moment) and the response of leverage to monetary policy (a conditional moment). This leads to the conclusion that monetary policy should 'lean against the wind' by tightening in response to increasing leverage. One particularly prominent, albeit highly stylised, paper that makes this type of argument is Woodford (2012). He provides a simple and reduced-form model of the way in which endogenous state variables affect the probability of a crisis and what this means for optimal monetary policy. To highlight in more detail how issues arise when using this type of procyclicality, I will focus on the set-up in Woodford (2012). The advantage of this model is in its simplicity which allows one to easily see the intuition.

The model is a fairly typical three-equation New Keynesian (NK) model except with two types of households: those that are credit constrained and those that are not. This is

represented by the existence of a credit friction Ω_t which essentially measures the gap at any point in time between the marginal utilities of the two types of households. Woodford (2012) then derives a modified intertemporal IS equation:

$$y_t - g_t + \chi\Omega_t = \mathbb{E}_t[y_{t+1} - g_{t+1} + \chi\Omega_{t+1}] - \sigma[i_t - \mathbb{E}_t\pi_{t+1}] \tag{19}$$

where y_t is the output gap, g_t is government purchases, i_t is the nominal interest rate set by the central bank, π_{t+1} measures inflation between period t and $t+1$, and the coefficients satisfy $\chi, \sigma > 0$. All variables represent deviations from the steady state. The only difference between equation (19) and the standard IS equation is the credit friction. Indeed, as one would expect, a higher credit friction would behave similarly to the effects of a reduction in government purchases. Therefore, real aggregate demand now also depends on the severity of credit frictions in the economy. A similar approach yields a modified NK Phillips curve.

$$\pi_t = \kappa_y y_t + \kappa_\Omega \Omega_t + \beta\mathbb{E}_t\pi_{t+1} + u_t \tag{20}$$

where u_t is a composite term denoting the different exogenous cost-push factors. Again, the Phillips curve is exactly the same as that in the standard model except for the additional credit friction. A key component of the model is to incorporate some endogeneity in how the credit fiction evolves. Ω_t is assumed to always be in one of two states: a normal state (low value of Ω_t) and a crisis state (high value of Ω_t). Each period, the probability of entering the normal state when in a crisis state is δ, while the probability of entering the crisis state when in a normal state is γ_t which is an increasing function of bank leverage (L_t). Intuitively, as leverage is higher, the probability of going into a crisis is higher. Therefore, to complete the model, Woodford (2012) connects leverage with the remaining endogenous variables by postulating a simple law of motion:

$$L_t = \rho L_{t-1} + \xi y_t + \nu_t \tag{21}$$

where ν_t represents an exogenous disturbance term and importantly ξ is assumed to be positive. Therefore, this law of motion embeds the procyclicality of leverage as leverage is an increasing function of the output gap. Indeed, this type of assumption is the core reason models in this class are unable to generate empirically consistent dynamics.

To complete the framework, Woodford (2012) assumes that the goal of policy is to minimise the following loss function:

$$\frac{1}{2}E_0 \sum_{t=0}^{\infty} \beta^t \left[\pi_t^2 + \lambda_y y_t^2 + \lambda_\Omega \Omega_t^2\right] \tag{22}$$

This is an intuitive form of the loss function as the central bank is simply minimising losses from inflation, output, and financial instability. However, the problem arises because of the way in which monetary policy and leverage now intertwine. A contractionary monetary shock will reduce the output gap as is typically the case. However, because of equation (21), the same shock will also reduce leverage. Indeed, Woodford (2012) concludes that the model implies one should use monetary policy to 'lean against' a credit

boom (which in this model would be to reduce leverage) even if it requires missing target values for inflation and the output gap. In this model, the primary prediction is inconsistent with my empirical findings and as such the consequences of following such a rule are more severe. For example, consider a central bank that is following such a rule when inflation and the output gap are on target, but credit frictions are far too high. As Woodford (2012) mentions, it would be appropriate for the central bank to use contractionary monetary policy. The consequences would not only see both inflation and the output gap falling below target, but leverage would actually rise due to increasing loan losses which are missing from the model. This would unambiguously worsen losses according to the central bank loss function.

The Woodford (2012) model, while highly stylised, is very influential as it builds on the workhorse NK structure. However, it entirely misses the empirical loan-loss mechanism and instead relies on a postulated law of motion that embeds procyclicality. This procyclicality between leverage and output is correlational, not structural. Indeed, when models rely on procyclicality in this way, they typically argue that monetary policy should lean against the wind because contractionary shocks, contrary to the evidence in this paper, reduce bank leverage.

D.3 Models that rely on a profitability channel

In this class of models, profitability and leverage move together and are connected by an incentive compatibility leverage constraint. Furthermore, these models have the feature that *any* negative shock will increase bank profitability as well as bank leverage. As such, while these models correctly show that leverage increases in response to a contractionary monetary policy shock, they have leverage increasing alongside an increase in profitability (which I term the profitability channel). This is at odds with the empirical evidence that the increase in leverage following a contractionary monetary policy shock *is caused by* a decrease in profits.

This class of models build on the canonical models of Gertler and Kiyotaki (2010) and Gertler and Karadi (2011) which relies on a Gertler-Karadi-Kiyotaki-type constraint (i.e., an incentive-compatibility leverage constraint) to model banks which generates the profitability channel.

Given the empirical inconsistencies arising from using a Gertler-Karadi-Kiyotaki-type constraint are intricate, I will focus on the specific set-up in Gertler and Karadi (2011) to highlight how the issues arise. I choose Gertler and Karadi (2011) for two reasons. First, given it is one of the foundational models, most models in this class typically have the same underlying structure. Second, while Gertler and Kiyotaki (2010) is also a foundational model, Gertler and Karadi (2011) incorporates nominal rigidities and so is better able to highlight the impact of monetary policy on bank leverage.[45]

Gertler and Karadi (2011) builds on the seminal monetary dynamic stochastic general equilibrium (DSGE) models of Christiano et al. (2005) and Smets and Wouters (2007)

[45] While Gertler and Kiyotaki (2010) is a purely real model, both models have the same underlying structure; one can think of Gertler and Karadi (2011) as extending the Gertler and Kiyotaki (2010) model to allow for nominal rigidities.

by incorporating banks that transfer funds between households and non-financial firms. Banks exist as they have expertise in evaluating and monitoring borrowers and a simple agency problem between banks and households constrains the ability of banks to raise deposits. The model features five different agents: households, goods producers, capital producers, monopolistically competitive retailers, and banks. Monetary policy is characterised with a simple Taylor rule. Without banks, the model is isomorphic to Christiano et al. (2005) and Smets and Wouters (2007). While the model is a sophisticated general equilibrium (GE) model, one need only analyse the banking block of the model to understand how Gertler and Karadi (2011) generate the correct leverage prediction as well as where the model is diverges from the empirical evidence. Therefore, I will focus on the partial equilibrium of the banking block to highlight the intuition and precisely depict the underlying mechanisms. For completeness, I will also show the results from simulating the full GE model to show that the core insights obtained from examining the banking block do not change once we account for GE dynamics.

I will follow a stylised version of the Gertler and Karadi (2011) model. Banks obtain deposits, B, from households. These funds are then 'lent' to non-financial firms which gives banks a claim on those firms where S depicts the quantity of those claims.[46] Each claim has price Q. Therefore, the net worth (equity), N, of the bank is given by the following balance sheet constraint:

$$N = QS - B \tag{23}$$

The stochastic return on a single unit of lending is R_k while a single unit of deposits pay a non-contingent return R. Both returns are determined endogenously. Given this structure, the bank's objective is to maximise the expected value of the bank, V, which is simply maximising the difference between the expected earnings on assets and interest payments on liabilities. The value of the bank is therefore given by the following:

$$V = R_k QS - RB \tag{24}$$

We can plug in the balance sheet constraint, equation (23), into the bank objective function above to yield the following:

$$\begin{aligned} V &= R_k QS - R(QS - N) \\ &= \underbrace{(R_k - R)}_{\text{profitability}} QS + RN \end{aligned} \tag{25}$$

Equation (25) shows that a bank's value is a function of the premium the bank earns on its assets, which I have termed profitability. We can already see that in this model there is no measure of loan losses that were key to the empirical mechanism documented in Section 3. While one could argue that loan losses might already be included in the endogenously determined R_k, I will explain how this is not the case.

Thus far, the model is fairly standard. However, an important feature of equation (25)

[46] Technically, these loans by banks to non-financial firms are perfectly state-contingent debt and so are better thought of as equity.

is that so long as the bank has positive profitability (i.e., $R_k - R > 0$), it will want to infinitely expand its assets. Put differently, bank value V is increasing in assets when banks have positive profitability. Therefore, a core component of this class of models is the introduction of a moral hazard/costly enforcement problem which generates an endogenous leverage constraint (i.e., the Gertler-Karadi-Kiyotaki constraint) and thus prevents banks from infinite expansion. The costly enforcement problem is modelled as follows. After households place their deposits in a bank, the bank can divert a fraction λ of the deposits for itself. However, if the bank diverts those deposits, the depositors will force the bank into bankruptcy and recover the remaining $1 - \lambda$ share of assets. Therefore, rational depositors will only deposit at a bank if the bank has no incentive to divert assets. This yields the following incentive constraint which must be satisfied:

$$V \geq \lambda QS \tag{26}$$

Intuitively, the incentive constraint above is saying that a depositor would only deposit at a bank if the bank value (i.e., the value the bank obtains from being honest) is greater than the value the bank receives if it diverts assets (i.e., the value the bank obtains from not being honest). One can already see that banks with high value will be able to attract more deposits and subsequently grow their assets. Therefore, the incentive constraint prevents banks from expanding their assets infinitely as they need their value, V, to be larger than the share of divertible assets. As such, banks will expand up to that point (so long as profitability is positive). This implies that equation (26) will hold with equality and so we can equate equations (25) and (26) together.[47] This yields the following:

$$\begin{aligned} \lambda QS &= (R_k - R)QS + RN \\ \implies \text{leverage} \equiv \frac{QS}{N} &= \frac{R}{\lambda - (R_k - R)} \end{aligned} \tag{27}$$

Now we have an equation for leverage (i.e., total assets divided by net worth). This equation, which is derived from the bank problem and incentive constraint alone, has a very important implication: leverage is increasing in profitability (where profitability is $R_k - R$). The intuition behind this implication is that if a bank is able to make more profits, then it has less incentive to divert assets and cheat depositors. As such, depositors are more willing to lend to the bank which enables the bank to increase its leverage. Note that because of equity issuance frictions, the adjustments come from leverage. We are now in a position to contrast this simple intuition to the empirical findings.

Recall, I show that a contractionary monetary policy shock reduces profits which depletes net worth and subsequently increases leverage. Note specifically that leverage is rising *because* of falling profits. On the other hand, the model has leverage rise together with profits rising (i.e., the profitability channel). This is an important inconsistency. The reason profits fall in the data is driven primarily from a rise in loan losses as borrowers with floating-rate loans are less able to repay. The model has no measure of loan losses and as such does not capture that profits fall following a contractionary monetary policy

[47] Gertler and Karadi (2011) explicitly state that the constraint always binds within a local region of the steady state.

shock. Therefore, even though the interest rate on lending, R_k, is endogenously determined, it is unable to capture the loan-loss dynamic. Hence, modelling banks through this type of Gertler-Karadi-Kiyotaki incentive constraint generates an empirically inconsistent profitability channel. While my empirical results were based on the monetary policy shocks identified in Romer and Romer (2004), one can actually use the monetary policy shock series in Gertler and Karadi (2015) to see whether the Gertler and Karadi (2011) model would be consistent with results using the Gertler and Karadi (2015) shock series.

Figure D.3: Impulse Response of Profits to Contractionary Monetary Shock

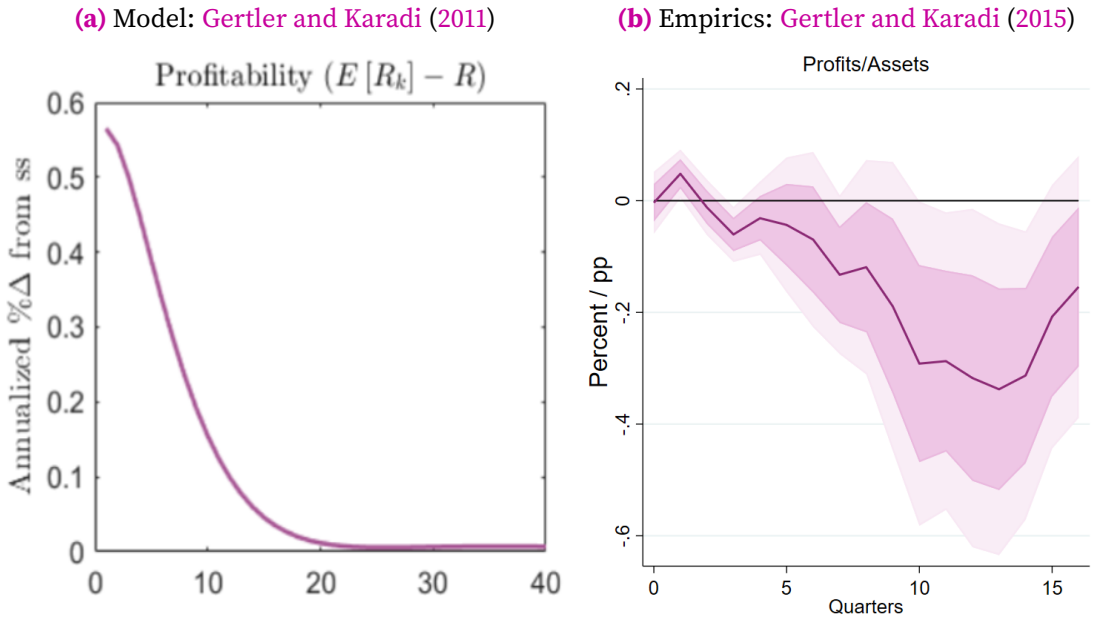


Figure D.3a shows that in the Gertler and Karadi (2011) model, profits increase following a contractionary monetary policy shock, before returning to steady state. However, Figure D.3b, which uses the same specification as throughout this paper, shows the shock series in Gertler and Karadi (2015) predicts a decrease in profits following a contractionary shock.[48] One possible explanation for the inconsistency with respect to profits is that $R_k - R$ can represent several different measures of profitability, where the book profits of banks is one possible measure. Other measures could include the risk premium in the economy or the expected return on bank stocks.

Moreover, one could argue that Gertler and Karadi (2011) and similar models are still able to predict that leverage rises following a contractionary monetary policy shock and perhaps that is sufficient despite the mechanism being empirically inconsistent. There are two important problems with this line of reasoning. First and foremost, one important rationale for developing macroeconomic models with a microfounded banking sector such as Gertler and Karadi (2011) is to help us understand the underlying economic mech-

[48] Given that the GK shock starts later than the RR shock, the data underlying the figure is from 1994 onwards and eight lags are used instead of sixteen due the shorter time horizon. The empirical measure of profits is profit divided by assets and so is measuring profitability in a way that closely resembles the measure of profitability in the model.

anism. However, not only does the model miss an important channel through which monetary policy is being transmitted to banks (i.e., loan losses), it suggests a mechanism that is contradicted by the data as profits rise in the theoretical model of Gertler and Karadi (2011) but fall according to the Gertler and Karadi (2015) empirical evidence.

Secondly, even if the primary objective of this class of models is prediction rather than capturing the underlying economic mechanism, the results may still be misleading. To highlight why, let us return to the Gertler and Karadi (2011) model and rewrite the definition of leverage using the incentive constraint (i.e., using equation (26) to replace QS). This yields the following:

$$\text{leverage} = \frac{V}{\lambda N} \tag{28}$$

In these types of models, bank value (V) is linear in bank assets and net worth[49]

$$V = \nu QS + \eta N \tag{29}$$

where ν is the marginal value of expanding assets and η is the marginal value of expanding net worth. Plugging equation (29) into equation (28) yields the following:

$$\begin{aligned} \text{leverage} &= \frac{\nu QS + \eta N}{\lambda N} \\ \implies \lambda \cdot \text{leverage} &= \nu \frac{QS}{N} + \eta \\ \therefore \text{leverage} &= \frac{\eta}{\lambda - \nu} \end{aligned} \tag{30}$$

where the last step makes use of the fact that leverage $\equiv \frac{QS}{N}$. Equation (30) highlights a very important implication of this type model structure: leverage is increasing in the marginal value of net worth (as well as the marginal value of assets). Given the equity frictions, *any* negative shock that increases the marginal value of net worth (η) and assets (ν) will also increase leverage.[50] Therefore, while this feature allows such models to correctly predict that leverage rises in response to a contractionary monetary policy shock, they also predict that all other negative shocks would yield a rise in leverage which is a much stronger claim. If this were true, then perhaps one could put less emphasis on the underlying economic mechanism. However, I have already provided one counterexample to the claim that any negative shock will increase bank leverage. Figure 5b shows a negative oil shock that leads to a decrease in leverage. So why are Gertler and Karadi (2011) able to accurately predict leverage in the case of the contractionary monetary policy shock scenario but not negative oil shock? One reason is because there is no distinction by type of shock in the

[49] Indeed, as highlighted in Van der Ghote (2021), having V proportional to net worth implies that the bank problem is scale invariant. As such, optimality implies that leverage is the same for all banks regardless of their net worth which allows for a representative bank.

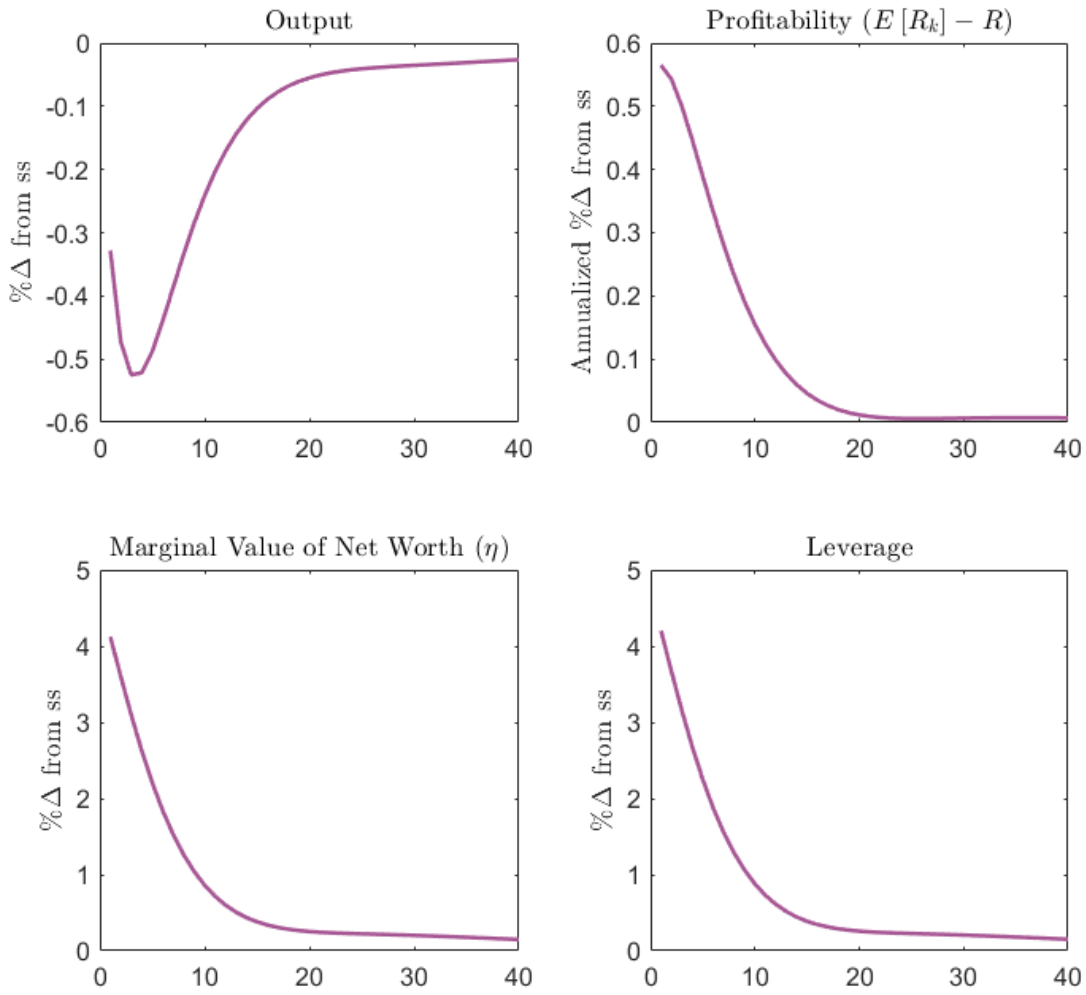
[50] A negative shock increases the marginal value of net worth because it causes an on-impact decrease in the price of capital, Q. This reduces bank net worth as bank assets are now worth less. However, a decline in net worth means banks are less able to lend which decreases total loans. A decline in total lending raises the expected profitability of lending which raises the marginal value of net worth.

model. However, as is evident in Figure 5, the type of shock matters empirically not just in terms of magnitude but also direction. While both an oil shock and monetary policy shock cause a decline in GDP, only the latter increases loan losses, which also highlights the role of floating-rate loans. This again underscores the importance of the underlying loan-loss mechanism; a component missing from Gertler and Karadi (2011). Ensuring the mechanism is modelled appropriately ensures that the predictions are made in the right context. In this sense, the prediction in this class of models may be misleading.

Thus far, we have only used a partial equilibrium analysis to understand how and why models that use a Gertler-Karadi-Kiyotaki type constraint to model banks generate implications that are inconsistent with empirical evidence. While such analysis more easily highlights the underlying intuition and dynamics, one might argue that the full GE model could generate different results. Therefore, in Figure D.4 below, I show the results obtained from the full GE model in response to a contractionary monetary policy shock.[51] As can be seen, in the full GE model, a contractionary shock decreases output, increases profitability, increases the marginal value of net worth, and increases leverage, all claims that were evident from analysing the banking block alone. Moreover, consistent with equation (30), Gertler and Karadi (2011) also show that a negative total factor productivity shock leads to an increase in leverage.

[51] The model code is obtained from the Macroeconomic Model Data Base (see https://www.macromodelbase.com/).

Figure D.4: Gertler and Karadi (2011) Model Response to Monetary Policy Contraction



Therefore, for understanding bank leverage, the set of results in this section highlights that the insights obtained from examining the structure of the banking sector alone survives GE dynamics. Indeed, given the implications of my analysis of the banking block, and that the remaining components of these model (i.e., households and firms) are fairly standard, it appears that the inconsistencies in such models arise primarily due to the profitability channel, which ignores the loan-loss mechanism.