Getting in all the Cracks: Monetary Policy, Financial Vulnerabilities, and Macro Risk *

Andrea Ajello†

Tyler Pike‡

August 10, 2022

Abstract

We estimate the effect of monetary policy on financial vulnerabilities and the implications for macroeconomic tail risk. We first extract a small set of common factors from a large dataset of financial vulnerability indicators, estimating a factor-augmented proxy SVAR to study the response of aggregate economic activity, inflation, and financial vulnerabilities to monetary policy shocks. We then estimate the effect of changes in the financial vulnerability factors on macroeconomic tail risk via quantile regressions. We find that an unexpected monetary policy tightening can lower asset valuation vulnerabilities in the short term and slow down credit growth in the medium term. As tighter monetary policy reduces asset valuation pressures, it does so at a cost of a sizable increase in macro tail risk in the short term that is only partially offset by a modest reduction in tail risk in the medium term, induced by a slowdown in credit growth.

Please do not cite without permission. Comments are welcome!
Click here for latest version.

† Corresponding author. andrea.ajello@frb.gov, Federal Reserve Board, 20th and C Street NW, Washington, DC 20550. ‡ PhD Student, University of Maryland - College Park

*We are grateful to participants at the Society for Economic Dynamics Conference 2022, the QCGBF Annual Conference on Monetary Policy at King's College London, the Federal Reserve Bank of Chicago seminar series, the Federal Reserve Symposium on Monetary Policy and Financial Stability for helpful comments. We are also grateful to Nina Boyarchenko, Ambrogio Cesa-Bianchi (discussant), Richard Clarida, Marco del Negro, Rochelle Edge, Giovanni Favara, Francois Gourio, Kurt Lewis, David López-Salido, Francesca Loria, Matteo Luciani, Michele Modugno, Andrea Tambalotti, and Min Wei for useful conversations, comments and suggestions. Part of this project was developed when Andrea Ajello was a visiting researcher at the Bank for International Settlements and gratitude goes to the BIS and its staff for the generous hospitality and interesting conversations. The views expressed herein are those of the authors and do not represent those of the Federal Reserve Board or of the Federal Reserve System. All errors are our own.

1 Introduction

"While monetary policy may not be quite the right tool [to pursue financial stability], it has one important advantage relative to supervision and regulation–namely that it gets in all of the cracks." Jeremy Stein, Fed Governor, 2013.

Monetary policymakers' interest rates deliberations aim to alter aggregate financial conditions to prompt changes in borrowing, lending, and risk-taking decisions of market participants, and ultimately affect aggregate demand. If prices are slow to adjust, shifts in demand can translate into changes in resource utilization, and monetary policy can prove effective in stabilizing business cycle fluctuations. As the effects of monetary policy decisions spread through the cracks of the financial system, what mark do they impress on indicators of financial vulnerability and, conversely, to the likelihood of financial crises and to the balance of risks to the macroeconomic outlook?

The answer to this question has profound consequences for the conduct of monetary policy. If tighter monetary policy can effectively reduce financial vulnerabilities, central bankers might wish to "lean against the wind" and, on average, adopt a more restrictive monetary policy stance–despite its negative impact on economic activity and inflation–to reduce downside risk to the macro outlook in the form (i.e., preventing financial crises and the large and persistent welfare losses they bring about). Conversely, if policymakers set interest rates "too low for too long" while pursuing their mandate of price stability and full employment, loose monetary policy could foster financial vulnerabilities that may amplify future economic downturns and increase the likelihood of financial disruptions.

To the best of our knowledge, our analysis is the first to quantify macroeconomic costs and benefits of monetary policy as it affects macro outcomes, transmits to financial vulnerabilities and, hence, varies the balance of risks to the outlook (see Boyarchenko, Favara, Schularick, 2022). To this end, we aim to: 1) measure the elasticity of common drivers of a wide array of financial vulnerabilities to exogenous changes in the monetary policy stance, and 2) quantify the effect of financial vulnerabilities on downside risk to the macroeconomic outlook. We find that monetary policymakers that wish to increase interest rates will be confronted with a weaker macroeconomic outlook and a sizable increase in downside risk in the short run, in exchange for lower financial vulnerabilities and a modest reduction in downside risk in the medium run.

We build a factor-augmented VAR that models the joint evolution of monetary policy, macro outcomes and a wide array of 41 time series that contain information about the state of financial vulnerabilities in different segments of the U.S. financial system. The dataset (Aikman et al. (2017)) forms a framework to assess system-wide vulnerabilities and includes measures of valuation pressure across asset and credit markets, indicators of leverage and default risk in the household and non-financial business sector, indicators of vulnerabilities in the financial sector that gauge fragility of intermediaries' balance sheets affecting their ability to provide credit, liquidity, and maturity transformation to the wider system. We find that four orthogonal factors can explain most of the cyclical variation in the panel of indicators and that the four factors correlate respectively with indicators of credit growth, risk appetite, the adjustment speed of debt over GDP, and the level of net leverage of risky borrowers.

We identify monetary policy shocks using external instruments, relying on high frequency surprises on Fed Funds futures quotes recorded around monetary policy announcements and purged of changes in outlook forecasts (Miranda-Agrippino and Ricco, 2021). We find that an unexpected tightening of the monetary policy stance through the model delivers a standard slowdown of macroeconomic activity and inflation and sizable, persistent, and conflicting changes on financial vulnerability indicators. Our analysis uncovers that policy tightening has a modest effect on average vulnerabilities, but has heterogeneous effects on the underlying indicators. Monetary policy has marked effects on the four orthogonal vulnerability factors: tighter policy hampers credit growth, tightens financial conditions, slows down the accumulation of mortgage debt as a fraction of GDP, but increases the net leverage ratio of risky businesses. More generally, looking at the broader cross-section of vulnerability indicators, tighter monetary policy puts marked downward pressure on risk appetite, shifting asset valuations downwards and tightening non-financial and financial sector lending standards. Relatedly, tighter monetary policy lowers debt growth and slows down the rate of change of credit aggregates over GDP. However, as financial conditions get tighter the economic outlook also weakens and indicators of debt sustainability such as debt service ratios, or indicators of risky leverage can deteriorate, at least in the short run.

We then turn to exploit the small set of financial vulnerability factors extracted from the model and use them to estimate how changes in vulnerabilities affect the predictive distribution of GDP growth and inflation at different horizons. We estimate how changes in vulnerabilities affect growth and inflation-at-risk by running quantile regressions of future average GDP growth and inflation over two forecasting windows (short-run with horizon $h \leq 12$ months, and medium-run with horizon $12 < h \leq 36$ months) on the four financial vulnerability factors (Adrian, Boyarchenko and Giannone (2019), Lopez-Salido and Loria (2021)).

We find evidence that lower vulnerabilities in the form of slower credit growth and tighter financial conditions can reduce future downside risk to the outlook in the medium run, albeit modestly. Conversely, we find evidence that in the shorter run (i.e., an horizon of less than a year) lower vulnerabilities translate primarily into tighter financial conditions that weaken the macroeconomic outlook and increase downside risk.

For perspective, we use our estimates to quantify the trade-off of leaning against the wind policy in a historical context. In anticipation of the GFC, vulnerabilities were elevated. As the crisis began, financial conditions tightened the distributions of future GDP growth and inflation became skewed toward less favorable outcomes. We simulate impulse responses from the FAVAR model under a surprise policy tightening that raised the level of short-term interest rates by 100-bps over the historical path in June 2005. The hypothetical rise in the level of rates pushes the unemployment rate up by around 1 percentage point by 2007, and lower inflation by around 40 basis points for 12 months. A year after the shock, vulnerabilities under tighter monetary policy would be modestly lower, on average, relative to their historical highs. In response, the left skewness of the distribution of predicted macro outcomes between 2007 - 2009 decreases, improving predicted tail outcomes of GDP growth by 1.5 percentage points, relative to the historical estimates in the absence of tightening.

Literature Review

After the GFC, a large body of research has used historical panels of aggregate data series for multiple countries and extended sample periods to evaluate the role of indicators of financial imbalances in predicting financial crises episodes (see for example Schularick and Taylor, 2012, Jorda and Schularick, 2013, Gourinchas and Obstfeld, 2012, Laeven and Valencia, 2013). A related effort was directed at building a system of indicators that could send early warnings when vulnerabilities were to emerge in the financial system and that policy makers could monitor to inform their macroprudential and monetary policy decisions. In particular, based on findings in the academic literature, Aikman et al. (2017) collect a database of indicators of valuation pressure across asset markets (Cecchetti, 2008, Reinhart and Rogoff, 2010, Campbell and Shiller, 1998, Brunnermeir and Sannikov, 2014), indicators of leverage and default risk in the nonfinancial sector (Mian and Sufi, 2009, Greenwood and Hansen, 2013), indicators of vulnerabilities in the financial industry, and of disruptions in market supply of liquidity and maturity transformation services (Diamond and Rajan, 2011, Adrian and Shin, 2010, Adrian et al., 2015, Brunnermeir and Oehmke, 2013, among others). Policy institutions, such as the Federal Reserve, the Office of Financial Research (OFR) at the U.S. Treasury, the IMF, and the BIS to name a few, rely on these measures to assess domestic and global financial stability risk and periodically report on them. We build on the work by Aikman et al. (2017) to model the joint evolution of macro variables and financial stability indicators and study the effect of monetary policy surprises in the context of a dynamic factor model.

Our work relates to the body of empirical literature that provides supportive evidence that an unexpected tightening of the monetary policy stance can reduce aggregate output (see, for example Sims (1980), Bernanke and Blinder (1992), Christiano, Eichenbaum, and Evans (1996), Romer and Romer (2004), in the macro VAR tradition, and Bernanke, Boivin, Eliasz (2004) for an extension to a factor-augmented VAR that is closer in spirit to our exercise). While the evidence in favor of real effects of monetary policy is strong on post World War II data, it has turned tenuous with the Great Moderation (see Ramey (2016) for a review on the topic). Recent work has resolved this tension and highlighted how including measures of financial conditions in a structural macro VAR increases the estimated size of the effect of monetary policy surprises on aggregate activity during the Great Moderation (Gertler and Karadi, 2015, Caldara and Herbst, 2019). Our dynamic factor model confirms their findings and extends their set-up to include information from a wide array of financial aggregates beyond interest rates, such as measures of asset valuations, credit aggregates, and risk-taking indicators.

We identify monetary policy shocks following closely the proxy SVAR methodology championed by Stock and Watson (2012) and Mertens and Ravn (2013). We use surprises built from changes in high-frequency financial data around monetary policy announcements to identify unexpected shocks to the stance of policy perceived by market participants (Kuttner (2001), Gurkanyak, Sack, and Swanson (2005)). In particular, we use a proxy that parses out the effect of revisions in the economic forecast from the high-frequency policy surprises, as proposed by Miranda-Agrippino and Ricco (2021), to focus our analysis around changes in the monetary policy stance rather than reactions to changes in economic conditions or to the economic outlook.

Our work is focused on quantifying the effect of the surprise component of monetary policy on financial indicators of vulnerabilities and and on changes in downside risk to the outlook mediated by changes in financial conditions (Adrian, Boyarchenko, Giannone (2019), Lopez-Salido and Loria (2021), Caldara, Cascaldi-Garcia, Cuba-Borda, Loria (2020)).

Finally, our analysis also relates to and can inform the findings of the literature that has assessed costs and benefits of systematic LATW policy in the context of calibrated structural DSGE models (see Bernanke and Gertler (1999), Svensson (2016, 2017), Gourio, Kayshap, and Sim (2017), Laseen, Pescatori, and Turunen (2018), Ajello, Laubach, Lopez-Salido, Nakata (2019)).

2 Data

We estimate our model on a panel of macroeconomic and financial vulnerability indicators over a sample period that starts in January 1990 and ends in December 2019. The dataset includes monthly data on the constant-maturity 1-year Treasury note yield as an indicator of the level of shorter-term interest rates that can respond endogenously to macroeconomic and financial developments as well as to changes in the monetary policy stance. The dataset also includes monthly year-on-year personal consumption expenditure (PCE) headline inflation rate and the unemployment rate (U3), as macro outcomes that the Fed influences in pursuit of its dual-mandate of stable prices and maximum employment. Finally, we include 41 indicators that measure a wide array of financial vulnerabilities for the U.S. economy. These indicators, collected by Aikman et al. (2017), combined and analyzed jointly, form a framework that can provide a broad and multi-dimensional assessment of vulnerabilities in the financial system.

The buildup of financial vulnerabilities can arise from routine functions of the financial system such as risk, liquidity, and maturity transformations. For example, financial intermediaries and markets can structure financing deals that transform a volatile stream of payoffs generated by risky assets into stable yield paid on relatively safe liabilities. Borrowers and lenders trade off costs and benefits of debt issuance, however leverage can become excessive and undesirable from the perspective of a social planner if defaults can lead to fire sales. Similarly, excessive liquidity and maturity transformation can make lenders' balance sheets prone to risk of runs. When vulnerabilities accumulate, a financial system can become unstable, amplifying aggregate shocks or becoming itself the source of unexpected disturbances with sizable macroeconomic consequences, such as financial crises.

Frameworks similar to the one proposed in Aikman et al. (2017) are in use and subject of periodic monitoring by policy institutions, such as the Federal Reserve Board, which publishes a biannual Financial Stability Report (FSR) that assesses the state of asset valuation, non-financial, and financial sector vulnerabilities, and the Office of Financial Research (OFR) that regularly updates heat maps that offer a visual representation of vulnerability in the markets and sectors that compose the U.S. financial system.

Following Aikman et al. (2017), the indicators in our sample can be classified into three broad categories that include 1) measures of **asset valuation pressure**, and measures of vulnerabilities related to 2) **non-financial sector leverage** and 3) **financial sector leverage and exposure to liquidity and maturity risk**.[1] Tables 1, 2, and 3 are adapted from Aikman et al. (2017) and describe the panel of data series, including information on: their frequency (monthly or quarterly), their availability in terms of sample period, and whether higher values of the indicator increase or decrease system's vulnerabilities (indicated with a + and − respectively). In what follows, we will describe the vulnerability indicators by broad classes and sectors within the classes, listing their italicized figure labels in parentheses, for reference.

Asset valuation pressure indicators are listed by sectors in Table 1. Asset valuation pressures can accrue in housing, commercial real estate, business lending, and equity markets. This class of indicators also includes indicators of financial market volatility.

Housing market valuations are considered elevated when the ratio of average house prices and rent is elevated relative to its 10-year trailing moving average (*AV House P/Rent*, Cecchetti (2008), Rogoff and Reinhart (2010)). Moreover, housing valuation vulnerabilities are considered elevated when mortgage lending standards are easing. The dataset includes two indicators of lending standards for the mortgage market: the Fed Senior Loan Officer Opinion Survey (SLOOS) mortgage lending standards index, that tracks the net share of banks tightening standards over the past calendar quarter (*AV Mrtg. Lend. Std.*), and the median FICO score of borrowers of newly originated mortgages sold to Government Sponsored Enterprises (GSEs) (*AV GSE FICO*).

Similarly for the commercial real estate sector, asset valuations pressure is considered elevated when commercial real estate prices are high, relative to their 10-year trailing moving average (*AV CRE Prices*) and the SLOOS index for Commercial Real Estate (CRE) lending is low, pointing to easing lending standards (*AV CRE Lend. Std.*).

Business sector valuation pressure is deemed high when bond spreads for BBB and high-yield bonds are compressed (respectively *AV BBB Spread*, and *AV HY Spread*), and corporate risk premia, as proxied by the excess bond premium (EBP) of Gilchrist and Zakrajsek (2012) (*AV EBP*), is low. Similarly, business valuation pressures are elevated if the SLOOS index for Commercial and Industrial (C&I) lending shows that bank standards are easing (*AV C&I Lend. Std.*) and if the

[1] For the purpose of this study we exclude indicators of vulnerabilities that might stem from financial sector's size and interconnectedness, as cyclical interest-rate policy surprises seem unlikely to sizably affect features of the financial system that appear to be structural and persistent.

issuance of riskier corporate credit, such as high-yield bonds and leveraged loans, is elevated (*AV Iss. of Risky Debt*).

Equity markets valuation pressure indicators include the earning-to-price ratio for the SP500 index as a measure of equity returns (*AV SP PE ratio*) and the difference between the earning-to-price ratio and the inflation-adjusted 10-year Treasury rate, as a proxy for the equity premium (*AV Equity Premium*). Valuations are considered elevated when equity returns and the equity premium are compressed.

The framework also includes measures of expected volatility on equity and corporate credit markets, respectively the Chicago Board Options Exchange's (CBOE) Volatility Index (or VIX) (*AV VIX*) and aggregate Corporate Default Swaps spreads (*AV CDS Spreads*). A lower value of the VIX indicate that market expectations of near-term volatility are subdued—periods that are generally accompanied by high risk appetite and positive asset valuation pressure. Similarly low CDS spreads point to high valuation pressure, suggesting that the expected default risk on corporate debt is low.

Indicators of **non-financial leverage** vulnerabilities in Table 2 are available for home mortgage, consumer credit, and non-financial business leverage.

Measures of the sustainability and prevalence of risky mortgage borrowing include the ratio of total mortgage debt owed by riskier borrowers over aggregate disposable personal income (DPI) (*NF Risky Mrtg/DPI*), the incidence of very rapid mortgage borrowing by riskier borrowers (Mian and Sufi (2009)) (*NF Risky Rapid Mrtg Borr*), and the incidence of piggy-back mortgages with new loans originated by riskier borrowers (Mayer et al. (2009)) (*NF Piggyback Loans*). The dataset also includes aggregate indicators of mortgage debt sustainability, such as home mortgage debt ratio to GDP relative to its 10-year trailing moving average (*NF Mortg/GDP*), and the mortgage debt service ratio (*NF Mrtg DSR*) defined as the the cost of servicing debt divided by aggregate disposable personal income. An increase in any of these measures points to higher vulnerabilities in residential real estate leverage.

Similarly, measure of consumer credit vulnerabilities include the ratio of consumer credit to GDP (*Con. Cred/GDP*), the debt service ratio of consumer credit to DPI (*NF Con. Cred. DSR*), the ratio of consumer credit owed by riskier borrowers as a fraction of aggregate DPI (*NF Risky Con. Credit/DPI*), and the incidence of very rapid borrowing by riskier borrowers (Mian and Sufi (2009)) (*NF Risky Rapid CC Borr*). An increase in any of these measures point to increased vulnerabilities related to consumers' leverage.

Indicators of vulnerabilities in the nonfinancial business sector include the time series of real business sector debt growth (Schularick and Taylor (2012)) (*NF Debt Growth*), the net leverage of risky firms (*NF Risky Net Levg.*), the share of deep junk bonds issuance relative to total bond issuance (Greenwood and Hansen (2013)) (*NF Deep Junk Iss. Share*), the ratio of interest expenses over available cash for high-yield firms (*NF In. Exp. (HY Firms)*). An increase in any of these measures point to increased vulnerabilities related to business sector leverage. Time series of business and households' saving as a percentage of aggregate income complement this set of indicators, where lower saving rates point to higher vulnerabilities.

The set of indicators of **financial sector** vulnerabilities in Table 3 contains measures of bank leverage, such as the risk-based capital ratio at bank holding companies (Diamond and Rajan (2001), Berger and Bouwman (2013)) (*F Risk-based Capital Ratio*), tangible equity over tangible assets (*F Tangible Equity to Assets*), and tier-1 common equity ratio for bank holding companies (*F Tier 1 Equity Ratio (BHC)*). An increase in the bank capital ratio indicators points to more solid equity positions of intermediaries and hence to lower vulnerabilities.

The list of imbalances also includes indicators of non-bank leverage such as the broker dealer leverage ratio (Adrian and Shin (2010)) (*F B-D Lev.*), broker dealer debt over GDP (*F BD Fin.*), and non-agency securitization volume (Adrian et. al. (2015)) (*F Securitization/GDP*).

Finally, the list of financial sector imbalance indicators also includes measures of maturity risk such as loans to deposit ratio at bank holding companies (*F Loans to Deposits (BHC)*), maturity gaps at commercial banks (Brunnermeier and Oehmke (2013)) (*F Maturity Gap*), the ratio of net wholesale debt to GDP for the financial sector (Brunnermeier et al. (2014)) (*F Net S-term Debt Nonbanks*), measures of short-term funding risk such as short-term money at bank holding companies (Hahm et al. (2013)) (*F Short-term Money (BHC)*), the ratio of gross short-term wholesale funding at nonbanks over GDP (Krishnamurthy and Vissing-Joergensen, (2013)) (*F Gr. S-term Debt Nonbanks*), and the ratio of total runnable liabilities of the financial sector over GDP (*F Runnables*). Higher values of the non-bank leverage, maturity risk, and short-term funding risk indicators all point to higher vulnerabilities.

We linearly interpolate an unbalanced panel of quarterly and monthly financial vulnerability indicators to create an unbalanced panel of monthly variables that starts in January 1991 and ends in December 2019.

Finally, we employ proxy measures of monetary policy surprises to study the effect of shocks to the policy stance on macro variables and vulnerabilities. We use external instruments and rely on high frequency surprises on the one-month Fed funds futures quotes (FF4) recorded around monetary policy announcements and purged of changes in the Fed staff's outlook to net them out the information or Delphic component (Miranda-Agrippino and Ricco (2021)).

3 Model and Estimation

We build and estimate a factor-augmented VAR (FAVAR)–or in the general terminology of Stock and Watson (2002) a dynamic factor model (DFM)–to describe the interactions between monetary policy, macroeconomic outcomes, and indicators of financial vulnerability. For convenience, we partition our panel of N standardized variables $\{Y_t^j\}_{j=1}^N$ into a policy indicator R_t, N^m macro indicators, Y_t^m, and N^v financial vulnerability indicators, Y_t^v:

$$Y_t = [R_t, Y_t^m, Y_t^v]; \tag{1}$$

so that $N = 1 + N^m + N^v$ and $t = 1, ..., T$.

The collection of observables Y_t is linearly spanned by a number K of contemporaneous factors x_t such that:

$$Y_t = \lambda x_t + \eta_t$$

where Λ is an $N \times K$ matrix of loadings on K state variables, or factors, x_t, and $\eta_t \sim N(0, \Omega)$ are idiosyncratic components, with Ω a diagonal covariance matrix.

The state vector x_t is composed of observed and latent factors. Observed factors include the policy indicator R_t, and K^m macroeconomic factors, x_t^m, while latent factors include K^v financial vulnerability factors, x_t^v so that:

$$x_t = [R_t, x_t^m, x_t^v]'.$$

We assume that the states x_t evolve according to a VAR(p) process of the type:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + ... + \phi_p x_{t-p} + \Sigma\epsilon_t$$

where Σ is the impact matrix of the structural shocks $\epsilon_t \sim N(0, I)$, assumed orthogonal to the idiosyncratic shocks in the measurement equation (3), $\epsilon_t \perp \eta_t$.

The state space form of the model in companion form is composed by the state evolution equation (2), and the observation equation, (3):

$$X_t = \Phi X_{t-1} + \Sigma\epsilon_t \tag{2}$$

$$Y_t = \Lambda X_t + \eta_t \tag{3}$$

where, as it is customary, $X_t = [x_t, x_{t-1}, ..., , x_{t-p+1}]$ is a $(K \times p) \times 1$ vector and the first K rows of Φ collect the autoregressive matrices $[\phi_1, ..., \phi_p]$ and the $(p-1) \times K$ remaining rows of Φ establish an identity between the $t-1$ to $t-p+1$ lags of the state vector in the matrix X_t and the same components in the matrix X_{t-1} , and with $\Lambda = [\lambda, \mathbf{0}_{(p-1)\times K}]$.

As in Gertler and Karadi (2015), we use the yield of the on-the-run 1-year Treasury note as our policy indicator, R_t, due to the presence of the zero lower bound in our sample period. We select our m observable macro factors as the two variables at the core of the Fed dual mandate, namely the year-on-year change in the headline PCE, π_t^{PCE}, and the unemployment rate, U_t.

3.1 Model Restrictions and Identification of Monetary Policy Shocks

We express the observation equation as:

$$\underbrace{\begin{bmatrix} R_t \\ Y_t^m \\ Y_t^v \end{bmatrix}}_{\mathbf{Y_t}} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & I_{m,m} & 0 \\ 0 & 0 & \Lambda_{v,v} \end{bmatrix}}_{\mathbf{\Lambda}} \underbrace{\begin{bmatrix} R_t \\ x_t^m \\ x_t^v \end{bmatrix}}_{\mathbf{X_t}} + \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Omega_{v,v} \end{bmatrix}}_{\mathbf{\Omega}} \underbrace{\begin{bmatrix} \eta_t^R \\ \eta_t^m \\ \eta_t^v \end{bmatrix}}_{\boldsymbol{\eta_t}}$$

so that the policy indicator R_t and the macro variables Y_t^m map identically into the states $[R_t; x_t^m]$, measured without error. The N^v vulnerability indicators load on the states x_t^v by means of a $N^v \times K^v$ matrix $\Lambda_{v,v}$. Ω is a $N^v \times N^v$ matrix that collects the standard deviations of the idiosyncratic components η_t.

Accordingly, we assume that:

- The north-west quadrant of the loading matrix Λ be an identity matrix of order $K^m + 1$. Moreover, the loading coefficients in the matrix Λ that map the macro variables, Y_t^m, on the financial vulnerability factors, x_t^v, are set to zero. Finally, $\Omega_{R,R} = 0$ and $\Omega_{m,m} = 0$, while $\Omega_{v,v}$ is diagonal.

- We standardize all observable variables Y_t to have mean zero and standard deviation equal to

1. Moreover we restrict the standard deviations of the idiosyncratic errors η_t^v to be the same across the financial vulnerabilities Y_t^v.[2]

- Financial vulnerability observables, Y_t^v load on the K^v vulnerability factors, $[x_t^v]$, and the submatrix $[\Lambda_{v,v}]$ is full rank. Financial vulnerability observables, Y_t^v do not load directly on the policy indicator and macro factors, so that monetary policy and macroeconomic conditions affects financial vulnerabilities Y_t^v through the state dynamics.
- While the space spanned by the factors is identified, the actual factors are not, since $\Lambda X_t = \tilde{\Lambda}\tilde{X}_t$ for any invertible matrix such that $\tilde{\Lambda} = \Lambda G^{-1}$ and $\tilde{X}_t = GX_t$. We rotate the factors X_t^v and loading submatrix $\Lambda_{v,v}$ so that the unconditional variance covariance matrix $Var(x_t^v) = \Sigma_{X^{FV}}$ is diagonal, and the product $\Lambda'_{v,v} \times \Lambda_{v,v} = I$.

Macro and financial vulnerability factors interact through the state dynamics (2) and state variables X_t follow an unrestricted VAR(p) process.

3.2 Estimation and Specification Testing

We estimate the model in two steps. Since the panel of financial vulnerability indicators is unbalanced, we extract K^v common latent factors x_t^v from the financial vulnerability indicators Y_t^v by maximum likelihood applied to equation (3) under the orthogonality restrictions described in section 3.1. The likelihood function is computed via the Expectation Maximization (EM) algorithm that allows for unspecified patterns of missing data in the observables treating missing observations as additional latent variables.

In the second step we collect the observed and latent factors in the state vector $x_t = [R_t; x_t^m; x_t^v]$ and estimate a VAR(p) for (2) via OLS. We estimate the matrix Φ and the full variance covariance matrix $(\Sigma \times \Sigma')$ before we employ external instruments to identify the first column of the matrix Σ, that is the impact vector Σ^R of monetary policy shocks ϵ_t^R on the state variables x_t (Stock and Watson (2012) and Mertens and Ravn (2013)). We describe this step in more details in section 3.3.[3]

[2] This parameterization forces the share of total variance attributed to the idiosyncratic components to be the same across the (standardized) financial vulnerability observables, Y_t^m. While this assumption is parsimonious and helps reach convergence, it can be relaxed without compromising the results of the analysis.

[3] Details of the estimation method are available in the appendix. We implement the VAR step in the Canova and Ferroni (2021) toolbox. In the spirit of robustness, the appendix also includes results from a one-step estimation of the state evolution equation (2) and the observations equation (3). To do so we adopt an EM algorithm specifically designed to estimate dynamic factor models on panels with arbitrary patterns of missing data (Bańbura and Modugno (2014)). The one-step and two-step estimation methods are equivalent when the state equation dynamics are left unrestricted (Stock and Watson, 2002b).

We rely on the Bai and Ng (2002) information criteria method to select the optimal number of factors K^v that explain common variation of the financial vulnerability indicators, Y_t^v. Figure 1 plots the Bai and Ng (2002) IC^3 information criterion as a function of the number of extracted factors. The plot shows that the optimal number of factors is $K^v = 4$.[4]

The Akaike, Bayesian, and Hannan-Quinn Information Criteria agree on parsimonious specification with an optimal number of lags $p = 2$. We conduct several robustness checks and estimate specifications of the lag structure $p < 12$ and the impulse responses of the model to a monetary policy shocks are qualitatively and quantitatively similar in the short-to-medium horizons with lags $p > 2$.

3.3 Identification of Monetary Policy Shocks

With the intent to study the impact and propagation of monetary policy shocks in the system, we rely on instruments that are external to the model as described so far, to identify the first column of the impact matrix:

$$\Sigma(:,1) = \begin{bmatrix} \underbrace{\sigma_{R,R}}_{1\times 1} \\ \underbrace{\sigma_{M,R}}_{K^m\times 1} \\ \underbrace{\sigma_{V,R}}_{K^v\times 1} \end{bmatrix}. \tag{4}$$

where $\sigma_{R,R}$ is the (scalar) impact of structural monetary policy shocks on the 1-year Treasury yield, R_t, and $\sigma_{M,R}$ and $\sigma_{V,R}$ are vectors that collect the impact parameters on the K^m macro and K^v

[4] Bai and Ng (2002) show that their IC^3 information criterion can be applied to any consistent estimator of the factors once that the penalty function reflects the correct convergence rate. Doz et. al. (2012) show that the convergence rate for the quasi-maximum likelihood extraction of factors equals:

$$C_{NT}^2 = \min\left\{\sqrt{T}, \frac{N}{log(N)}\right\}$$

where N and T denote the cross-section and the time dimensions, respectively. A modified Bai and Ng (2002) information criterion:

$$IC(K) = log(V(\kappa, F(\kappa))) + \kappa\frac{log(C_{NT}^2)}{C_{NT}^2}$$

can be used to select the optimal number of factors when estimation is performed by quasi-maximum likelihood: κ denotes the number of factors, $F(\kappa)$ are the estimated factors and $V(\kappa, F(\kappa))$ is the mean, over time and cross-section, of the squared idiosyncratic components under κ factors. The penalty function $g(N,T)$ is a function of both N and T that is increasing in C_{NT}^2, the convergence rate of the estimator. Figure 2 also shows the scree plot as a function of the number of factors. The plot displays the average R^2 of the N^v regressions of the Y_t^v financial vulnerability indicators on an increasing number K^v of factors x_t^v. The first four factors explain 70% of the average unconditional variance across the vulnerability indicators. Improvements in the average R^2 for $K^v > 4$ become smaller and are more than offset by the increase in model complexity.

financial vulnerability factors. As it is common in this literature, we implicitly assume that all state variables x_t may respond contemporaneously to exogenous monetary policy shocks that perturb the policy indicator, R_t.

We adopt the methodology described in Gertler and Karadi (2016) in the context of their proxy structural VAR, and estimate the elements of $\Sigma(:,1)$ in sequence. For a given estimator of the autoregressive matrix, labeled $\hat{\Phi}$ and estimated states $\hat{X}_t$, we compute the VAR residuals $u_t = (\hat{X}_t - \hat{\Phi}\hat{X}_{t-1})$. The first $1 \times T$ row of this matrix of residuals is the vector $\hat{\varepsilon}^R_t$ collects the residuals of the law of motion of the monetary policy indicator, R_t. If the estimated FAVAR model is a good representation of the systematic response of the policy rate the endogenous states, the residuals u^R_t would represent a linear combination of the structural shocks in the vector ϵ^i_t for $i = 1, ..., K$, each weighted by their impact parameters $\sigma_{R,i}$, including monetary policy shocks indexed by R,ϵ^R_t, and all other structural shocks indexed by q, ϵ^q_t:

$$u^R_t = \Sigma^K_{i=1}\sigma_{R,i}\epsilon^i_t = \sigma_{R,R}\epsilon^R_t + \sigma_{R,q}\epsilon^q_t$$

Monetary policy shocks are identified by external proxy, using the intraday movements in the fourth federal funds futures contracts that are registered within a 30-minute window surrounding the time of the FOMC announcements, as proposed by Gürkaynak, Sack, and Swanson (2005). The interday change in the level of interest rate futures reflects changes in market participants' expectations over the path of the policy rate–an exogenous policy shock, described as a change in the degree of tightness of the monetary policy stance. The change in the level of interest rate futures can also reflect revision in the expectation of market participants over current and future economic outcomes based on the content of the policy statement. In order to focus on shocks that originate from changes in the policy stance, we follow Miranda-Agrippino and Ricco (2021) and purge the changes in Fed Funds futures quotes of the Greenbook forecasts and revisions to forecasts for output, inflation, and unemployment, thereby netting them of the information component that the FOMC statement convey about the economic outlook. Greenbook data are made publicly available with a five-year lag, and therefore we only include shocks from 1991 to 2015 in this part of the analysis, despite estimating the model through the end of 2019.

We use a two-step instrumental variable procedure to estimate the impact vector (4). In the first step we regress the residuals of the policy indicator equation on the Miranda-Agrippino and Ricco's monetary policy surprises, $\hat{\epsilon}^R_t$, to identify the component of the variation in the policy indicator, R_t, left unexplained by the lag states in the VAR that can be attributed to exogenous changes in the monetary policy stance:

$$u_t^R = \mu_\epsilon + \beta_\epsilon \hat{\epsilon}_t^R + \omega_t$$

To be a valid set instruments for the policy shock, $\hat{u}_t^R$ must be correlated with ϵ_t^R but orthogonal to other structural shocks ϵ_t^q. In the second stage we use the predictive component of the first regression:

$$\hat{u}_t^R = \mu_\epsilon + \beta_\epsilon \hat{\epsilon}_t^R$$

to estimate the impact of monetary policy shocks on other state variables in the system, regressing the residuals of the macro and financial stability state equations, u_t^q, on $\hat{u}_t^R$:

$$\hat{u}_t^q = \beta_{\hat{u}^R} \hat{u}_t^R + \xi_t$$

The regression parameter of $\beta_{\hat{u}^R}$ offers an estimate of the impact of monetary policy shocks on the macro and financial vulnerability factors in the state equation, scaled by the impact on the policy indicator, R_t. In other words the estimator of $\beta_{\hat{u}^R}$ can identify $\frac{\sigma_{M,R}}{\sigma_{R,R}}$ and $\frac{\sigma_{V,R}}{\sigma_{R,R}}$. The impact $\sigma_{R,R}$ is then derived by decomposing the estimated reduced form variance-covariance matrix $\Sigma\Sigma' = E[u_t u_t']$ as described in Gertler and Karadi (2016). This allows us to identify the full vector $\Sigma(:,1)$ defined in expression (4) and, given the estimates of the matrix Φ and loading parameters Λ, we can use equations (3) and (2) to compute responses of macroeconomic outcomes and of the full set of financial vulnerability indicators included in Y_t to monetary policy surprises.

4 Results

In this section, we plot and describe the impulse responses of the macro and the orthogonal financial vulnerability factors to a monetary policy surprise, standardized so that the a tightening shock pushes up the 1-year Treasury yield by 100 basis points on impact. We display the responses of the 1-year Treasury yield, unemployment, inflation, the excess bond premium as an indicator of financial conditions, as well as the common factors extracted from the financial vulnerability observables. Appendix 6.2 presents and describes the responses of all model observables to a monetary policy tightening shock. We also frame such responses in a historical perspective by simulating a similarly-sized policy tightening shock in June of 2005, during the policy tightening cycle that preceded the Great Financial Crisis.

4.1 Financial Vulnerability Factors

Figure 3 displays the four common factors extracted from the FAVAR model. Identifying the effect of monetary policy shocks on financial vulnerabilities does not require for us to impose a model restrictions that could provide a structural interpretation of the parameters and of the shocks that drive them. However, for ease of reference, in figure 3 we compare the four orthogonal factors $x_t^v = (F1, F2, F3, F4)$ with highly correlated indicators in the dataset, namely Nonfinancial Business Credit Growth, SLOOS C&I Loans Lending Standards, the first difference of Mortgage over GDP, and Net Leverage of Risky Firms. The four factors correlate with variables that bear heterogenous information about the cyclicality of the quantity and quality of risk in the financial system (Nonfinancial Business Credit Growth, Net Leverage of Risky Firms), the speed at which risk is increasing or decreasing (first difference of Mortgage over GDP), and the price of risk (Lending Standards, a measure of intermediaries' risk appetite). All variables and factors are signed so that higher values point to higher financial vulnerabilities.

4.2 Impulse Responses to a Monetary Policy Surprise

We use the estimated model and the identified impact of monetary policy shocks to compute and plot median and 68% bootstrapped confidence interval impulse response functions for macro outcomes and vulnerability indicators to an increase in 100 basis points in the 1-year Treasury yield induced by a surprise tightening of the monetary policy stance.[5] All responses are plotted over a 48-month period.

Figure 4 reports the responses of the 1-year Treasury rate, the PCE headline 12-month trailing rate of inflation, the unemployment rate, as well as the excess bond premium that while being treated as an indicator of vulnerabilities arising from asset valuation pressure, can also be interpreted as a gauge of financial conditions. The responses suggest that an increases in the level of

[5]The confidence intervals are produced through wild bootstrap, as in Mertens and Ravn (2013), applied to the state evolution equation (2). Using the point estimates of the autoregressive matrix Φ, we compute the OLS residuals $\hat{\epsilon}_t$, multiply them by random draws from a Rademacher distribution (-1 or 1 with equal probability) and reconstruct 10,000 artificial histories for the variables in our dataset. For each artificial sample we can estimate the autoregressive matrix Φ_k via OLS, and identify an impact vector Σ_k^R as discussed in section 3.3 via the bootstrapped proxies. For each of these artificial samples, we then compute the impulse responses to a monetary policy shock of all variables in the system and use the simulated sample to compute the 68% confidence interval. Throughout the process we fix the matrix of loadings Λ and the idiosyncratic errors η_t to the solution of the maximization problem described in section 3.2.

interest rates induced by a surprise monetary policy hike tightens financial conditions, increases unemployment persistently, while temporarily reducing inflation pressure, largely in line with previous findings in the proxy-SVAR literature (see for example Gertler and Karadi, 2015). At the bottom of the chart we report the F-statistics (16.51) for the first-stage of the IV identification of the monetary policy shocks in the historical sample.

We report the impulse responses of the financial vulnerability factors in figure 5, expressed in standard deviations of the series in figure 3. The confidence interval are shaded in red for the months in which the responses point to increased financial vulnerability, and in green for the months in which the impulse responses point to reduced vulnerabilities, and in grey when the response is not statistically significantly different from zero.

Monetary policy tightening has sizable short and medium-run effects on the financial vulnerability factors. A 100 basis points increase in the 1-year Treasury yield reduces vulnerabilities by putting downward pressure on the quantity of credit risk (a decline of 0.5 standard deviations in "F1 - NF Debt Growth" over the span of two years), while reducing risk appetite (bottoming at -0.8 standard deviations in F2 - C & I Lending Standards by one year after the shock), and slowing down the accumulation of residential mortgage imbalances (a decline of 0.5 standard deviations in F3 - Change in Mortgage Debt over GDP ratio six months after the shock). Remarkably, quality of credit risk deteriorates in the face of a sudden tightening of the monetary policy stance (an increase of 1.3 standard deviations in "F4 - NF Risky Net Leverage" by 1 year after the shock).

As the impulse responses of the vulnerability factors show—and the related responses of the Aikman et al. (2017) indicators in the appendix confirm—the transmission of monetary policy makes its ways through the cracks of the financial system, tightening lending standards and spreads, slowing down the issuance of credit and the rate of change non-financial debt vulnerabilities in the residential mortgage market. As policy tightening weakens the macroeconomic outlook, a broad reduction in asset valuations and reduction in income and earnings might worsen balance sheet positions of riskier borrowers, tighten borrowing constraints, and increase debt service ratios.

5 Financial Vulnerabilities and Risks to the Outlook

We have learned from the impulses responses of the FAVAR model that vulnerabilities respond to monetary policy tightening with credit growth and asset valuation vulnerabilities subsiding, as lending standards tighten, while the quality of credit risk deteriorates. We have also learned that the response of the underlying indicators of vulnerabilities can offset each other, so that the effect of tightening in the policy stance on overall vulnerabilities can be very modest in comparison to sizable macroeconomic costs.

Policymakers assessing costs and benefits of using interest-rate policy to "lean against the wind" wish to quantify how changes in interest rates affect different types of financial vulnerabilities and how in turn these vulnerabilities can affect the balance of risks to the macroeconomic outlook– i.e., if taming financial vulnerabilities by raising interest rates could help stave off severe economic contractions in the future. Furthermore, policymakers may wish to assess the elasticity of financial vulnerabilities to changes in the level of interest rates, and whether policy transmission is more or less effective in taming financial imbalances when vulnerabilities are low, are building up, or are already elevated.

While the linear structure of our model cannot speak of the dynamics of the distribution of predicted macro outcomes and its relationship to the evolution of financial vulnerabilities, we can make use of the information contained in the simple structure of four orthogonal factors extracted from our FAVAR to estimate the effect of vulnerabilities on risks to the macroeconomic outlook via quantile regressions.

Our intent is now to study whether interest-rate policy can impact tail macroeconomic risk, via financial vulnerabilities. In particular, we aim to unconver information about the derivatives:

$$\frac{dPr(Y^m_{t+h} \leq q|t)}{dR_t} = \underbrace{\frac{dX^v_{t+h|t}}{dR_t}}_{\text{A}} \times \underbrace{\frac{dPr(Y^m_{t+h} \leq q|t)}{dX^v_{t+h|t}}}_{\text{B}} \tag{5}$$

where changes in policy rate dR_t can affect financial vulnerability factors $X^v_{t:t+h}$, over a time period from time t to $t+h$, and such changes in vulnerabilities in turn can affect the quantiles q of the predictive distribution of future macro outcomes, $Y^M_{q,t:t+h}$.

While the FAVAR model offers direct estimates of the derivative in (A) in equation (5), we run quantile regressions of to estimate the derivative B in equation (5) to quantify if and how the financial vulnerability factors, X^v_t, can help forecast the conditional distribution of future macro outcomes.

Finally, we offer an example set in the context of the monetary policy tightening cycle of the mid 2000s of the trade-offs that policymakers would have faced if they had surprised markets with a 100bps additional increase in the policy rate.

5.1 Can Financial Vulnerability Factors Predict Tail Outcomes? Risks to GDP growth, Inflation, and Unemployment.

In this section we explore how our vulnerability factors affect the quantiles of the predictive distributions of GDP growth and inflation. The literature on growth and inflation at risk finds that changes in financial conditions (measured as changes in the the Chicago Fed's National Financial Condition Index, or in corporate bond spreads) have a larger effect on the lower quantiles of GDP growth and inflation than on the median. In particular, a deterioration in financial conditions carries substantial risk to the macro outlook (see, for example, Adrian, Boyarchenko, Giannone (2019), Lopez-Salido and Loria (2020)).

We take a similar approach and estimate quantile regressions of the conditional distribution of h-period ahead GDP growth and inflation outcomes, denoted by $Y^m_{i,t}$, as a linear function of the pooled set of financial vulnerabilities, rather than just one indicator of financial conditions.

$$\mathbb{Q}_q(Y^m_{t:t+h}) = \Sigma^4_{i=1}\beta_{i,q}x^v_{i,t} + \beta_{5,q}Y^m_{t-1} + \epsilon_{t,q} \tag{6}$$

where the quantile $\mathbb{Q}_q(Y^m_{t+h})$ of the future macroeconomic outcome over the time window $t : t + h$, $Y^m_{t:t+h}$, is a linear function of the set of named financial vulnerability factors, $x^v_{i,t}$, at time t for $i = 1, ..., 4$ extracted via the FAVAR model, and where $\beta_{i,q}$ the elasticity of the q quantile of the macro outcome to the same vulnerability factor i.[6]

Figures 7 and 8 plot the average elasticity of the quantiles of the predictive distribution of macroeconomic outcomes, GDP growth and inflation, to an increase in financial vulnerability factors over short- and medium-term horizons in response to a one standard deviation increase in each financial vulnerability factor (by column), over the medium time horizon with $12 < h \leq 36$ (row 1) and the short time horizon ($with\ h \leq 12$). More precisely, the figures reports the average value of $\beta_{i,q}$, the percentage-point change in the 10th, 50th, or 90th, quantile of predicted average macroeconomic outcomes over horizon h, due to a change in financial vulnerability factor i. The

[6] In the Appendix we describe quantile regression models and their estimation. We run a battery of alternative model specifications that include more lags of the left-hand side variable and additional controls such as lagged macroeconomic and policy indicators, and indicators of financial conditions:

$$\mathbb{Q}_q(Y_h) = \beta_{1,q}R_t + \beta_{2,q}\pi_t + \beta_{3,q}U_t + \beta_{4,q}EBP_t +_i \beta_{i,q}x^v_{i,t} + \epsilon_{t,q} \tag{7}$$

where $x^v_{i,t}$ is the i-th named financial vulnerability factor at time t, $\beta_{i,q}$ denotes factor-i-th beta for the q-th quantile, inflation, π_t, and unemployment U_t are the macro data used in the estimation of the model, and the EBP is the Excess Bond Premium of Gilchrist and Zakrajsek (2012) included in the regression to control for financial conditions, and R_t is a policy indicator, proxied by the 1-year constant maturity Treasury yield Result are similar to those of our baseline specification and are available upon request.

whisker plots around each point estimate show the 68% bootstrapped confidence intervals over 2,000 draws.

5.1.1 GDP Growth

In the case of GDP growth, in the short run (first row), the estimated coefficients of all factors are positive and show very similar patterns across the different quantiles: increasing financial vulnerabilities tend to push the 0.1 quantile upward by more than the median outcome, reducing growth at risk, while the effect of increasing vulnerabilities on upside risk to growth are muted.[7] Conversely, a negative change in vulnerabilities translates into a drop in business debt growth drops (factor 1), lower risk appetite and tightening of lending standards (factor 2), and a slowdown in the rate of change of the mortgage debt over GDP ratio (factor 3), and risky businesses delevering (factor 4). Mirroring the findings in Adrian, Boyarchenko, Giannone (2019), as vulnerabilities drop credit tightens and GDP growth at risk increases, as negative tail outcome becoming more likely.

Notably, the sign of the coefficients of the 0.1 quantile change sign for factors 1 and 2, as we move from the short run to the medium run regressions (second row). This indicates that, as vulnerabilities that correlate with debt growth and risk appetite rise at time t, tail risk in the medium run increases. One standard deviation increase in factors 1 and 2, tilts the balance of risk to the outlook to the downside, pushing the 0.1 quantile of the distribution of medium-run average growth to the left by -0.5 percentage points. Conversely as factor 4 raises, vulnerabilities that correlate with the leverage ratio of risky business borrowers and more broadly with debt service ratios increase, and predict improved tail outcomes for growth in the medium term. Arguably the positive 0.1-quantile coefficient on factor 4 for such variables has an easy interpretation, as indicators that are constructed as ratios with asset valuations or aggregate income at the denominator tend to be highly countercyclical: positive coefficients on factor 4 in the pooled regressions that control for all other factors and lagged GDP growth line up with this intuition, as low and decreasing values of factor 4 during expansion predict economic downturns (i.e., periods of negative GDP growth), while quick upward mean reversions at the height of economic contractions predict the future economic recoveries, (i.e., periods of positive GDP growth).

[7] In the Appendix, we report quantile regression results that use unemployment as a left-hand-side variable, rather than GDP growth, to be consistent with the specification of the FAVAR model. Results are consistent with the GDP growth quantile regressions.

5.1.2 Inflation

The elasticity of the quantiles of future inflation to factor 1 in Figure 8 are positive across factors for most quantiles in the short run (first row), while there is some evidence that increased vulnerabilities that correlate positively with debt growth (factor 1) can modestly increase inflation at risk in the medium run (second row), drawing the 0.1 quantile of the distribution of inflation outcomes downward. A one-standard deviation increase in factor 1 at time t would the predict lower tail risk in the short run and higher tail risk in the medium run, with the two effects of similar magnitude balancing out. Increases in other vulnerabilities generally have a uniform positive effect across the distribution of future inflation outcomes, or tend to reduce downside risks, as it is the case for factor 4.

Finally, we find evidence that the elasticities of the quantiles of the predictive distribution of inflation to factor 1 (business credit growth) and factor 4 (net leverage of risky businesses) switch sign along the predictive distribution in the short run. The coefficients $\beta_{1,q}$ and $\beta_{4,q}$ are positive for the lower quantiles, and negative for the upper quantiles. Therefore, a decrease in factor 1 (credit growth) or factor 4 (net leverage of risky businesses) will push down the bottom quantiles of the predictive distribution of inflation, increasing downside risk in inflation, while also pushing the upper quantiles upward, increasing upside risk in inflation. When inflation is low—normally in times of recession—a shock that causes a contraction in credit growth or pushes risky businesses to delever may force businesses to lower their prices to maintain market shares over their competitors. When inflation is elevated, however, strategic considerations might be less pressing and the same credit tightening shock can lead liquidity-constrained firms to increase their prices to boost their revenues, passing higher costs of financing to their customers and increasing upward pressure on overall inflation. Firm-level empirical evidence of this cost-push channel of transmission of financial shocks is described in Gilchrist et al. (2017). A one-standard deviation drop in factor 1 will shift the left tail of the predictive distribution of inflation down by as much as 10 basis points at the one-year horizon, while it will push the right tail of the distribution up by 5 basis points. A one-standard deviation drop in factor 4, instead, will shift the left tail of the predictive distribution of inflation down by 5 basis points at the one-year horizon, while it will push the right tail of the distribution up by 7 basis points.

Finally, the elasticities of the quantiles of the predicted distribution inflation to changes in factor 2 (risk appetite/lending standards) and 3 (first difference in mortgage over GDP ratio) are all positive and of comparable magnitudes. A negative shock to such factors will push the predictive distribution of inflation at a 12-month horizon uniformly downward across its quantiles. A one-standard deviation drop in factors 2 or 3 will shift the all quantiles of the predictive distribution of inflation down by less than 10 basis points in the short term and between 5 and 20 basis points in the medium term.

5.2 Surprise Tightening ahead of the Great Recession: Policy Trade-offs

In this section we provide historical context to the impulse responses to a surprise monetary policy tightening described in section 4.2 and to the implied effects on vulnerabilities and macro risk quantified in section 5. We simulate the effect of an increase of approximately 100-bps in the level of the 1-year Treasury rate induced by a monetary policy tightening surprise in June of 2005. Figure 6 shows the response of unemployment, PCE inflation, and an aggregate financial vulnerability index defined by Aikman et al. (2017), built as the an arithmetic average of classes of indicators described in section 2, signed so that an increase in each variable points to an increase in vulnerabilities.[8]

The fourth quadrant of 6 displays the Aikman et al. (2017) overall vulnerability index as the percentile of the aggregate index level at each point in time over the distribution of the most recent 25 years of data. The fourth quadrant is paired with a vertical heat map: an index value lower than 0.1 means that the overall index sits under its first decile and corresponds to blue on the heat map: this indicates that overall vulnerabilities are very low. As the index increases toward 1, the

[8]Aikman et al. (2017) build an overall index from the financial vulnerabilities listed in Tables 1, 2, and 3. They first average individual indicators into sectoral vulnerability indexes and, second, they average sectoral indexes into an overall index. They show that such overall index can pick up rising imbalances in the U.S. financial system through the mid-2000s, and forecast the advent of the Great Financial Crisis.

The model offers the ability to produce impulse responses for the indicators of financial vulnerability at hand. We can mirror the Aikman et al. methodology to aggregate individual responses of vulnerability indicators into sectoral responses, and then average over the sectoral responses to compute a summary impulse response function for each class of vulnerabilities, and for overall vulnerabilities.

For any sector i, for example Housing (within the wider class of Asset Valuation vulnerabilities), composed of $j = 1, ..., N_i$ standardized indicators, the sectoral impulse response at horizon $t + h$ will add together the positive responses of indicators for which an increase points to a higher degree of vulnerability, indicated by V_t in shorthand, (for example the ratio of house prices over rent) and instead subtract the positive responses of indicators whose increase points to reduced V_t (for example indicators of mortgage lending standards).

$$IRF^i_{t+h} = \frac{1}{N_i}\Sigma_j^{N_i}\left\{IRF^j_{t+h}\mathbb{1}\left[\frac{dY_tj}{dt} > 0 \Longrightarrow \frac{\partial V_t}{\partial Y_t^j} > 0\right] - IRF^j_{t+h}\mathbb{1}\left[\frac{dY_tj}{dt} > 0 \Longrightarrow \frac{\partial V_t}{\partial Y_t^j} < 0\right]\right\}.$$

Figure 22 in the Appendix shows the impulse responses of the average indexes of asset valuation, non-financial leverage, financial leverage, and short-term funding and maturity transformation vulnerabilities to the monetary policy tightening shock, computed by averaging over the sectoral impulse responses IRF^i_{t+h}.

We use the same methodology to produce the historical impulse responses plotted in this section.

heat map color transitions to warmer hues pointing to modest, moderate, and high vulnerabilities, while culminating in red, signaling that vulnerabilities are very elevated when the index sits above the 90th percentile.

A tightening shock that raised the level of the one-year Treasury by around 100 basis points in June of 2005 would have pushed the unemployment rate up by around 1% by the end of 2007, and inflation down by 0.4%, while only mildly reducing aggregate financial vulnerabilities in the short run, relative to the historical peak reached before the Great Recession. The 68% bootstrapped confidence bands around the median simulation (the dashed line) that accounts for parameter and state uncertainty show that after approximately a year from the sudden tightening of the monetary policy stance the index under the simulated tightening is statistically indistinguishable from the historical index (the solid line). Ultimately, while the estimated costs in terms of unemployment and inflation of running a tighter monetary policy stance are sizable, the reduction in overall vulnerabilities in the Aikman et al. (2017) framework appears to be very modest.

Finally, based on the quantile regression coefficients in figures 7 and 8 and by comparing the historical values of the financial vulnerability factors with the FAVAR simulations under the additional policy tightening, we can compute the difference in the predicted quantiles of the distributions of GDP growth and inflation in the short and medium run. We choose June of 2006 as our point of observation, as twelve months after the shock represents the point of maximum distance of each factor under the simulated tightening relative to their historical values. As policymakers surprise markets with a monetary policy stance tightening, factors 1, 2, and 3 decrease moderately, financial conditions tighten and growth in credit aggregates slows down pushing the 0.1 quantile of short-run GDP growth down, hence increasing downside risk to the outlook relative to history. Factor 4 instead increases in response to the monetary policy tightening, lowering downside risk. On net, the changes in the factors induced by policy move down both the 0.1 quantile and the median of the predictive distribution of GDP growth within a year by around -0.7 percentage points, with no material change in the 0.9 percentile. We obtain these estimates by multiplying the point estimates of the quantile regression coefficients of each factor in figure 7 by the difference between the historical factors extracted from the FAVAR and the ones obtained through the model under the simulated monetary policy tightening in combination with the historical shocks. With the same approach we can establish that in the medium run growth-at-risk decreases moderately in response to monetary policy tightening, with the 0.1 quantile of the predictive distribution of average GDP growth 13-to-36 months out moving up by 1.5 percentage points, while the median and 0.9 quantiles remain largely unchanged, on net. Similar computations for the predictive distribution of inflation show that the surprise tightening would have had close to zero net effect on downside risk implied by financial vulnerabilities.

Policymakers that wished to engineer additional monetary policy tightening in 2005 would trade off a deterioration of macroeconomic outcomes and a modest increase in downside risk in the short run, in exchange for a moderate decrease in downside risk in the medium run.

6 Conclusion

We estimate the effect of monetary policy on macro outcomes, financial vulnerabilities and on the balance of risks to the macroeconomic outlook. We show that a small number of common factors drives the cyclical behavior a wide array of indicators of financial vulnerabilities and that monetary policy can have sizable and contrasting effects on vulnerabilities. We find evidence that tighter monetary policy can reduce vulnerabilities connected to risk appetite and the growth rate of credit aggregates, but can also increase vulnerabilities that relate to debt sustainability. On net, we estimate that a meaningful trade-off does exists between the macroeconomic costs of lower aggregate activity and inflation in response to a policy tightening and a moderate reduction of downside risk to the macro outlook in the medium run. Our paper focuses solely on studying the transmission of monetary policy shocks in the estimation of LATW policy trade-offs. We leave the identification of other financial and macroeconomic disturbance, and the study of the policy rules and "Lucas-consistent" counterfactual experiments in the spirit of Sims (1998) and McKay and Wolf (2021) to future research.

Appendix

Alternative Model Specifications, and Robustness Checks

TO BE COMPLETED

6.1 Quantile Regressions

A quantile regression takes the form

$$y_i = x_i\beta_q + e_i$$

where the regression estimator $\widehat{\beta}_q$, a column vector, minimizes the weighted absolute loss function,

$$\min_{\beta_q} \sum_{i:y_i \geq x_i\beta_q}^{N} q|y_i - x_i\beta_q| + \sum_{i:y_i < x_i\beta_q}^{N} (1-q)|y_i - x_i\beta_q|,$$

and q is the quantile of interest. The sample is indexed by i, while y_i an observed outcome and x_i is a row vector of predictors. Intuitively, the quantile regression is estimated by weighing the positive errors by the targeted quantile - this has the effect of minimizing the loss function when q percent of the errors are are negative - effectively fitting the model to predict the qth quantile of the distribution of the left-hamd side variable, y.

6.2 Impulse Responses of Financial Vulnerability Indicators in Aikman et al. (2017)

This section presents and comments on the responses of all model observables to a monetary policy tightening shock. It also produces responses for the sectoral and aggregate vulnerability indexes introduced in Aikman et al. (2017).

6.2.1 The Response of Asset Valuations Vulnerabilities

In this section we will describe the responses of indicators of asset valuation vulnerabilities, grouped by sectors.

Figures 9 and 10 show the effect of policy tightening on real estate valuations in the housing and CRE sectors. When the monetary policy stance tightens, all measures of vulnerability in the housing and CRE sectors subside (as signaled by the green color of the confidence bands). As the level of the 1-year Treasury rate increases by 100bps, mortgage and CRE SLOOS lending standard indexes tighten so that the net share of respondent banks that tightened standards in the preceding quarter rises by around 20 percentage points, while the median FICO credit score of borrowers whose mortgage is sold to GSEs increases at first by 5 points. Consequently, tighter policy and financing conditions apply modest downward pressure to the ratio of house prices over rent and CRE prices relative to their longer-run trends (Del Negro and Otrok (2007), Jarocinski and Smets (2008), and Paul (2021)).

Equity and business valuation vulnerabilities in figures 11 and 12 also decrease uniformly, with equity returns (gross SP500 PE ratio) and the equity premium (measured as the 12-month forward SP500 PE ratio net of the 10-year Treasury rate) increasing by around 1 percentage points (broadly in line with existing evidence in Bernanke and Kuttner (2005), Rigobon and Sack (2004), Nakamura and Steinsson (2018)). Similarly, corporate bond spreads widen by as much as 80bps (Gertler and Karadi (2015), Gilchrist, Lopez-Salido and Zakrajsek (2015)), while SLOOS lending standards for C&I loans tighten, and the issuance of riskier corporate debt (high-yield bonds and leveraged loans) over GDP declines over the course of 2 years.

Finally, 13 shows that monetary policy tightening pushes the VIX and CDS spreads–two indicators of expected volatility in equity and corporate debt markets.

Accordingly, panel A in figure 22 shows that tighter monetary policy puts marked downward pressure on the aggregate index of asset valuation vulnerabilities and figure 23 confirms that the response is uniform across all sectors (housing, CRE, business, equity valuations, and volatility).

6.2.2 The Response of Non-Financial Leverage Vulnerabilities

In this section we will describe the responses of indicators of non-financial leverage vulnerabilities, grouped by sectors.

Figure 14 displays the full breakdown of indicators for the residential mortgage market. Tighter monetary policy modestly reduces vulnerabilities by slowing down the growth of mortgage debt as a fraction of GDP, of the mortgage debt service ratio, and of the total home mortgage owed by riskier borrowers relative to disposable personal income, and the issuance of piggyback loans that allow borrowers to take out high loan-to-value ratio mortgages. Tighter lending standards in the real estate market appear effective in reducing the issuance of new mortgage debt, penalizing and effectively rationing new risky borrowers, in the face of the deterioration in the macroeconomic outlook.

The opposite holds true for consumer credit imbalances, shown in figure 15: the ratio of consumer credit over disposable personal income of riskier borrowers, the consumer credit debt service ratio to disposable personal income, as well as the ratio of consumer credit over GDP, and the incidence of very rapid borrowing by riskier borrowers all accelerate following a tightening of the monetary policy stance. As economic conditions deteriorate, consumers may find it difficult to delever, while borrowing rates increase, and disposable income drops rapidly.

Similarly, figure 16 shows that, among business credit imbalances, the ratio of business debt to income rises, together with interest expenses of high-yield firms and the net leverage of risky firms, as income and asset valuations declines, and interest expenses on variable rate loans increase. Conversely, in line with findings in Crouzet (2021), non-financial business credit growth drops over the medium run and the deep junk issuance share of total corporate bond issuance also tends to decrease over time, pointing to a higher degree of persistence of credit variables that the model is able to fit compared to the quicker mean reverting behavior of credit spreads, lending standards, and debt service ratios among the observable variables.

Finally, figure 17 shows that while tighter monetary policy reduces business' net savings in the short term, household net savings as a share of GDP increase.

To sum up, panel B in figure 22 shows that tighter monetary policy raises the overall index of nonfinacial imbalances for about two years. As we have discussed, the sectoral breakdown in figure 23 points to consumer and business credit imbalances as the driving forces behind the deterioration in non-financial vulnerabilities. Tighter monetary policy, however, tends to reduce residential mortgage debt vulnerabilities and to have a zero net effect on non-financial sector savings.

6.2.3 The Response of Financial Leverage, Short Term Funding, and Maturity Risk Vulnerabilities

In response to a surprise tightening, bank profits drop due to a weaker macroeconomic outlook and higher liability costs, so that bank capital ratios in figure 18 plunge (in line with evidence in Cecchetti, Mancini-Griffoli, and Narita (2020), and Miranda Agrippino and Rey (2020)). Similarly, measures of broker dealer leverage (F B-D Lev.) in figure 19 increase, despite the slowdown in external financing (F B-D Fin.), while the issuance of non-agency securitized loans relative to GDP (F Securitization/GDP) grows higher in the short term, while subsiding in the medium term.

Vulnerabilities connected to maturity transformation and short-term funding risk tend to decrease for banks, as higher short-term interest rates translate into lower loans-to-deposit ratios and a reduced maturity gap between assets and liabilities. Runnable liabilities in the financial sectors decrease overall, and reliance of bank holding companies on more expensive short-term debt drops. However, short-term wholesale funding at nonbanks' tends to increase in the short-term, pointing to a temporary increase in their exposure to maturity and funding risk following a surprise monetary policy tightening.

To sum up, Panels C and D in figure 22 show that tighter policy also causes a modest short-term increase and a longer-term decline in financial leverage vulnerabilities, and a more prolonged decline in vulnerabilities related to maturity transformation and short-term funding risk.

References

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." American Economic Review, 109 (4): 1263-89.

Adrian, Tobias, Daniel Covitz and Nellie Liang (2013), "Financial stability monitoring," *Finance and Economics Discussion Series 2013-21*, Board of Governors of the Federal Reserve System (U.S.).

Adrian, Tobias, and Hyun Song Shin (2010), "Liquidity and leverage," *Journal of Financial Intermediation* 19(3), pages 418-437, July.

Aikman, David, Kiley, Michael, Lee, Seung Jung, Palumbo, Michael G. and Warusawitharana, Missaka (2017). "Mapping heat in the U.S. financial system," *Journal of Banking and Finance*, Elsevier, vol. 81(C), pages 36-64.

Ajello, Andrea, Boyarchenko, N., Francois Gourio, and Andrea Tambalotti (2022) “Financial Stability Considerations for Monetary Policy: Theoretical Mechanisms” *FEDS Working paper*, 2022-05.

Ajello, Andrea and Laubach, Thomas and López-Salido, J. David and Nakata, Taisuke, (2019) Financial Stability and Optimal Interest-Rate Policy, *International Journal of Central Banking.*

Arouba, Diebold, and Scotti, 2009, Real-Time Measurement of Business Conditions, *Journal of Business and Economic Statistics*, 27(4), 417-427 (lead article).

Bańbura, Marta and Modugno Michele, 2014, Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data, Journal of Applied Econometrics 29 (1), 133-160

Bernanke, B. S., and M. Gertler. 1999. “Monetary Policy and Asset Price Volatility.” Economic Review (Federal Reserve Bank of Kansas City)(Q IV): 17–51.

Borio, C. (2012) “The financial cycle and macroeconomics: What have I learnt?,” *Bank for International Settlements Working Papers*, 395.

Boyarchenko, N., Giovanni Favara, Moritz Schularick (2022) “Financial Stability Considerations for Monetary Policy: Empirical Evidence and Challenges” *FEDS Working paper*, 2022-06.

Brunnermeier, Markus, Gary Gorton, and Arvind Krishnamurthy (2012), “Risk topography,” *NBER Macroeconomics Annual* 2011, 26, pages 149-176.

Brunnermeier, Markus and Martin Oehmke (2013), “The maturity rat race,” *Journal of Finance*, vol. 68(2), pages 483-521.

Brunnermeier, Markus and Yukiy Sannikov (2014), “A macroeconomic model with a financial sector,” *American Economic Review*, 104(2), 379-421.

Caldara, Dario, Cascaldi-Garcia D., Cuba-Borda, P., Loria, F. (2021) ”Understanding growth-at-risk: a markov-switching approach” with Dario Caldara, Pablo Cuba-Borda and Francesca Loria, Working Paper.

Campbell, John Y. and Robert J. Shiller (1998), “Stock prices, earnings, and expected dividends,” *Journal of Finance*, Vol. 43, No. 3, 661-676.

Canova, Fabio and Filippo Ferroni, “A Hitchhiker’s Guide to Empirical Macro Models”, Federal Reserve of Chicago Working Paper, No. 2021-15, October 2021

Cecchetti, Stephen G. (2008), “Measuring the macroeconomic risks posed by asset price booms,” in: *Asset Prices and Monetary Policy*, pages 9-43. National Bureau of Economic Research, Inc.

Dickey, D. A.; Fuller, W. A. (1979). ”Distribution of the Estimators for Autoregressive Time Series with a Unit Root”. Journal of the American Statistical Association. 74 (366): 427–431.

doi:10.1080/01621459.1979.10482531. JSTOR 2286348.

Doz, Catherine, Domenico Giannone, Lucrezia Reichlin; A Quasi–Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models. The Review of Economics and Statistics 2012; 94 (4): 1014–1024.

Gertler, Mark, and Peter Karadi (2015). "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics*, 7 (1): 44-76.

Gilchrist, Simon, Raphael Schoenle, Jae Sim, and Egon Zakrajšek. 2017. "Inflation Dynamics during the Financial Crisis." American Economic Review, 107 (3): 785-823.

Gourinchas, P.O., and M. Obstfeld (2012) "Stories of the Twentieth Century for the Twenty-First," *American Economic Journal: Macroeconomics*, 4(1), 226-265.

Gourio, Francois, Anil K. Kashyap, Jae W. Sim (2018). "The Trade-offs in Leaning Against the Wind," *IMF Economic Review*;66(1), 70-115, March.

Gregory., Karl B., Soumendra N. Lahiri, and Daniel J. Nordman, (2018). "A smooth block bootstrap for quantile regression with time series." *Annals of Statistics*, 46 (3), 1138 - 1166, June.

Gürkaynak Refet S., Brian Sack, and Eric Swanson, 2005. "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," International Journal of Central Banking, International Journal of Central Banking, vol. 1(1), May.

Hamilton, James D. (2018). "Why You Should Never Use the Hodrick-Prescott Filter," The Review of Economics and Statistics, MIT Press, vol. 100(5), pages 831-843, December.

Hanson S.G., J.C. Stein. 2015. Monetary policy and long-term real rates. Journal of Financial Economics. 115(3):429–48

Jorda, O., M. Schularick, and A. M. Taylor (2013) "When Credit Bites Back," *Journal of Money Credit and Banking*, 45(s2), 3-28.

Laeven, L., and F. Valencia (2013) "Systemic Banking Crises Database," *IMF Economic Review*, 61(2), 225-270.

López-Salido, David, and Francesca Loria (2021). "Inflation at Risk," Finance and Economics Discussion Series 2020-013. Washington: Board of Governors of the Federal Reserve System.

McKay, Alisdair, and Wolf, K., 2021 "What Can Time-Series Regressions Tell Us About Policy Counterfactuals?", Working Paper.

Mertens, K. and M. O. Ravn (2013): "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, 103, 1212-47.

Miranda-Agrippino, Silvia, and Giovanni Ricco. 2021. "The Transmission of Monetary Policy Shocks." American Economic Journal: Macroeconomics, 13 (3): 74-107.

Reinhart, Carmen M. and Kenneth S. Rogoff (2010), This Time is Different: Eight Centuries of Financial Folly, *Princeton University Press*, Princeton, N.J.

Schularick, M., and A. M. Taylor (2012) "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008," *American Economic Review*, 102(2), 1029-1061

Sim, Christopher, 1998. "Role of interest rate policy in the generation and propagation of business cycles: what has changed since the '30s?," Conference Series ; [Proceedings], Federal Reserve Bank of Boston, vol. 42(Jun), pages 121-175.
Stein, Jeremy (2013) Lean, Clean, and In-Between, *Remarks at the National Bureau of Economic Research Conference: Lessons from the Financial Crisis for Monetary Policy*, October 2013.

Stock, James and Mark Watson, 2002. Macroeconomic forecasting using diffusion indexes. J. Bus. Econ. Stat. 20, 147–162.

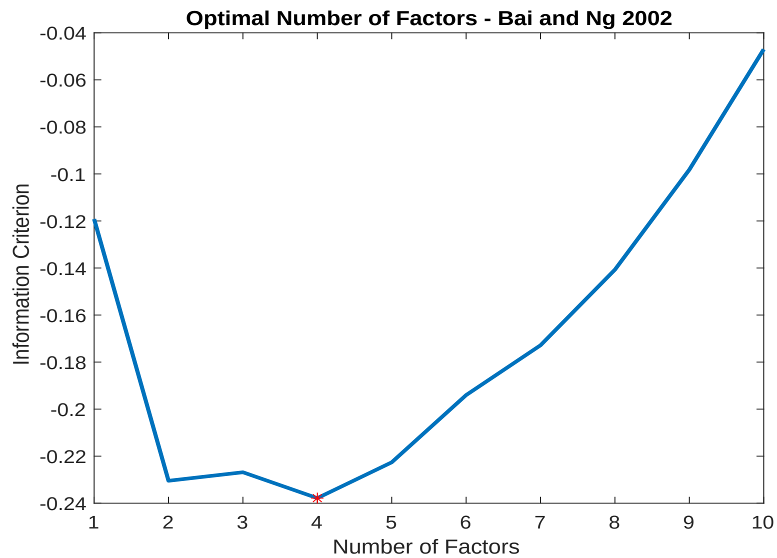
Stock, James and Mark Watson (2012) "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activity*, Spring, 81-135.

Stock, James and Mark Watson (2016) Dynamic Factor Models, Factor-Augmented Vector Autoregressions, and Structural Vector Autoregressions in Macroeconomics, *Handbook of Macroeconomics*, Elsevier

Svensson, L. E. O. (2017) "Leaning Against the Wind: Costs and Benefits, Effects on Debt, Leaning in DSGE Models, and a Framework for Comparison of Results," *International Journal of Central Banking* 13 (September 2017) 385-408.

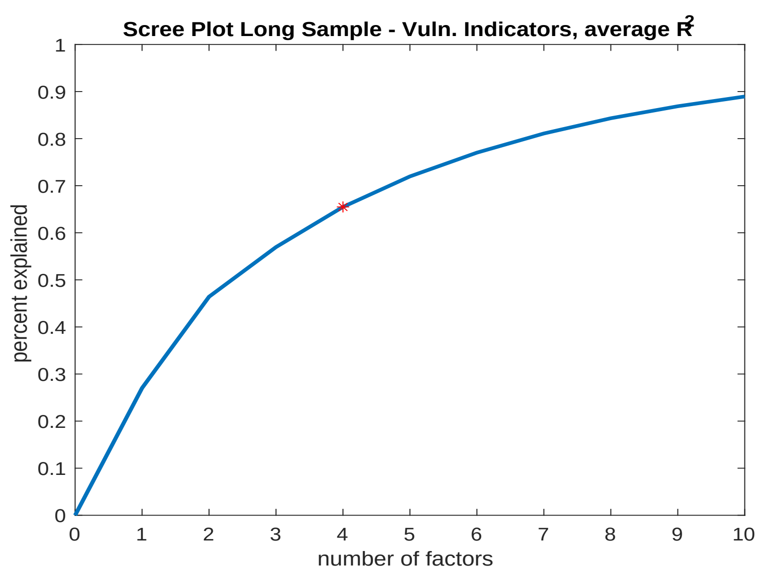
Svensson, L. E. O. (2017) "Cost-Benefit Analysis of Leaning Against the Wind," *Journal of Monetary Economics* 90 (2017) 193-213.

Figure 1: Optimal Number of Common Factors - Bai and Ng (2002) Information Criterion



NOTE: This figure shows the Bai and Ng (2002) modified IC^3 information criterion detailed in footnote 6, for $K^v = 1, ..., 10$ common factors extracted by maximum likelihood estimation, as described in section 3.2. The red asterisk shows that the IC^3 points to $K^v = 6$ as the optimal number of factors.
DATA SOURCE: Authors' calculations.

Figure 2: Optimal Number of Common Factors - Scree Plot



NOTE: This figure shows the average cumulative R^2 of the financial vulnerability indicators Y_t^v regressed on $K^v = 1, ..., 10$ common factors extracted by maximum likelihood estimation, as described in section 3.2. The red asterisk shows that $K^v = 6$ explain around 91% .
DATA SOURCE: Authors' calculations.

Figure 3: Counterfactual Tightening - 2005

Note: This figure shows the time series representation of the estimated factors (red solid lines), against highly correlated financial vulnerability observables (dashed blue lines).
Data Source: Authors' calculations.

Figure 4: Impulse Responses to a Monetary Policy Surprise - Macro Outcomes and Financial Conditions

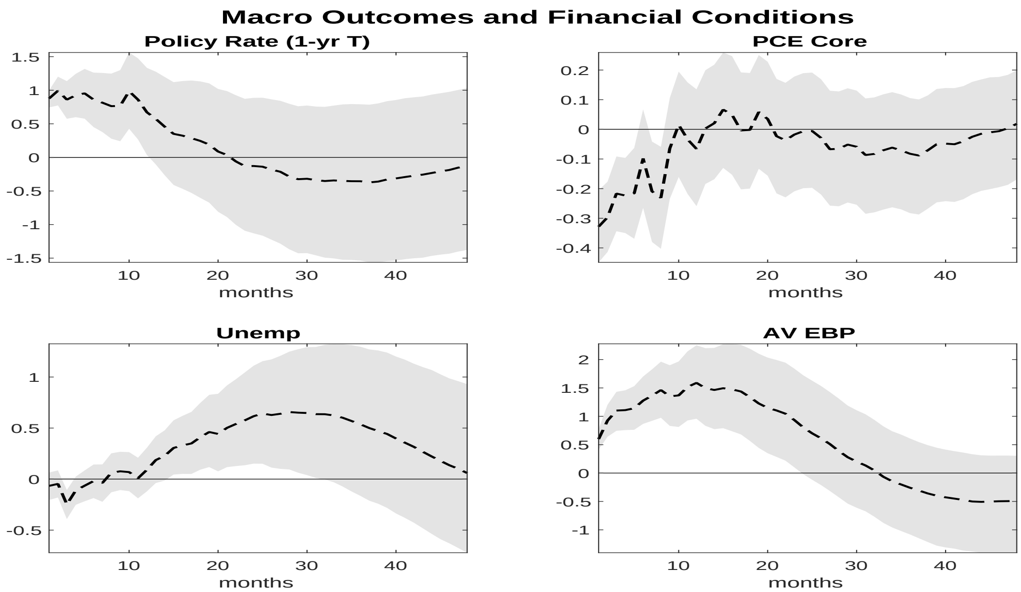


Figure 5: Impulse Responses to a Monetary Policy Surprise - Financial Vulnerability Factors

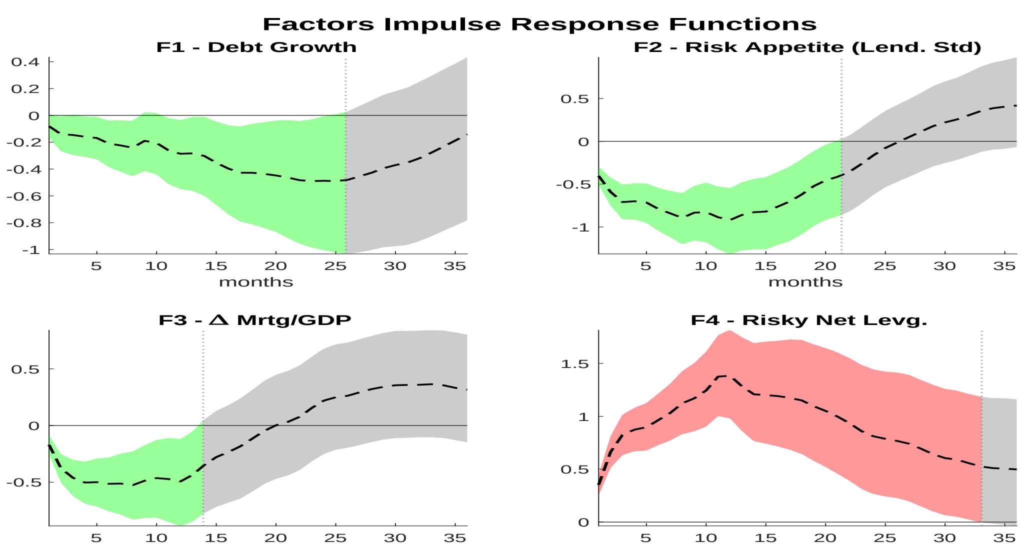


Figure 6: Tightening Shock - 2005

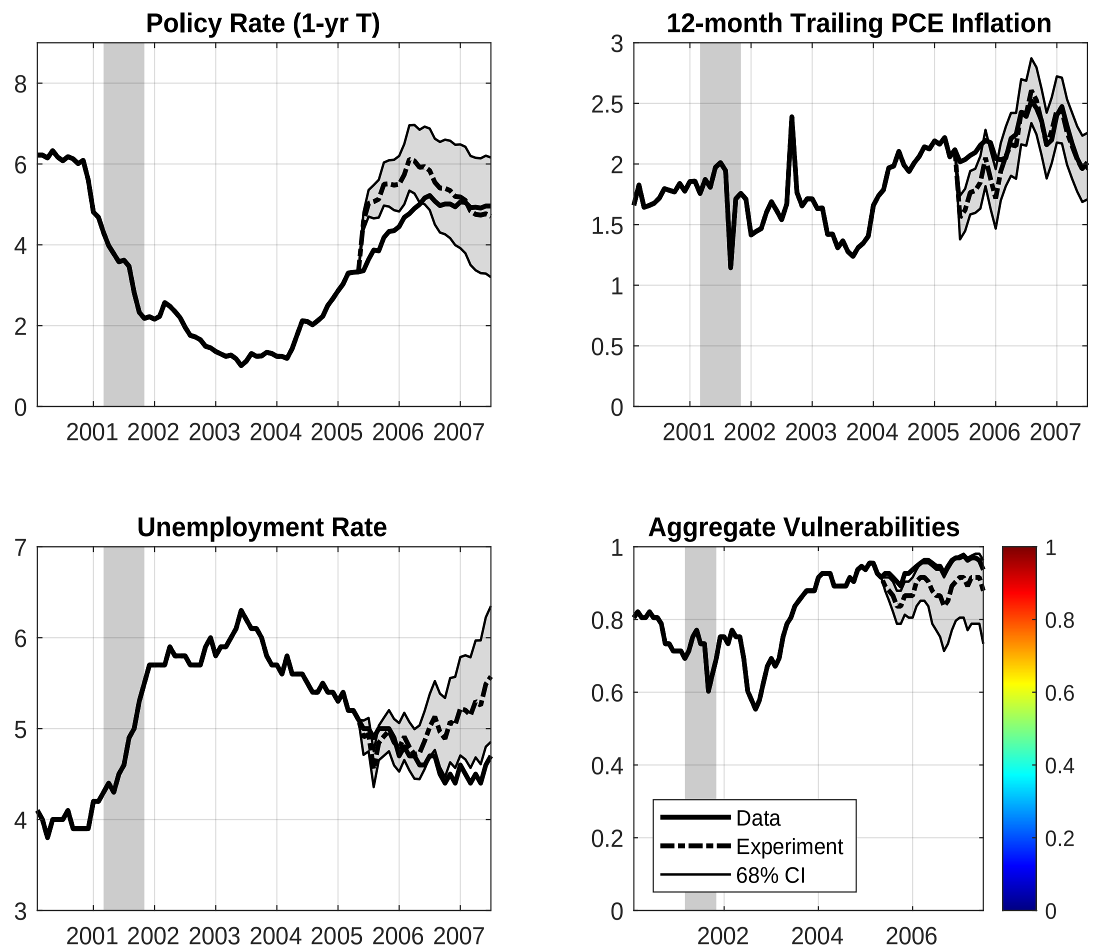
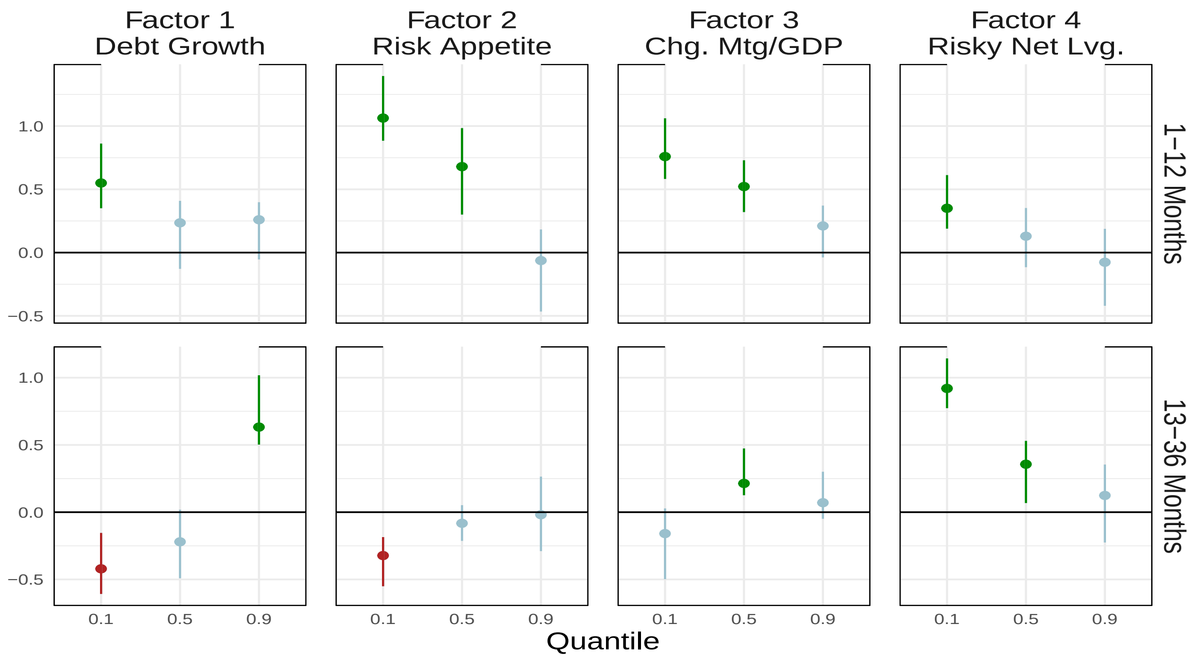
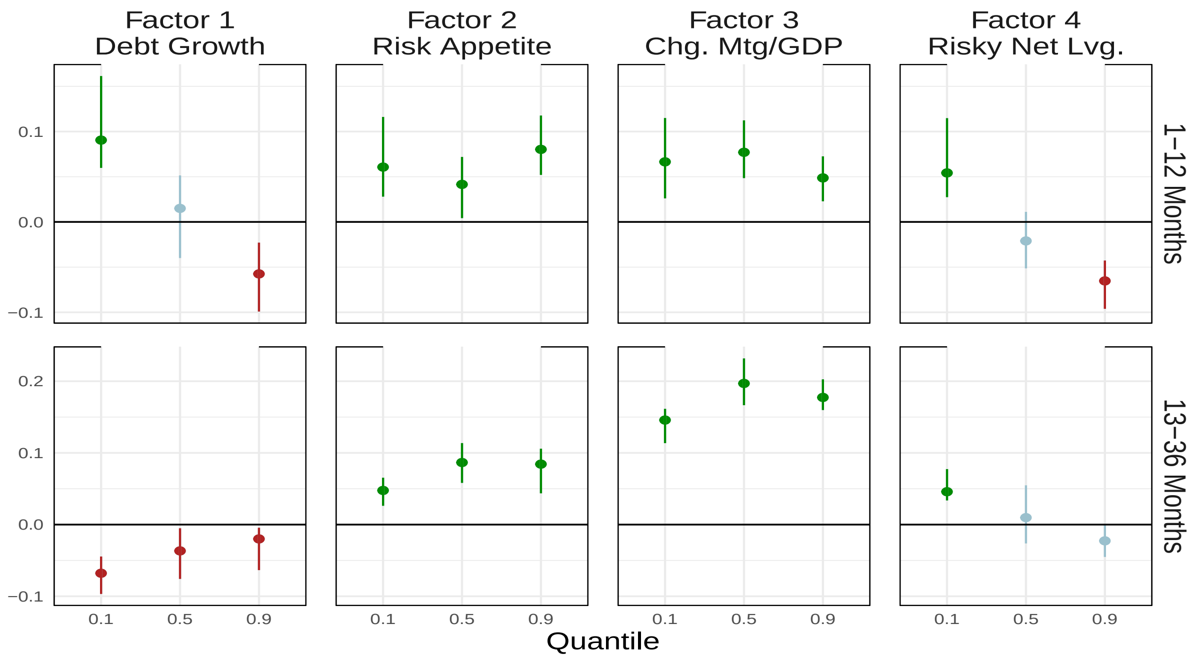


Figure 7: Quantile Regressions - Response of quantiles of predicted GDP growth to financial vulnerabilities



NOTES: The whisker plots depict the point estimate of $\beta_{i,q}$ from Equation 7 for quantiles [0.1, 0.5, 0.9]. Coefficients are expressed in percentage points in response to a one-standard deviation increase in the factors. Dots depict point estimates and verticals lines depict 68-percent confidence bands, based on smooth block bootstraps, à la Gregory, Lahiri, and Nordman (2018). Regressions are estimated on quarterly data from 1991:Q1 through 2019:Q4.
DATA SOURCE: Authors' calculations.

Figure 8: Quantile Regressions - Response of quantiles of predicted PCE Inflation to financial vulnerabilities



NOTES: The whisker plots depict the point estimate of $\beta_{i,q}$ from Equation 7 for quantiles [0.1, 0.5, 0.9]. Coefficients are expressed in percentage points in response to a one-standard deviation increase in the factors. Dots depict point estimates and verticals lines depict 68-percent confidence bands, based on smooth block bootstraps, à la Gregory, Lahiri, and Nordman (2018). Regressions are estimated on monthly data from 1991:1 through 2019:12.
DATA SOURCE: Authors' calculations.

Table 1: Asset Valuation Vulnerabilities

	Valuation Pressures/Risk Appetite			
Vulnerability	Description	Data availability	Frequency	Direction of increased vulnerability
	Housing			
House Prices/rents	Price-to-rent ratio (national averages)	Mid-1970s to 2019	Monthly	+
SLOOS res lending standards	Net fraction of banks reporting having tightened standards for home-purchase mortgages	1990 to 2019	Quarterly	-
FICO scores, new mortgages	Median credit score of residential mortgages sold to GSEs	2003 to 2019	Monthly	-
	Commercial Real Estate			
CRE prices	Commercial Real Estate Prices	1950s-2019	Quarterly	+
SLOOS CRE lend. Standards	Net fraction of banks reporting having tightened standards for CRE lending	1990-2019	Quarterly	-
	Business debt and loans			
Bbb bond spread	Bond spreads (Baa and high yield)	1980s-2019	Monthly	-
High Yield bond spreads	0	0	Monthly	0
Share of junk debt	Issuance of riskier corporate credit (high-yield bonds and leveraged loans)	1997-2019	Quarterly	+
SLOOS CI lend. Standards	Net fraction of banks reporting having tightened standards for C&I lending	1990-2019	Quarterly	-
	Equity Markets			
E/P ratio (SP 500)	P/E ratio	0	Monthly	+
E/P ratio rel to treasury yield	P/E ratio (adjusted for Treasury yields)'	d measure, mid-1980	Monthly	+
	Price volatility			
VIX	VIX	1990-2019	Monthly	-
CDS Spreads	CDS spreads	0	Quarterly	-

Table 2: Non-financial Sector Vulnerabilities

Nonfinancial sector imbalances				
Vulnerability	Description	Data availability	Frequency	Direction of increased vulnerability
	Home mortgages			
Total mortgage debt/GDP	Home mortgage debt ratio to GDP	1952–2019	Quarterly	+
Home mortgage DSR	Mortgage debt service	1980–2019	Quarterly	+
Mortgage borrowing, riskier borrowers	Total home mortgage debt owed by riskier borrowers (ratio to aggregate DPI)	1999-2019	Quarterly	+
Rapid mortgage growth, riskier borrowers	Incidence of very rapid mortgage borrowing by riskier borrowers (pct)	2000-2019	Quarterly	+
Piggyback mortgage loans	Incidence of piggy-back mortgages with newly originated loans to riskier borrowers (pct)	1999–2019	Quarterly	+
	Consumer credit			
Total consumer credit outset	Consumer credit ratio to GDP	1952–2019	Quarterly	+
Consumer credit DSR	Consumer credit debt service ratio to DPI	1980–2019	Quarterly	+
Consumer credit, riskier borrower	Consumer credit owed by riskier borrowers (ratio to aggregate DPI)	1999-2019	Quarterly	+
Rapid credit growth, riskier borrowers	Incidence of very rapid borrowing by riskier borrowers	2000-2019	Quarterly	+
	Nonfinancial business			
Debt growth	Real debt growth	1959-2019	Quarterly	+
Net leverage, riskier firms	Net leverage of risky firms	1982-2019	Quarterly	+
Debt/income ratio	Debt-to-income ratio	1985-2019	Quarterly	+
Interest expense/cash	Interest expenses	1982-2019	Quarterly	+
Deep junk share of bonds issued	Deep junk issuance share	1993-2019	Quarterly	+
	Net Savings			
Household net savings	Personal saving	1952-2019	Quarterly	-
Business net savings	Business saving	1952-2019	Quarterly	-

Table 3: Financial Sector Vulnerabilities

Financial sector vulnterabilities				
Vulnerability	Description	Data availability	Frequency	Direction of increased vulnerability
	Bank Leverage			
Risk based capital ratio	Total risk-based bank capital ratio	1990-2019	Quarterly	-
Tangible equity to tangible assets	Tangible equity to tangible assets ratio	1986-2019	Quarterly	-
Tier 1 common equity ratio	Tier 1 common ratio at all BHCs	2001-2019	Quarterly	-
	Nonbank leverage			
Broker-dealer leverage ratio	Broker-dealer leverage	1951-2019	Quarterly	+
Broker-dealer debt	Broker-dealer financing	2001-2019	Quarterly	+
Non-agency securitization volume	Non-agency securitization issuance	2002-2019	Quarterly	+
	Maturity transformation			
Loans to deposits at BHCs	Loan-to-deposit ratio at BHCs	1996-2019	Quarterly	+
Maturity gap at banks	Maturity gap at commercial banks	1997-2019	Quarterly	+
Net ST wholesale funding	Net short-term wholesale funding at nonbanks	1956-2019	Quarterly	+
	Short-term funding			
Short-term money at BHCs	Short-term money at BHCs	2001-2019	Quarterly	+
ST wholesale funding at nonbanks	Gross short-term wholesale funding at nonbanks	1956-2019	Quarterly	+
Runnable liabilities in financial sec	Runnable liabilities in the financial sector	1985-2019	Quarterly	+

Figure 9: Impulse Responses to a Monetary Policy Surprise - Housing Valuation Vulnerability Indicators

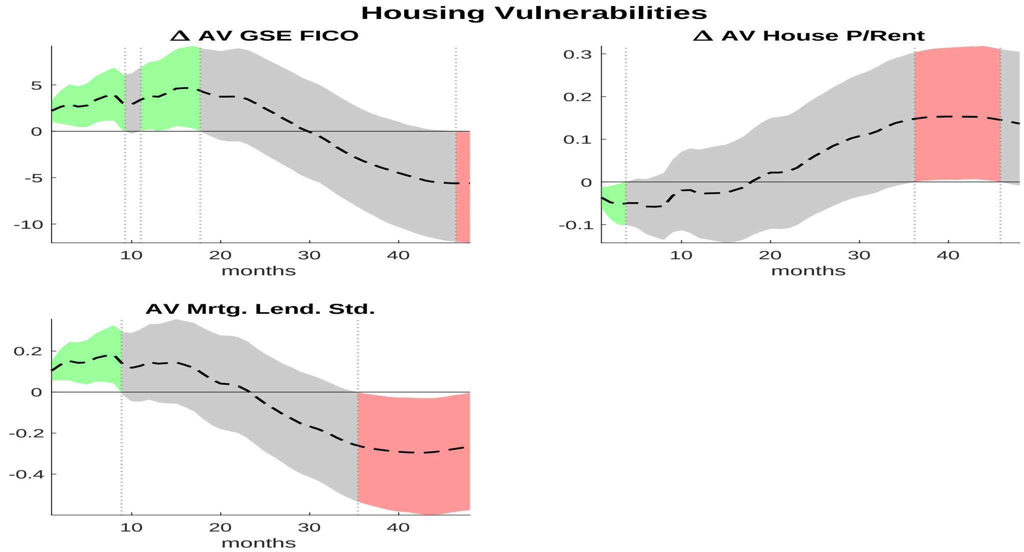


Figure 10: Impulse Responses to a Monetary Policy Surprise - CRE Valuation Vulnerability Indicators

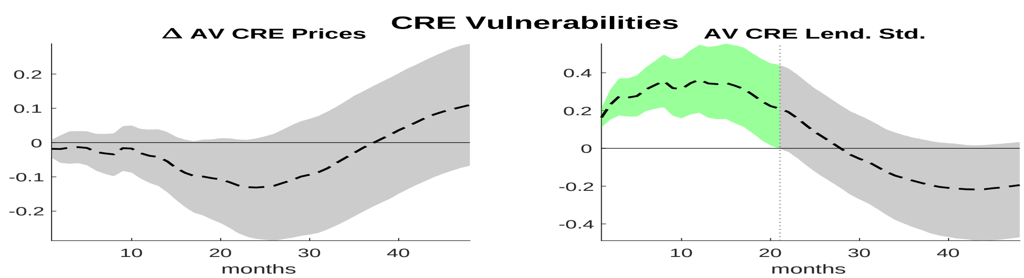


Figure 11: Impulse Responses to a Monetary Policy Surprise - Equity Valuation Vulnerability Indicators

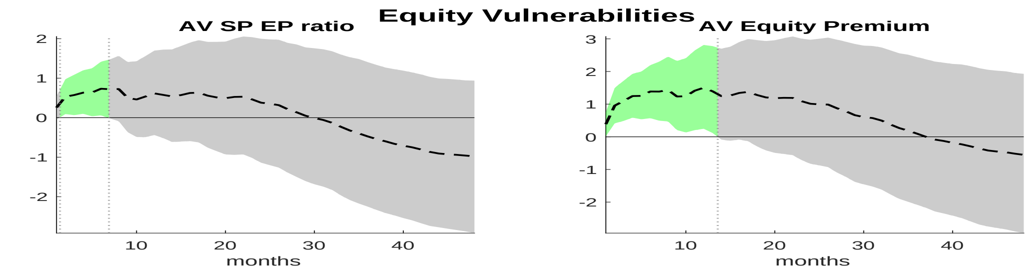


Figure 12: Impulse Responses to a Monetary Policy Surprise - Business Valuation Vulnerability Indicators

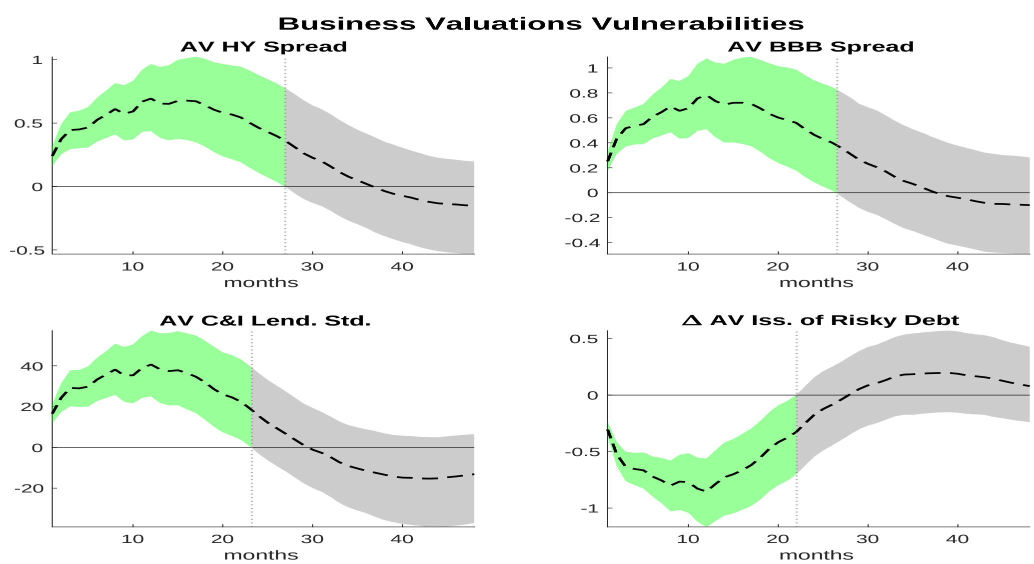


Figure 13: Impulse Responses to a Monetary Policy Surprise - Volatility Vulnerability Indicators

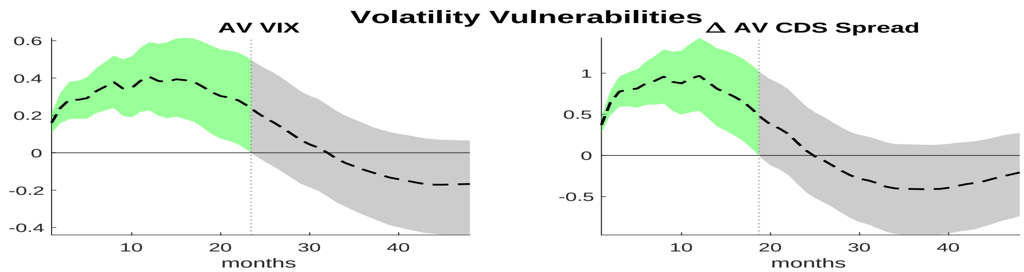


Figure 14: Impulse Responses to a Monetary Policy Surprise - Mortgage Financing Vulnerability Indicators

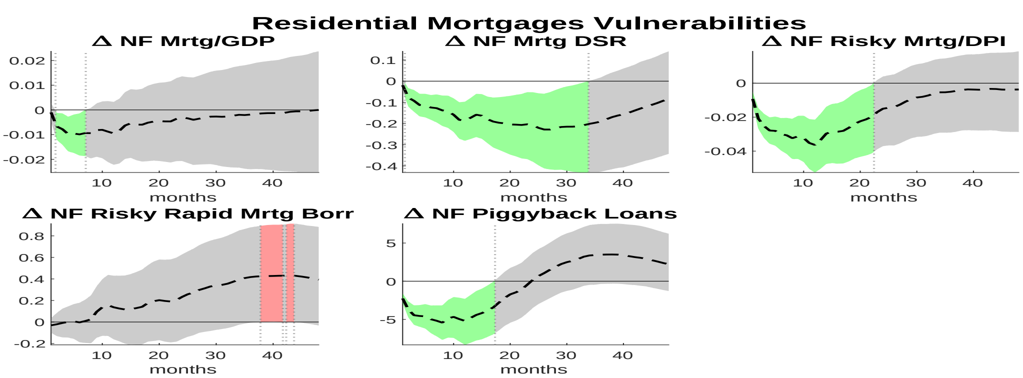


Figure 15: Impulse Responses to a Monetary Policy Surprise - Consumer Credit Vulnerability Indicators

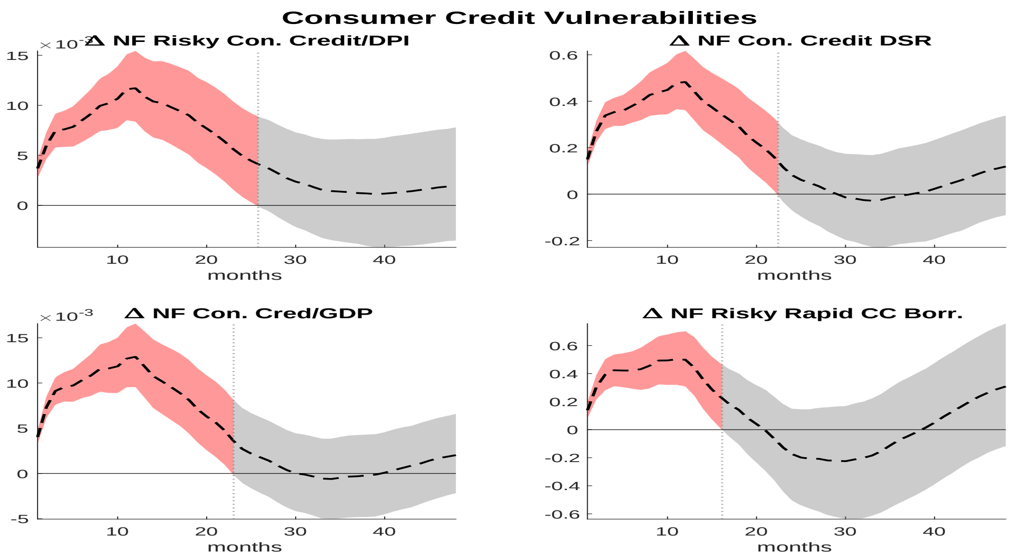


Figure 16: Impulse Responses to a Monetary Policy Surprise - Business Credit Vulnerability

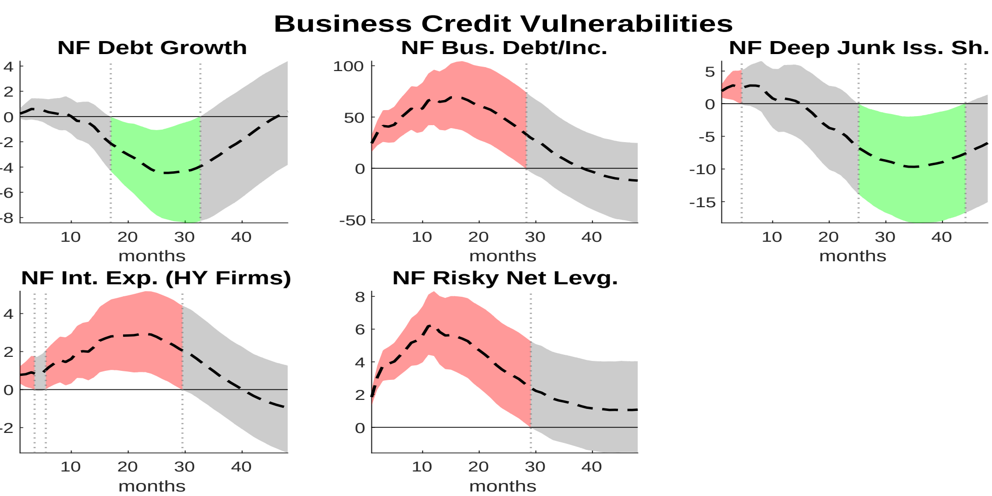


Figure 17: Impulse Responses to a Monetary Policy Surprise - Net Savings Vulnerability Indicators

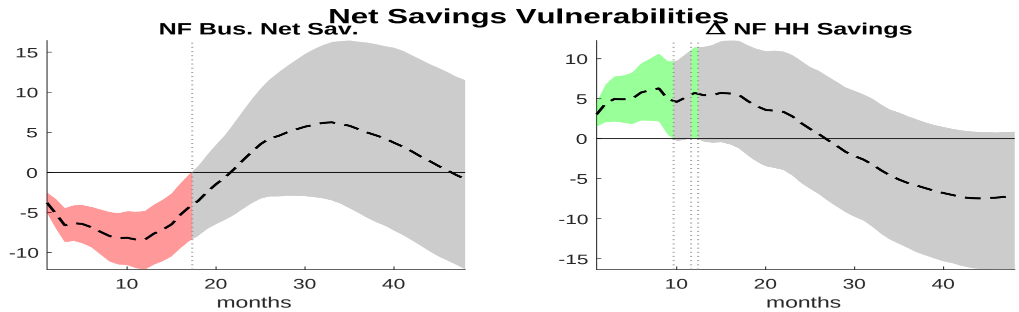


Figure 18: Impulse Responses to a Monetary Policy Surprise - Bank Leverage Vulnerability Indicators

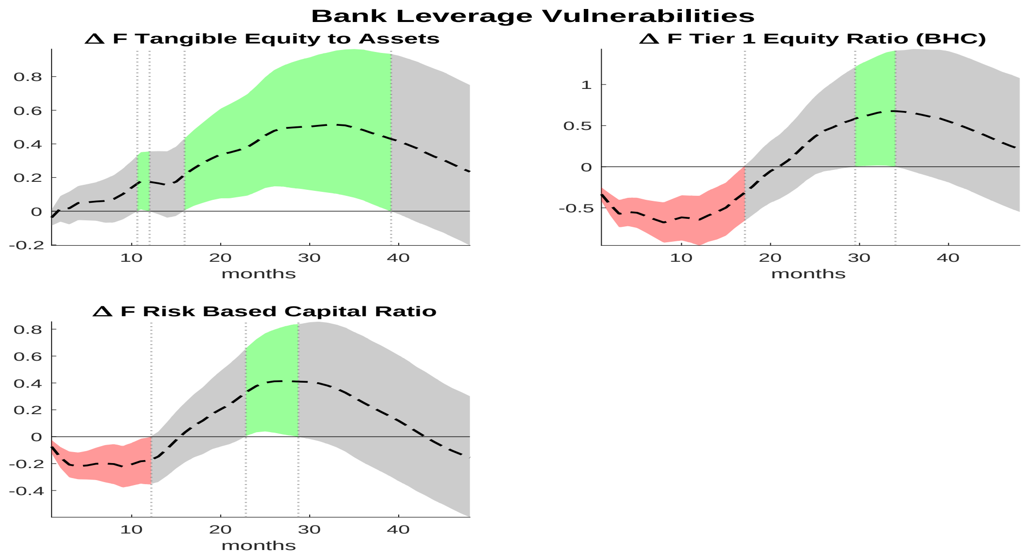


Figure 19: Impulse Responses to a Monetary Policy Surprise - Non-Bank Leverage Vulnerability Indicators

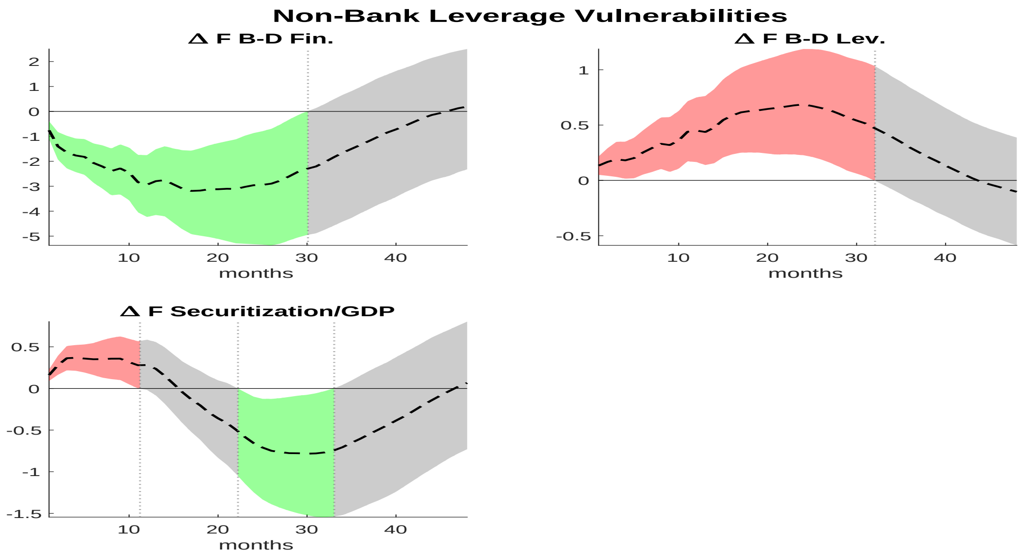


Figure 20: Impulse Responses to a Monetary Policy Surprise - Maturity Transformation Vulnerability Indicators

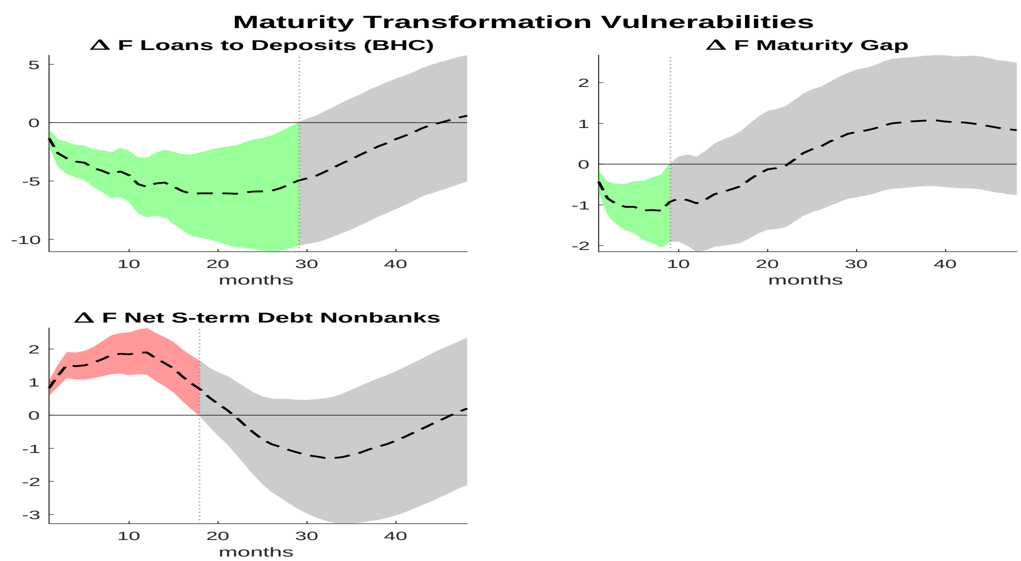


Figure 21: Impulse Responses to a Monetary Policy Surprise - Maturity Transformation Vulnerability Indicators

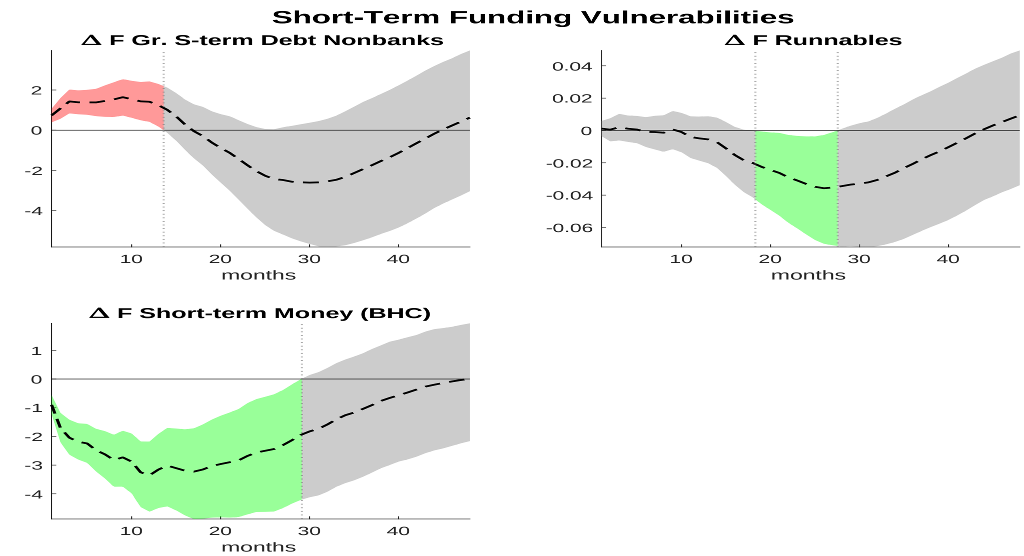


Figure 22: Impulse Responses to a Monetary Policy Surprise - Vulnerability Indexes

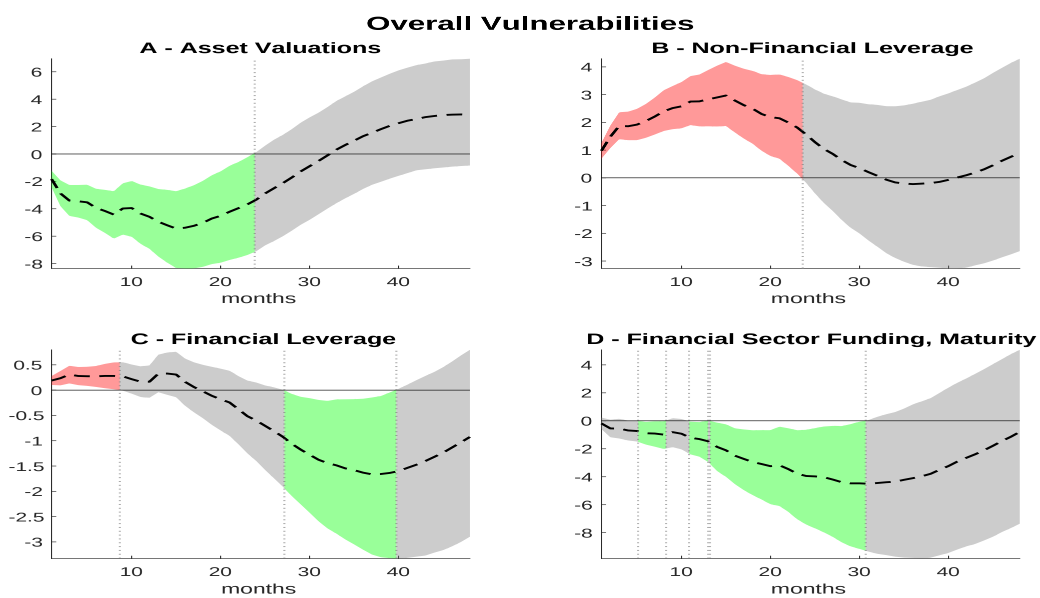


Figure 23: Impulse Responses to a Monetary Policy Surprise - Asset Valuation Pressure

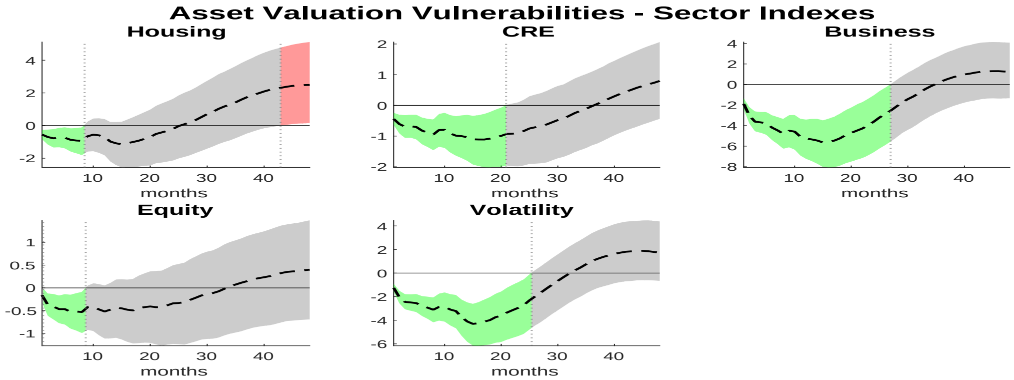


Figure 24: Impulse Responses to a Monetary Policy Surprise - Non-Financial Sector Vulnerabilities

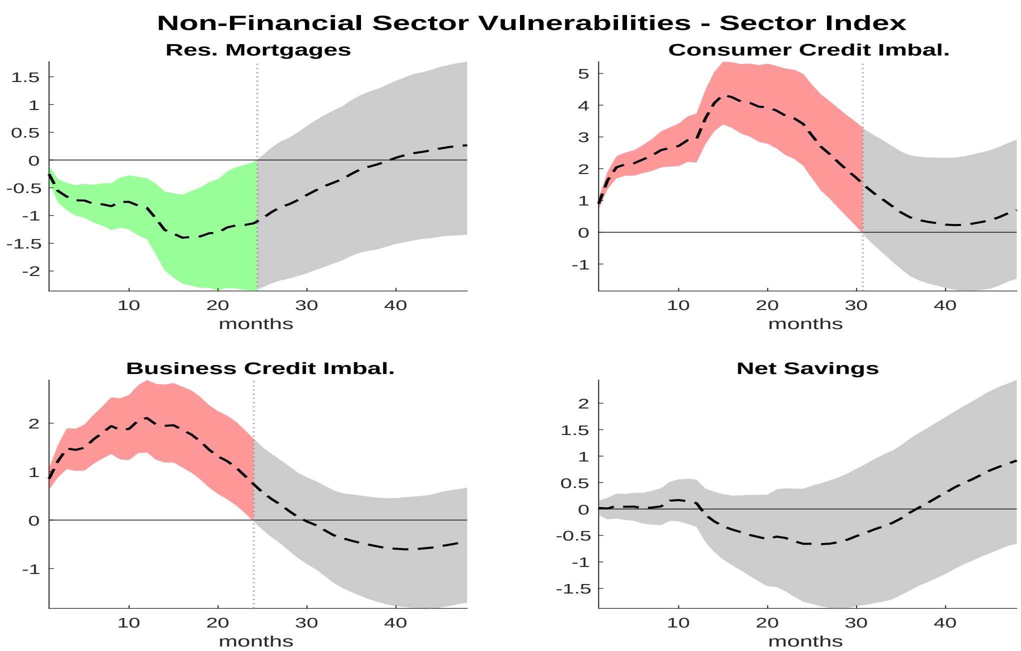


Figure 25: Impulse Responses to a Monetary Policy Surprise - Financial Sector Vulnerabilities