Getting in all the Cracks: Monetary Policy and Indicators of Financial Stability*

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Abstract

We study the effect of monetary policy surprises on aggregate economic activity, price dynamics, and a wide array of measures of financial stability. We do so by building a monetary proxy dynamic factor model (proxy DFM), in which the policy rate, prices, and aggregate activity dynamics interact with measures of asset valuation pressure, and indicators of financial vulnerability stemming from the financial and non-financial sectors. We find that monetary policy surprises have long-lasting effects on financial stability. On the wake of a surprise tightening, asset valuations drop on impact and credit standards tighten in the short-to-medium run. While aggregate activity contracts and inflation pressure subsides, leverage and risk-taking indicators drop and non-financial and financial sector vulnerabilities remain low 3 years past the initial shock.

PRELIMINARY AND INCOMPLETE

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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.

Policymakers' interest rates deliberations alter aggregate financial conditions and asset valuations, prompt changes in borrowing and lending decisions, and affect aggregate demand. If prices are sticky, 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 system, what mark do they impress on indicators of financial stability?

The answer to this question has profound consequences for the conduct of monetary policy. If its effects on financial vulnerabilities are sizable, central bankers might consider this in addition to the typical considerations of full employment and price stability. For example, tightening the stance of policy to"lean against" financial tailwinds could be optimal if the social benefits of increased resilience of the financial system outweigh the costs of reduced economic activity and missed inflation. 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 boost asset valuations, encourage excessive leveraging and risk-taking behavior in the private sector, and favor the insurgence of vulnerabilities that may amplify future economic downturns.

We find that monetary policy surprises have significant, short- and medium-term effects on financial stability. On the wake of a surprise monetary tightening, asset valuations drop on impact and credit standards tighten in the short run. As aggregate activity contracts and inflation pressure subsides, leverage and risk-taking indicators fall and non-financial and financial sector vulnerabilities remain low longer than 3 years past the initial shock.

We establish these results in a dynamic factor model (DFM) that explains the joint evolution of macroeconomic conditions, monetary policy instruments, and a large dataset of 44 financial vulnerability indicators collected for the United States by Aikman et al. (2017) that includes measures 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 non-financial 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).

Our contribution is two-fold: through the lens of the DFM we estimate the impact of exogenous monetary policy surprises (identified using event-study changes in high-frequency financial data as proxies) on aggregate activity, inflation, and financial stability indicators. Secondly, our model is able to filter a limited set of latent factors that describe the common variation of a large number of financial stability indicators over time. We find that our vulnerability factors can provide real-time warning on the resilience of the financial system.

Literature Review

After the Great Recession, 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 an actor-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 in our DFM 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 (2018), to focus our analysis around changes in the monetary policy stance rather than reactions to changes in economic conditions or to the economic outlook.

2 Data

We use data on macroeconomic and financial variables from January 1984 to October 2018. Our macro indicators include monthly measures of logged industrial production, the logged level of the Personal Consumption Expenditure (PCE) price index, and the monthly average of the 1-year on-the-run Treasury yield.

In order to measure financial vulnerabilities we use a wide range of financial indicators from different sectors of the economy. Our dataset includes 44 of the indicators that Aikman et al. (2017) use to build indexes of financial vulnerabilities for the U.S. economy. The indicators are available at different frequency (monthly or quarterly) and over different time periods. Details on the series definitions, frequency, and availability are reported in tables 1, 2, and 3 in the appendix.

We follow Aikman et al. (2017) and classify our indicators into measures of risk appetite, and gauges of vulnerability that arise within the financial sector, and the non-financial sector.[1] Our categorization of indicators closely follows the breakdown adopted by the Federal Reserve Board and by the Office of Financial Research in their periodic reports on financial stability for the U.S. economy.

The risk appetite category consists of 13 indicators that include measures of asset valuations, such as asset earnings to price ratios; measures of price volatility, such as the VIX; and changes in various lending rates and standards. The risk appetite category includes an equal mix of variables included at a monthly and quarterly frequency.

The non-financial sector imbalances category consists of 16 indicators of debt and leverage among households and non-financial businesses. These indicators include measures of consumer and business leverage, and measures of debt sustainability such as the debt-to-service ratio and credit to GDP; credit growth, an indicator shown to predict financial crises (Schularick and Taylor, 2012); and household and business net savings.

Finally, our financial sector imbalances category contain 15 indicators of vulnerabilities that include measures of bank and non-bank leverage, maturity mismatch, short-term funding risks, and vulnerability measures based on system size and interconnectedness. The category also includes commonly used regulatory indicators, such as the tier 1 common ratio; measures of system concentration, such as the proportion of assets held by the 5 largest Bank Holding Companies; and measures of liquidity risk such as the share of short term debt in the financial sector.

[1] We refer the reader to their paper for a detailed description of the indicators that includes a full list of academic references.

3 Model and Estimation

We use a dynamic factor model (DFM) to describe the interactions between macroeconomic variables and indicators of financial stability. For convenience, we partition our panel of J observable variables $\{Y_t^j\}_{j=1}^J$ into sets of M macro indicators, Y_t^M, R risk-appetite indicators, Y_t^R, N indicators of household and business sector financial imbalances, Y_t^N and F indicators of financial sector imbalances, Y_t^F.

$$Y_t = [Y_t^M, Y_t^R, Y_t^N, Y_t^F];$$

We follow the approach in Stock and Watson (2016) and present the model in its state-space form, for which the $J \times 1$ vector of observables at time $t = 1, ..., T$, Y_t, is a linear combination of a collection of $K \times 1$ states X_t and J i.i.d. disturbances $\eta_t \sim N(0, \Omega)$:

$$Y_t = \Lambda X_t + \eta_t \tag{1}$$

where Λ is a matrix of loadings and Ω is diagonal. We assume that the states X_t evolve according to an VAR(p) process of type:

$$X_t = \mu + \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + ... + \Phi_p X_{t-p} + \epsilon_t \tag{2}$$

which can be condensed using the lag operator into:

$$\Phi(L) X_t = \mu + \epsilon_t.$$

where μ is a vector of constants and $\epsilon_t \sim N(0, \Sigma)$ are (potentially correlated) state disturbances. We assume that $\epsilon_t \perp \eta_t$.

3.1 Baseline Model

In our baseline model configuration, we choose the M macro factors to be:

$$Y_t^M = [R_t, PCE_t, IP_t]'$$

where R_t is the on-the-run 1-year Treasury yield, PCE_t is the personal consumption expenditure price index (PCE), and IP_t is industrial production (both in levels). As described in section 2, we observe a wide range of indicators of financial vulnerability, grouped into measures of risk appetite and valuation pressure, Y_t^{RA}, measures of vulnerability in the non-financial sector, Y_t^{NF}, and measures of vulnerability in the financial sector, Y_t^F.

We partition the state vector into macroeconomic and financial vulnerability factors $X_t = [X_t^M, X_t^{FS}]'$. Following on Onatski (2011), we determine that the optimal number of factors, X_t^{FS} that span the space of our dataset of financial vulnerability indicators is $K^{FS} = 6$. We adopt the following identifying restrictions:

- We assume that the first M factors X_t^M map identically to the macro observables Y_t^M. This implies that the top-left quadrant of Λ is an identity matrix of order M, and the loadings of macro variables on the financial stability factors in the top-right quadrant of Λ are set to zero. The macro variables Y_t^M are observed without error.

- We assume that the risk-appetite, non-financial-sector, and financial-sector vulnerability indicators load on the K^{FS} latent factors, but not on the observable macro factors. The bottom-right quadrant of Λ is unrestricted, while the bottom-left K^{FS} submatrix in Λ has all elements set to zero. We impose the additional over-identifying restriction that each of the three subsets of vulnerability variables only load onto two of the K^{FS} factors. In particular risk appetite indicators load only on the first two elements of X_t^{FS}, non-financial-sector indicators load on the third and fourth elements of X_t^{FS}, while financial-sector indicators load on the fifth and sixth elements of X_t^{FS}. This helps us give the factors a structural interpretation in the analysis that follows.

- We allow macro and financial variables to interact through the state dynamics. We assume that all latent factors X_t, macro and financial, depend on their lagged realizations, $\{X_{t-j}\}_{j=1,\ldots,p}^{J}$. We normalize the standard deviations of the innovations to the latent financial factors to one and assume that the innovations are correlated with each other only through non-zero covariances with the observed macro factors. Finally for each pair of financial factors, we exclude rotational indeterminacy by restricting the lag-dependence of the second factor.

3.2 Estimation

At this stage we set $p = 1$ and estimate the model by maximizing the likelihood function, built using a Kalman filter that was appropriately modified to account for the mixed frequency and unbalanced nature of the panel data (see Arouba, Diebold, and Scotti (2009)).

4 Results

4.1 Responses to a Monetary Policy Surprise

Figure plots the median and 90% bootstrapped confidence interval for the responses of the state variables in X_t to a one-standard deviation monetary policy surprise. The impact of the shock is identified as the average effect of changes in the high-frequency proxy described by Miranda-Agrippino and Ricco (2018) on the filtered residuals of the state variables of the DFM.

Figures 2, 3, and 4 show the implied impulse responses of, respectively, the risk-appetite, the non-financial, and the financial-sector observables in the dataset, as listed in tables 1, 2, and 3.[2]

An unexpected rise of around 25 basis points in the 1-year Treasury rate delivers a prolonged drop in industrial production 0.30% below its trend. Total PCE grows around 0.1% below trend for two years following the tightening in the monetary policy stance.

The two latent factors that explain the variability of the risk-appetite and valuation-pressure latent factors, RA_1 and RA_2, respond significantly to the monetary policy shocks. Figure 2 shows the implied responses of the risk-appetite observables: the monetary policy shock leads to an increase in corporate BBB and more prominently high-yield spreads, a surge in market volatility (VIX), and in CDS spreads, and a prolonged tightening in lending standards for all types of loans, as well as a generalized drop in asset valuations indicators, such as the house price-rent ratio, commercial real estate prices, and the equity premium.

Non-financial vulnerabilities also respond significantly to the monetary policy surprise, generally reducing vulnerabilities. The unexpected monetary tightening prompts a marked increase in household and business net savings, and describes a long-lasting moderation in the growth rate of aggregate credit as well as in the extension of risky credit (rapid credit growth to risky borrowers, piggyback loans, deep junk share of bond issuance) that extends well into the third years after the shock. As a notable exception, net leverage of riskier firms increases significantly after the shock, likely in response to changes in asset valuations.

The response in financial-sector indicators of vulnerability also point to changes that increase aggregate resilience in the wake of an unexpected monetary policy tightening. While financial sector debt drops, so do several measures of liquidity and short-term funding risk

[2]Note that the impulse responses for the financial stability indicators are scaled up by the standard deviation of the original data series before it was whitened to estimate the dynamic factor model, and expressed as percentage deviation from their historical mean. In the next draft we will provide more intuitive readings of the impulse responses, expressing them all as percentage deviation from trend and steady state, depending on whether the variables have unit roots or not.

exposure of banks and non-banks a year ore more past the monetary policy surprise, despite short-lived increases.

A common features of the impulse responses for the non-financial and financial sectors is the sign of the impact of the shock on "Stock over Flow" indicators, such as Credit over GDP, or Debt over GDP. While industrial production and GDP drop in the short run, credit aggregates tend to be more persistent and to fall with a lag. In the wake of a monetary policy surprise, such indicators all point to a short-lived increase in financial vulnerability in the short-run but to lower vulnerability in the medium run.

4.2 Alternative Model Configurations and Robustness

TO BE COMPLETED

4.3 Filtered Factors as Real-Time indicators of Financial Stability

TO BE COMPLETED

4.4 Leaning-against-the-Wind: A Cost-Benefit Accounting Exercise à la Svensson

TO BE COMPLETED

5 Conclusion

TO BE COMPLETED

6 References

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Figures and Tables

This section contains figures and tables for the paper.

Figure 1: Impulse Responses to a Monetary Policy Surprise - State Variables

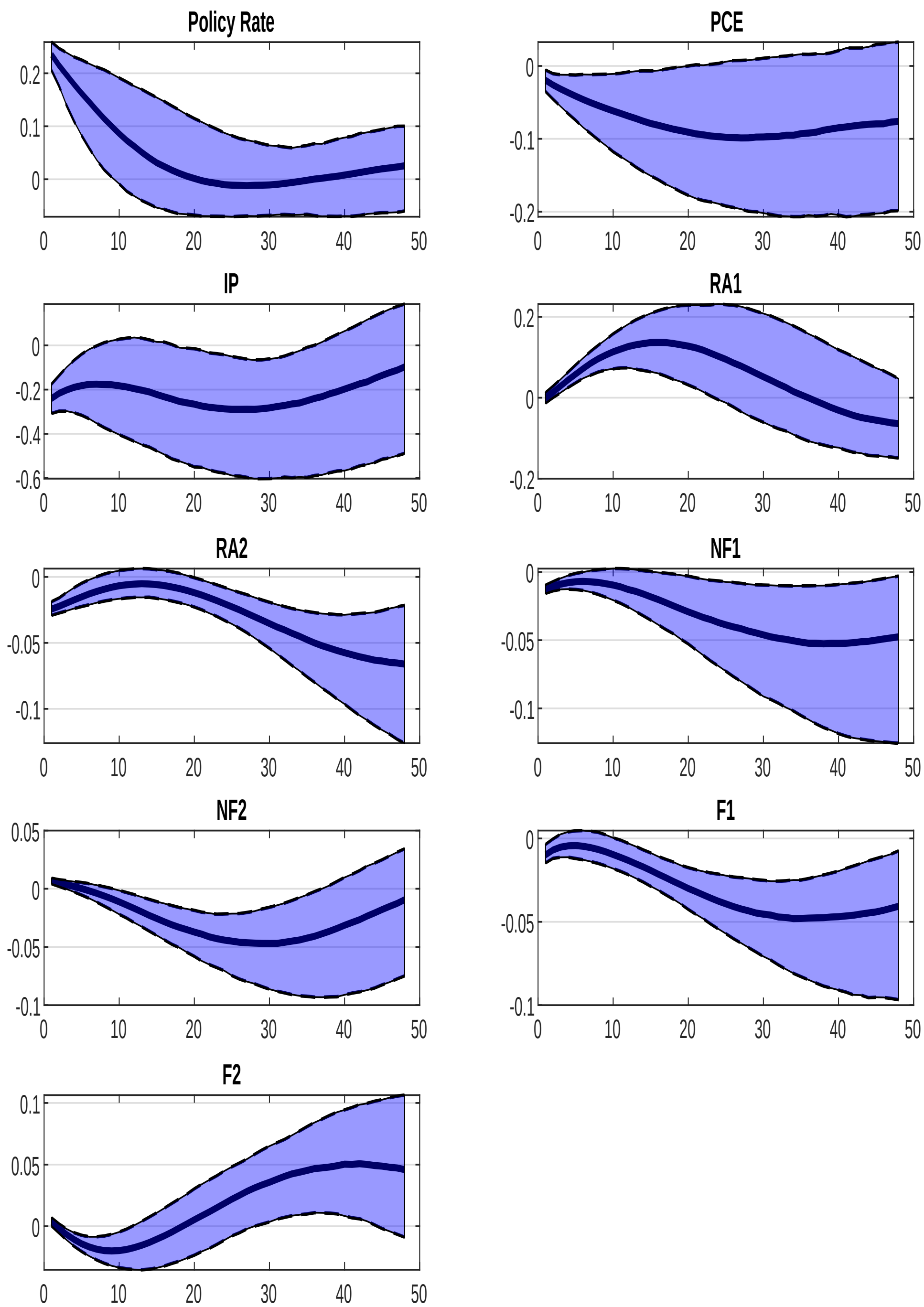

Figure 2: Impulse Responses to a Monetary Policy Surprise - Risk Appetite Indicators

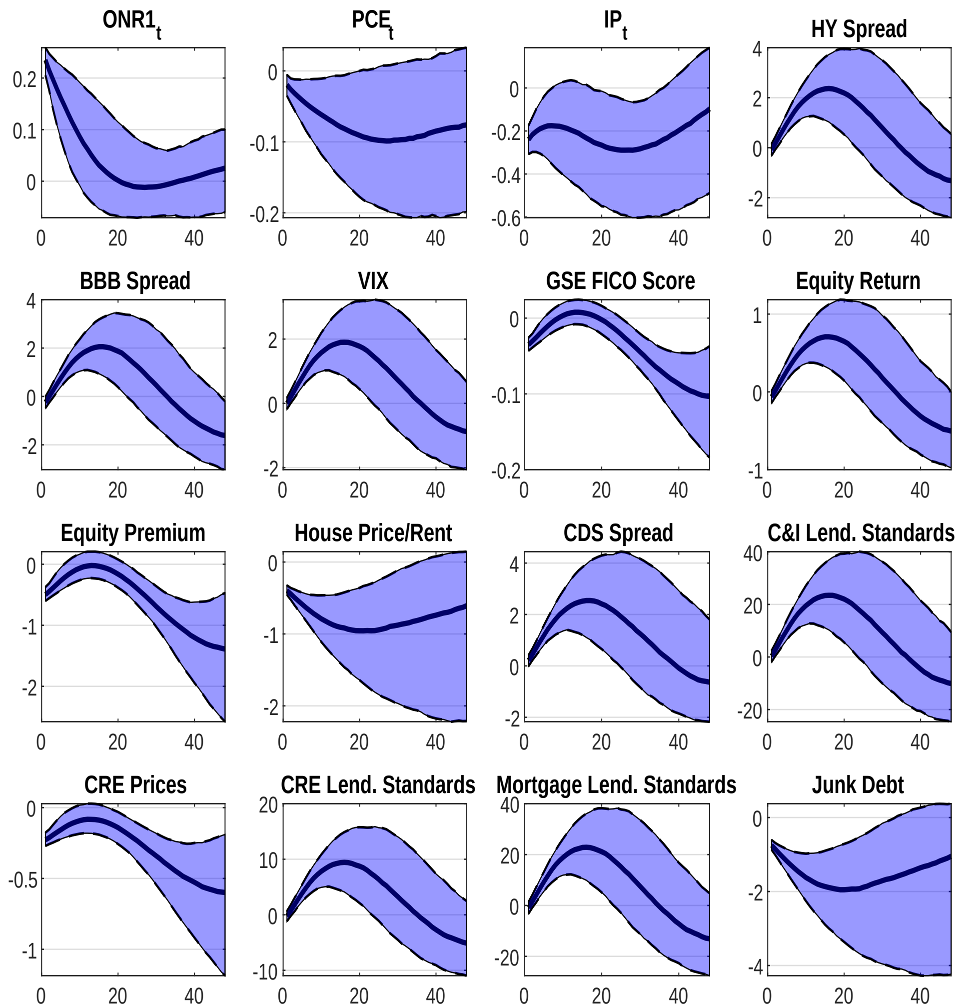

Figure 3: Impulse Responses to a Monetary Policy Surprise - Non-Financial Sector Indicators

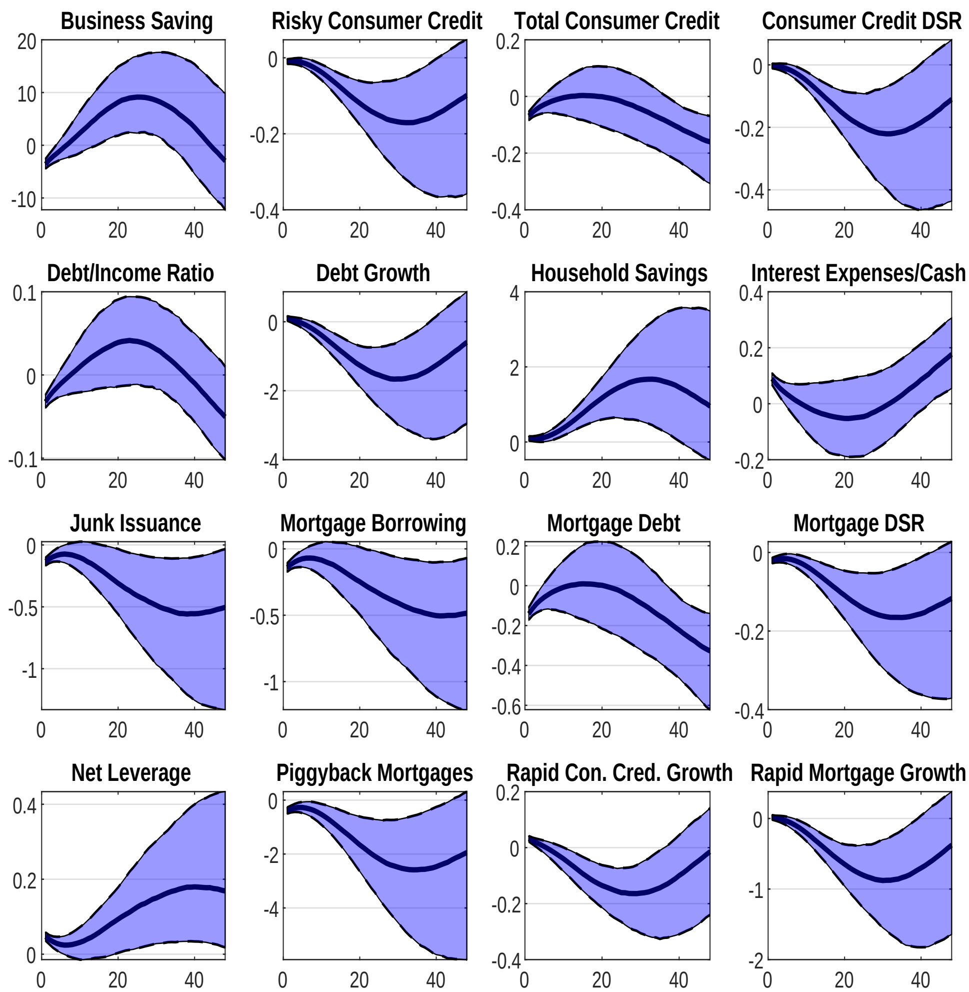

Figure 4: Impulse Responses to a Monetary Policy Surprise - Financial Sector Indicators

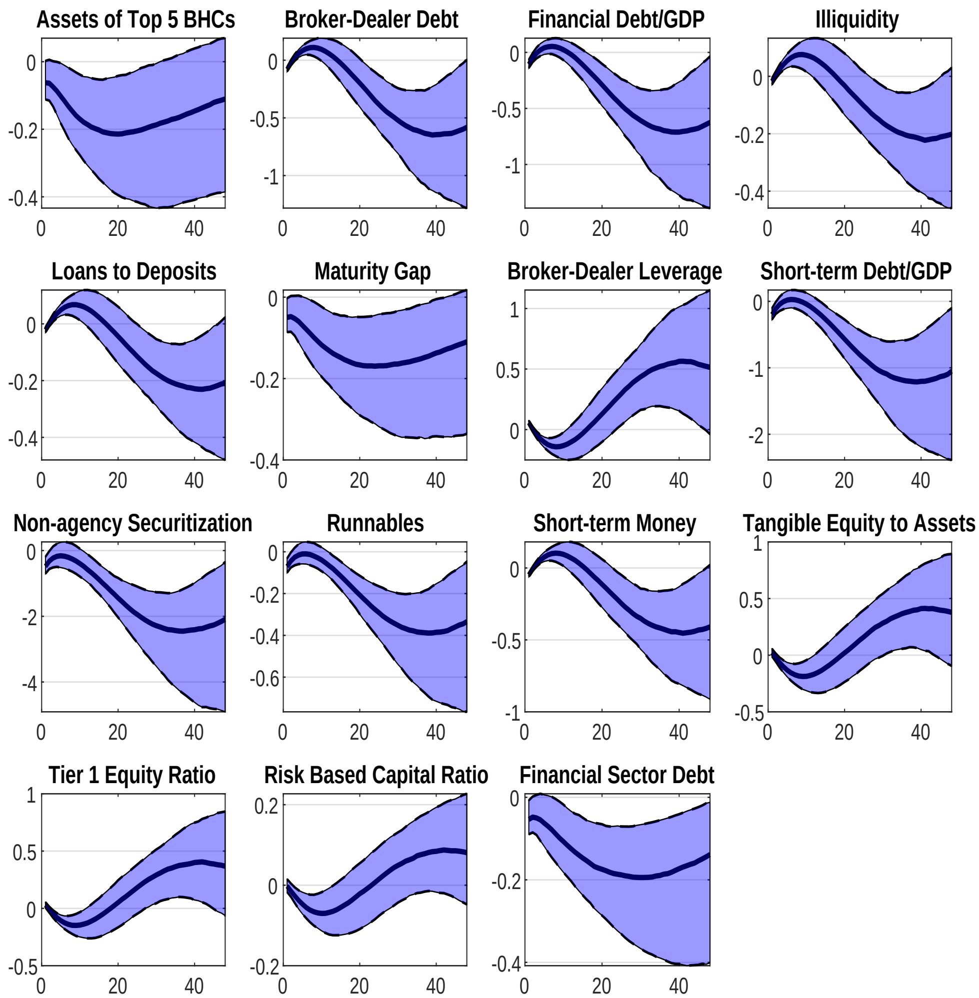

Table 1: Risk Appetite Indicators

Valuation Pressures/Risk Appetite				
Vulnerability	**Description**	**First Observation**	**Last Observation**	**Frequency**
Housing				
House Prices/rents	Price to rent ratio	6/30/1976	10/31/2018	Monthly
SLOOS res lending standards	Net fraction of banks reporting having tightened standards for home purchase mortgages	6/30/1990	9/30/2018	Quarterly
FICO scores, new mortgages	Median credit score of residential mortgages sold to GSEs	1/31/1994	10/31/2018	Monthly
Commerical Real Estate				
CRE prices	Commercial real estate price index divided by PCE	12/31/1983	9/30/2018	Quarterly
SLOOS CRE lend. Standards	Net fraction of banks reporting having tightened standards for CRE lending	6/30/1990	9/30/2018	Quarterly
Business debt and loans				
Bbb bond spread	10 yr BBB yield - 10yr treasury yield	2/28/1990	10/31/2018	Monthly
High Yield bond spreads	Merrill Lynch High Yield Master II yield - 10 yr treasury yield	1/31/1997	10/31/2018	Monthly
Share of junk debt	Sum of nonfinancial junk-grade issuance, financial junk-grade issuance, and leveraged loans over GDP	3/31/1993	9/30/2018	Quarterly
SLOOS CI lend. Standards	Net fraction of banks reporting having tightened standards for CI lending	3/31/1990	9/30/2018	Quarterly
Equity Markets				
E/P ratio (SP 500)	S&P 12mo. Forward E-P (earnings yield)	9/30/1978	1/31/2018	Monthly
E/P ratio rel to treasury yield	S&P 12mo. Forward E-P (earnings yield) less 10yr treasury and core CPI	9/30/1978	11/30/2017	Monthly
Price volatility				
VIX	VIX Index	1/31/1990	10/31/2018	Monthly
CDS Spreads		6/30/2005	9/30/2018	Quarterly

Note: Adapted from Aikman et al. (2107) table A1.

Table 2: Non-financial Imbalance Indicators

Nonfinancial sector imblanaces				
Vulnerability	**Description**	**First Observation**	**Last Observation**	**Frequency**
	Home mortgages			
Total mortgage debt/GDP	Household and nonprofit home mortgages divided by GDP	12/31/1983	9/30/2018	Quarterly
Home mortgage DSR	Mortgage debt service ratio	12/31/1983	9/30/2018	Quarterly
Mortgage borrowing, riskier borrowers	Home mortgage debt owned by riskier borrowers (ratio to DPI) divided by personal income	3/31/1999	9/30/2018	Quarterly
Rapid mortgage growth, riskier borrowers	Incidence of very rapid mortgage borrowing by riskier borrowers	3/31/2000	9/30/2018	Quarterly
Piggyback mortgage loans	Incidence of piggy back mortgages by riskier borrowers	6/30/1999	9/30/2018	Quarterly
	Consumer credit			
Total consumer credit outset	Household and nonprofit consumer credit divided by GDP	12/31/1983	9/30/2018	Quarterly
Counsumer credit DSR	Consumer debt service ratio	12/31/1983	9/30/2018	Quarterly
Consumer credit, riskier borrower	Consumer credit owned by riskier borrowers (ratio to DPI) divided by personal income	3/31/1999	9/30/2018	Quarterly
Rapid credit growth, riskier borrowers	Incidence of rapid consumer borrowing by riskier borrowers	3/31/2000	9/30/2018	Quarterly
	Nonfinancial business			
Debt growth	Nonfinancial business debt growth less inflation	12/31/1983	9/30/2018	Quarterly
Net leverage, riskier firms	Mean net leverage for speculative grade and unrated firms	12/31/1983	9/30/2018	Quarterly
Debt/income ratio	Nonfinancial corporate business debt over gross value added of nonfinancial corporate business	6/30/1995	9/30/2018	Quarterly
Interest expense/cash	Mean interest expense ratio for speculative grade and unrated firms	12/31/1983	9/30/2018	Quarterly
Deep junk share of bonds issued	Deep junk share of bonds issued	12/31/1983	9/30/2018	Quarterly
	Net Savings			
Household net savings	Households and nonprofits net saving less net capital transfers and less capital formation over GDP	12/31/1983	9/30/2018	Quarterly
Business net savings	Nonfinancial corporate business net savings less net capital formation (including equity and REIT residential structures) all over GDP	12/31/1983	9/30/2018	Quarterly

Note: Adapted from Aikman et al. (2107) table A2.

Table 3: Financial Imbalance Indicators

Financial sector vulnerabilities				
Vulnerability	**Description**	**First Observation**	**Last Observation**	**Frequency**
	Bank Leverage			
Risk based capital ratio	Total capital/asset ratio (all bank holding companies)	3/31/1990	9/30/2018	Quarterly
Tangible equity to tangible assets	Tangible common equity to tangible assets	6/30/1986	12/31/2017	Quarterly
Tier 1 common equity ratio	Tier 1 common ratio (all bank holding companies)	3/31/2001	9/30/2018	Quarterly
	Nonbank leverage			
Broker-dealer leverage ratio	Non-bank leverage ratio	12/31/1983	9/30/2018	Quarterly
Broker-dealer debt	Gross dealer borrowing to GDP	9/30/2001	9/30/2018	Quarterly
Non-agency securitization volume	US securitization issuance	12/31/2002	9/30/2018	Quarterly
	Maturity transformation			
Loans to deposits at BHCs	Loans to deposit ratio	12/31/1996	9/30/2018	Quarterly
Maturity gap at banks	Maturity gap at commercial banks	6/30/1997	9/30/2018	Quarterly
Net ST wholesale funding	Net short-term wholesale debt of financial sector to GDP	12/31/1983	9/30/2018	Quarterly
	Short-term funding			
Short-term money at BHCs	Short-term money as a share of assets	3/31/2001	9/30/2018	Quarterly
ST wholesale funding at nonbanks	Gross short-term wholesale debt of financial sector to GDP	9/30/2001	9/30/2018	Quarterly
Runnable liabilities in financial sector	Total runnables (excluding VRDOs, securities lending, and FABS) over nominal GDP	6/30/1985	9/30/2018	Quarterly
	Size/interconnectedness			
Financial sector debt/GDP	Total liabilities to GDP	12/31/1983	9/30/2018	Quarterly
Assets of 5 largest BHCs relative to total	Total assets of top 5 BHCs relative to total	3/31/1987	9/30/2018	Quarterly
Illiquidity concentration	Illiquidity index	3/31/1996	12/31/2017	Quarterly

Note: Adapted from Aikman et al. (2107) table A3.