The Market Price of Risk and Macro-Financial Dynamics

Tobias Adrian
IMF

Fernando Duarte
Brown University

Tara Iyer
IMF

May 2023

. The views expressed here are the authors' and are not necessarily representative of the views of the International Monetary Fund, its Management, or its Executive Directors.

Motivation

- Financial conditions indices (FCIs) are widely used by policymakers and practitioners, and increasingly by academics
- But they are typically statistical and lack a solid link to theory
- Using an FCI derived from fundamentals, are there dynamic feedback effects between the pricing of risk and monetary policy?

A New Financial Conditions Index Based on Theory

- We propose a new financial conditions index that is the market price of risk
- Estimate it as the volatility of GDP growth spanned by financial asset returns
- We call it the **V**olatility **F**inancial **C**onditions **I**ndex, or VFCI
- First FCI with rigorous theoretical foundations
- Explains bond and stock premia better than other FCIs

A New Financial Conditions Index with Causal Macro Effects

- We use a variety of identification approaches and instruments
  - Baseline model: Conditional heteroskedastic BVAR
  - Other identification: SVAR, local projections, sign restrictions
  - Instruments for VFCI, monetary policy, GDP
- VFCI tightening shock leads to
  - Immediate easing of monetary policy
  - A persistent contraction of output
  - No response of inflation

Innovations to SDF Give Price of Risk

- No arbitrage implies existence of a stochastic discount factor (SDF) that prices all assets

$$1 = \mathbb{E}_t[SDF_{t+1} R_{t+1}]$$

- Can decompose

$$\begin{aligned} SDF_{t+1} &= \mathbb{E}_t[SDF_{t+1}] + (SDF_{t+1} - \mathbb{E}_t[SDF_{t+1}]) \\ &= \mathbb{E}_t[SDF_{t+1}] + \lambda_t \varepsilon_{t+1} \end{aligned}$$

where ε_{t+1} is a vector of fundamental shocks and λ_t is a vector of prices of risk

FOC of Representative Agent Links Consumption to SDF

- The FOC of a CRRA representative agent is

$$
\begin{aligned}
SDF_{t+1} &= \exp(\log \beta - \gamma \Delta c_{t+1}) \\
&\approx 1 + \log \beta - \gamma \Delta c_{t+1}
\end{aligned}
$$

- We can then write

$$
\begin{aligned}
\Delta c_{t+1} &= a + bSDF_{t+1} \\
&= a + b\mathbb{E}_t[SDF_{t+1}] + b\lambda_t \varepsilon_{t+1}
\end{aligned}
$$

The Conditional Volatility of Consumption Growth is the "Price of Risk"

- Combining,

$$\Delta c_{t+1} = a + b\mathbb{E}_t[SDF_{t+1}] + b\lambda_t \varepsilon_{t+1}$$
$$= a + b\mathbb{E}_t[SDF_{t+1}] + \sigma_t \epsilon_{t+1}$$

where $Var_t(\epsilon_{t+1}) = Var(\epsilon_{t+1}) = 1$ and

$$\sigma_t \equiv b\sqrt{Var_t(\lambda_t \varepsilon_{t+1})}$$
$$= b\,\|\lambda_t\|$$

- The market prices of risk, VFCI, is defined as

$$VFCI_t \equiv \log \sigma_t^2$$

Financial Factors

- Denote the vector of financial factors by X_t, where we assume that the observable financial variables F_t are affine functions of the financial state factors
- We can extract the factors X_t from the observable financial variables F_t using filtering techniques such as Principal Components Analysis (PCA).
- F_t specified to capture financial conditions across risky asset markets
- Require time series to have long length (from early 1960s) and be publicly available. Use variables in existing FCIs as starting point

The Asset Span

- Use six standard financial series

Variable	Description
SP500RET	Equity market returns – S&P500 annual returns
SP500SD	Equity market volatility – S&P500 annualized daily standard deviation
T10Y3M	Term spread of 10 year over 3 month Treasuries
3MY-FF	Spread of 3 month Treasuries over Federal Funds rate
AAA-10Y	Spread of Moody's AAA corporate bond yield over 10 year Treasuries
BAA-AAA	Spread of Moody's BBB corporate bond yield over AAA bond yield

- Use first 4 principal components to estimate VFCI (88% of variance)

Association between PCs and leading FCIs

- PCs are highly correlated with leading measures of financial conditions

	NFCI	GSFCI	VIX
PC1	0.152***	0.374***	3.683***
	(0.023)	(0.067)	(0.202)
PC2	0.609***	1.109***	2.173***
	(0.023)	(0.111)	(0.443)
PC3	-0.243***	-1.889***	-0.270
	(0.033)	(0.114)	(0.578)
PC4	0.041	-0.382***	3.221***
	(0.037)	(0.111)	(0.381)
Num.Obs.	207	157	131
R2	0.805	0.721	0.809

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Empirical Estimation of VFCI

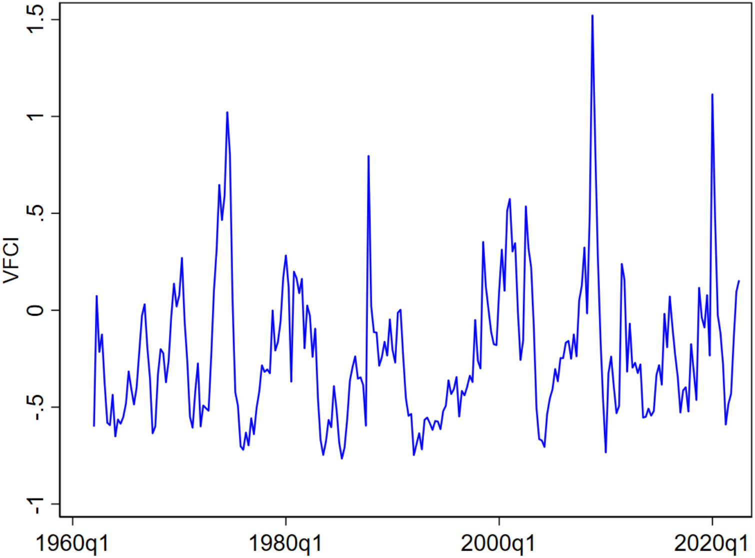
- Run a conditional heteroskedastic linear regression with financial variables in the conditional mean and the conditional volatility
- The variance is an exponential function of the regressors in the mean equation

$$\Delta gdp_t = \theta PC_t + \varepsilon_t$$
$$\sigma_t^2 = \exp(\delta PC_t)$$

where σ_t^2 is the variance of ε_t

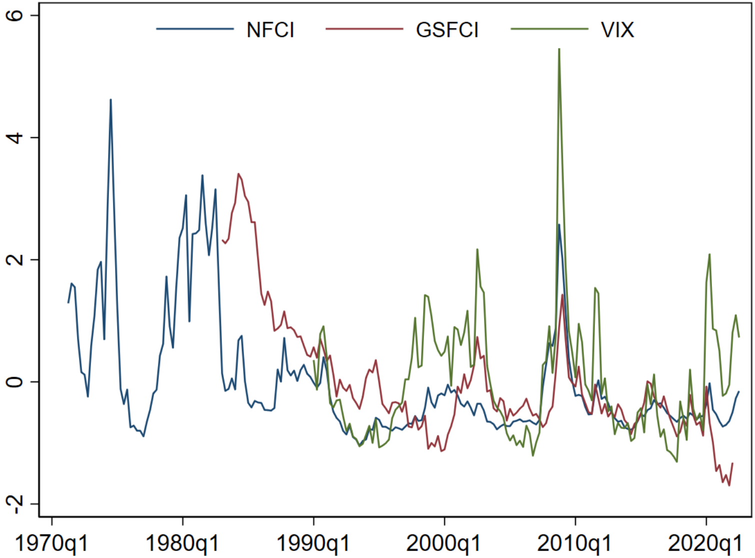
- Estimate by maximum likelihood (can also use two-step GLS)
- The VFCI is the (log of the) predicted conditional volatility of GDP: $VFCI = \log \sqrt{\hat{\sigma}_t{}^2} = \hat{\delta} PC_t$

The VFCI



Popular FCIs

- NFCI: Chicago Fed's National Financial Conditions Index
  - Weighted average of 105 measures money markets, debt and equity markets, and the traditional and "shadow" banking systems
  - No theoretical motivation/interpretation
- GSFCI: Goldman Sachs Financial Conditions Index
  - Weighted average of short- and long-term rates, trade-weighted dollar, an index of credit spreads, and S&P500 PE ratio with weights proportional to impact on real GDP growth
  - Focus on mean, not volatility; partial theoretical foundation
- VIX
  - Market's expectation of future volatility based on options of the S&P 500
  - Only stock market, ignores other assets and macroeconomy


NFCI
GSFCI
VIX
6
4
2
0
-2
1970q1
1980q1
1990q1
2000q1
2010q1
2020q1

The VFCI Explains Risk Premia Better Than Other FCIs

Regression of excess CAPE yield (ECY) from Shiller (2000) on its lag and FCIs

	(1)	(2)	(3)	(4)	(5)
	ECY	ECY	ECY	ECY	ECY
Lag ECY	0.977***	0.924***	0.900***	0.942***	0.963***
	(52.48)	(48.29)	(37.26)	(30.52)	(36.15)
VFCI	0.767***				0.840***
	(7.18)				(5.03)
NFCI		0.265***			-0.119
		(3.98)			(-0.70)
GSFCI			0.040		0.048
			(1.60)		(1.17)
VIXCLS				0.030***	-0.001
				(4.16)	(-0.11)
N	242	207	157	131	129
R^2	0.96	0.95	0.93	0.92	0.94

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

t statistics in parentheses

Regression of GZ spread from Gilchrist and Zakrajšek (2012) on its lag and FCIs

	(1)	(2)	(3)	(4)	(5)
	GZ	GZ	GZ	GZ	GZ
Lag GZ	0.857***	0.908***	0.890***	0.775***	0.708***
	(14.75)	(11.76)	(10.37)	(14.31)	(12.31)
VFCI	0.462***				0.359*
	(3.61)				(1.96)
NFCI		0.077			0.432
		(1.56)			(1.61)
GSFCI			0.008		0.045
			(0.37)		(0.95)
VIXCLS				0.034***	-0.001
				(2.92)	(-0.17)
N	197	197	157	131	129
R^2	0.85	0.82	0.79	0.82	0.86

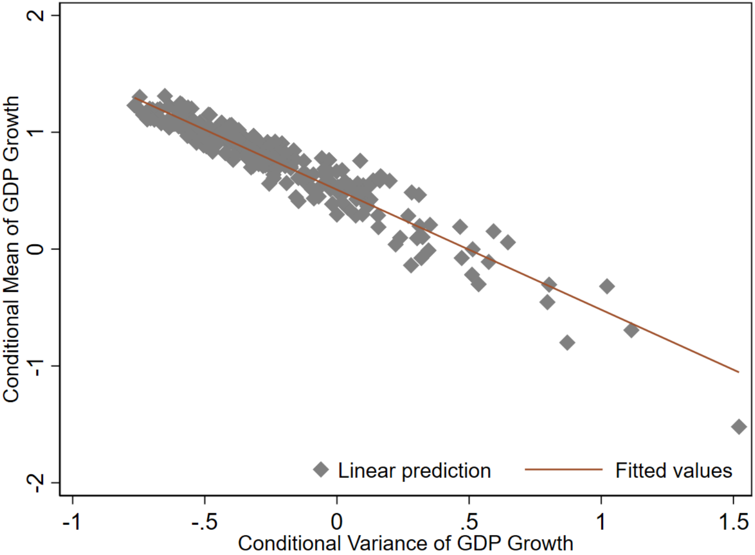
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

t statistics in parentheses

Growth-at-Risk

- VFCI is tightly linked to the conditional mean of GDP growth
- The conditional mean and volatility are negatively related, generating strong negative skewness of the conditional GDP growth distribution as periods of low expected growth tend to have high volatility
- Downside risks increase as financial conditions become tighter, "vulnerable growth." (Adrian, Boyarchenko, and Giannone 2019)

Conditional Mean and Volatility of GDP Growth



Macro-Financial Dynamics

- Empirical questions
  - Does financial tightening lead to monetary policy easing and a contraction of output?
  - Conversely, do contractionary monetary policy and adverse output shocks lead to a tightening of financial conditions?
- Dynamic impact and response of the price of risk, VFCI, is identified using a number of identification techniques and instruments
  - Volatility-identified BVAR, SVAR-IV, LP-IV, sign restrictions
  - Instruments for VFCI, monetary policy, and GDP growth
- Variables in the VARs: $X_t = [\log GDP_t, \log PCE_t, FedFunds_t, VFCI_t]$

Identification through Heteroskedasticity

- Consider a VAR of order p with n variables and j lags

$$A_0 y_t = \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t$$

- In a VAR, $\varepsilon_t \sim (0, \sigma_\varepsilon)$, but in a volatility-identified VAR, the conditional variance of the ε_t differs over time based on certain volatility change points $m \in M$

$$E[\varepsilon_t \varepsilon_t'] = \Lambda_{m,t}$$

- Only identifying restriction is that the variance of shocks is time-varying
- Allows for the identification of all shocks

Identification through Heteroskedasticityy

Based on Brunnermeier et al. 2021

- Volatility regimes in the BVAR

Time Period	Description
1962Q1-1979Q3	Oil crisis and stagflation
1979Q4-1982Q4	Volcker disinflation
1983Q1-1989Q4	Major S&L crisis defaults
1990Q1-2007Q4	Great Moderation
2008Q1-2010Q4	Financial crisis
2011Q1-2019Q4	Zero Lower Bound, Recovery from crisis
2020Q1-2022Q3	Covid-19 pandemic and war in Ukraine

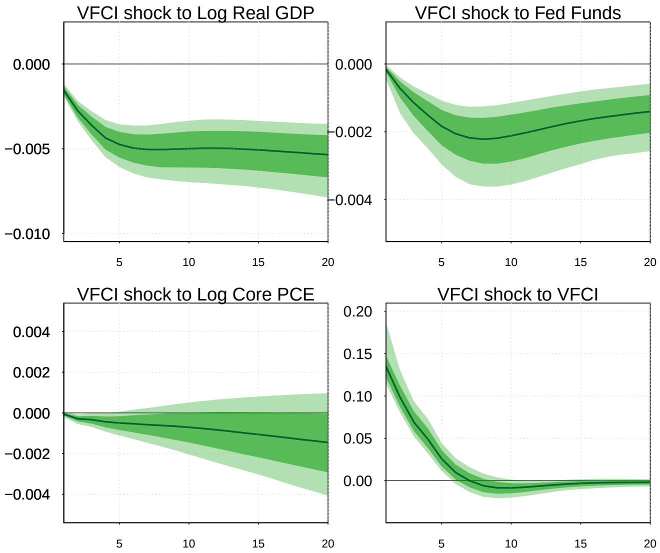
Identification Through Heteroskedasticity

Based on Brunnermeier et al. 2021

- We estimate a Bayesian VAR with nonnormal (Student's t) distributed errors
- Report Median IRFs across 10,000 MCMC draws simulated across 20 quarters
- Posterior relative variance of shocks differs substantially across regimes

	1962Q1-1979Q3	1979Q3-1982Q4	1983Q1-1989Q4	1990Q1-2007Q4	2008Q1-2010Q4	2011Q1-2019Q4	2020Q1-2022Q3
Log GDP	1.61	1.21	0.40	0.63	1.16	0.30	1.55
Log PCE	0.45	1.71	0.63	0.15	0.59	0.13	3.25
VFCI	0.67	0.83	0.94	0.70	1.75	0.86	1.10
Fed Funds	1.28	3.29	0.59	0.20	0.48	0.06	1.01

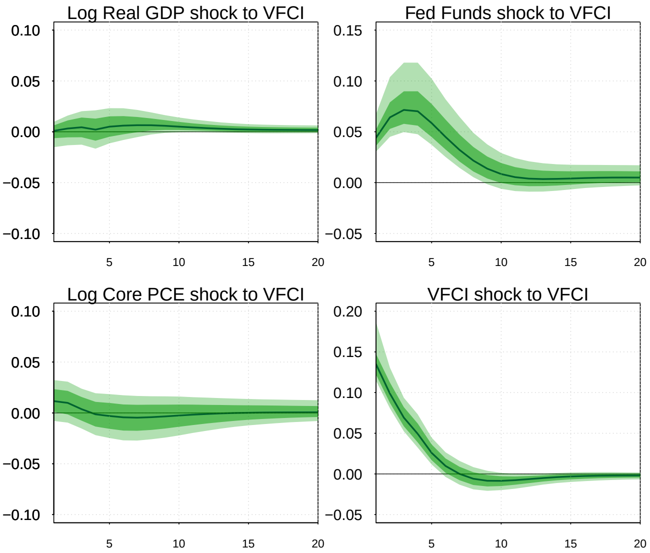
BVAR IRFs: VFCI Shocks



BVAR IRFs: VFCI Shocks

- Response of macro variables to one standard deviation VFCI shock
  - Real GDP decreases by 0.4 percent over 6 quarters
  - Fed Funds rate eases by 0.2 percentage points at the peak response of 7 quarters
  - Weak evidence of price decrease
  - We estimate a more accomodative response of monetary policy (0.2 p.p) compared to Brunnermeier et al. 2021 who find a peak decrease of the Fed Funds rate of 0.1 p.p. in response to two financial stress shocks

BVAR IRFs: VFCI Responses



BVAR IRFs: VFCI Responses

- Response of financial conditions to one standard deviation monetary policy shock
  - VFCI tightens by 5 percent upon impact (one-seventh of sample standard deviation), increasing to around 7.5 percent over 3 quarters before dying down over three years
  - Corroborates evidence of impact of monetary policy shocks on (different types of) financial variables in Gertler and Karadi 2015, Caldara and Herbst 2019 and Brunnermeier et al. 2021

Results are Robust to Alternative Identification Strategies

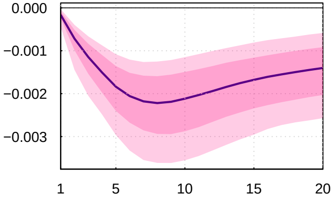
1. Structural VAR with external instruments (SVAR-IV)
2. Local projections with external instruments (LP-IV)
3. Sign restricted BVAR
   - Restriction: VFCI tightening shock $\longrightarrow$ lowers prices
4. Recursive VAR
   - VFCI and Fed Funds ordered last

Instruments

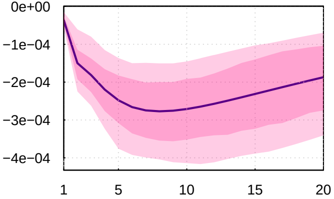
- **Monetary policy instrument** from Nakamura and Steinsson 2018, who use a high-frequency identification strategy
- **GDP growth instrument** from Cieslak and Pang 2021, who use sign restrictions in the responses of stocks and bonds to news
- **VFCI instrument** generated through sign restrictions, with the restriction on a price decrease upon impact of financial tightening shock

Causal Impact of VFCI Shocks on Monetary Policy in 5 Models

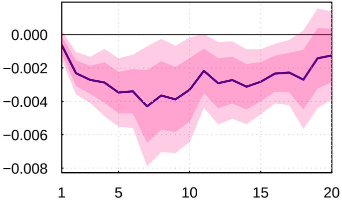
Vol−BVAR



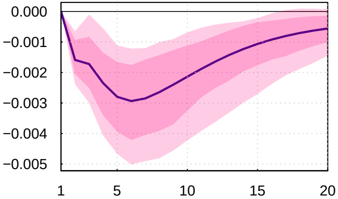
SVAR−IV



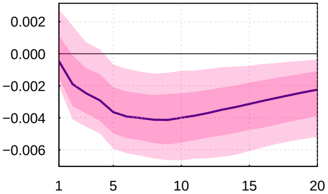
LP−IV



Cholesky

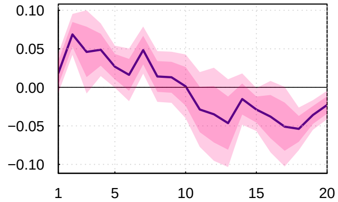


Sign Restr

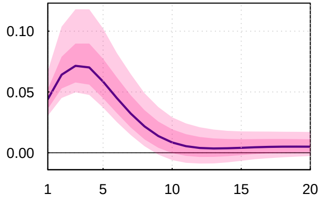


Causal Impact of Monetary Policy Shocks on VFCI in 5 Models

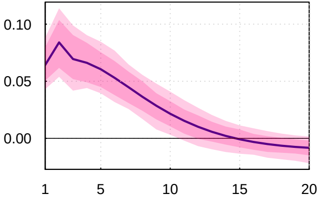
LP−IV



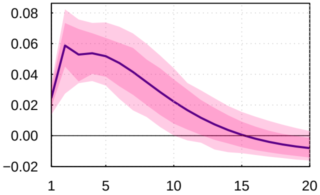
Vol−BVAR



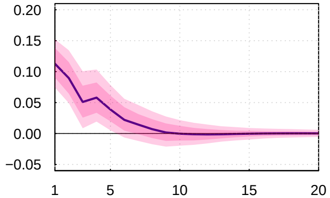
Cholesky



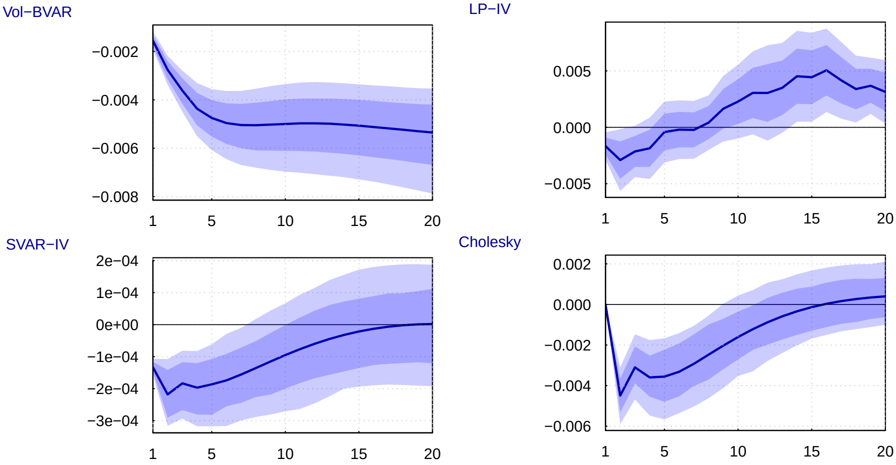
SVAR−IV



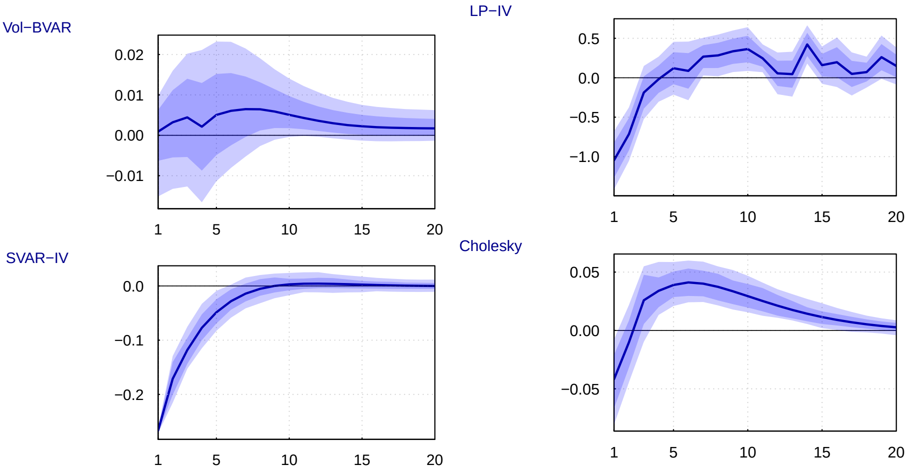
Sign Restr



Causal Impact of VFCI Shocks on GDP



Causal Impact of Output Shocks on VFCI



Contributions

- The asset pricing theory used to derive the financial conditions index is general and makes few assumptions
- Estimating the VFCI is simple and can be done easily in real time
- The empirical results are strong and hold across an extensive range of identification schemes
- The paper lays the foundation for a real macro financial theory on the market price of risk and its interaction with macroeconomic variables

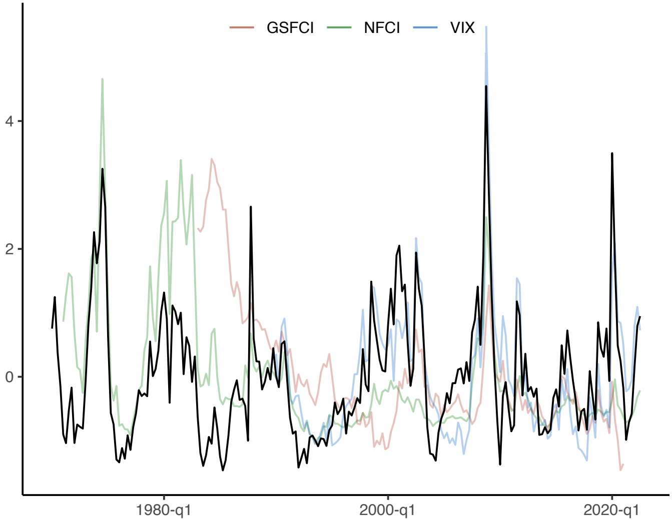
Conclusion

- We propose a novel theoretically-motivated financial conditions index, the VFCI
    - Computationally tractable and easy to estimate empirically
    - Uses widely available financial data
- VFCI better explains stock and bond premia compared to other FCIs
- Range of identification schemes used to estimate impact and response of the price of risk to macroeconomic variables
    - A tightening of financial conditions triggers an immediate easing of monetary policy and a persistent contraction of output.
    - Conversely, contractionary monetary policy shocks lead to a tightening of financial conditions

References

- **Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone.** 2019. "Vulnerable Growth." *American Economic Review* 109, no. 4 (April): 1263–89. https://doi.org/10.1257/aer.20161923.
- **Brunnermeier, Markus, Darius Palia, Karthik Sastry, and Christopher Sims.** 2021. "Feedbacks: Financial Markets and Economic Activity." *American Economic Review* 111, no. 6 (June): 1845–79. https://doi.org/10.1257/aer.20180733.
- **Caldara, Dario, and Edward Herbst.** 2019. "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs." *American Economic Journal: Macroeconomics* 11 (1): 157–92. https://doi.org/10.1257/mac.20170294.
- **Cieslak, Anna, and Hao Pang.** 2021. "Common Shocks in Stocks and Bonds." *Journal of Financial Economics* 142 (2): 880–904. ISSN: 0304-405X. https://doi.org/10.1016/j.jfineco.2021.06.008.
- **Gertler, Mark, and Peter Karadi.** 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics* 7 (1): 44–76. https://doi.org/10.1257/mac.20130329.
- **Gilchrist, Simon, and Egon Zakrajšek.** 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720. https://doi.org/10.1257/aer.102.4.1692.
- **Nakamura, Emi, and Jon Steinsson.** 2018. "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect." *Quarterly Journal of Economics* 133, no. 3 (January): 1283–1330. https://doi.org/10.1093/qje/qjy004.
- **Plagborg-Møller, Mikkel, and Christian K. Wolf.** 2021. "Local Projections and VARs Estimate the Same Impulse Responses." *Econometrica : journal of the Econometric Society* 89 (2): 955–980. https://doi.org/10.3982/ECTA17813.
- **Ramey, Valery.** 2016. "Chapter 2 - Macroeconomic Shocks and Their Propagation." In *Handbook of Macroeconomics,* edited by John Taylor and Harald Uhlig, 2:71–162.
- **Shiller, Robert.** 2000. "Irrational Exuberance." In *Irrational Exuberance.* Princeton University Press.
- **Stock, James, and Mark Watson.** 2018. "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments." *Economic Journal* 128, no. 610 (May): 917–948. https://doi.org/10.1111/ecoj.12593.

VFCI and Other FCIs



Identification through SVAR-IV

- Consider the following reduced-form VAR for a vector of variables, $y(t)$

  $$B(L)y_t = \eta_t$$

  where $\eta_t \sim (0, \Sigma_\eta)$ with $E[\eta_s \eta_t'] = 0$ for $s \neq t$. The η are related to the structural shocks, ε, as follows: $\eta_t = H\varepsilon_t$
- H can be written as $H = C(L)^{-1}\Theta(L) = I + B_1 L + \ldots)(\Theta_0 + \Theta_L + \ldots) = \Theta_o +$terms in $L, L^2, \ldots$. The impact effect is $H = \Theta_0$, which implies that $\eta_t = \Theta_0 \varepsilon_t$ (Stock and Watson 2018). Identification of Θ_0 is done by finding a suitable external instrument, Z_t, that satisfies the following conditions

  $$E\varepsilon_{1,t} z_t' = \alpha \neq 0, E\varepsilon_{2:n,t} z_t' = 0$$

- To estimate the dynamic causal effects, the structural shocks, ε_t, are retrieved by sequentially fitting and estimating the vector of η_t using the instruments.

Identification through LP-IV

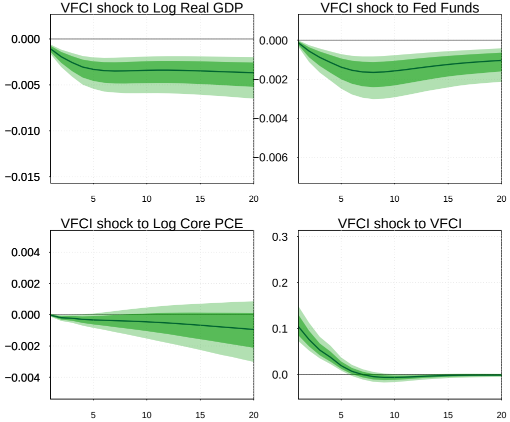
- While SVAR-IV and LP-IV have been shown to estimate the same IRFs as long as a sufficient amount of lags are accounted for and the entire population is modeled (Plagborg-Møller and Wolf 2021), Ramey 2016 finds some differences which could arise due to finite samples in practice. We estimate both models
- The LP impulse response of Y_i at horizon h of $Y_t = \Theta(L)\varepsilon_t$ is estimated from a single regression equation as follows

$$y_{i,t+h} = \Theta_{h,i1} y_{1,t} + u^h_{i,t+h}$$

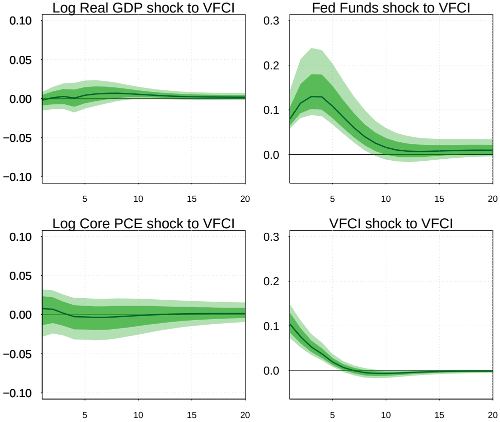
where $u^h_{i,t+h} = \varepsilon_{t+h}, \ldots, \varepsilon_{t+1}, \varepsilon_{2:n,}, \varepsilon_{t-1}\varepsilon_{t-2,\ldots}$. We estimate the equation and identify the structural shock using external instruments
- The LP-IV and SVAR-IV identification of VFCI shocks lead to somewhat less persistent dynamics than the heteroskedastic BVAR

Regime 2 Dynamics: 1979Q4-1982Q4 Volcker Disinflation

VFCI shocks

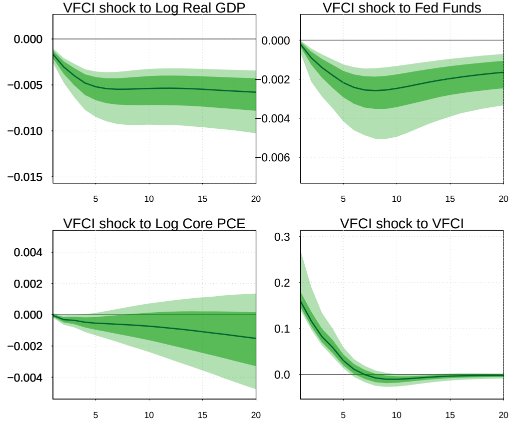


VFCI responses

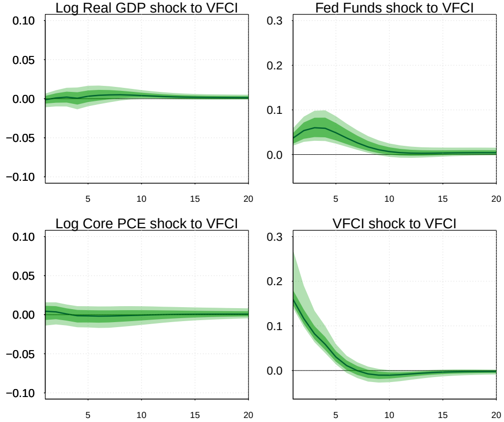


Regime 5 Dynamics: 2008Q1-2010Q4 Financial Crisis

VFCI shocks

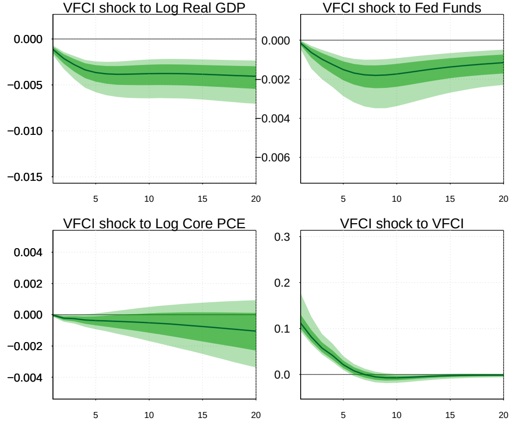


VFCI responses

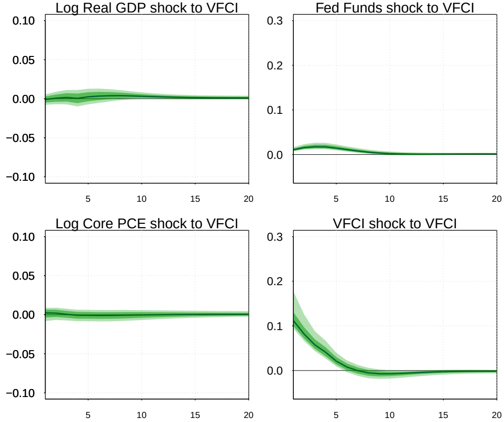


Regime 6 Dynamics: 2011Q1-2019Q4 Zero Lower Bound

VFCI shocks

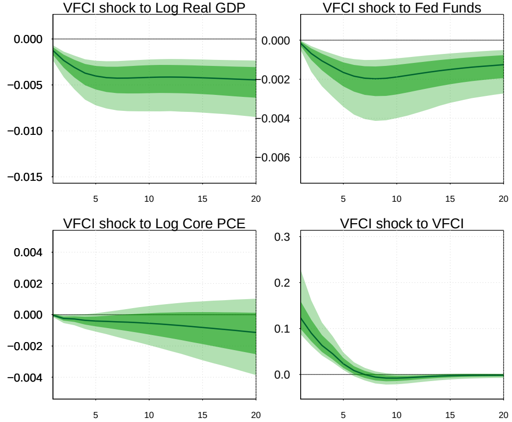


VFCI responses

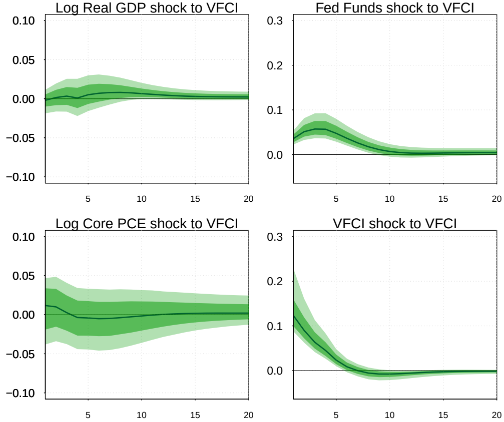


Regime 7 Dynamics: 2020Q1-2022Q3 Covid-19 Pandemic

VFCI shocks



VFCI responses



The VFCI in an Expanded Setup

- There exists a representative agent with a set of feasible consumption streams denoted by $\mathcal{C}$. The set $\mathcal{C}$ encodes all the constraints faced by the representative agent. We assume that there is a unique optimal C^* in the interior of $\mathcal{C}$ that maximizes $U(C)$.
- This general setup allows for a broad range of models and economic environments including incomplete markets, non-Markovian dynamics, trading frictions, any convex and some non-convex constraints on the representative agent or on asset prices, illiquidity, partial information, real and nominal rigidities, etc
- The logic continues to hold and the VFCI is derived as a forward-backward looking measure of past, current and future expected prices of risk

$$VFCI_t = \log Var_{t-1}\left(m^{-1}(L)[\lambda_{t-1}'\varepsilon_t^R]\right)$$