DISCUSSION PAPER SERIES

DP17777
(v. 2)

THE MARKET PRICE OF RISK AND MACRO-FINANCIAL DYNAMICS

Tobias Adrian, Fernando Duarte and Tara Iyer

MONETARY ECONOMICS AND FLUCTUATIONS

ISSN 0265-8003

THE MARKET PRICE OF RISK AND MACRO-FINANCIAL DYNAMICS

Tobias Adrian, Fernando Duarte and Tara Iyer

Discussion Paper DP17777
First Published 01 January 2023
This Revision 01 January 2023

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

This Discussion Paper is issued under the auspices of the Centre’s research programmes:

- Monetary Economics and Fluctuations

Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Copyright: Tobias Adrian, Fernando Duarte and Tara Iyer

THE MARKET PRICE OF RISK AND MACRO-FINANCIAL DYNAMICS

Abstract

We propose the log conditional volatility of GDP spanned by financial factors as ``Volatility Financial Conditions Index'' (VFCI) and derive conditions under which it is the log market price of risk. The VFCI exhibits superior explanatory power for stock and bond risk premia compared to other FCIs. We use a variety of identification strategies and instruments to demonstrate robust causal relationships between the VFCI and macroeconomic aggregates: a tightening of the VFCI leads to a persistent contraction of output and triggers an immediate easing of monetary policy. Conversely, contractionary monetary policy shocks cause tighter financial conditions.

JEL Classification: E44, E52, G12

Keywords: Macro-Finance, Monetary Policy, Financial Conditions, Growth-at-Risk

Tobias Adrian - tadrian@imf.org
International Monetary Fund and CEPR

Fernando Duarte - fernando.duarte@gmail.com
Brown University

Tara Iyer - taraiyer8@gmail.com
International Monetary Fund

Acknowledgements
The views expressed this paper are those of the authors and do not necessarily represent the views of the International Monetary Fund, its Management, or its Executive Directors.

The Market Price of Risk and Macro-Financial Dynamics*

Tobias Adrian[1], Fernando Duarte[2], and Tara Iyer[1]

[1]International Monetary Fund
[2]Brown University

January 1, 2023

Abstract

We propose the log conditional volatility of GDP spanned by financial factors as "Volatility Financial Conditions Index" (VFCI) and derive conditions under which it is the log market price of risk. The VFCI exhibits superior explanatory power for stock and bond risk premia compared to other FCIs. We use a variety of identification strategies and instruments to demonstrate robust causal relationships between the VFCI and macroeconomic aggregates: a tightening of the VFCI leads to a persistent contraction of output and triggers an immediate easing of monetary policy. Conversely, contractionary monetary policy shocks cause tighter financial conditions.

Keywords: Macro-Finance, Monetary Policy, Financial Conditions, Growth-at-Risk
JEL Codes: E44, E52, G12

*The views expressed this paper are those of the authors and do not necessarily represent the views of the International Monetary Fund, its Management, or its Executive Directors. We would like to thank Miguel Acosta for sharing an updated dataset of monetary policy shocks from Nakamura and Steinsson (2018), Anna Cieslak for sharing a updated dataset of the news shocks from Cieslak and Pang (2021), and Brunnermeier et al. (2021) for making their code available. We thank Markus Brunnermeier, John Campbell, Emi Nakamura, and Harald Uhlig for helpful comments. We also thank Luu Zhang for outstanding research assistance.

1 Introduction

Financial conditions indices (FCIs) are widely used by policy makers and practitioners, and are also increasingly common in the academic literature. However, FCIs are largely empirically motivated and lack a solid link to economic theory. In this paper, we propose an FCI that is the market price of risk in the economy under general circumstances and estimate it as the conditional volatility of GDP spanned by financial factors. We call this FCI the VFCI, or Volatility-FCI.

We start with a general framework for modeling macro-financial interactions. The absence of arbitrage implies the existence of a state price density that prices all assets in the economy. The volatility of the pricing kernel is generally referred to as the "market price of risk". When a representative consumer with time separable preferences exists, the market price of risk can be measured as volatility of aggregate consumption (see Breeden (1979), Duffie and Zame (1989b)) and, more generically, the volatility of measures of aggregate economic activity such as GDP.[1] This theoretical framework implies that the VFCI can be estimated as the conditional volatility of consumption or GDP that is spanned by financial factors.[2]

Empirically, we run a conditional heteroskedastic regression with financial variables in the conditional mean and the conditional volatility, and we use the (log of the) predicted conditional volatility of GDP to denote the VFCI. Hence, the VFCI is the log conditional GDP volatility spanned by financial factors, our measure of the market price of risk in the economy. Our results are robust to using the real PCE consumption instead of GDP in the VFCI construction.

The 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. Therefore, the empirical approach replicates the stylized facts of the literature on growth-at-risk (Adrian et al. (2019), Adrian et al. (2022)).

From a theoretical point of view, it is the volatility of GDP, not the mean of GDP, that is related to the pricing of risk in the economy. Hence, we use the conditional volatility, not the conditional mean, to construct our VFCI. This is a departure from the Goldman Sachs FCI (GSFCI of Hatzius and Stehn (2018)), which is estimated as conditional mean of future GDP growth.

Our estimate also deviates from the NFCI proposed by the Federal Reserve Bank of Chicago (Brave and Butters (2011)). The NFCI uses a Kalman Filter to extract

[1] When preferences are not time separable, but consumption volatility is stochastic, the market price of risk features additional terms related to the non-time-separability. Leading examples are the habit formation model of Campbell and Cochrane (1999) and the Epstein-Zin model by Bansal and Yaron (2004).

[2] Jurado et al. (2015) pursue a multifactor approach to measure the common movement in macroeconomic volatility.

a common component from 105 financial variables (based on Doz et al. (2012)). The NFCI is a purely statistical measure of financial conditions. In contrast, our index is derived from economic theory and thus has a more rigorous interpretation.

An alternative estimate of the price of risk in the macroeconomy is equity implied volatility, as measured by the VIX. If the entire capital stock was publicly traded, the VIX might be a good estimate of the aggregate volatility of output. Yet it is well known that only a fraction of the overall capital stock is traded, and hence the VIX is only an imperfect measure of the market price of risk.

Of course, the VFCI, NFCI, GSFCI, and the VIX are correlated. Yet simple regressions show that the VFCI is better at explaining common measures of stock and bond risk premia than the NFCI, GSFCI, or the VIX. In particular, we use a credit spread, the GZ-spread, as a measure of the corporate bond risk premium (the GZ-spread is by Gilchrist and Zakrajšek (2012a)), and CAPE is by Shiller (2000)) as metric of risk premium in stock markets. In each case, the VFCI has higher significance than the alternative FCIs, and makes the alternative FCIs insignificant when included jointly. Hence we conclude that the VFCI is the preferable metric of the price of risk in the economy from both a theoretical and an empirical perspective.

An important contribution of our paper is to study the causal relationships between the VFCI and macroeconomic aggregates. Using a variety of identification approaches and instruments, we show that a tightening of the VFCI leads to an immediate easing of monetary policy and a persistent contraction of output. Conversely, contractionary monetary policy shocks lead to tighter financial conditions.

More specifically, we start with the conditional heteroskedasticity identification of Brunnermeier et al. (2021) to estimate a baseline macro-financial specification. We work with time series of quarterly frequency from 1962Q1:2022Q3 to allow a long enough time period to capture various regime shifts in the data. The dynamic causal impact of structural shocks is estimated through a volatility-identified Bayesian SVAR with non-normal (Student's t) distributed errors. This approach accounts for the volatility that is a pervasive feature of macro-financial data, and permits the retrieval of all structural shocks, including the VFCI shock.

In order to gain confidence in the causal relationship between the VFCI and macroeconomic aggregates, we then review the literature for instrumental variables for monetary policy shocks, GDP shocks, and financial condition shocks. We generate an external instrument for VFCI using a penalized sign restrictions approach as in Uhlig (2005). External instruments for monetary policy and output are obtained from Nakamura and Steinsson (2018) and Cieslak and Pang (2021), updated through 2022Q3. The former uses a high-frequency approach to identify monetary policy shocks while the latter also uses sign restrictions to identify news shocks.

The external instruments are used to estimate the dynamic causal impact of shocks in the Structural VAR with Instrumental Variables (SVAR-IV) and Local Projections with Instrumental Variables (LP-IV) frameworks. Based on recent results in Plagborg-Møller and Wolf (2021), LP and SVAR models 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. However, Ramey (2016) reviews various alternative identification schemes and finds differences in the IRFs from SVARs and LPs in applications. In light of these results, which could arise due to the finite sample length, and to be confident that the causal effects remain robust empirically, we look at VFCI in both LP-IV and SVAR-IV models. We then go back a step and estimate a simple recursive VAR without instruments. Finally, we estimate a sign-restricted BVAR to identify the causal impact of monetary policy and VFCI shocks.

In all instances, we find robust causal, economically large and statistically highly significant effects from the VFCI to monetary policy and GDP and from monetary policy to the VFCI. We do not find a tight link between the VFCI and inflation in either direction. From our reading of the literature, this is the first time that causal effects to and from macroeconomic aggregates have been documented systematically.

We present an extensive review of the literature in Section 10. Our contribution is related to the consumption capital asset pricing model (CCAPM) based on our theoretical motivation. We do show that the VFCI has better explanatory power for common stock and bond risk premia than other FCIs. However, we leave further asset pricing tests to future research, and instead focus on the causal relationships between the market price of risk and macroeconomic dynamics. The causal identification is the main contribution relative to the existing macro-financial literature. Furthermore, we are the first to propose an FCI that is based on rigorous asset pricing theory.

The remainder of the paper is organized as follows. Section 2 exhibits a simple theory of the price of risk that justifies the estimation of the VFCI as the projection of GDP volatility onto the span of financial variables. Section 3 surveys existing FCIs. Section 4 presents the data. Section 5 estimates the VFCI. Section 6 shows that the VFCI is better at explaining common measures of stock and bond risk premia than alternative FCIs. Section 7 estimates the causal impact and response of VFCI on monetary policy and US macroeconomic aggregates, using a heteroskedastic Bayesian SVAR to identify structural shocks. Section 8 augments Section 7 with further identification schemes including external instruments and sign restrictions. Section 9 discusses additional robustness checks. Section 10 reviews how our contributions relate to the literature on consumption based asset pricing and macro-finance. Section 11 concludes.

2 The VFCI as Price of Risk

Financial assets are defined by their cash flows. Asset i pays a cash flow D_{it} at time t, with $\{D_{it}\}_{t=1}^{\infty}$ an adapted integrable stochastic process. We denote the price of asset i at time t by P_{it}, and use the convention that buying asset i at time t for a price P_{it} entitles the buyer to the sequence of cash flows $D_{i,t+1}$, $D_{i,t+2}$, ... that does not include D_{it}, i.e., prices are ex-dividend prices. Then, the (gross) return for asset i at time t is

$$R_{it} = \frac{P_{it} + D_{it}}{P_{i,t-1}}.$$

A trading strategy θ is an integrable adapted process $\theta = \{\theta_t\}_{t=0}^{\infty}$. We say that a trading strategy finances a cash flow $\{C_i\}_{t=1}^{\infty}$ if

$$C_0 = -\theta_0 \cdot P_0, \tag{1}$$

$$C_{t+1} = \theta_t \cdot (P_{t+1} + D_{t+1}) - \theta_{t+1} \cdot P_{t+1} \quad \text{for } t = 1, 2, ..., \tag{2}$$

where the dot denotes the inner product. The asset span $\mathcal{M}$ is the set of cash flows that can be financed via some trading strategy.

The absence of arbitrage is equivalent to the existence of a strictly positive adapted stochastic process $\{\pi_t\}_{t=0}^{\infty}$ in the asset span $\mathcal{M}$ such that

$$\pi_t = E_t[\pi_{t+1} R_{i,t+1}] \tag{3}$$

for all i and t. Such a process $\{\pi_t\}_{t=0}^{\infty}$ with $\pi_0 = 1$ is called a pricing kernel. Defining the risk-free rate $R_{f,t} \equiv \frac{\pi_t}{E_t[\pi_{t+1}]}$ and using the definition of covariance, equation (3) can be rewritten as

$$E_t[R_{i,t+1}] - R_{f,t} = -Cov_t\left[\frac{\pi_{t+1}}{E_t[\pi_{t+1}]}, R_{i,t+1}\right]. \tag{4}$$

We define the innovation (or expectational error)

$$\epsilon_{t+1} \equiv \frac{\pi_{t+1}}{E_t[\pi_{t+1}]} - 1$$

and decompose it as

$$\epsilon_{t+1} = \eta_t \tilde{\varepsilon}_{t+1}, \tag{5}$$

where η_t is a random variable revealed at time t, and $\tilde{\varepsilon}_{t+1}$ is a random variable revealed at $t+1$ with $E_t[\tilde{\varepsilon}_{t+1}] = 0$ and $Vol_t[\tilde{\varepsilon}_{t+1}] = 1$.[3] In general, $\tilde{\varepsilon}_{t+1}$ can be a function of

[3] For any integrable process ϵ_{t+1}, the decomposition $\epsilon_{t+1} = \eta_t \varepsilon_{t+1}$ with η_t a predictable integrable process and ε_t a martingale difference sequence always exists (see, for example, Blanchet-Scalliet and Jeanblanc (2020)).

all stochastic disturbances of the economy, including fundamental (such as exogenous shocks) and non-fundamental (such as sunspots) ones. Re-writing equation (4) in terms of η_t gives

$$E_t[R_{i,t+1}] - R_{f,t} = -\eta_t Cov_t\left[\tilde{\varepsilon}_{t+1}, R_{i,t+1}\right]. \tag{6}$$

This equation allows us to interpret η_t as the market price of risk. The market price of risk gives the risk premium – the expected excess returns – associated with exposure to the economy's sources of risk $\tilde{\varepsilon}_{t+1}$. The risk of asset i is measured by the covariance of its return with $\tilde{\varepsilon}_{t+1}$; η_t then gives the risk premium of "one unit" of risk.

When a representative consumer with time seperable utility exists, the market price of risk is equal, in equilibrium, to the volatility of aggregate consumption. To see this, consider a representative consumer with initial wealth W that maximizes utility over non-negative consumption sequences $C = \{C_t\}_{t=0}^{\infty}$ and trading strategies $\theta = \{\theta_t\}_{t=0}^{\infty}$ subject to a sequence of budget constraints:

$$\max_{C\geq 0,\theta} E_0\left[\sum_{t=0}^{\infty}\beta^t u(C_t)\right] \tag{P}$$

$$s.t.$$

$$W = \theta_0 \cdot P_0, \tag{7}$$

$$C_{t+1} + \theta_{t+1}\cdot P_{t+1} = \theta_t \cdot (P_{t+1} + D_{t+1}), \quad \text{for } t = 1, 2, ... \tag{8}$$

The existence of a solution to (P) implies no-arbitrage. Conversely, if u is continuous, no-arbitrage implies (P) has a solution. A necessary condition for a solution to (P) is the FOC

$$\beta^t u'(C_t) = \lambda \pi_t, \tag{9}$$

where $\lambda > 0$. If u is strictly concave for all t, then equation (9) is also sufficient. A first-order approximation of

$$\beta u'(C_{t+1})/u'(C_t)$$

around $C_{t+1}/C_t = 1$ gives

$$\beta\frac{u'(C_{t+1})}{u'(C_t)} \approx \beta + \beta\frac{u''(C_t)}{u_t'(C_t)}\left(\frac{C_{t+1}}{C_t} - 1\right). \tag{10}$$

Using equations (5), (9) and (10), and defining

$$\varepsilon_{t+1} \equiv \frac{u_t'(C_t)}{\beta u''(C_t)}\tilde{\varepsilon}_{t+1},$$

we have that, to first order,

$$\frac{C_{t+1}}{C_t} = E_t\left[\frac{C_{t+1}}{C_t}\right] + \eta_t \varepsilon_{t+1}. \tag{11}$$

Equation (11) shows that η_t is the conditional volatility of consumption growth.

What matters for the pricing of risk is what is spanned by financial factors. Hence for the purpose of asset pricing, only the projection of consumption growth and consumption volatility onto the asset span $\mathcal{M}$ is priced. We consider financial factors X_t that span $\mathcal{M}$. Hence for the purpose of asset pricing, expected consumption growth and the price of risk can be written as affine functions of financial factors X_t, so that equation (11) gives

$$C_{t+1}/C_t = \gamma_0 + \gamma_1 X_t + \eta_t \varepsilon_{t+1} \tag{12}$$

$$ln(\eta_t) = \delta_0 + \delta_1 X_t \tag{13}$$

We follow the New Keynesian literature and use GDP growth Y_{t+1} instead of aggregate consumption growth C_{t+1}/C_t as measure of aggregate activity, though our appendix shows that results hold with consumption instead of GDP.

The asset pricing theory thus gives rise to a conditional heteroskedastic model of GDP growth. We use a straightforward Gaussian maximum likelihood (the linear heteroskedastic regression model) to estimate the conditional mean and volatility of GDP. The model assumes the variance of the error terms is an exponential function of a linear combination of the financial variables, giving rise to heteroskedasticity. Maximum likelihood is used to fit the multiplicative heteroskedasticity regression model. The model can be written as

$$Y_{t+1} = \gamma_0 + \gamma_1 X_t + vol_t(Y_{t+1})\epsilon^y_{t+1} \tag{14}$$

$$ln(vol_t(Y_{t+1})) = \delta_0 + \delta_1 X_t \tag{15}$$

where, $\epsilon^y_{t+1} \sim N(0,1)$. Y_t denotes GDP growth, and X_t is the set of financial state variables. We define the VFCI as the log price of risk, as measured by the conditional volatility of GDP spenned by financial variables:

$$VFCI_{t+1} \equiv ln(vol_t(Y_{t+1})) \tag{16}$$

Hence the VFCI is an estimate of the log price of risk. As such, it should be a close proxy for risk premia, as all asset pricing in the economy is a function of the price of risk. Furthermore, we would expect it to be highly correlated with macroeconomic aggregates, giving rise to macro-financial feedbacks. The remainder of the paper will estimate the VFCI, study its relationship to risk premia, and then analyze causal macro-financial dynamics.

While our empirical implementation is focused on the VFCI estimation as log-volatility of GDP, it is also possible to estimate the VFCI as conditional consumption volatility. We show in the robustness section that it makes little difference whether the GDP or the PCE based VFCI is implemented, see Section 9.

3 Review of Existing FCIs

In this section we review two popular FCIs, the NFCI and the GSFCI, as well as the VIX which can be viewed as another metric of the price of risk.

The NFCI provides a weekly estimate of US financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems.[4] The index is a weighted average of 105 measures of financial activity, each expressed relative to their sample averages and scaled by their sample standard deviations. When the NFCI is positive, financial conditions are tighter than average. The methodology for the NFCI is described in Brave and Butters (2011) and is based on the quasi-maximum likelihood estimators for large dynamic factor models developed by Doz et al. (2012). The data for the NFCI start in January 1973.

The GSFCI is defined as a weighted average of riskless interest rates, the exchange rate, equity valuations, and credit spreads, with weights that correspond to the direct impact of each variable on GDP.[5] Hence the GSFCI is constructed to be a measure of conditional GDP growth. Hatzius and Stehn (2018)—which is updating the original GSFCI by Dudley and Hatzius (2000)—decompose the IS curve into 1) the response of GDP to the FCI and 2) the response of the FCI to the federal funds rate. The authors show that monetary policy innovations measured as changes in Treasury yields in one-hour windows around FOMC announcements are highly significant predictors of FCI changes. Monetary policy influences the GSFCI.

The VIX index is calculated by the Chicago Board Options Exchange (CBOE) from the cross section of S&P 500 (SPX) options.[6] The VIX Index measures the level of option implied volatility of the S&P 500 index over the next 30 days that is implied by quotations of SPX options. The VIX Index is a forward-looking measure, in contrast to realized volatility, which measures the variability of historical prices. Unfortunately, the VIX only starts in 1990 and is available at a daily and even intraday frequency.

Figure 1 shows a time series plot of the three alternative FCIs. While there is

[4] https://www.chicagofed.org/research/data/nfci/current-data

[5] https://www.goldmansachs.com/insights/pages/case-for-financial-conditions-index.html

[6] https://www.cboe.com/tradable_products/vix/

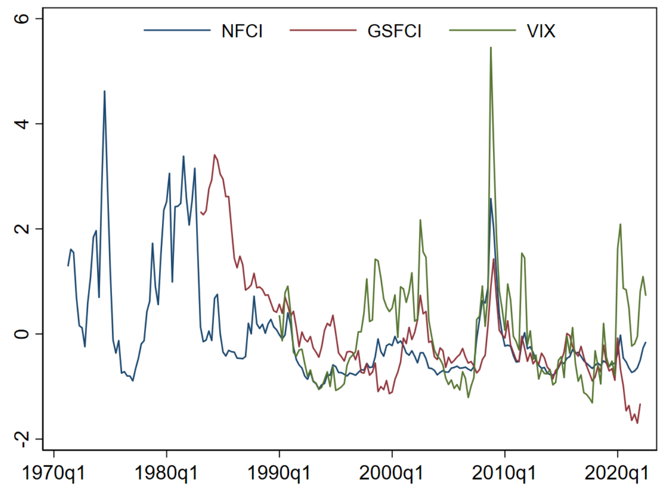

Figure 1. **Common FCIs (Standardized)**

clear correlation, particularly in times of stress such as the 2008 global financial crisis, there are also notable differences. For example, the GSFCI eased much more than the two other FCIs in 2021. The VIX was very elevated around the tech bubble in the late 1990s, while the other two FCIs were moderate. And the NFCI declined rapidly following the 1982 recession, while the GSFCI remained elevated much longer.

Such stark differences among the FCIs raises the obvious question of which one is the right metric. In this paper, we propose yet another FCI, the VFCI, which measures the market price of risk in the economy. Unlike existing FCIs, the VFCI is derived from the economic theory in Section 2, and thus straightforward to interpret. We turn to the financial factors that span the VFCI next, and then to its estimation in Section 5.

4 Financial Factors

We denote the vector of financial factors by X_t. We assume that observable financial variables F_t are affine functions of the financial state factors plus a noise term η_t.

$$F_t = f_0 + f_1 X_t + \eta_t \tag{17}$$

where F is a $k \times 1$ vector of financial variables, X is a $l \times 1$ vector of state variables, f_1 is a $k \times l$ matrix, and η is a $k \times 1$ vector of shocks, with $k > l$. Hence we can extract the financial factors X_t from observable financial variables F_t using filtering techniques such as Principal Components Analysis (PCA). PCA is widely used in financial economics to extract common principal components (PCs) from financial variables such as asset prices or spreads, the method that we adopt here. The conditions on equation 17 under which PCAs are optimal are well understood.

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
TB3SMFFM	Spread of 3 month Treasuries over Federal Funds rate
AAA10YM	Spread of Moody's AAA corporate bond yield over 10 year Treasuries
BAAMAAA	Spread of Moody's BBB corporate bond yield over AAA bond yield

Table 1. **Financial Variables used to Construct the Financial Factors X_t:** The data is from the FRED databasse of the Federal Reserve Bank of St Luois, and from Yahoo Finance.

We specify a set of financial variables F_t that capture financial conditions across risky asset markets. We use the existing FCIs as starting point, and select variables that have a long historical time series. In particular, we require each of the financial variables to be available since the early 1960s to generate a consistent time series with a relatively long history. All the financial time series that we use are publicly available from the St. Louis Federal Reserve Economic Data (FRED) and Yahoo Finance databases. We use a quarterly frequency in our estimation. Based on the availability of the earliest data points for some series of interest, the sample period for analysis is 1962Q1:2022Q3. The set of variables are listed in Table 1, and cover a wide variety of financial time series including various credit spreads (BAA minus AAA and AAA minus 10-year Treasury), US Treasury term spreads (10-year minus three months and three months minus Federal Fund rate), as well as equity volatility (computed quarterly from daily data) and equity returns (computed as annual return for each quarter).

		Factor Loadings					
	Cumul. Variance	TB3SMFFM	AAA10YM	BAAMAAA	T10Y3M	SP500RET	SP500SD
PC1	34.3%	-0.03	-0.49	-0.48	-0.36	0.34	-0.53
PC2	62.7%	0.66	0.33	-0.27	0.47	0.36	-0.19
PC3	76.2%	-0.28	-0.25	0.60	0.46	0.41	-0.35
PC4	88.0%	0.20	-0.33	-0.03	0.34	-0.76	-0.40

Table 2. **Cumulative Variance explained by PCs and PC Loadings of Variables**

We estimate the financial state variables X_t using PCA to extract the relevant variation across the financial series. The first four PCs are chosen to represent the financial state variables. Table 4 reports the cumulative variance explained by the first five PCs, as well as the factor loadings of the financial variables, F_t. As shown, the first four PCs explain close to 90 percent of the variance in the underlying data. As noted in Table 4, all of these PCs are highly correlated with leading measures of financial conditions: (1) NFCI of the Federal Reserve Bank of Chicago, (2) the CBOE's (VIX), and (3) the GSFCI. The regression results suggest that the PCs have high explanatory power for the FCIs with R-squares of around 70 percent or higher.

	NFCI		GSFCI		VIX	
PC1	-0.00540	(0.795)	-0.0365	(0.604)	1.853***	(0.000)
PC2	-0.603***	(0.000)	-1.041***	(0.000)	-4.383***	(0.000)
PC3	0.109***	(0.000)	-0.918***	(0.000)	0.456	(0.151)
PC4	0.289***	(0.000)	1.554***	(0.000)	0.947	(0.161)
R^2	80.0%		73.9%		70.0%	
N	207		157		131	

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3. **Association between FCIs and PCs**

We view these results as evidence that the four PCAs do indeed proxy for the span of financial asset returns in the economy, and hence represent a good basis for estimating the market price of risk, the VFCI. We will turn to its estimation next.

5 VFCI Estimation

The PCA estimates of the financial factors from the previous section are used to estimate the VFCI. The VFCI is is the log conditional volatility of GDP growth, a measure the economy wide market price of risk. We also model the conditional mean of GDP growth as depending on those PCs. We use a maximum likelihood approach with conditionally Gaussian shocks.

Table 4 shows the dependence of the conditional mean and the conditional volatility on the four financial components. All four components are highly statistically significant in predicting the conditional mean and the conditional volatility of both real GDP growth and real PCE growth.

Figure 2 shows the VFCI for GDP. Note that VFCI exhibits large spikes during the 2008-10 financial crisis and more recently during the Covid-19 crisis. The VFCI exhibits higher volatility during more recent recessions than alternative FCIs, but lower volatility in times of financial stress before the 2000s such as the period of recession in the early 1980s.

Figure 3 shows the relationship between the conditional mean and volatility of GDP growth. The figures corroborate the results in Adrian et al. (2019) who find that the conditional mean of GDP growth is negatively correlated with conditional volatility and that periods of low volatility in growth precede negative growth outcomes. This gives

	Real GDP Growth		Real PCE Growth	
Conditional Mean				
PC1	-0.169***	(0.000)	-0.120***	(0.003)
PC2	0.157***	(0.004)	0.109**	(0.024)
PC3	-0.208***	(0.000)	-0.184***	(0.000)
PC4	0.173***	(0.004)	0.114**	(0.027)
_cons	0.743***	(0.000)	0.807***	(0.000)
Log Conditional Volatility				
PC1	0.151**	(0.034)	0.204***	(0.009)
PC2	-0.499***	(0.000)	-0.405***	(0.000)
PC3	0.181*	(0.069)	0.341***	(0.004)
PC4	-0.411***	(0.000)	-0.497***	(0.000)
_cons	-0.485***	(0.000)	-0.631***	(0.000)
N	242		242	

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4. **Heteroskedasticity Linear Regression of GDP and PCE Growth on PCs**

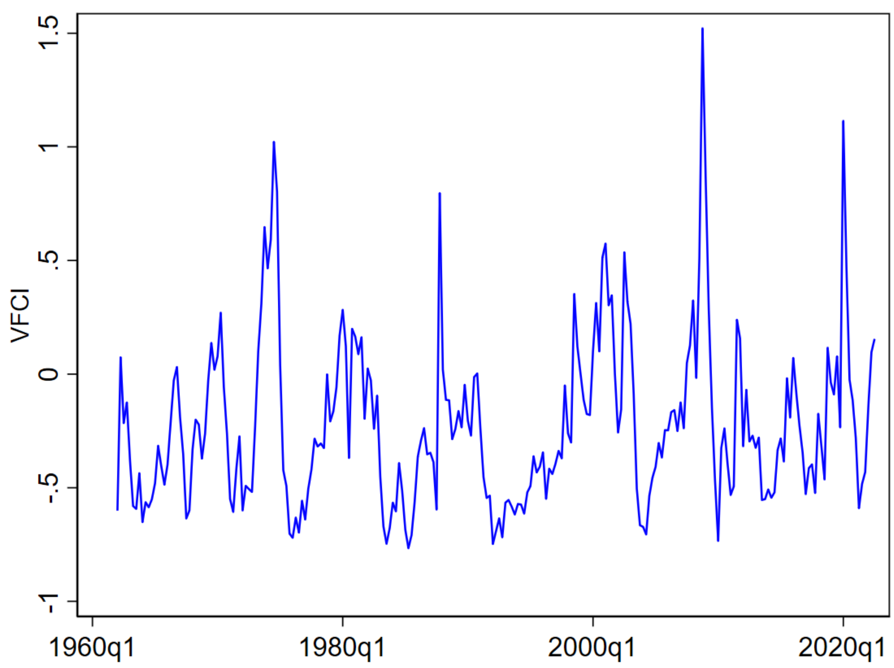

Figure 2. **The VFCI**

rise to a highly negatively skewed conditional GDP growth distribution, "vulnerable growth."

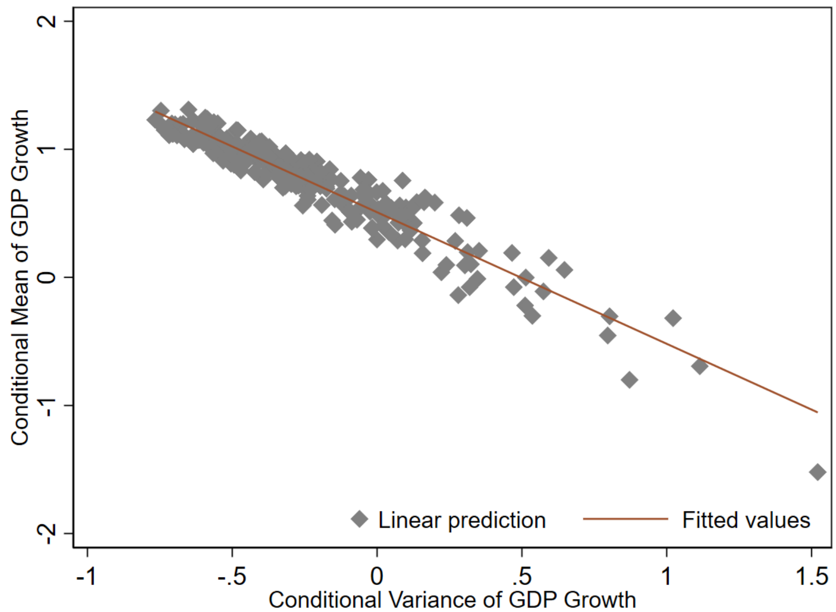

Figure 3. **Conditional Mean and Volatility of One Quarter Ahead GDP growth**

6 The VFCI and Common Risk Premia

The previous section documented the estimation of the VFCI, and provided some comparison to alternative FCI measures. The key question in this section is whether the VFCI is better at explaining common metrics of stock, bond, and Treasury risk premia than alternative FCIs. The goal of any FCI is to proxy for the cost of funding in the economy, and the theory-based VFCI is explicitly linked to the price of risk in the economy. We would therefore expect the VFCI to outperform the alternative FCIs in terms of explaining risk premia across the stock and bond markets.

The Gilchrist and Zakrajšek (2012a) bond spread and the Shiller (2000) CAPE equity market premium, or the excess CAPE yield (ECY), are commonly used as metrics of risk premia in the corporate bond and equity markets.

Tables 5 and 6 provide regression results of these risk premia on alternative FCIs. The VFCI generally has higher significance than the other FCIs, especially in the stock and bond market regressions. However, in all the regressions, it serves to make the alternative FCIs insignificant when included jointly. Hence we conclude that the VFCI is the preferable metric of the market price of risk in the economy from a theoretical as well as an empirical perspective.

Of course, many additional risk premium estimates have been proposed in the literature. We leave it to future research to explore further asset pricing implications of the VFCI, including more formal cross sectional asset pricing tests.

	GZ	GZ	GZ	GZ	GZ
L.GZ	0.856***	0.908***	0.890***	0.775***	0.707***
	(14.78)	(11.76)	(10.37)	(14.31)	(12.29)
VFCI	0.461***				0.362**
	(3.62)				(2.00)
NFCI		0.0768			0.433
		(1.55)			(1.61)
GSFCI			0.00829		0.0441
			(0.37)		(0.93)
VIX				0.0344***	-0.00145
				(2.92)	(-0.18)
R^2	84.7%	81.8%	78.7%	82.3%	85.7%
N	197	197	157	131	129

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5. **Association between GZ spread and FCIs:** The GZ spread is a corporate bond risk premium measure of Gilchrist and Zakrajšek (2012a).

	ECY	ECY	ECY	ECY	ECY
L.ECY	0.977***	0.924***	0.900***	0.942***	0.963***
	(52.54)	(48.26)	(37.26)	(30.52)	(36.10)
VFCI	0.764***				0.832***
	(7.24)				(5.08)
NFCI		0.265***			-0.118
		(3.97)			(-0.69)
GSFCI			0.0398		0.0467
			(1.60)		(1.13)
VIX				0.0300***	-0.0009
				(4.16)	(-0.11)
R^2	95.8%	95.0%	93.2%	92.1%	93.6%
N	242	207	157	131	129

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. **Association between ECY and FCIs:** The ECY stands for the excess CAPE yield of Shiller (2000) and is a commonly used measure of the equity market CAPE equity risk premium.

7 The VFCI and Macro-Financial Dynamics

We estimate the dynamic impact and response of the price of risk, VFCI, using a number of identification techniques, and a dataset of time series variables that are part of a familiar laboratory in the empirical macroeconomics literature. The preferred method is a volatility-identified BVAR and the focus is on US macroeconomic aggregates observed since the early 1960s. The extended sample provides enough time variation to allow for potentially better identification of the structural shocks. A quarterly dataset is compiled from 1962Q1 to 2022Q3 on the main set of variables–VFCI, real GDP, the core PCE index, and the Federal Funds rate. The interest rate is in decimal units and all other variables are in log levels, as described in Table 7.

	Mean	SD	Min	Max	N
Federal Funds Rate	0.05	0.04	0.00	0.18	243
VFCI	-0.23	0.37	-0.77	1.52	243
log of Real GDP	9.15	0.50	8.16	9.91	243
log of Core PCE Deflator	4.01	0.62	2.86	4.82	243

Table 7. **Descriptive Statistics for the Macro-Financial Variables:** The VFCI is constructed in the previous section, the remaining data is from the FRED database of the Federal Reserve Bank of St Louis.

7.1 Identification through Heteroskedasticity

The empirical analysis investigates whether a tightening of financial conditions, as captured by VFCI, leads 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? The baseline identification technique used to estimate the causal effects of shocks is identification through heteroskedasticity using a Bayesian SVAR with nonnormal (Student's t) distributed errors as in Brunnermeier et al. (2021). This approach models the time variation in the variances of each of the shocks.

Identification through heteroskedasticity allows for the plausible identification of all shocks, importantly including the VFCI shock. Furthermore, in a volatility-identified BVAR, there is no need to impose any identifying restrictions other than that the variance of shocks is time-varying. This relaxation of the usual constant covariance matrix assumption is reasonable especially if heteroskedasticity is present in the data.

To illustrate the basic setup of the model, consider the following VAR of order p with n variables and j lags

$$A_0 y_t = \sum_{j=1}^{p} A_j y_{t-j} + \varepsilon_t \tag{18}$$

where A_0 is a matrix of simultaneous relationships among the n variables, the A_j matrices are coefficient matrices, and ε_t is a $nx1$ vector of structural shocks. In a VAR model where the volatility of the residuals is not modeled, the structural shocks would be serially uncorrelated with zero mean, so that $\varepsilon_t \sim (0, \sigma_\varepsilon)$.

In a volatility-identified VAR, however, the conditional variance of the ε_t differs over time based on certain volatility change points. Designating a set of volatility change points $m \in M$, the variance of the structural shocks is written as follows

$$E[\,\varepsilon_t \varepsilon_t'] = \Lambda_{m,t} \tag{19}$$

where $\Sigma_{m,t}$ is the time-varying covariance matrix of shocks conditional on m. Of note is that the time-varying volatility is used for the purposes of identification to estimate the median IRFs, which we report. The coefficients, A_j, are fixed across the change points so that the economy is assumed to react to shocks of different magnitudes in the same way across time. The IRFs are therefore scaled to an "average" regime.[7]

Volatility Regimes

To identify the volatility change points in M, we use the six macroeconomic regimes specified in Brunnermeier et al. (2021). We also incorporate a seventh regime to include the Covid-19 pandemic era. The six regimes are based on turning points in US macroeconomic history where the underlying shock processes were plausibly different (Table 8). Within each regime, it is assumed that the macroeconomic dynamics are constant, but the variance of the structural shocks differs.

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

Table 8. **Volatility Regimes:** Brunnermeier et al. (2021) provide the first six regimes.

[7] While we report in the main set of results the "average" way that the economy responds to shocks, these results are robust to alternate specifications where we allow for regime-specifics IRFs, i.e. where the VAR dynamics change along with the covariance matrix of shocks (see the appendix).

Bayesian Priors and Structural Shocks

The volatility-identified SVAR is estimated using Bayesian methods. We generally follow the calibration of priors in Brunnermeier et al. (2021). A Gaussian prior is placed on A_0 with a standard deviation of 0.01. A Minnesota prior with tightness as 3 and decay as 0.5 is placed on the reduced-form coefficients. We impose the restriction that the cross-period structural variances average to one, or that $\frac{1}{M}\sum_{m=1}^{M}\lambda_{i,m(t)} = 1$, where the $\lambda_{i,m(t)}$'s are the diagonal elements of the covariance matrix of structural shocks. This requires that a Dirichlet prior with $\alpha = 2$ is placed on each element of the vector $\lambda_{.,i} = \lambda_{1,i}...\lambda_{M,i}$ normalized by M, the number of volatility change points.

Each structural shock ε_{it} is assumed to follow an independent t distribution with α degrees of freedom. To estimate α, the distribution of residuals is fit for the volatility-identified BVAR with normally distributed structural shocks. This implies that the data would be fit by a t distribution with 2.6 degrees of freedom. The t distribution has the advantage of potentially better fitting the data if there are large shocks as it puts a greater probability on tail events compared to the normal distribution.

7.2 Dynamic Causal Effects

Conditional on the specification of the model priors, regimes, and shock distributions, we simulate 5000 posterior draws based on the Gibbs sampling procedure, and estimate the median IRFs over 5 years, or 20 quarters. The BVAR includes VFCI, Fed Funds rate, real GDP, and prices, with all variables in logs apart from the interest rate.

The IRFs represent the average across the volatility regimes. As can be seen in Table 9, which reports the posterior median relative variance for each of the t-distributed structural shocks, the variance of the structural shocks differs substantially across the volatility change points. This evidence of time-varying variance suggests that estimation using the t-distributed shocks would be more efficient than drawing shocks from a Gaussian distribution, although they would both be consistent.

	1962Q1-1979Q4	1979Q4-1982Q4	1983Q1-1989Q4	1990Q1-2007Q4	2008Q1-2010Q4	2011Q1-2019Q4	2020Q1-2022Q3
Log GDP	1.25	1.38	0.34	0.47	0.62	0.22	2.54
Log PCE	0.44	2.16	0.70	0.17	0.50	0.16	2.84
VFCI	0.55	0.83	0.92	0.69	1.79	0.91	1.28
Fed Funds	1.29	3.33	0.69	0.22	0.56	0.05	0.76

Table 9. **Relative Variances for the Four Structural Shocks in Seven Regimes**

VFCI shocks exhibit the largest variance during the period of the global financial crisis (2008-10), which saw a substantial tightening of financial conditions. Monetary policy shocks conversely exhibit higher volatility in the regimes before the early 1980s, which accords with thinking that policy errors and monetary policy shocks have dampened over more recent years Ramey (2016). Output shocks exhibit the highest volatility during 2020-22, which is not surprising given the sharp decline in US GDP relatively quickly upon the Covid-19 shock. Price shocks are also the most volatile in the latest regime, reflecting the sharp uptick in inflation in the US starting in 2021.

We report IRFs that are the median across the MCM draws, with 68th and 90th percentile posterior error bands. Figure 4 shows the dynamic response of each variable to a one standard deviation increase in the VFCI structural shock, where the shocks are drawn from a t distribution with 2.5 degrees of freedom. Note that while there is no significant effect on prices, a tightening of financial conditions leads to a statistically significant easing of monetary policy upon impact. VFCI shocks also induce a significant and persistent contraction in output.

Figure 5 shows the response of VFCI to each of the four structural shocks identified using the heteroskedastic BVAR. Note that contractionary monetary policy shocks lead to a statistically significant tightening of financial conditions upon impact.

These results suggest that monetary policy and financial conditions are highly responsive to each other, corroborating the results in Cieslak et al. (2019) and Cieslak and Vissing-Jorgensen (2020). Furthermore, the simulations provide further evidence that the conditional volatility of aggregate consumption based on fundamental asset pricing theory, VFCI, is a strong measure of financial conditions.

7.3 Robustness of the Heteroskedastic BVAR

We conduct a range of robustness exercises that amount to small perturbations around the baseline set of results. The core set of results on the significant responses of VFCI to monetary policy shocks and monetary policy and output to VFCI shocks are assessed through the following set of exercises

- alternative specifications of stationarity by replacing GDP and PCE with stationary variables – output gap or GDP growth instead of GDP, and PCE inflation instead of the PCE index
- alternative specifications of VFCI such as using VFCI in levels rather than logs
- alternative number of PCs instead of the baseline case of 4 PCs in the heteroskedasticity linear regression to construct VFCI
- alternative specifications of the distribution of structural shocks such as simulating draws from a normal distribution instead of the t distribution
- alternative number of posterior draws in the MCMC chain i.e. increasing the draws from the baseline of 5,000 to 50,000 and 100,000

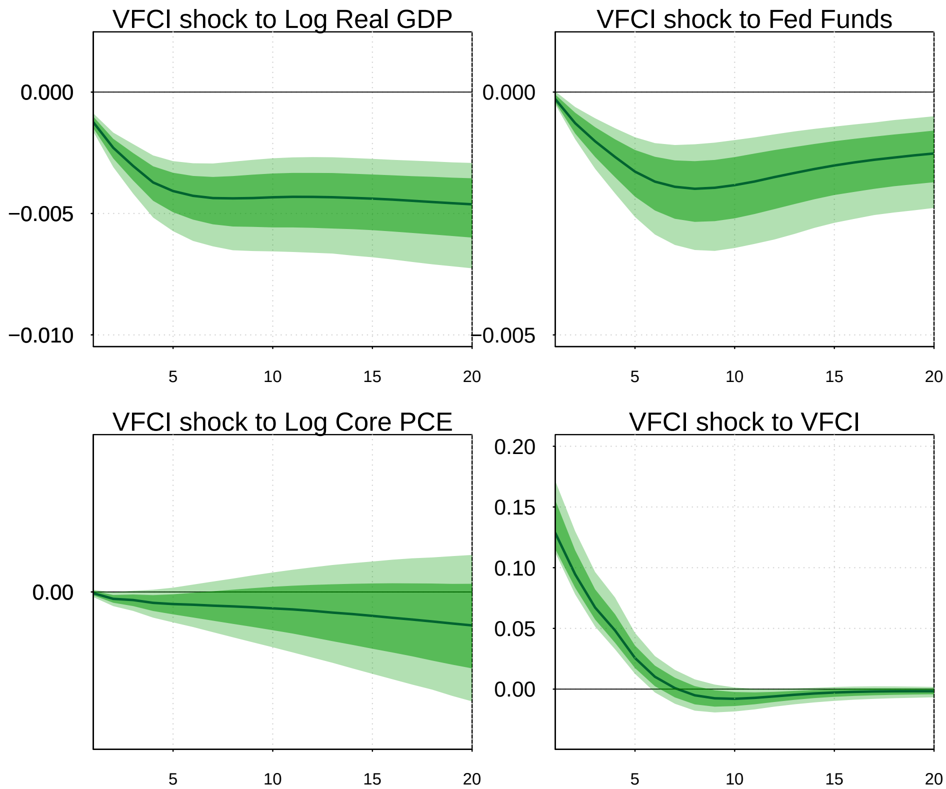

Figure 4. **IRFs: VFCI Shocks** Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

- alternative shapes of the Minnesota prior i.e. varying the calibration from $[1, 3]$ for the tightness and $[0.3, 0.7]$ for the decay
- alternative time period i.e. ending just before the 2008-10 global financial crisis to mitigate the effect of unusually large structural shocks
- alternative specifications of the baseline BVAR with regime-specific IRFs where the VAR dynamics change over time
- alternative specifications of the baseline BVAR with the inclusion of a second financial variable (such as the Gilchrist and Zakrajsek (2012) bond spread or the spread of 3-month Eurodollars over 3-month Treasuries)

The original conclusions are broadly robust to these changes.

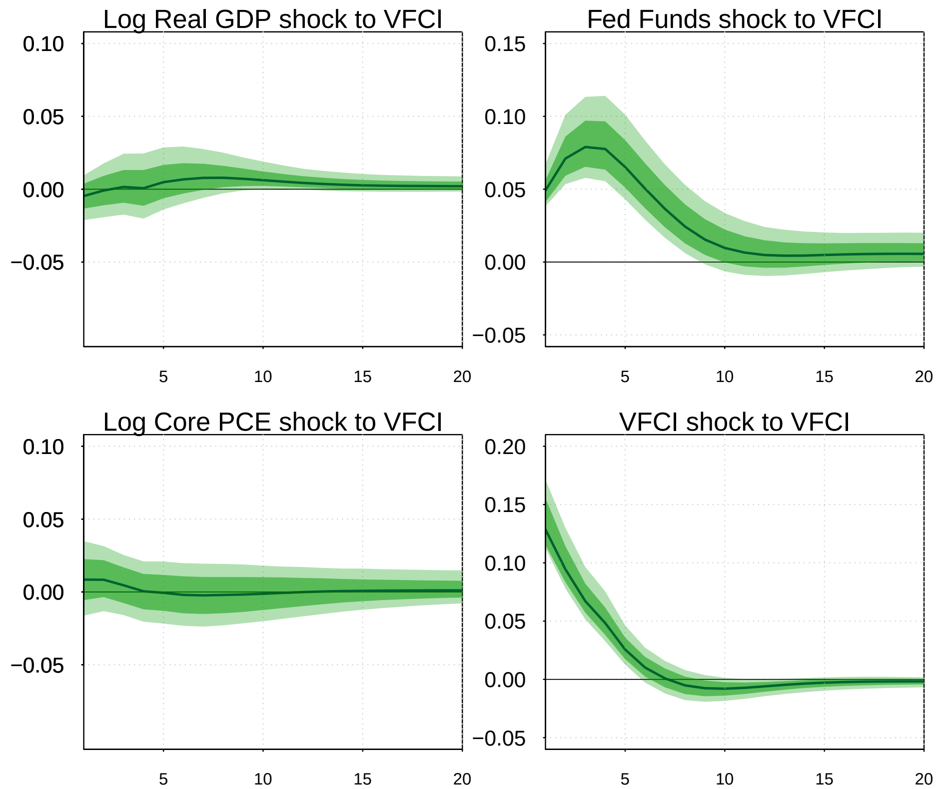

Figure 5. **IRFs: VFCI Responses** Impulse responses of VFCI to the four structural shocks in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an “average” period with unit scale.

8 Alternative Identification

Studies in the empirical macroeconomics literature have generally tended to identify shocks by imposing exclusion restrictions on the reduced-form coefficient matrices, by using narrative approaches, or by finding external instruments. While there are benefits to these methods, challenges could arise as instruments are not easy to find and restricting the reduced-form matrices can sometimes be viewed as arbitrary. To mitigate some of these issues, and also to account for the volatility we believe is a pervasive feature of historical macroeconomic data, we follow the approach of estimating a volatility-identified BVAR as the preferred identification scheme. To check that the results on VFCI are not restricted to this particular model, however, we augment the analysis with some other methods of identification.

First, we estimate an SVAR-IV model that augments the oft-used SVAR system with external instruments. Further details on the construction of our instruments can be found in the next section. Second, we employ the LP-IV method proposed by Jordà et al. (2015), which uses external instruments in a local projections framework. Third, we also estimate a simple recursive VAR without instruments. We vary the recursive ordering of VFCI and monetary policy as the forcing variable. Fourth, we impose sign restrictions Uhlig (2005) to identify the causal impact of monetary policy and VFCI shocks.

8.1 External Instruments

Studies in the empirical macroeconomic literature have generally used internal instruments, or shocks identified within the model, to estimate dynamic causal effects. Stock and Watson (2018) consolidate the derivation of dynamic causal effects and asymptotic theory for external instruments in LP and SVAR frameworks and find that the use of external instruments can potentially lead to more credible identification. As discussed in that paper, external instruments in macroeconometric models comprise a relatively new but promising avenue of research. We build on this literature by also using instruments for VFCI, monetary policy, and output in LP and SVAR models as alternative identification strategies to estimate dynamic causal effects.

VFCI Instrument

The external instrument for VFCI is constructed based on a sign-restricted VAR approach using Bayesian methods (see Uhlig (2005)). The restrictions are imposed on the shape of the orthogonalized impulse response functions. The identifying assumption is that a VFCI shock reduces prices upon impact. This is not a stringent identifying assumption in light of the evidence from the volatility-identified BVAR that prices fall, albeit not significantly, when there is a surprise tightening of financial conditions.

To implement the sign restrictions approach, we start by fitting a reduced-form Bayesian VAR on VFCI, GDP, PCE, and the Fed Funds rate, assuming that the structural shocks are distributed as $\varepsilon_t \sim (0, \sigma_\varepsilon)$. Imposing the Normal-Wishart prior on the BVAR and using an MCMC chain, a posterior distribution is formed to estimate the reduced-form coefficient and error variance matrices.

The structural shocks are then recovered using a Cholesky decomposition with resulting IRFs. At this point, an orthogonalized IRF, α, is randomly drawn. As in Uhlig (2005), we impose a function that penalizes sign restriction violations, $\Psi(\alpha)$ for a set of constrained responses $j \in J$ and constrained periods $k \in K$, that solves the following minimization problem

$$min_\alpha \Psi(\alpha) = \sum_{j\in J} \sum_{k \in JK} b(l_j) \frac{r(j,\alpha)(k)}{\sigma_j} \tag{20}$$

where $r(j,\alpha)(k)$ is the response of j at step k to α and b is an imposed penalty. The IRFs from the Cholesky decomposition are then multiplied with α, and the sequence of steps is repeated based on the MCMC algorithm to ultimately derive an IRF that minimizes the overall penalty function for the restricted variables.

This procedure generates an external instrument for VFCI based on the VFCI structural shock identified in the sign-restricted model. A similar sequence of steps is followed to retrieve the VFCI shock with the model in stationary terms.

Robustness of the VFCI instrument We derive an alternative version of the VFCI instrument that slightly deviates from the baseline case for the purposes of robustness. To do so, we use a rejection algorithm that keeps all the posterior draws that satisfy the imposed sign restrictions instead of choosing draws that minimize the penalty function. The steps to retrieve the structural shocks remain the same, but in this case, the random orthogonal IRF, α, is estimated based on the following formula

$$\alpha = Ba \tag{21}$$

where $BB' = \sigma_\varepsilon$, and a is an $n \times 1$ vector so that $||a|| = 1$.

Monetary Policy Instrument

The estimation of monetary policy shocks has been oft-explored in the literature starting from Romer and Romer (2004)'s estimation of this shock through a narrative approach. Since then, the literature used various techniques to identify monetary policy shocks Ramey (2016), such as the high-frequency identification strategy used in Nakamura and Steinsson (2018). Our instrument for the Federal Funds rate is the Romer and Romer monetary policy shock, which starts from 1969Q1 and extends until 1994Q4, interpolated with the Nakamura and Steinsson shock, which was updated and kindly shared with us, from 1995Q1 to 2022Q3.

GDP Growth Instrument

The external instrument related to GDP was kindly shared by the authors of Cieslak and Pang (2021) and extends from 1983Q1-2022Q3. This shock is estimated through a sign-restricted VAR approach that places identifying restrictions on the differential response of stock and bond market prices to key macroeconomic announcements. The authors identify growth news shocks among other shocks, and we use the GDP growth shock as an external instrument for GDP growth in a stationary version of our model.

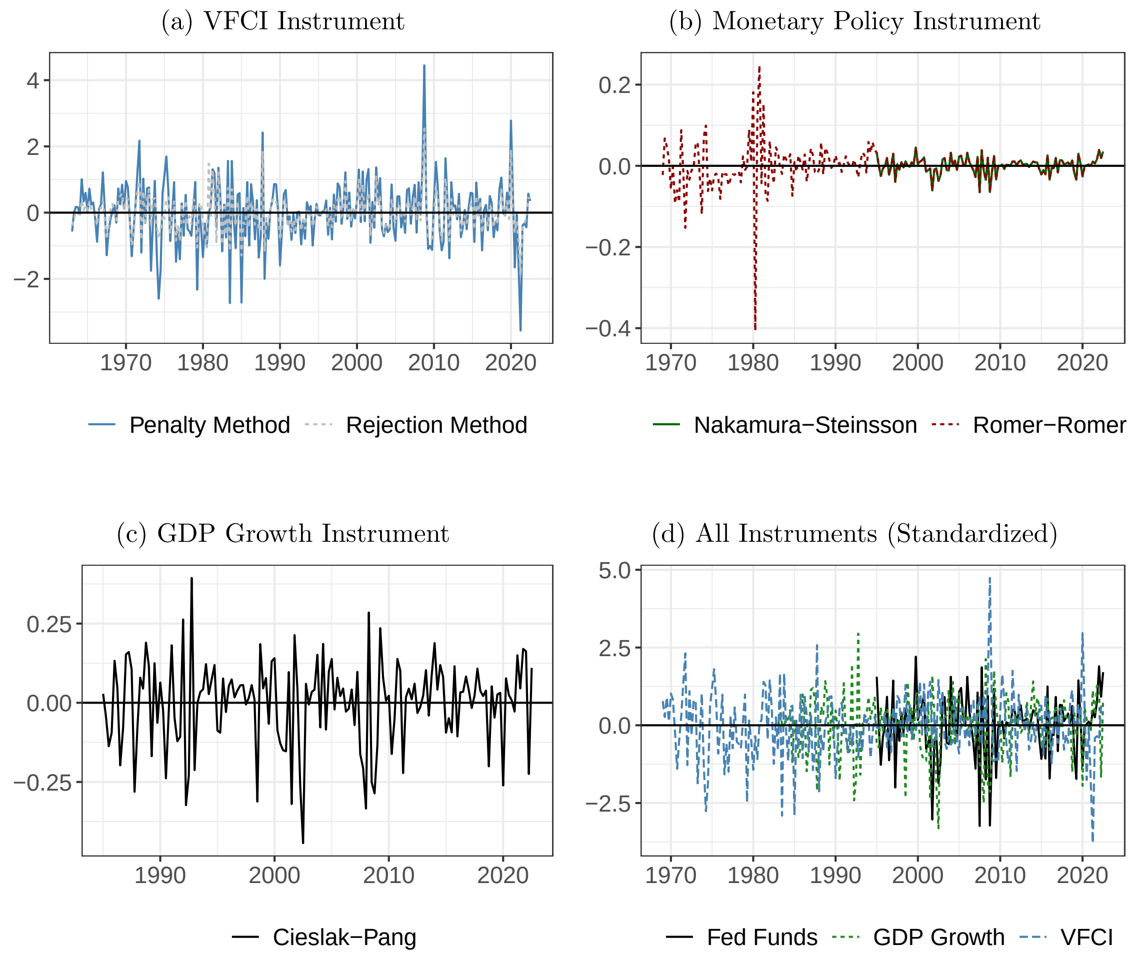

Figure 6. **External Instruments for VFCI, Monetary Policy, and GDP Growth**

8.2 Identification through SVAR-IV

To outline the SVAR-IV identification problem, consider the following reduced-form version of equation 18 for a vector of endogenous variables, $y(t)$

$$B(L)y_t = \eta_t \tag{22}$$

where the reduced-form innovations, η_t, satisfy $\eta_t \sim (0, \Sigma_\eta)$ with $E[\eta_s \eta_t'] = 0$ for $s \neq t$ and the polynomial lag operator is $B(L) = I - \sum_{k=1}^{p} B_k L^k$. The innovations, η, are related to the structural shocks, ε, as follows

$$\eta_t = H\varepsilon_t \tag{23}$$

where H is invertible. Here, in contrast to the time-varying variance assumption in the previous section, the structural shocks are distributed as $\varepsilon_t \sim (0, \sigma_\varepsilon)$.

Equations 18 and 22 can be written in terms of their structural moving average representations as $Y_t = \Theta(L)\varepsilon_t$ and $Y_t = C(L)v_t$, where $C(L) = [B(L)]^{-1}$ and $\Theta(L) = C(L)H$. Therefore, H can be written as $H = C(L)^{-1}\Theta(L)= I + B_1L + ...)(\Theta_0 + \Theta_L + ...)= \Theta_o$+terms in $L, L^2, ...$. The impact effect is $H = \Theta_0$, which implies that $\eta_t = \Theta_0\varepsilon_t$ Stock and Watson (2018). The SVAR-IV identification problem is to identify Θ_0 by finding a suitable external instrument, Z_t, that satisfies the following conditions

$$E\varepsilon_{1,t}z_t' = \alpha{\neq}0 \tag{24}$$

$$E\varepsilon_{2:n,t}z_t' = 0 \tag{25}$$

Equations 24 and 25 are the instrument relevance and exogeneity conditions, meaning that the instrument must be contemporaneously correlated with the structural shock, $\varepsilon_{1,t}$, and uncorrelated with the other structural shocks.

The basic idea to estimate Θ_0 is as follows, with further theory, including on the asymptotics and inference, found in Stock and Watson (2018). Suppose conditions 24 and 25 are satisfied, we are able to identify the first structural shock, $\varepsilon_{1,t}$. To recover the other structural shocks in a VAR with n endogenous variables, the reduced form system in equation 22 is first fit to estimate the vector of innovations η_t.

All the reduced-form innovations apart from those of the first variable, $\eta_{2:n,t}$, are then regressed on $\eta_{1,t}$, using z_t as an instrument. The residuals of this sequence of regressions form a vector $\kappa_{2:n,t}$. Finally, $\eta_{1,t}$ is regressed sequentially on $\eta_{2:n,t}$, using $\kappa_{2:n,t}$ as the instruments. This allows for the identification of the $\varepsilon_{2:n,t}$. Using the identified structural shocks, ε_t, the dynamic causal effects are estimated.[8]

The impact of the VFCI, monetary policy, and output shocks identified through external instruments in an SVAR-IV model corroborate the results from the heteroskedastic BVAR. A tightening of financial conditions caused by a positive VFCI shock, as identified by the penalty function approach, triggers an immediate easing of monetary policy and a contraction in output. The dynamic responses of both output and monetary policy, and output in particular, are somewhat less persistent compared to the heteroskedastic BVAR, but their negative responses upon impact to tight financial conditions are highly significant and similar in magnitude.

We also estimate the impact of monetary policy and growth shocks in the SVAR-IV model.[9] A surprise increase in GDP growth leads to an immediate tightening of monetary policy and easing of financial conditions. Financial conditions ease upon impact of

[8]Of note is that this method is related to, but different, from the approach of using an external instrument in a recursive VAR, as in Romer and Romer (2004). As discussed in Ramey (2016), the SVAR-IV method was developed as an alternative way to use external instruments in a VAR framework.

[9]The GDP growth shocks are estimated in a stationary VAR due to the nature of the news shock in Cieslak and Pang (2021) (it is to growth, not output)

the positive growth news shock, but tighten in the following quarters. The immediate loosening of financial conditions in response to growth shock may be accorded to the plausibly better identification of these shocks using an external instrument.

8.3 Identification through LP-IV

The Local Projections (LP) approach Jordà (2005) has become a popular method of estimating IRFs. The LP model estimates the parameters sequentially through simple linear regressions and is computationally straightforward in practice. LP estimates can theoretically be more robust if a linear VAR is misspecified, although this is not always the case (Plagborg-Møller and Wolf (2021)). The LP model can also be estimated using external instruments Jordà et al. (2015). We use our instruments to estimate a local projections-IV (LP-IV) model for VFCI, output, inflation, and monetary policy.

SVAR and LP models were considered conceptually different in the past, but 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 as in Plagborg-Møller and Wolf (2021). Ramey (2016), in reviewing the literature, estimates similar models with LPs and SVARs and finds some differences, which—in light of the recent results demonstrating equivalence— could be due to assumptions, lags, samples, etc. We take note of these previous results and given the choice of a particular sample and time period in this study, we estimate the dynamic causal effects by additionally using an LP-IV approach.

To outline the LP-IV identification problem, consider the moving average version of equation 18, which, as discussed previously, is $Y_t = \Theta(L)\varepsilon_t$. The impulse response of Y_i at horizon h is estimated from a single regression equation as follows

$$y_{i,t+h} = \Theta_{h,i1} y_{1,t} + u^h_{i,t+h} \tag{26}$$

where $u^h_{i,t+h}= \varepsilon_{t+h}, ..., \varepsilon_{t+1}, \varepsilon_{2:n,}, \varepsilon_{t-1}\varepsilon_{t-2,...}$. OLS estimation of 26 is not valid since $Y_{1,t}$ is correlated with $u^h_{i,t+h}$. However, 26 can be estimated if we use a suitable external instrument that satisfies the instrument relevant and exogeneity conditions, 24 and 25, along with a third condition

$$E\varepsilon_{t+j,t} z'_t = 0, j \neq 0 \tag{27}$$

which denotes the requirement that the instrument satisfy lead-lag exogeneity. This means that z_t should be uncorrelated with historical as well as future shocks. A separate LP-IV regression is estimated for each horizon, h. Also, serial correlation in the errors is modeled since the errors, ε_{t+h}, are serially correlated for all $h > 0$ as ε_{t+h} is the moving average of the forecast errors from t to h. In practice 26 can be estimated with control variables. The extension of LP-IV with control variables is straightforward, and discussed further in Stock and Watson (2018).

The LP-IV model is estimated both in levels and in stationary terms when estimating the causal impacts of the VFCI and monetary policy shocks, but in stationary terms with the growth shock due to the nature of the instrument. While the identified monetary policy shock has insignificant effects, the GDP growth shock leads to a tightening of the Fed Funds rate and a loosening of financial conditions upon impact.

The VFCI shock exhibits some of the same properties as in the volatility-identified BVAR and SVAR-IV models, that is, it leads to a significant easing of monetary policy and a significant contraction in output. The dynamic causal effects, as in the SVAR-IV model, are somewhat less persistent than in the heteroskedastic BVAR.

8.4 Identification through a Recursive VAR

We take one step back and estimate a simple recursive VAR with the ordering defined as output, prices, monetary policy, and financial conditions. VFCI is ordered last in the baseline case, but we assess the robustness of this assumption by ordering the Federal Funds rate last in an alternative specification. Financial conditions and monetary policy could be endogenous based on the empirical evidence in Cieslak et al. (2019) and Cieslak and Vissing-Jorgensen (2020), and we mitigate such concerns by changing the forcing variable.

While the magnitude and significance of the IRFs vary, especially with output, which we attribute to a less well-defined identification scheme, the conclusion is the same. Contractionary monetary policy shocks trigger a tightening of financial conditions. Conversely, a tightening of financial conditions leads to an easing of monetary policy and a contraction of output.

8.5 Identification through Sign Restrictions

Sign restrictions are used on the shape of the IRFs in response to the structural shocks following the penalty function approach based on Uhlig (2005) discussed in 8.1. To estimate the causal impact of monetary policy and VFCI shocks, we restrict the response of prices and output to be negative in identifying the monetary policy structural shock, and prices to be negative in identifying the VFCI structural shock.

As can be noted from the sign-restricted IRFs, monetary policy shocks lead to an immediate tightening of financial conditions. At the same time, VFCI shocks lead to an easing of monetary policy and decline in output. The IRFs, similar to those obtained from the LP-IV approach, are less persistent than the volatility-identified BVAR.

8.6 A Comparison of All Identification Schemes

Figures 7 and 8 provide a comparison across the different identification schemes estimated in this paper to model the macro-financial dynamics. Each row reports the IRFs from a different identification scheme. Note that the IRFs estimated using the volatility-identified BVAR and the sign-restricted BVAR are the median across 5000 MCMC draws, whereas the other three identification schemes follow a frequentist approach. External instruments are used in the SVAR-IV and LP-IV schemes as discussed previously. The instruments are used in standardized terms. In each instance, we estimate the responses of all variables to a one standard deviation increase in the estimated structural shock and look at the evolution of the variables over 20 quarters.

VFCI and Monetary Policy

As can be seen in Figure 7 which examines the dynamic causal effects of VFCI and monetary policy on each other, a contractionary monetary policy shock leads to an immediate tightening of financial conditions (first column). This holds true for the preferred identification scheme of a heteroskedastic BVAR, but the jump in VFCI in response to a Fed Funds shock is consistent across all five models. Financial conditions remain tight for 5-6 quarters in the LP-IV and sign restricted models. This effect is more persistent for the volatility BVAR, SVAR-IV, and Cholesky schemes, where financial conditions remain tight for 10-15 quarters following the monetary policy shock.

In response to a VFCI shock, we find that there is an immediate easing of monetary policy regardless of identification scheme (column 2). This effect is statistically significant, and fairly persistent, in the heteroskedastic BVAR as well as most of the other identification schemes including those with external instruments. A tightening of financial conditions causes the Fed to lower the policy rate.

VFCI and GDP

Figure 8 examines the dynamic causal effects of VFCI and GDP on each other. Of note is that the models are in levels for all schemes apart from those using external instruments, and that the sign restrictions model is not estimated for the output shock. The SVAR-IV and LP-IV models are estimated in stationary terms (GDP growth, PCE inflation, VFCI, and the Fed Funds rate) since our external instrument from Cieslak and Pang (2021) is for GDP growth. This affects the magnitudes of the responses, but the initial response of GDP to a VFCI shock remains similar across all schemes.

There is an immediate and statistically significant decline in GDP and GDP growth, across all models, in response to a surprise tightening of financial conditions. In particular, the fall in output is highly significant and persistent in the preferred identification

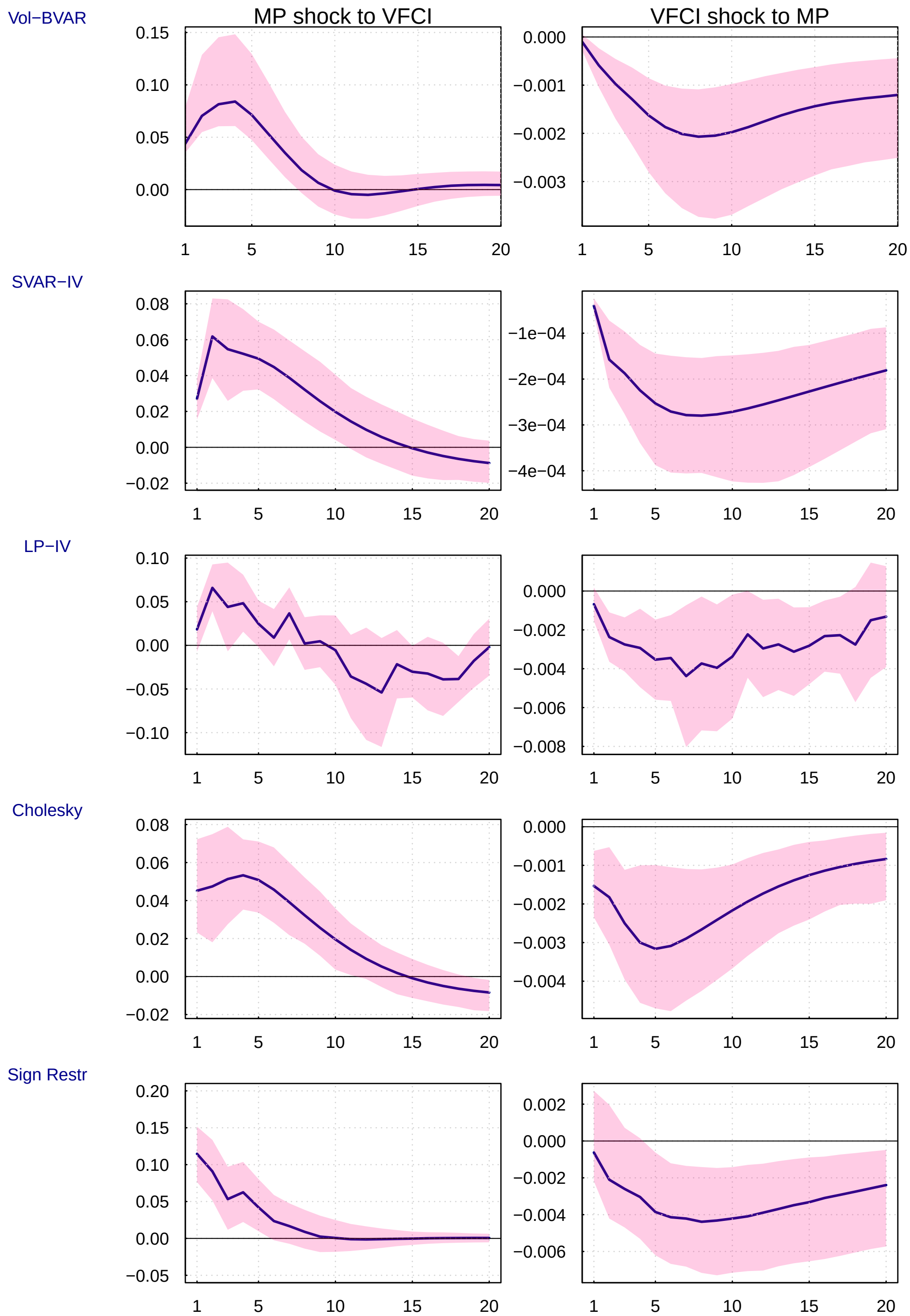

Figure 7. **Comparison of Impulse Responses Across Identification Schemes: VFCI and Monetary Policy** The plot shows impulse responses to a one standard deviation increase in the Federal Funds and VFCI structural shocks identified through five different identification schemes over 20 quarters, with 90 percent confidence bands.

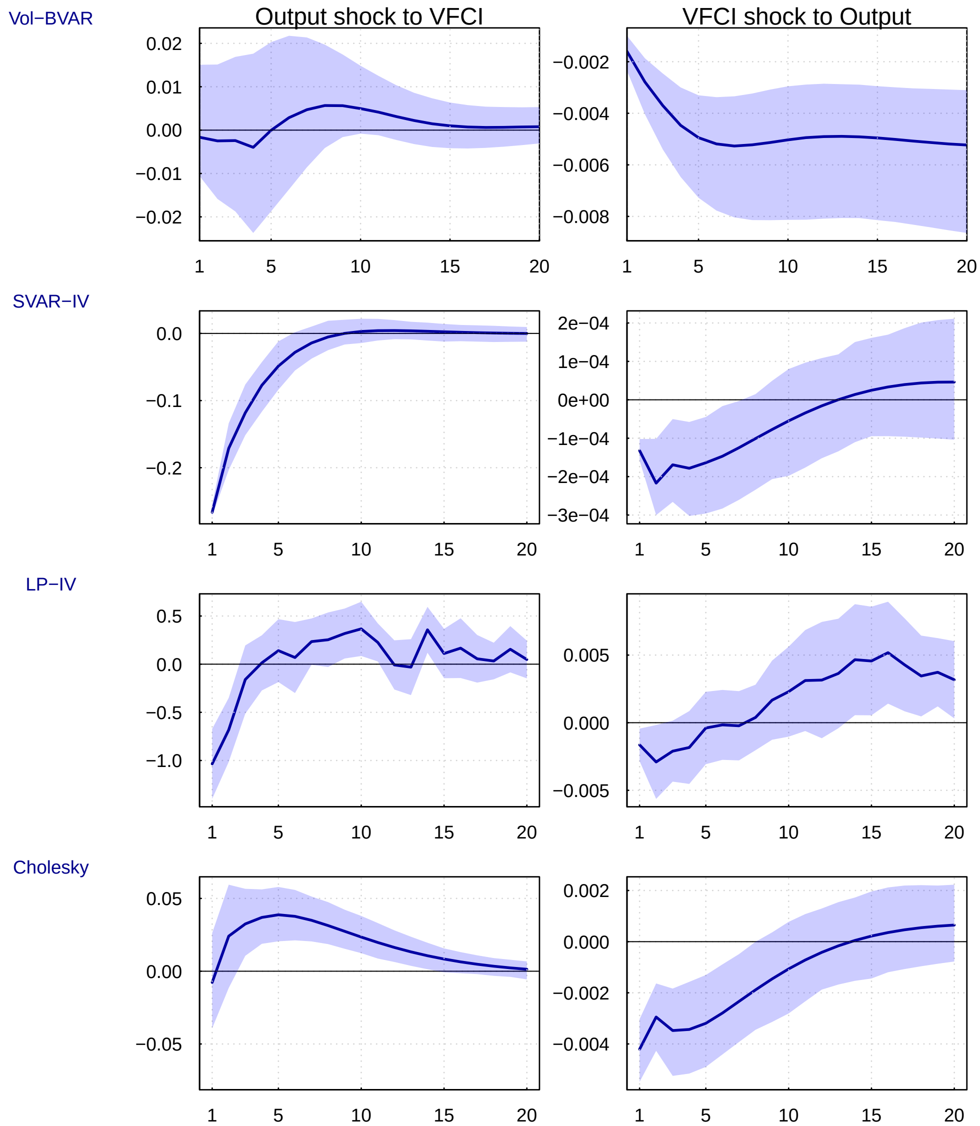

Figure 8. **Comparison of Impulse Responses Across Identification Schemes: VFCI and GDP** Impulse responses to a one standard deviation increase in the GDP and VFCI structural shocks identified through five alternative identification schemes over 20 quarters, with 90 percent confidence bands.

scheme of a heteroskedastic BVAR.

The response of financial conditions to an output shock is less clear-cut. While VFCI responds ambiguously in the preferred scheme, financial conditions significantly loosen upon impact in the SVAR-IV and LP-IV models. This could potentially reflect better identification when using an external instrument for GDP growth.

8.7 Robustness of Identification through External Instruments and Sign Restrictions

We perform sensitivity analysis by perturbing the baseline set of results for the LP-IV, SVAR-IV, and sign-restricted BVAR models. The causal impact of VFCI shocks on monetary policy and output, and of monetary policy shocks on VFCI, is checked for robustness as follows

- alternative specifications of stationarity by replacing GDP and PCE with stationary variables – output gap or GDP growth instead of GDP, and PCE inflation instead of the PCE index
- alternative specifications of VFCI such as using VFCI in levels rather than logs
- alternative specifications of the external instrument for VFCI by using a rejection algorithm instead of the penalty function algorithm
- alternative time period i.e. ending just before the 2008-10 global financial crisis to mitigate the effect of unusually large structural shocks

9 Additional Robustness Checks

In this section, we briefly discuss additional approaches to calculate the VFCI.

First, real PCE can be used instead of real GDP to compute the VFCI. Table 5 already showed that the regression of the GDP-VFCI and the PCE-VFCI gave rise to very similar coefficients. Here, we show graphically that the two series are virtually indistinguishable. In calculations not reported here, we also find that the remaining results of the paper hold for the case of the PCE-VFCI.

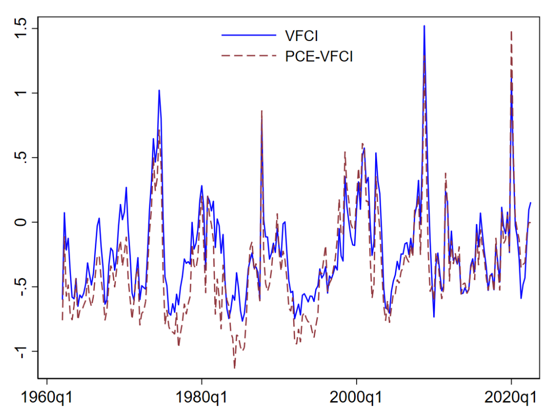

Figure 9. **The GDP VFCI and PCE VFCI**

Another question is whether we need the computation of the PCAs. Instead of constructing the VFCI from the PCAs, one could directly run a heteroskedastic regression GDP growth on the seven financial variables. It turns out that, because of the high collinearity of some of those variables, not all individual variables are statistically significant. However, the resulting VFCI is again virtually indistinguishable from our original PCA-based VFCI.

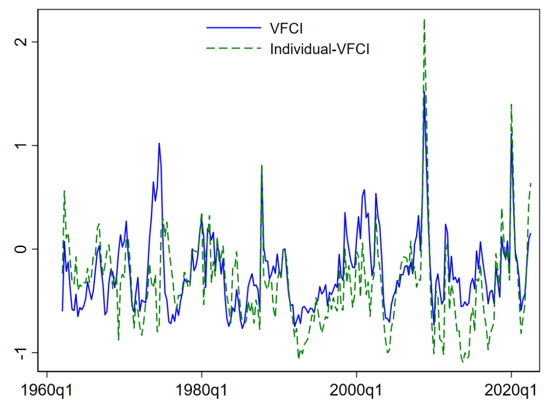

Figure 10. **The PCA VFCI and Individual VFCI**

Finally, we can compute the VFCI for other countries. To illustrate, we compute the VFCI for Europe based on the underlying data of the CISS from the ECB.[10] The Euro Area (EA) VFCI (EA-VFCI) does look materially different from the US-VFCI, but that is to be expected. We leave it for future research to examine the VAR evidence for Europe.

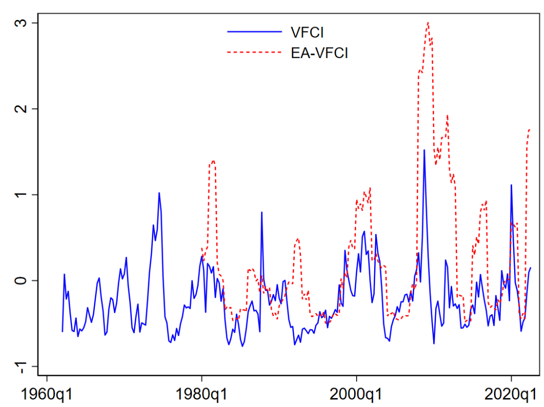

Figure 11. **US VFCI and EA VFCI**

[10] https://sdw.ecb.europa.eu/browseExplanation.do?node=9689686

10 Literature

The most closely related literature is by Brunnermeier et al. (2021), who investigate alternative financial variables in macroeconomic dynamics, and document that the corporate bond risk premia of Gilchrist and Zakrajšek (2012a) and the 3-month Libor-US Treasury spread (the so-called TED spread) are significantly related to macroeconomic activity. Instead of trying alternative financial indicators as Brunnermeier et al. (2021), we estimate the price of risk in the economy from a broad cross section of financial assets, and show that this theoretically based macro-financial variable is highly significant for macroeconomic aggregates. Furthermore, we use instrumental variables to estimate robust causal relationships, in addition to the heteroskedasticity based identification.

Other empirical strategies in this area use: (i) a small number of variables, usually focusing on single-equation projection methods (e.g., Mian et al. (2017); Jordà et al. (2015), Jordà et al. (2016), López-Salido et al. (2017), Krishnamurthy and Muir (2017), or (ii) binary outcomes (such as crisis/no crisis) or analysis limited to crisis periods (e.g., Schularick and Taylor (2012); Drehmann and Juselius (2014), Stock and Watson (2012), or (iii) reduced-form multi-equation specifications (e.g., Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012b)). Identification of causal effects, when present, is typically only focused on the effects of monetary policy shocks Gertler and Karadi (2015) and Caldara and Herbst (2019). In addition to Brunnermeier et al. (2021), another notable exception is Stock and Watson (2012), who use 18 instruments external to their vector auto-regression.

Compared to the one-equation specification in which only levels of some relevant state variable are considered, we introduce explicit time variation in the price of risk that is driven by financial variables in a different manner than the levels of consumption or output growth (our state variables). In addition, our results indicate that to estimate causal relations without endogeneity problems, multiple variables are required. We use continuous (rather than binary-outcome) variables and look at periods with and without crisis because we are interested in all business cycle variation and not just crisis episodes. Moreover, a binary variable is too coarse a measure to price financial assets. Compared to reduced-form approaches, we provide a direct theoretical justification to our empirical specification, and can trace back the connection of our empirical results to the model's primitives straightforwardly. In terms of identification, we allow for multiple causal channels and show robustness across four different identification schemes, including those in Brunnermeier et al. (2021) and in Stock and Watson (2012).

Our contribution is closely related to consumption-based asset pricing and, more broadly, to the endeavour of understanding the joint behavior of macroeconomic risk and asset prices. Consumption-based asset pricing – the idea that risk compensation is driven by the covariance of asset payoffs with consumption growth or more broadly marginal rates of substitution – originates with the foundational contributions of Rubinstein (1976), Lucas Jr (1978), Breeden (1979), Duffie and Zame (1989a). Theoretical advances have followed in many dimensions, including an understanding of existence and uniqueness of single and multi-agent equilibria, martingale methods to solve the consumption-portfolio problem, transaction costs and other frictions, dynamically complete and incomplete markets, among others (see Duffie (1991), Sundaresan (2000), Mehra (2012) and Breeden et al. (2015) for reviews). While we do relate our estimate of the market price of risk to common risk premium measures of stocks and bonds, the main goal of the paper is to study how the market price of risk interacts with macroeconomic dynamics. Broader research on asset pricing using the VFCI is left for future research.

The empirical assessment of consumption-based asset pricing remains mixed. Hansen and Singleton (1982), Hansen and Singleton (1983), Mankiw and Shapiro (1986) find evidence against consumption pricing. Chen et al. (1986) conclude that "... the rate of change in consumption does not seem to be significantly related to asset pricing. The estimated risk premium is insignificant and has the wrong sign." Subsequent work argues that consumption data might be noisy or poorly measured (see Campbell and Cochrane (2000)). Our approach is not focused on measurement error, but rather on causal identification, employing various identification strategies including instrumental variables.

One strand of asset pricing considers consumption growth mimicking portfolios by projecting consumption growth onto the space of traded assets and creating maximally correlated portfolios. In fact, Breeden et al. (1989) proves that if one would first find the maximum correlation portfolio with real consumption growth, then the CCAPM should hold where betas are measured against the returns of that portfolio. In contrast, we focus on the the market price of risk, which is the projection of conditional consumption (or GDP) *volatility* onto the span of financial factors. We do not postulate a contemporaneous projection of consumption growth onto the span of financial assets. Instead, our framework implies that financial factors are predictors of consumption growth, see equation (14). In the end, we do find strong correlation of the VFCI with the conditional mean of consumption growth, but that is an empirical result and not an assumption in our framework.

However, when Aıt-Sahalia and Lo (2000) and Jackwerth (2000) estimate pricing kernels projected onto equity return states using equity index option prices, they find non-monotonic pricing kernels. Rosenberg and Engle (2002) document that it is empirically difficult to pin down which variables belong in the pricing kernel. In contrast to these approaches, we project the conditional volatility of consumption or GDP growth onto the span of financial factors to estimate the market price of risk, which is one component of the pricing kernel. Campbell and Cochrane (2000) surveys the poor performance of consumption-based asset pricing.

Jagannathan and Wang (2007) and Malloy et al. (2009) use projections of consumption growth onto the span of financial factors for asset pricing and find support in favor of the CCAPM. Lettau and Ludvigson (2001) construct the consumption–wealth ratio variable *cay* and use it to find support in favor of the conditional CCAPM. Parker and Julliard (2005) develop a model of "ultimate" consumption risk that captures the longer-run relationship of consumption with asset returns, again supporting the consumption-based paradigm. Subsequently, consumption-based models that go beyond the basic CCAPM including, among others, the long-run risk model of Bansal and Yaron (2004), the habits model of Campbell and Cochrane (1999) and the disaster risk models of Rietz (1988) and Barro (2006), have been able to successfully match many joint patterns of asset prices taking macroeconomic aggregates, especially consumption, as given. They have been able to successfully resolve several asset pricing puzzles, including the equity premium puzzle of Mehra and Prescott (1985), even if they are econometrically rejected in formal tests (Ludvigson (2013)). While all of these approaches are somewhat related to our setup, we are less focused on the asset pricing implications, and more focus on the macro-financial dynamics.

One further point of contact with our paper in the long-run risk model of Bansal and Yaron (2004) is the presence of stochastic volatility of consumption growth. While we model the time-variation in the volatility of consumption as a function of several financial factors, the long-run risk model posits an exogenous AR(1) process, which has been generalized by Bollerslev et al. (2015) to a two-factor volatility structure. More generally, the literature consistently finds time variation in the volatility of consumption. For example, Ludvigson (2013) documents a sizable degree of stochastic volatility in aggregate consumption data. Campbell et al. (2018) derive an intertemporal CAPM with stochastic volatilty. Bansal et al. (2005) shows that the volatility of aggregate consumption is time varying, predicts, and is predictable by the market price–dividend ratio. A large literature has estimates and models stochastic volatility of macroeconomic or financial variables going back to the ARCH-GARCH seminal contributions of Engle (1982) and Bollerslev (1986), as does the closely related stochastic volatility filtering literature (e.g., Bidder and Smith (2018), van Binsbergen and Koijen (2010)). All of these approaches are fully consistent with our own approach, though none of them modeled the VFCI in the way we did. Future work could consider time-varying conditional betas in combination with the VFCI, as suggested by equation (6).

Our asset pricing framework is at the core of a vast literature that studies macro-financial interactions. The general consumption-based theoretical setup and the rich empirical specification with macroeconomic variables, monetary policy and other identified shocks, and asset prices, can be used as a way to empirically distinguish among different transmission and amplification mechanisms. A very partial list of models with financial frictions includes Bernanke et al. (1996), Kiyotaki and Moore (1997), Holmström and Tirole (1998), Brunnermeier and Sannikov (2014), He and Krishnamurthy (2013). More recently, also within the consumption-based paradigm, Adrian and Duarte (2018), Bianchi et al. (2022a), Bianchi et al. (2022b), Caballero and Simsek (2020), Caballero and Simsek (2022), and Kashyap and Stein (2022) provide a risk-centric view of macroeconomic fluctuations, emphasizing the interaction between monetary policy, asset prices, and macroeconomic fluctuations, although focusing on different frictions and mechanisms. Relative to those contributions, we emphasize the central role of the market price of risk as measured by the VFCI, as well as causal identification of macro-financial interactions using a variety of methods.

11 Conclusion

In this paper, we propose a novel financial conditions index, the VFCI, derived from asset pricing theory. The VFCI is a measure of the price of risk in the economy when a representative consumer with time seperable utility exists. In contrast to other FCIs that are mostly atheoretical, the VFCI is the first FCI to be derived from solid theoretical underpinnings. VFCI is correlated with other leading FCIs, but has notable differences. In particular, it exhibits superior explanatory power for stock and bond risk premia compared to other FCIs. The VFCI is constructed using widely available financial data, is computationally tractable, and has a relatively long time series history. The VFCI could be computed globally, thus being able to track financial conditions in real-time across countries.

We use a range of identification schemes to demonstrate the robust dynamic causal impact of VFCI on monetary policy and output, and vice versa. These identification schemes include a volatility-identified BVAR, Local Projections with external instruments (LP-IV), a structural VAR with external instruments (SVAR-IV), and sign restrictions. Regardless of identification scheme, the original conclusions remain the same: a tightening of financial conditions based on VFCI leads to an immediate easing of monetary policy and a persistent contraction of output. Conversely, contractionary monetary policy shocks lead to a tightening of financial conditions. These results are encouraging as they suggest a step forward in estimating financial conditions based on economic theory, with broad applicability and uses in policymaking.

Further research could compute the VFCI for additional countries, conduct asset pricing tests, and embed the VFCI into structural macro-financial models.

References

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

Adrian, Tobias, and Fernando Duarte. 2018. "Financial Vulnerability and Monetary Policy." *Federal Reserve Bank of New York Staff Report* (804): 1–53.

Adrian, Tobias, Federico Grinberg, Nellie Liang, Sheheryar Malik, and Jie Yu. 2022. "The Term Structure of Growth-at-Risk." *American Economic Journal: Macroeconomics* 14 (3): 283–323.

Aıt-Sahalia, Yacine, and Andrew Lo. 2000. "Nonparametric Risk Management and Implied Risk Aversion." *Journal of Econometrics* 94 (1-2): 9–51.

Bansal, Ravi, Varoujan Khatchatrian, and Amir Yaron. 2005. "Interpretable Asset Markets?" *European Economic Review* 49 (3): 531–560.

Bansal, Ravi, and Amir Yaron. 2004. "Risks for the Long run: A Potential Resolution of Asset Pricing Puzzles." *Journal of Finance* 59 (4): 1481–1509.

Barro, Robert. 2006. "Rare Disasters and Asset Markets in the Twentieth Century." *Quarterly Journal of Economics* 121 (3): 823–866.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist. 1996. "The Financial Accelerator and the Flight to Quality." *Review of Economics and Statistics* 78 (1): 1–15.

Bianchi, Francesco, Martin Lettau, and Sydney Ludvigson. 2022a. "Monetary Policy and Asset Valuation." *Journal of Finance* 77 (2): 967–1017.

Bianchi, Francesco, Sydney Ludvigson, and Sai Ma. 2022b. "Monetary-Based Asset Pricing: A Mixed-Frequency Structural Approach." *NYU Working Paper.*

Bidder, Rhys, and Matthew Smith. 2018. "Doubts and Variability: A Robust Perspective on Exotic Consumption Series." *Journal of Economic Theory* 175 689–712.

van Binsbergen, Jules, and Ralph Koijen. 2010. "Predictive Regressions: A Present-Value Approach." *Journal of Finance* 65 (4): 1439–1471.

Blanchet-Scalliet, Christophette, and Monique Jeanblanc. 2020. "Enlargement of Filtration in Discrete Time." In *From Probability to Finance: Lecture Notes of BICMR Summer School on Financial Mathematics*, edited by Jiao, Ying, Chap. 2 71–144, Springer Singapore.

Bollerslev, Tim. 1986. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31 (3): 307–327.

Bollerslev, Tim, Lai Xu, and Hao Zhou. 2015. "Stock Return and Cash Flow Predictability: The Role of Volatility Risk." *Journal of Econometrics* 187 (2): 458–471.

Brave, Scott, and Andrew Butters. 2011. "Monitoring Financial Stability: A Financial Conditions Index Approach." *Economic Perspectives* 35 (1): 22.

Breeden, Douglas. 1979. "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities." *Journal of Financial Economics* 7 (3): 265–296.

Breeden, Douglas, Michael Gibbons, and Robert Litzenberger. 1989. "Empirical Tests of the Consumption-oriented CAPM." *Journal of Finance* 44 (2): 231–262.

Breeden, Douglas, Robert Litzenberger, and Tingyan Jia. 2015. "Consumption-Based Asset Pricing, Part 1: Classic Theory and Tests, Measurement Issues, and Limited Participation." *Annual Review of Financial Economics* 7 (1): 35–83.

Brunnermeier, Markus, Darius Palia, Karthik Sastry, and Christopher Sims. 2021. "Feedbacks: Financial Markets and Economic Activity." *American Economic Review* 111 (6): 1845–79.

Brunnermeier, Markus, and Yuliy Sannikov. 2014. "A Macroeconomic Model with a Financial Sector." *American Economic Review* 104 (2): 379–421.

Caballero, Ricardo, and Alp Simsek. 2020. "A Risk-centric Model of Demand Recessions and Speculation." *Quarterly Journal of Economics* 135 (3): 1493–1566.

Caballero, Ricardo, and Alp Simsek. 2022. "A Monetary Policy Asset Pricing Model."

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.

Campbell, John, and John Cochrane. 1999. "By Force of Habit: A Consumption-based Explanation of Aggregate Stock Market Behavior." *Journal of Political Economy* 107 (2): 205–251.

Campbell, John, and John Cochrane. 2000. "Explaining the Poor Performance of Consumption-based Asset Pricing Models." *Journal of Finance* 55 (6): 2863–2878.

Campbell, John, Stefano Giglio, Christopher Polk, and Robert Turley. 2018. "An Intertemporal CAPM with Stochastic Volatility." *Journal of Financial Economics* 128 (2): 207–233.

Chen, Nai-Fu, Richard Roll, and Stephen Ross. 1986. "Economic Forces and the Stock Market." *Journal of Business* 383–403.

Cieslak, Anna, Adair Morse, and Annette Vissing-Jorgensen. 2019. "Stock Returns over the FOMC Cycle." *Journal of Finance* 74 (5): 2201–2248.

Cieslak, Anna, and Hao Pang. 2021. "Common Shocks in Stocks and Bonds." *Journal of Financial Economics* 142 (2): 880–904.

Cieslak, Anna, and Annette Vissing-Jorgensen. 2020. "The Economics of the Fed Put." *Review of Financial Studies* 34 (9): 4045–4089.

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

Drehmann, Mathias, and Mikael Juselius. 2014. "Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements." *International Journal of Forecasting* 30 (3): 759–780.

Dudley, William, and Jan Hatzius. 2000. *The Goldman Sachs Financial Conditions Index: the Right Tool for a New Monetary Policy Regime.* Volume Volume 44 of Global economics paper: Goldman Sachs. Goldman Sachs.

Duffie, Darrell. 1991. "The Theory of Value in Security Markets." Volume 4. of Handbook of Mathematical Economics 1615–1682.

Duffie, Darrell, and William Zame. 1989a. "The Consumption-Based Capital Asset Pricing Model." *Econometrica* 57 (6): 1279–1297.

Duffie, Darrell, and William Zame. 1989b. "The Consumption-Based Capital Asset Pricing Model." *Econometrica* 1279–1297.

Engle, Robert. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica* 987–1007.

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

Gilchrist, Simon, Vladimir Yankov, and Egon Zakrajšek. 2009. "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets." *Journal of Monetary Economics* 56 (4): 471–493.

Gilchrist, Simon, and Egon Zakrajšek. 2012a. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720.

Gilchrist, Simon, and Egon Zakrajšek. 2012b. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720.

Hansen, Lars Peter, and Kenneth Singleton. 1982. "Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models." *Econometrica* 1269–1286.

Hansen, Lars Peter, and Kenneth Singleton. 1983. "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns." *Journal of Political Economy* 91 (2): 249–265.

Hatzius, Jan, and Sven Jari Stehn. 2018. "The Case for a Financial Conditions Index." *Economic Research, Global Economics Paper.*

He, Zhiguo, and Arvind Krishnamurthy. 2013. "Intermediary Asset Pricing." *American Economic Review* 103 (2): 732–70.

Holmström, Bengt, and Jean Tirole. 1998. "Private and Public Supply of Liquidity." *Journal of political Economy* 106 (1): 1–40.

Jackwerth, Jens Carsten. 2000. "Recovering Risk Aversion from Option Prices and Realized Returns." *Review of Financial Studies* 13 (2): 433–451.

Jagannathan, Ravi, and Yong Wang. 2007. "Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns." *Journal of Finance* 62 (4): 1623–1661.

Jordà, Òscar, Moritz Schularick, and Alan Taylor. 2015. "Betting the House." *Journal of International Economics* 96 S2–S18.

Jordà, Òscar, Moritz Schularick, and Alan Taylor. 2016. "The Great Mortgaging: Housing Finance, Crises and Business Cycles." *Economic policy* 31 (85): 107–152.

Jordà, Oscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95 (1): 161–182.

Jordà, Oscar, Moritz Schularick, and Alan Taylor. 2015. "Betting the House." *Journal of International Economics* 96 2–18, 37th Annual NBER International Seminar on Macroeconomics.

Jurado, Kyle, Sydney Ludvigson, and Serena Ng. 2015. "Measuring Uncertainty." *American Economic Review* 105 (3): 1177–1216.

Kashyap, Anil, and Jeremy Stein. 2022. "Monetary Policy When the Central Bank Shapes Financial-Market Sentiment."

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2): 211–248.

Krishnamurthy, Arvind, and Tyler Muir. 2017. "How Credit Cycles Across a Financial Crisis."

Lettau, Martin, and Sydney Ludvigson. 2001. "Resurrecting the (C) CAPM: A Cross-sectional Test when Risk Premia are Time-varying." *Journal of Political Economy* 109 (6): 1238–1287.

López-Salido, David, Jeremy Stein, and Egon Zakrajšek. 2017. "Credit-Market Sentiment and the Business Cycle." *Quarterly Journal of Economics* 132 (3): 1373–1426.

Lucas Jr, Robert. 1978. "Asset Prices in an Exchange Economy." *Econometrica* 1429–1445.

Ludvigson, Sydney. 2013. "Advances in Consumption-based Asset Pricing: Empirical Tests." *Handbook of the Economics of Finance* 2 799–906.

Malloy, Christopher, Tobias Moskowitz, and Annette Vissing-Jørgensen. 2009. “Long-run Stockholder Consumption Risk and Asset Returns.” *Journal of Finance* 64 (6): 2427–2479.

Mankiw, Gregory, and Matthew Shapiro. 1986. “Risk and Return: Consumption Beta Versus Market Beta.” *Review of Economics and Statistics* 68 (3): 452–459.

Mehra, Rajnish. 2012. “Consumption-Based Asset Pricing Models.” *Annual Review of Financial Economics* 4 (1): 385–409.

Mehra, Rajnish, and Edward Prescott. 1985. “The Equity Premium: A Puzzle.” *Journal of Monetary Economics* 15 (2): 145–161.

Mian, Atif, Amir Sufi, and Emil Verner. 2017. “Household Debt and Business Cycles Worldwide.” *Quarterly Journal of Economics* 132 (4): 1755–1817.

Nakamura, Emi, and Jon Steinsson. 2018. “High-Frequency Identification of Monetary Non-Neutrality: The Information Effect.” *Quarterly Journal of Economics* 133 (3): 1283–1330.

Parker, Jonathan, and Christian Julliard. 2005. “Consumption Risk and the Cross Section of Expected Returns.” *Journal of Political Economy* 113 (1): 185–222.

Plagborg-Møller, Mikkel, and Christian K. Wolf. 2021. “Local Projections and VARs Estimate the Same Impulse Responses.” *Econometrica* 89 (2): 955–980.

Ramey, Valery. 2016. “Chapter 2 - Macroeconomic Shocks and Their Propagation.” In *Handbook of Macroeconomics*, edited by Taylor, John, and Harald Uhlig Volume 2. 71–162.

Rietz, Thomas. 1988. “The Equity Risk Premium a Solution.” *Journal of Monetary Economics* 22 (1): 117–131.

Romer, Christina, and David Romer. 2004. “A New Measure of Monetary Shocks: Derivation and Implications.” *American Economic Review* 94 (4): 1055–1084.

Rosenberg, Joshua, and Robert Engle. 2002. “Empirical Pricing Kernels.” *Journal of Financial Economics* 64 (3): 341–372.

Rubinstein, Mark. 1976. “The Valuation of Uncertain Income Streams and the Pricing of Options.” *Bell Journal of Economics* 407–425.

Schularick, Moritz, and Alan Taylor. 2012. “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008.” *American Economic Review* 102 (2): 1029–61.

Shiller, Robert. 2000. “Irrational Exuberance.” In *Irrational Exuberance*, Princeton University Press.

Stock, James, and Mark Watson. 2012. “Disentangling the Channels of the 2007-09 Recession.” *Brookings Papers on Economic Activity* 120–157.

Stock, James, and Mark Watson. 2018. “Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments.” *Economic Journal* 128 (610): 917–948.

Sundaresan, Suresh. 2000. “Continuous-Time Methods in Finance: A Review and an Assessment.” *Journal of Finance* 55 (4): 1569–1622.

Uhlig, Harald. 2005. “What are the Effects of Monetary Policy on Output?: Results from an Agnostic Identification Procedure.” *Journal of Monetary Economics* 52 381–419.

Internet Appendix

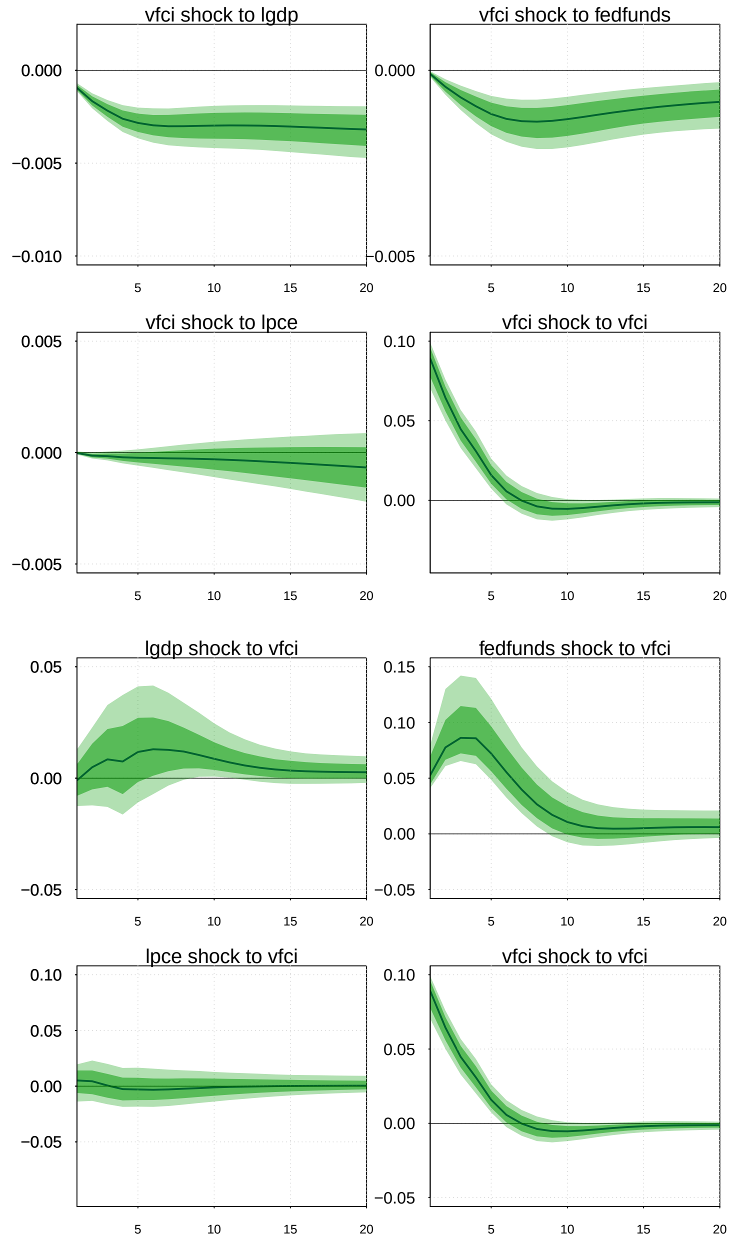

Figure 12. **Regime 1 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

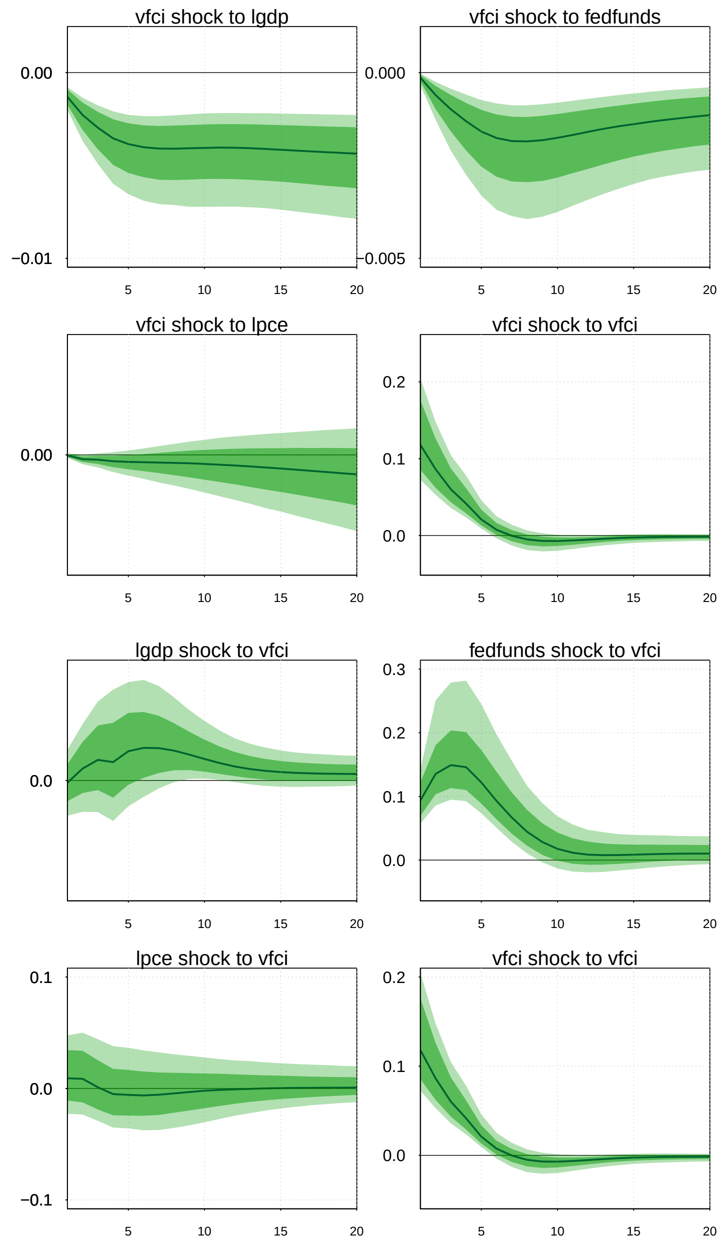

Figure 13. **Regime 2 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

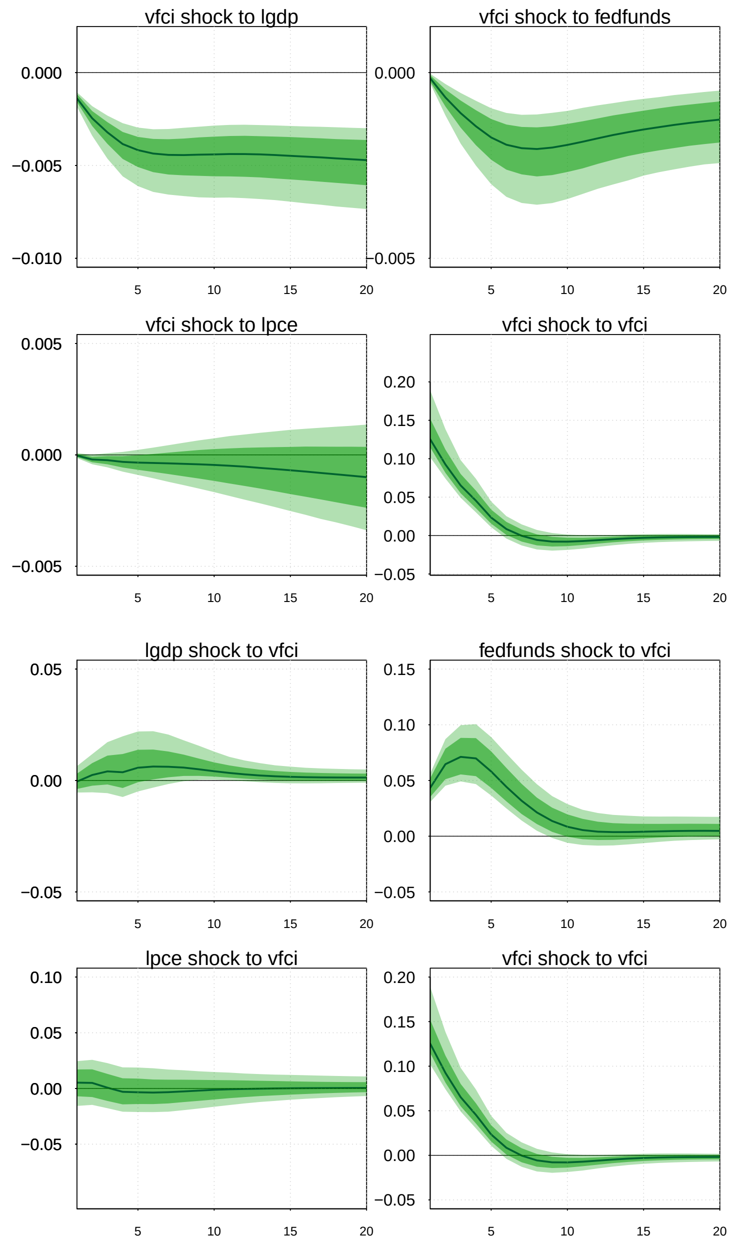

Figure 14. **Regime 3 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

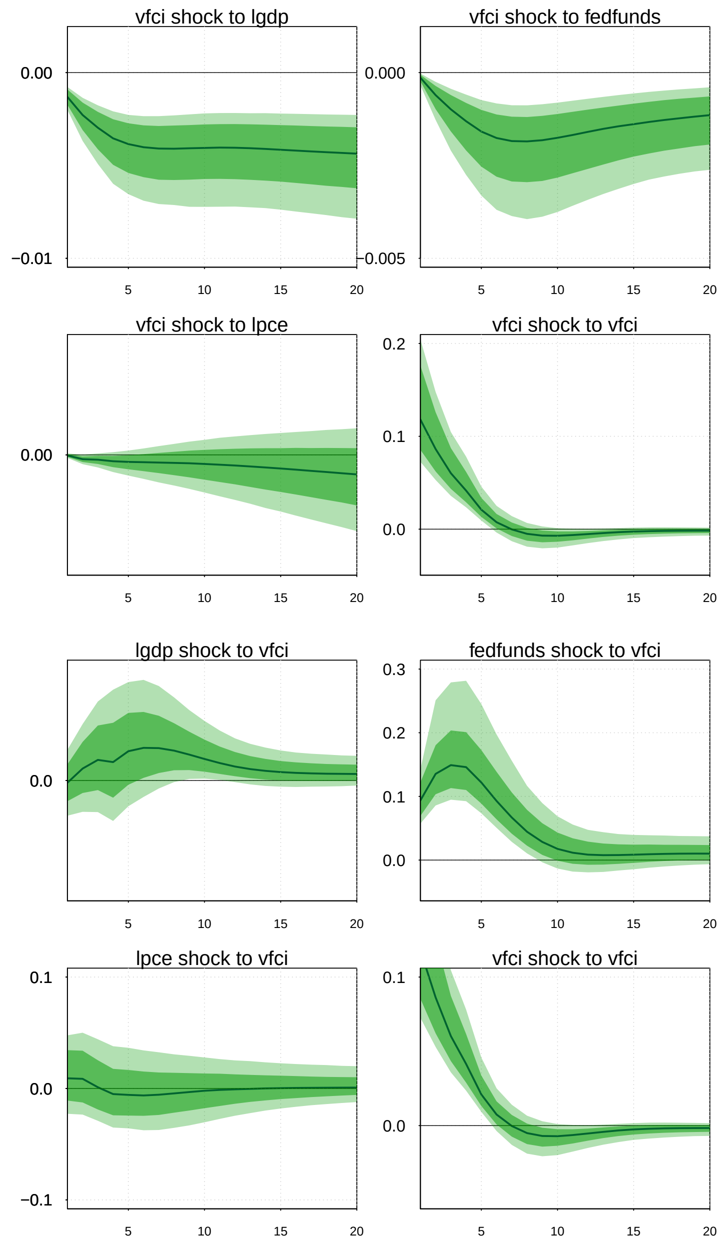

Figure 15. **Regime 4 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

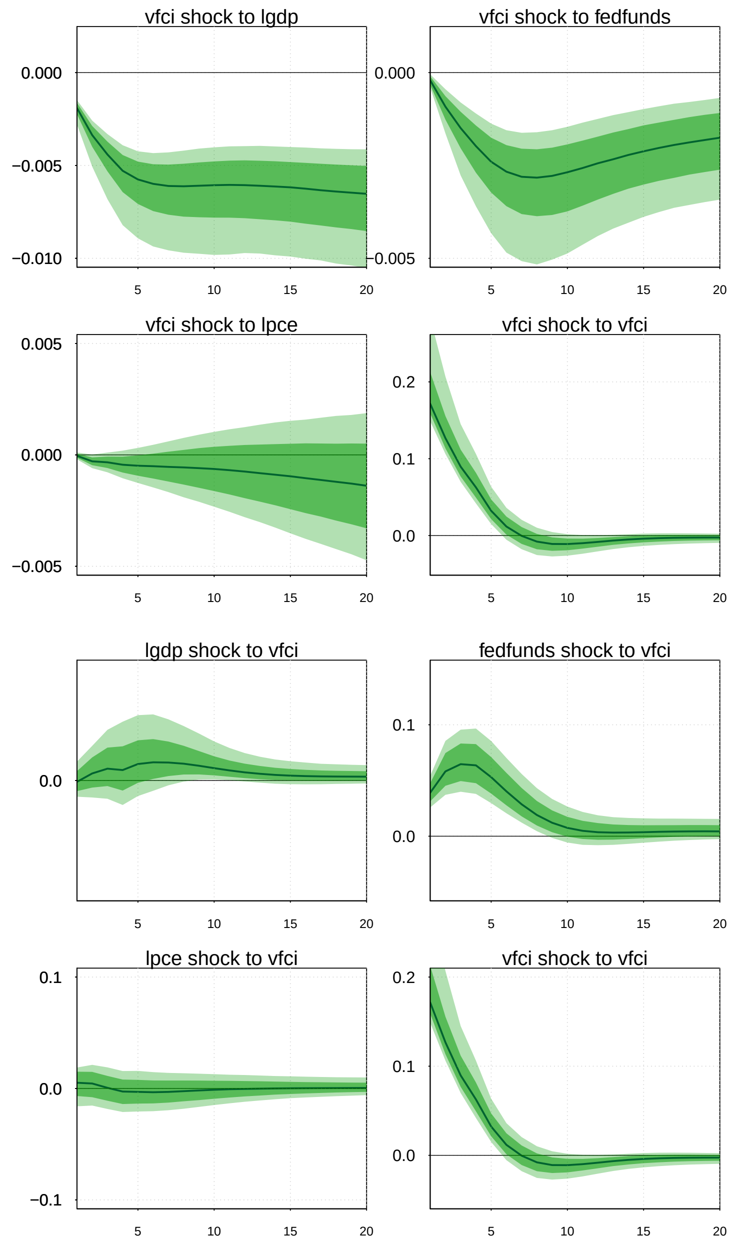

Figure 16. **Regime 5 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

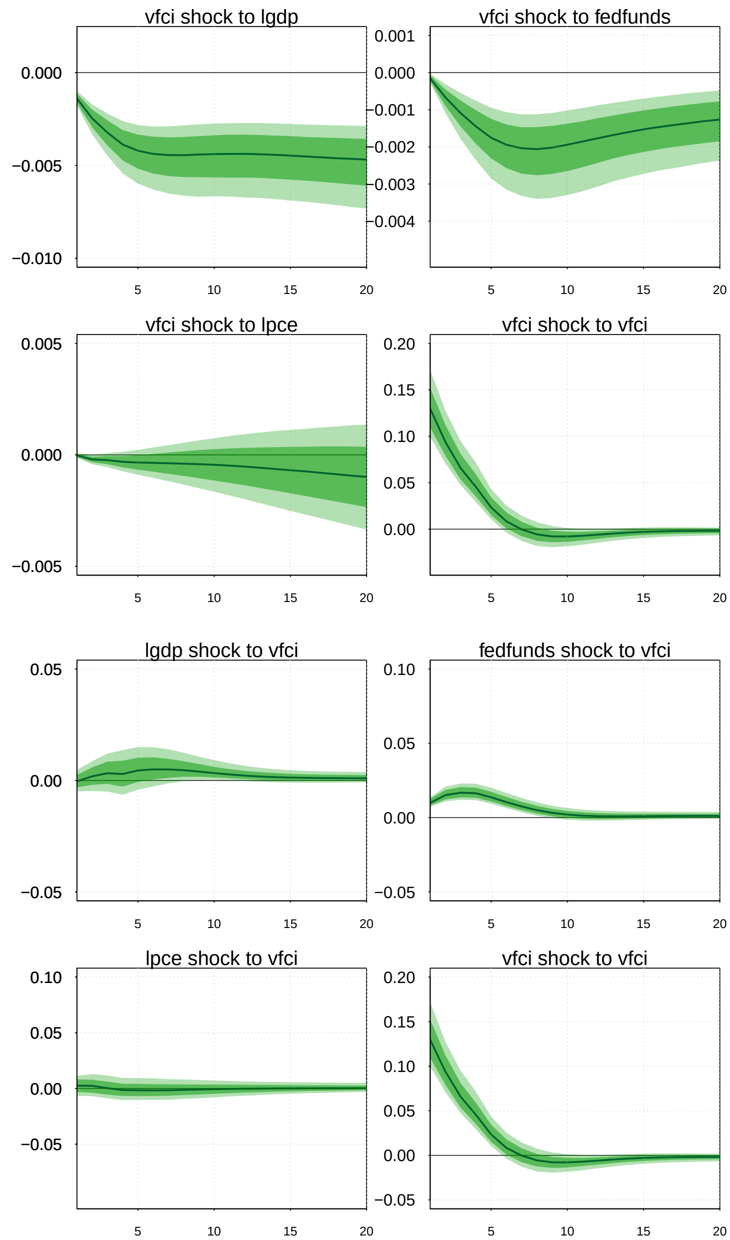

Figure 17. **Regime 6 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

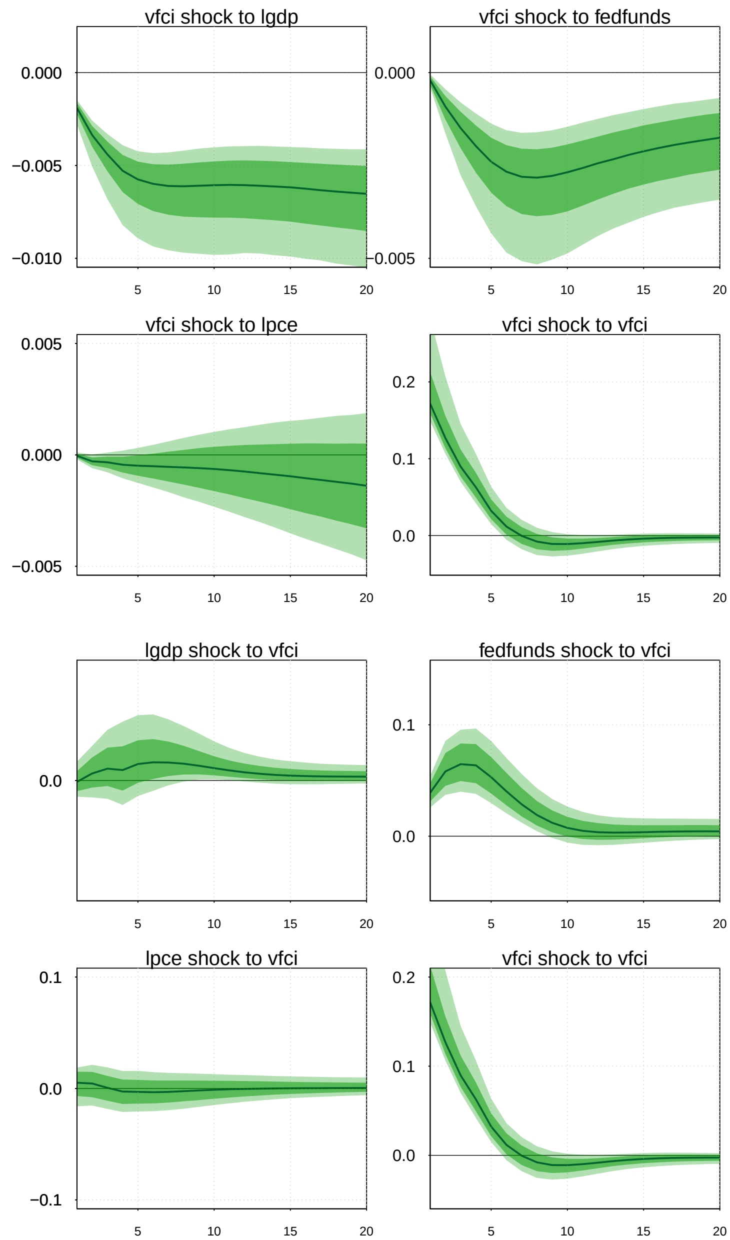

Figure 18. **Regime 7 Dynamics: VFCI Shocks and Responses** Impulse responses of VFCI to the four structural shocks, and the responses of the four variables to the VFCI structural shock, in the volatility-identified BVAR model with t distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands.

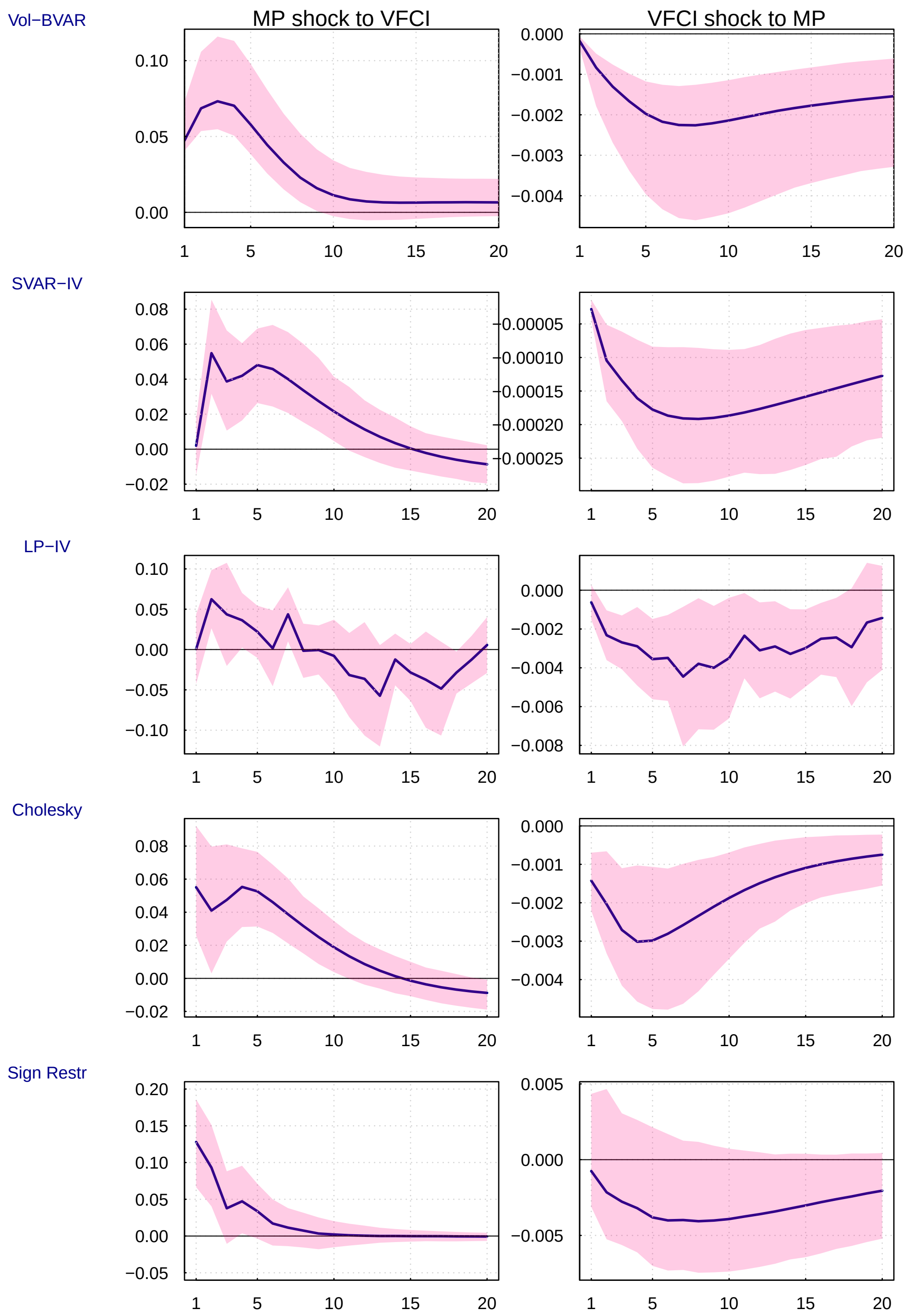

Figure 19. **VFCI in Levels - Comparison of Impulse Responses Across Identification Schemes: VFCI and Monetary Policy** The plot shows impulse responses to a one standard deviation increase in the Federal Funds and VFCI structural shocks identified through five different identification schemes over 20 quarters, with 90 percent confidence bands.

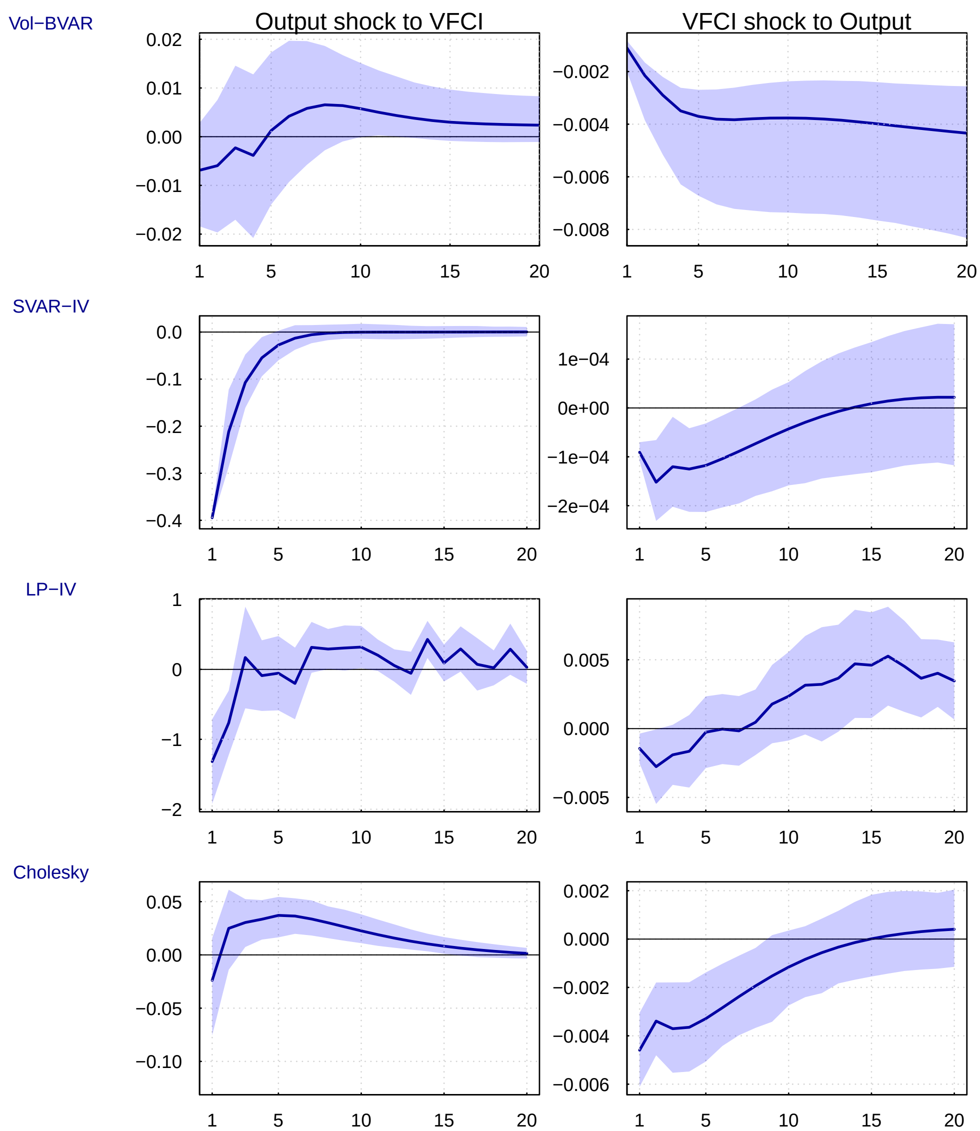

Figure 20. **VFCI in Levels - Comparison of Impulse Responses Across Identification Schemes: VFCI and GDP** Impulse responses to a one standard deviation increase in the GDP and VFCI structural shocks identified through five alternative identification schemes over 20 quarters, with 90 percent confidence bands.

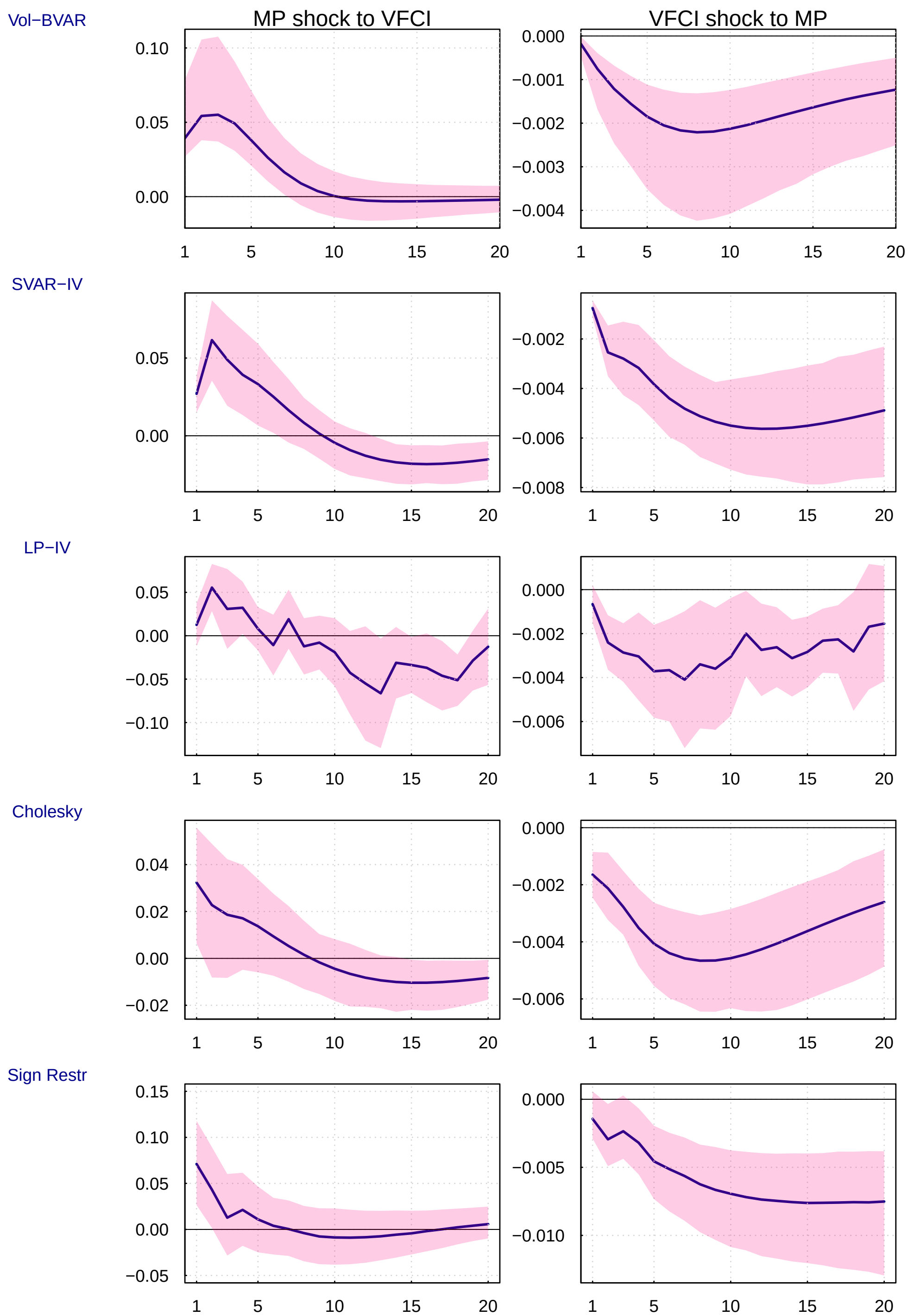

Figure 21. **Stationary Models - Comparison of Impulse Responses Across Identification Schemes: VFCI and Monetary Policy** The plot shows impulse responses to a one standard deviation increase in the Federal Funds and VFCI structural shocks identified through five different identification schemes over 20 quarters, with 90 percent confidence bands.

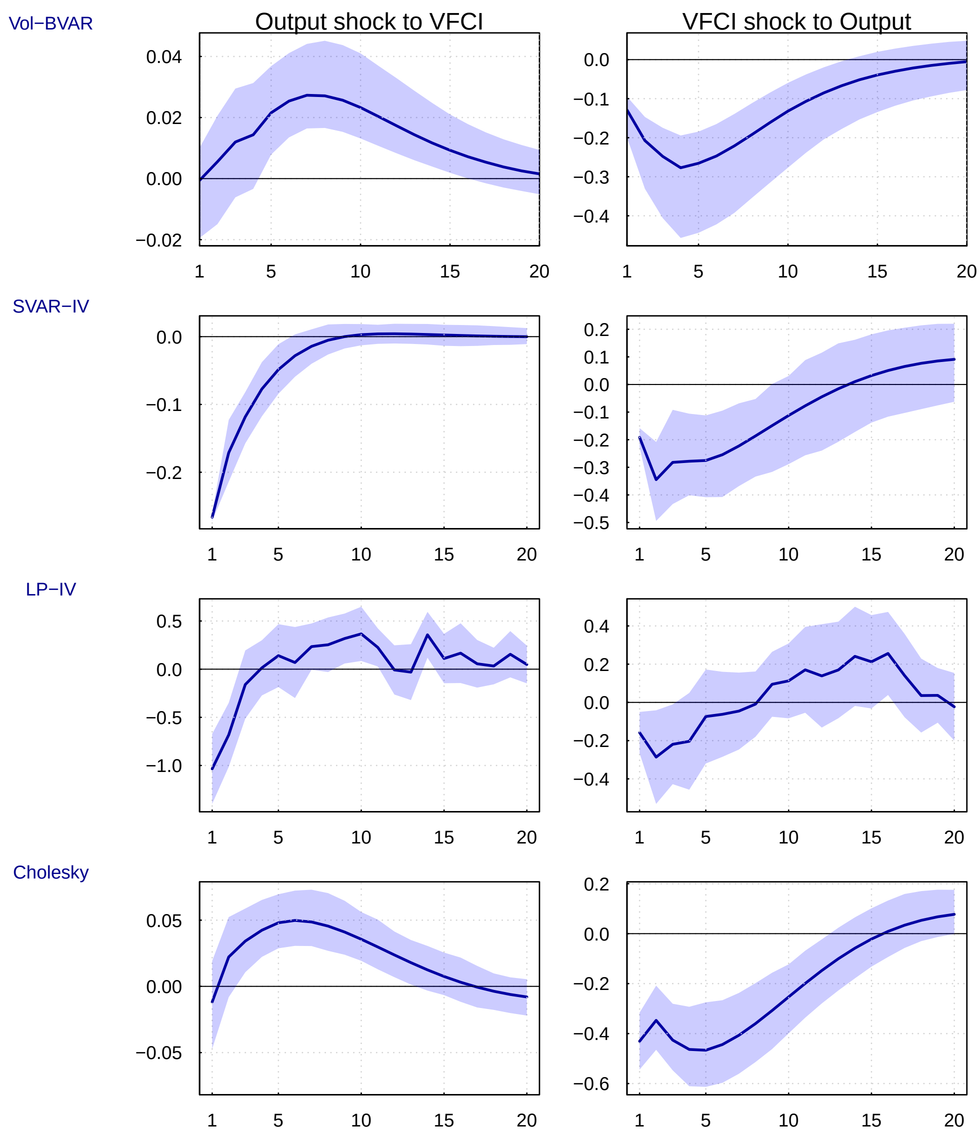

Figure 22. **Stationary Models - Comparison of Impulse Responses Across Identification Schemes: VFCI and GDP** Impulse responses to a one standard deviation increase in the GDP and VFCI structural shocks identified through five alternative identification schemes over 20 quarters, with 90 percent confidence bands.