The Market Price of Risk and Macro-Financial Dynamics*

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

[1]International Monetary Fund
[2]Brown University

March 20, 2025

Abstract

We propose the conditional volatility of GDP spanned by financial factors as a "Volatility Financial Conditions Index" (VFCI) and show its relation to the 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 financial conditions as measured by 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, FCI, Market price of risk, Consumption volatility.

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 Lu Zhang for outstanding research assistance.

1 Introduction

Financial conditions indices (FCIs) are widely used by policy makers, practitioners and, increasingly, academics. However, FCIs are mostly 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 pricing kernel 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 (1989)) and, more generically, the volatility of measures of aggregate economic activity such as GDP. When preferences are not time separable[1], the VFCI is a forward-looking measure of current and future expected prices of risk. This theoretical framework implies that the VFCI can be estimated as the conditional volatility of consumption or GDP that is spanned by financial factors.

Empirically, we run a linear regression with conditional heteroskedasticity where real GDP growth is the dependent variable, and lagged financial variables are the independent variables that determine the conditional mean and the conditional volatility of GDP growth. We define the VFCI to be the (log of the) predicted conditional volatility from this regression. Hence, the VFCI is the log conditional volatility of GDP growth spanned by financial factors, which, as mentioned earlier, is determined in our theoretical framework by the (current and future expected) market price of risk in the economy, motivating the interpretation of the VFCI as a measure of financial conditions. Our results are robust to using real consumption instead of GDP in the VFCI construction.

The VFCI is empirically also tightly linked to the conditional mean of GDP growth, constructed as the predicted value for the mean in the heteroskedastic regression used to construct the VFCI. Empirically, the conditional mean and conditional volatility of GDP growth are negatively correlated, generating long left tails in the *un*conditional distribution of GDP growth, as periods of low expected growth tend to have high volatility, creating periods of "vulnerability" in which amplification of shocks is largest precisely when growth expectations are already low. Therefore, our simple empirical approach replicates one of the main stylized facts (the negative conditional correlation between mean and volatility

[1]Leading examples are the habit formation model of Campbell and Cochrane (1999) and the Epstein-Zin model by Bansal and Yaron (2004).

of GDP growth) of the literature on growth-at-risk (Adrian, Boyarchenko, and Giannone (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 estimates the 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 dynamic factor analysis to extract a common component from 105 financial variables (based on Doz, Giannone, and Reichlin (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 wealth portfolio were publicly traded, the VIX might be a good estimate of the aggregate volatility of output or other macroeconomic variables. However, 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. Simple regressions show that the VFCI is better at explaining common measures of stock and bond risk premia than any of the other measures. 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 (2012)) and Shiller's CAPE (Shiller (2000)) as metric of risk premium in stocks. 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.

Our next contribution is to study the causal relationship 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 model the dynamics of the economy by a structural vector autoregression (SVAR) and identify the structural shocks by exploiting the conditional heteroskedasticity of the SVAR variables, as in Brunnermeier et al. (2021). We work with time series of quarterly frequency from 1962Q1 to 2022Q3 to allow for a long enough time period to capture various shifts in the data and use Bayesian methods to estimate the model.

In our view, identification through heteroskedasticity requires assumptions that are more

likely correct and less controversial than those from alternative identification strategies, such as those requiring particular timing or dynamic restrictions that are difficult, if not impossible, to test. In order to give economic meaning to the structural shocks identified through heteroskedasticity and gain confidence in the causal relationship between the VFCI and macroeconomic aggregates, we use external instruments proposed in the literature to estimate the causal impact of shocks in an SVAR with instrumental variables and using local projections (LP) with instrumental variables. Based on recent results in Plagborg-Møller and Wolf (2021b), the LP and SVAR models have been shown to estimate the same IRFs as long as a sufficient amount of lags are included and the entire population is modeled. However, Ramey (2016) reviews various alternative identification strategies and finds differences in the IRFs from SVARs and LPs in applications, so we show our results hold for both specifications. We also estimate a simple recursive VAR without instruments, where identification is attained through the "ordering" of the variables, that is, by assuming that certain variables respond to certain shocks contemporaneously and to other shocks with a lag. Finally, we estimate a sign-restricted SVAR that identifies the causal impact of monetary policy and VFCI shocks.

In all instances, we find robust causal, economically large, and statistically strong effects of VFCI shocks on monetary policy and GDP, and of monetary policy shocks on the VFCI. We do not find a tight link between the VFCI and inflation in either direction.

Related Literature. The most closely related literature is from Brunnermeier et al. (2021), who investigate alternative financial variables in macroeconomic dynamics, and document that the corporate bond risk premia of Gilchrist and Zakrajšek (2012) 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. Nevertheless, we show that including the two financial variables that Brunnermeier et al. (2021) use in our SVAR leaves the IRF of VFCI shocks on output and monetary policy, and of monetary policy shocks on the VFCI, virtually unchanged.

Other empirical strategies in this area use: (i) a small number of variables, usually focusing on single-equation projection methods (e.g., Mian, Sufi, and Verner (2017); Jordà, Schularick, and Taylor (2015), Jordà, Schularick, and Taylor (2016), López-Salido, Stein, and Zakrajšek (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, Yankov, and Zakrajšek (2009), Gilchrist and Zakrajšek (2012)). Identification of causal effects, when present, is typically focused only 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 instruments external to their vector auto-regression.

Our contribution is closely related to consumption-based asset pricing and, more broadly, to the effort to understand the joint behavior of macroeconomic risk and asset prices. In 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 (1989). 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, Litzenberger, and Jia (2015) for reviews). While we do relate our estimate of the market price of risk to common risk measures of risk premia for stocks and bonds, our main goal is to study how the market price of risk interacts with macroeconomic dynamics. Other 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, Roll, and Ross (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, Gibbons, and Litzenberger (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. 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.

An important 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, Xu, and Zhou (2015) to a two-factor volatility structure. More generally, the literature consistently finds time variation in the volatility of consumption. For example, Ludvigson (2013) document a significant degree of stochastic volatility in aggregate consumption data. Campbell et al. (2018) derive an intertemporal CAPM with stochastic volatility. Bansal, Khatchatrian, and Yaron (2005) shows that the volatility of aggregate consumption is time varying, predicts, and is predictable by the market price–dividend ratio. A large literature 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.

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, Gertler, and Gilchrist (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 (2020), Bianchi, Lettau, and Ludvigson (2022), Bianchi, Ludvigson, and Ma (2022), 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.

2 The VFCI as Price of Risk

Time is discrete and indexed by $t = 0, 1, 2, \ldots$. There exists a representative agent who values non-negative aggregate consumption streams $C = \{C_t\}_{t=0}^{\infty}$ according to a utility function $U(C)$ that is strictly increasing, concave, and differentiable. The set of feasible consumption streams is denoted by $\mathcal{C}$. The set $\mathcal{C}$ encodes all the constraints faced by the representative agent. We assume that there is a unique optimal C^* in the interior of $\mathcal{C}$ that maximizes $U(C)$.

The setup just described allows for a broad range of models and economic environments including incomplete markets, non-Markovian dynamics, trading frictions, any convex and some non-convex constraints on the representative agent or on asset prices, illiquidity, partial information, real and nominal rigidities, etc. For example, the setup encompasses the habit formation model of Campbell and Cochrane (1999), the long-run risk model of Bansal and Yaron (2004), the disaster risk models of Barro (2006) and Gabaix (2012), preferences with ambiguity aversion and robustness as in Hansen and Sargent (2010), and essentially all New Keynesian models that admit a representative agent, including some with heterogeneous agents.[2]

Let the continuation value of U from the point of view of time t be U_t. We denote the gradient[3] of U_t by ∇U_t, and note that $\nabla U_t(C)$ is a vector known at time t. To work with with consumption growth $\Delta c_t = \log C_t - \log C_{t-1}$ rather than with consumption levels, we write

$$\frac{\nabla U_t(C)}{\nabla U_{t-1}(C)} = G_t(\Delta c)$$

for some functions G_t, where $\Delta c = \{\Delta c_t\}_{t=0}^{\infty}$ is the entire path of consumption growth.

The absence of arbitrage opportunities is a necessary condition for equilibrium. The Fundamental Theorem of Asset Pricing (FTAP), implies that, in equilibrium, there exists at

[2]For an overview of conditions under which a representative agent of the type we assume exists, see Skiadas (2009). For the most general (that is, weakest) conditions under which our framework applies, see Matoussi and Xing (2018) and Monoyios (2022). These references also show that we could further weaken our assumptions to utility functions that are not differentiable but have a well-defined "supergradient density".

[3]Let the continuation value of U from the point of view of time t be U_t, and let the set of feasible consumption streams be $\mathcal{C}_t \subseteq \mathcal{C}$. The time-$t$ directional derivative of U at $C = \{C_s\}_{s=t}^{\infty}$ in the direction $h = \{h_s\}_{s=t}^{\infty}$ is the limit

$$U_t'(C; h) := \lim_{\alpha \downarrow 0} \frac{U_t(C + \alpha h) - U_t(C)}{\alpha}.$$

The time-t gradient of U at C is a vector $\nabla U_t(C) = \{d_s\}_{s=t}^{\infty}$ such that

$$U_t'(C; h) := \mathbb{E}_t \sum_{s=t}^{\infty} d_s h_s \quad \text{for all } h \in \mathcal{C}_t.$$

least one stochastic discount factor $SDF = \{SDF_t\}_{t=0}^{\infty}$ such that

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

for all t and for all returns R_{t+1} that can be obtained by trading financial assets.[4] There exists a unique SDF if, and only if, markets are complete (which we do not assume). We refer to the set of all possible cash flows that can be generated by trading financial assets as the asset span. Despite the possibility of non-uniqueness for the SDF, the orthogonal projection of any given SDF onto the asset span is the same as the projection of any other SDF. Furthermore, if we denote this unique projection by SDF^*, then we have that

$$1 = \mathbb{E}_t[SDF^*_{t+1}R_{t+1}]$$

for all t and for all marketed returns R_{t+1}, which means that SDF^* is also a valid stochastic discount factor.

The FOC for optimal consumption for the representative agent is

$$G(\Delta c) = SDF_t \tag{1}$$

Under the assumptions we have made, the FOC is both necessary and sufficient for optimality. Linearizing G_t around a constant value $\overline{\Delta c}$ gives a first-order approximation to equation (1)

$$G_t(\Delta c) \approx \overline{g} + \sum_{s=-\infty}^{\infty} g_s \mathbb{E}_t[\Delta c_s], \tag{2}$$

where the $\overline{g}$ and g_s are linearization constants. Using (2) in (1), we get

$$\overline{g} + \sum_{s=-\infty}^{\infty} g_s \mathbb{E}_t[\Delta c_s] = SDF_t \tag{3}$$

If we truncate the limits of the sum to finite values, equation (3) is a linear rational expectations equation. Assuming that a solution exists and that $g_t \neq 0$, equation (3), after truncating the limits of the sum to finite values, gives

$$\Delta c_t = \mathbb{E}_t[m^{-1}(L)SDF_t]$$

[4] For a comprehensive exposition of the FTAP, including many extensions and references, see Duffie (2010). For the broad range of conditions under which the FTAP holds, see Delbaen and Schachermayer (2006) and Kabanov and Safarian (2009) for overviews, and Bálint and Schweizer (2022) for a recent formulation with particularly mild conditions.

where L is the lag operator and $m(\cdot)$ is a polynomial. We first decompose the SDF into its expected and unexpected components

$$\Delta c_t = \mathbb{E}_{t-1}[m^{-1}(L)SDF_t] + \epsilon_t$$

where $\epsilon_t := (\mathbb{E}_t - \mathbb{E}_{t-1})[m^{-1}(L)SDF_t]$. Next, we decompose ϵ_t into a predictable and an unpredictable multiplicative components[5]

$$\Delta c_t = \mathbb{E}_{t-1}[m^{-1}(L)SDF_t] + \eta_{t-1}\varepsilon_t \tag{4}$$

where η_{t-1} is known at $t-1$. Last, we write $\mathbb{E}_{t-1}[m^{-1}(L)SDF_t]$ and $\log \eta_{t-1}^2$ as the sum of their orthogonal projections onto the asset span and its orthogonal complement,

$$\begin{aligned}\mathbb{E}_{t-1}[m^{-1}(L)SDF_t] &= \sum_i \beta_i R_{t-1}^i + \nu_{t-1}^{sdf} \\ \log \eta_{t-1}^2 &= \sum_i \delta_i R_{t-1}^i + \nu_{t-1}^{\eta}\end{aligned}$$

where β_i and δ_i are the projections of $\mathbb{E}_{t-1}[m^{-1}(L)SDF_t]$ and η_{t-1} on R_{t-1}^i, respectively. Using the last two equations in equation (4) gives

$$\Delta c_t = \sum_i \beta_i R_{t-1}^i + \nu_{t-1}^{sdf} + \sqrt{\exp(VFCI_{t-1})}\varepsilon_t \tag{5}$$

$$VFCI_t = \sum_i \delta_i R_{t-1}^i + \nu_{t-1}^{\eta} \tag{6}$$

where we have defined the volatility financial conditions index VFCI by

$$VFCI_t := \log \eta_t^2$$

We will use equations (5) and (6) to empirically estimate the VFCI in the next section.

To see the relation between the VFCI and the price of risk, we start by writing innovations in the projected SDF as

$$(\mathbb{E}_t - \mathbb{E}_{t-1})SDF_t^* = \lambda_{t-1}'\varepsilon_t^R$$

where λ_t is a vector of prices of risk and ε_t^R are innovations in returns scaled to have unit

[5]For any integrable process x_t, the decomposition $x_t = \eta_t\varepsilon_t$ with η_t a predictable integrable process and ε_t a martingale difference sequence always exists (see, for example, Blanchet-Scalliet and Jeanblanc (2020)).

variance (with the corresponding scaling absorbed by the prices for risk). Then,

$$\begin{aligned}\epsilon_t &= (\mathbb{E}_t - \mathbb{E}_{t-1})[m^{-1}(L)SDF_t^*] \\ &= m^{-1}(L)(\mathbb{E}_t - \mathbb{E}_{t-1})SDF_t^* \\ &= m^{-1}(L)(\lambda_{t-1}'\varepsilon_t^R) \\ &= \sqrt{\exp(VFCI_{t-1})}\varepsilon_t\end{aligned}$$

so that

$$VFCI_t = \log Var_t\left(m^{-1}(L)[\lambda_t'\varepsilon_{t+1}^R]\right)$$

We have shown that the VFCI is a forward-looking measure of current and future expected prices of risk.

When the representative's agent utility is a standard time-separable CRRA utility function, $m^{-1}(L)$ is the identity operator and therefore

$$VFCI_t = \log \|\lambda_t\|^2, \tag{7}$$

so the VFCI is, in this time separable case, the squared norm of the current vector of prices of risk.

3 VFCI Estimation

In this section, we estimate equations (5)-(6) and construct the VFCI.

3.1 Data

Table 1 shows the variables we use to construct the VFCI. All series are publicly available and free, in quarterly frequency from 1962Q1 to 2022Q3, totaling 243 observations. The sample start date is the earliest for which all series available.

Ret are S&P 500 returns, calculated as the percentage price change between the last trading day of the current quarter and of the same quarter a year earlier, obtained from Yahoo Finance.[6] *Vol* is the annualized standard deviation of daily S&P 500 returns in the current quarter.

The rest of the variables are constructed using data from the FRED database of the Federal Reserve Bank of St. Louis. The term spread *Term* is the difference between the 10-

[6]The Yahoo Finance series, which we use, is identical to the one in the Center for Research in Security Prices (CRSP).

TABLE 1
Variables used to construct the volatility financial conditions index (VFCI)

Panel A: financial variables	
Variable	Description
Ret	S&P 500 returns
Vol	S&P 500 volatility
Term	10-year minus 3-month Treasury yields
Liq	3-month Treasury secondary market rate minus effective federal funds rate
Cred	Aaa corporate bond yield minus 10-year Treasury yield
Def	Aaa minus Baa corporate bond yield
Panel B: macroeconomic variables	
Variable	Description
GDP	Real GDP
C	Real aggregate consumption

Notes: All series are quarterly from 1962Q1 to 2022Q3 (243 observations). S&P 500 returns, *Ret*, are percentage price changes between the last day of the current quarter and the last day of the same quarter of the previous year, obtained from Yahoo Finance. S&P 500 volatility, *Vol*, is the annualized standard deviation of daily S&P 500 returns in the current quarter, also from from Yahoo Finance. All other variables are from FRED. Corporate bond yields are Moody's Seasoned Bond Yields. Real GDP, Y, is seasonally adjusted real gross domestic product. Aggregate consumption, C, is seasonally adjusted real personal consumption expenditures.

year and the 3-month Treasury yields (FRED code GS10 minus FRED code TB3MS). The liquidity spread *Liq* is the difference between the secondary market 3-month Treasury rate and the effective federal funds rate (TB3SMFFM). The credit spread *Cred* is the difference between Moody's Aaa corporate bond yield and the 10-year Treasury yield (AAA10YM). The default spread *Def* is the difference between Moody's Aaa and Baa corporate bond yields (BAA10YM minus AAA10YM). *Term*, *Liq*, *Cred*, and *Def* are quarterly averages of monthly observations.

GDP is seasonally adjusted real gross domestic product (GDPC1). Aggregate consumption C is seasonally adjusted real personal consumption expenditures (PCECC96).

3.2 The Asset Span

In Section 2, we showed that the returns R^i that appear in equations (5)-(6) are returns that together span the set of all possible cash flows that can be generated by trading financial

TABLE 2
Properties of principal components of financial variables

	Loadings						Cumulative variance
	Ret	*Vol*	*Term*	*Liq*	*Cred*	*Def*	
PC1	0.33	−0.55	−0.35	−0.02	−0.50	−0.47	34.1%
PC2	0.38	−0.21	0.48	0.65	0.33	−0.23	62.8%
PC3	0.52	−0.27	0.34	−0.32	−0.19	0.63	77.4%
PC4	−0.65	−0.37	0.50	0.12	−0.41	0.04	88.3%

Notes: *PC1–PC4* are the first four principal components of the financial variables listed in Panel A of Table 1. Row i of the "Loadings" column shows the weight of the i^{th} principal component on each of the financial variables. Row i of the "Cumulative variance" column gives the share of the total variance explained jointly by the first i principal components.

assets, that is, the asset span.

Of course, any empirical estimate of the asset span will involve only a subset of the true asset span, since including every single traded asset in the world is infeasible. Indeed, for our purposes, the goal is not to find a large number of assets that capture as much of the asset span as possible. Instead, we seek a small number of assets that cover a subspace of the asset span that contains enough information about the price of macroeconomic risk – about SDF^* – to estimate a useful VFCI.

To this effect, we use the six financial variables listed in Table 1 as the "base assets" whose span we believe captures a large share of the price of risk that is relevant for macroeconomic dynamics. We construct an orthogonal basis for the space spanned by these six financial assets by computing their principal components (PCs). We only use the first four PCs, which together explain 88% of the variance of the underlying base assets.

Table 2 reports the cumulative variance explained by the PCs and the factor loadings for each of the base financial variables.

3.3 VFCI Estimation

To construct the VFCI, we first estimate the following linear regression model with multiplicative heteroskedasticity:

$$\Delta gdp_{t+1} = \theta PC_t + \varepsilon_t, \tag{8}$$

$$Var_t(\varepsilon_{t+1}) = \exp(2\delta PC_t), \tag{9}$$

where $\Delta gdp_{t+1} := \log(GDP_{t+1}/GDP_t)$ is quarterly real GDP growth, PC_t is the vector $[1, PC1_t, \ldots, PC4_t]$ with first component equal to 1 followed by the four principal components of financial variables constructed earlier, ε_t is a zero-mean, i.i.d. normal disturbance term, and θ and δ are 5×1 parameters vectors to be estimated. Equations (8) and (9) model, respectively, the first and second conditional moments of real GDP growth as linear functions of the principal components.

TABLE 3
Means and volatilities of GDP growth and consumption growth spanned by financial assets

Panel A: conditional mean			Panel B: log conditional volatility		
	GDP	*C*		*GDP*	*C*
PC1	0.19^{***}	0.15^{***}	*PC1*	-0.22^{**}	-0.17^{***}
	(4.14)	(3.93)		(−3.03)	(−2.43)
PC2	0.16^{***}	0.10^{**}	*PC2*	-0.34^{***}	-0.26^{***}
	(3.34)	(2.67)		(−3.35)	(−2.70)
PC3	0.15^{***}	0.16^{***}	*PC3*	-0.26^{*}	0.30^{***}
	(2.56)	(3.48)		(−2.85)	(−2.99)
PC4	0.12^{***}	0.07^{**}	*PC4*	-0.34^{***}	-0.72^{***}
	(1.90)	(1.37)		(−3.36)	(−7.09)

Notes: This table shows maximum likelihood estimates of the model

$$\Delta y_{t+1} = \theta PC_t + \varepsilon_t,$$
$$Var_t(\varepsilon_{t+1}^2) = \exp(2\delta PC_t),$$

where y_{t+1} is either real quarter-over-quarter GDP growth (columns labeled *GDP*) or real quarter-over-quarter aggregate consumption growth (columns labeled *C*); PC_t is a vector with a 1 followed by the first four principal components *PC1*–*PC4* of the financial variables in Table 1; ε_t is zero-mean, i.i.d. normal; θ and δ are vectors of parameters to be estimated.

Panel A shows estimates $\hat{\theta}$ and Panel B shows estimates $\hat{\delta}$ for each of the principal components (the estimate for the intercept is not displayed).

All series are quarterly from 1962Q1 to 2022Q3 (243 observations). *GDP* is seasonally adjusted real gross domestic product and *C* is seasonally adjusted real personal consumption expenditures.

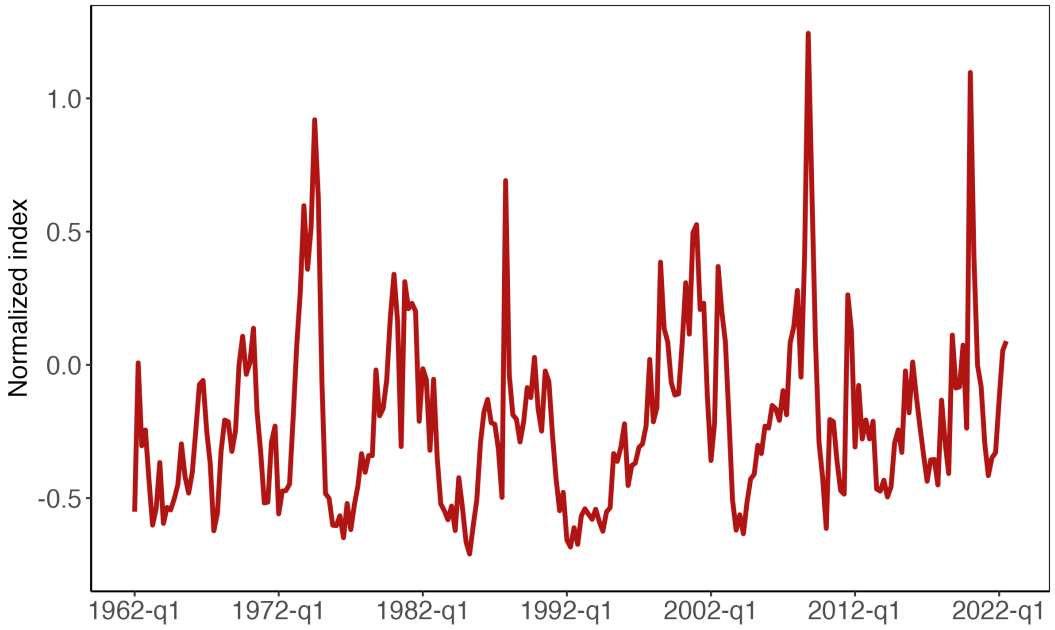
Numbers in parenthesis are *t*-statistics computed using the negative inverse Hessian matrix of the restricted log-likelihood as covariance matrix.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

The GDP column in Table 3 shows restricted maximum likelihood estimates of $\hat{\theta}$ in Panel A and $\hat{\delta}$ in Panel B. Standard errors, in parentheses, are computed using the negative inverse Hessian matrix of the (restricted) log-likelihood as the covariance matrix. The Consumption

column uses consumption growth $\Delta c_{t+1} := \log(C_{t+1}/C_t)$ instead of GDP growth Δgdp_{t+1} as the dependent variable in equation (8). Table 3 indicates most estimates are significant at the 1% level, with the rest significant at the 5% or 10% levels.

FIGURE 1
The volatility financial conditions index (VFCI)



Notes: The volatility financial conditions index, or VFCI, is defined by $\hat{\delta} PC_t$, with $\hat{\delta}$ is the maximum likelihood estimate of δ in the model

$$\Delta y_{t+1} = \theta PC_t + \varepsilon_t,$$
$$Var_t(\varepsilon_{t+1}^2) = \exp(2\delta PC_t),$$

where Δy_{t+1} is real quarter-over-quarter GDP growth, PC_t is a vector with a 1 followed by the first four principal components *PC1–PC4* of the financial variables in Table 1, ε_t is zero-mean, i.i.d. normal, and θ, δ are vectors of parameters.
The figure shows $\hat{\delta} PC_t$ normalized to have zero mean and unit variance.
All series used in the construction of the VFCI are quarterly from 1962Q1 to 2022Q3.

We define the VFCI – the volatility financial conditions index – as the fitted value of the logarithm of the conditional volatility of GDP growth:

$$VFCI := \hat{\delta} PC_t.$$

Figure 1 plots the time series of the VFCI, normalized to zero mean and unit variance. The figure shows that the behavior of the VFCI is consistent with the theoretical characterization of the VFCI as a measure of risk compensation and, more broadly, of overall financial

conditions. The two largest spikes occur druing the global financial crisis in 2008-2009 and the onset of the Covid-19 pandemic in 2020. The VFCI also shows marked increases around other periods of financial distress: the tumultuous 2000-2002 period that included the burst of the dot-com bubble, the 9/11 terrorist attacks, and the corporate scandals of the early 2000's; the 1994 bond market crisis; the "black Monday" stock market crash of 1987; the savings and loans crisis of the early 1980s; and the 40% stock market decline in 1973–1974. Furthermore, financial conditions and real aggregate activity are, even if tightly related, not one and the same. The VFCI, being a measure of financial conditions, is thus related to real economic activity but not a pure reflection of it. Indeed, the VFCI can be low during macroeconomic downturns and high during booms. For example, the VFCI does not show unusually high levels during the 1990-1991 recession. Conversely, the VFCI increased steadily between 1996Q2 and 2000Q2 and spiked in 1998Q3 during the collapse of Long-Term Capital Management and the Russian financial crisis, while real economic performance was superb, with year-over-year real GDP growth above 4% every quarter, and unemployment and core inflation declining from 5.5% to 4% and from 3% to 2%, respectively.

Since the sign of each of the PCs used in the estimation of equations (8)-(9) is not identified, the signs of the coefficients $\hat{\theta}$ are arbitrary. We select the signs of the PCs so that the coefficients of $\hat{\theta}$ in Panel A of Table 3 are all positive. Once the signs of the PCs (and therefore of the elements of $\hat{\theta}$) are chosen, the signs of the coefficients $\hat{\delta}$ in the volatility equation are determined by the data and are *not* arbitrary. Comparing the signs of the coefficients $\hat{\delta}$ in Panel A and $\hat{\theta}$ in Panel B shows that all of the PCs induce movements of the conditional mean and the conditional volatility of GDP growth and consumption growth that go in opposite directions. This means that periods with of high expected GDP growth are usually accompanied by a low conditional volatility of GDP growth – a low VFCI.

Figure 2 shows a scatter plot of the VFCI – the logarithm of the fitted values of the conditional volatility of GDP growth from equation (9) – against the fitted values for equation (8), $\widehat{\Delta gdp_t} = \hat{\theta} PC_t$. There is a tight linear relation with a negative slope, shown by the OLS line in red. In periods of tight financial conditions – when the VFCI is high – the economy tends to be in the bottom right part of the figure. In these low-mean, high-volatility states, negative shocks of a given magnitude translate into much larger declines in GDP than at the top left part of the figure, when volatility is low. Therefore, a high VFCI indicates greater financial amplification of shocks with a higher likelihood of sizable declines in GDP. In contrast, a low VFCI tends to be accompanied by relatively long periods of positive growth that are more resilient to shocks.[7]

[7]Using the national financial conditions index published by the Federal Reserve Bank of Chicago instead of the VFCI, Adrian, Boyarchenko, and Giannone (2019) find similar results using a more general estimation approach. Adrian and Duarte (2018) find that the same pattern also holds for the output gap, but not for

4 Comparison With Other Financial Conditions Indices

In this section, we review three popular financial conditions indices (FCIs), the national financial conditions index (NFCI) published by the Federal Reserve Bank of Chicago, the Goldman Sachs financial conditions index (GSFCI), and the VIX index from the Chicago Board Options Exchange.

The NFCI is a weighted average of 105 indicators of financial activity that provides a "weekly update on US financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems" starting in January 1973.[8] The weights are obtained through a mixed-frequency dynamic factor analysis and capture the relative importance of historical fluctuations in each of the variables (Brave and Butters (2011), Doz, Giannone, and Reichlin (2012), Aruoba, Diebold, and Scotti (2009)). The NFCI is renormalized each week so that its sample mean and standard deviation are one and zero, respectively, with higher values indicating tighter financial conditions. Brave and Butters (2011) find that the portion of the NFCI that cannot be predicted based on its historical dynamics is a good predictor of future economic activity.

The GSFCI is a weighted average of short-term interest rates, long-term interest rates, a trade-weighted dollar exchange rate, an index of credit spreads, and the ratio of aggregate stock market prices to the 10-year average of earnings per share. It is available at a daily frequency starting January 1, 1983. The weight of each variable reflects the impact that a shock to the variable has on GDP growth over the four quarters following the shock, estimated from quarterly OLS regressions starting in 1984.[9] Hence, the GSFCI is designed to be a measure of conditional GDP growth, with higher values of the GSFCI indicating tighter financial conditions and lower expected GDP growth over the following year. The 10-year Treasury yield and the index of credit spreads account for most of the index, with a sum of their weights equal to 84.7%. Hatzius and Stehn (2018) show that one-hour changes in bond yields around FOMC announcements are correlated with daily changes in the GSFCI.

The VIX Index is a measure of expected volatility of the aggregate US stock market over the next 30 days[10]. It is available daily (and at higher frequencies) since January 1, 1990. It is derived from real-time, mid-quote prices of S&P 500 Index call and put options. The VIX is often referred to as a "fear gauge" by market participants and can also be viewed as an indicator for the price of risk of the aggregate stock market.

---

inflation, and propose a model that rationalizes these empirical patterns by modeling shocks to financial intermediaries that, in equilibrium, affect the conditional mean and volatility of consumption and output growth via changes in the price of risk.

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

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

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

Figure 3 shows the three FCIs. While there is clear comovement, particularly in times of financial stress such as around the 2008 global financial crisis, there are also notable differences. For example, the GSFCI eased more than the two other FCIs in 2021; the VIX was more elevated around the tech bubble in the late 1990s; and the NFCI declined faster after the 1982 recession. 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.

To further understand the relation of the VFCI with the other FCIs, we run the following linear regression for each FCI:

$$FCI_t = \alpha + \beta PC_t + \varepsilon_t,$$

where FCI is one of $\{NFCI,\ GSFCI,\ VIX\}$, the intercept α and the 4×1 vector β are parameters to be estimated, PC_t are the first four principal components of the six financial variables listed in Table 1, and ε_t is an error term. Table 4 shows the estimated coefficients $\hat{\beta}$ and Huber–White standard errors in parentheses. The PCs have high explanatory power for all the FCIs, with R^2 between 70 and 80 percent and all but two coefficients statistically significant at the 1% level. We view these results as evidence that the four PCAs are informative about financial conditions and that the price of risk is tightly linked to financial conditions. In addition, none of the FCIs is well explained by just one or two PCs and three or four PCs are needed to achieve the high R^2s shown in the table.

TABLE 4

Regressions of financial conditions indices on principal components of financial variables

	NFCI	*GSFCI*	*VIX*
PC1	-0.15^{***}	-0.33^{***}	-3.73^{***}
	(-6.57)	(-5.04)	(-18.0)
PC2	-0.60^{***}	-1.07^{***}	-2.06^{***}
	(-26.3)	(-9.97)	(-4.66)
PC3	0.30^{***}	1.72^{***}	0.82
	(9.04)	(15.2)	(1.44)
PC4	0.00	0.92^{***}	-2.92^{***}
	(0.00)	(8.45)	(-7.38)
Num. Obs.	207	157	131
R^2	0.81	0.73	0.80

Notes: This table shows OLS estimates $\hat{\beta}$ for regressions

$$FCI_t = \alpha + \beta PC_t + \varepsilon_t,$$

where FCI_t is a financial conditions index, PC_t is a vector with the first four principal components *PC1–PC4* of the financial variables in Table 1; ε_t is a zero-mean, i.i.d. disturbance; α and β are parameters to be estimated.

Each column corresponds to a single regression that uses a different FCI_t measures: column *NFCI* uses the Federal Reserve Bank of Chicago's national financial conditions index, column *GSFCI* uses the Goldman Sachs financial conditions index, and column *VIX* uses the VIX index from the Chicago Board Options Exchange. All series are quarterly and use the longest sample available for each FCI.

Numbers in parenthesis are t-statistics.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

TABLE 5 continued

TABLE 5
Financial conditions indices' explanatory power of risk premia

Panel A: Stocks					
	Excess PE ratio (ECY)				
	(1)	(2)	(3)	(4)	(5)
Lag ECY	0.98***	0.93***	0.90***	0.94***	0.96***
	(51.3)	(48.6)	(37.3)	(30.5)	(36.6)
$VFCI$	0.80***				0.91***
	(6.2)				(4.4)
$NFCI$		0.26***			−0.11
		(3.9)			(−0.7)
$GSFCI$			0.04		0.07*
			(1.6)		(1.7)
VIX				0.03***	0.00
				(4.2)	(−0.1)
Num. Obs.	242	207	157	131	129
R^2	0.96	0.95	0.93	0.92	0.94

TABLE 5 continued

Panel B: Corporate bonds					
	Credit spread (GZ)				
	(1)	(2)	(3)	(4)	(5)
Lag GZ	0.87***	0.91***	0.89***	0.78***	0.73***
	(14.5)	(11.7)	(10.4)	(14.3)	(13.4)
$VFCI$	0.98***				0.82***
	(3.8)				(3.5)
$NFCI$		0.08			0.35
		(1.6)			(1.5)
$GSFCI$			0.01		0.06
			(0.4)		(1.2)
VIX				0.03***	0.00
				(2.9)	(0.4)
Num. Obs.	197	197	157	131	129
R^2	0.84	0.82	0.79	0.82	0.85

Panel C: Treasuries					
	Term Premium (TP)				
	(1)	(2)	(3)	(4)	(5)
Lag TP	0.85***	0.83***	0.85***	0.92***	0.85***
	(17.0)	(16.7)	(20.0)	(26.6)	(20.4)
$VFCI$	−0.04				−0.19***
	(−0.7)				(−3.2)
$NFCI$		0.04			0.03
		(1.5)			(0.7)
$GSFCI$			0.02*		0.01
			(1.8)		(0.9)
VIX				0.00	0.01*
				(0.3)	(1.9)
Num. Obs.	242	207	157	131	129
R^2	0.73	0.74	0.87	0.85	0.86

TABLE 5 continued

Notes: This table shows OLS estimates $\hat{b}$ and $\hat{c}$ for regressions

$$RP_t = a + bRP_{t-1} + cFCI_t + \varepsilon_t,$$

where RP_t is a measure of risk premia, FCI_t is either a financial conditions index or a vector of financial condition indices, ε_t is a zero-mean, i.i.d. disturbance; a, b and c are parameters to be estimated.

As measures of risk premia RP_t, Panel A uses *ECY*, the excess cyclically adjusted PE ratio of Shiller (2000), which captures equity premia of the aggregate stock market; Panel B uses *GZ*, the corporate bond credit spread index of Gilchrist and Zakrajšek (2012), which captures risk premia in corporate bonds; and Panel C uses TP, the 1-year Treasury term premium of Adrian, Crump, and Moench (2013), which captures risk premia in government bonds.

Within each panel, each column corresponds to a single regression that uses different variables for the financial condition indices FCI_t: column (1) uses *VFCI*, the volatility financial conditions index constructed in Section 3, (2) uses *NFCI*, the Federal Reserve Bank of Chicago's national financial conditions index, (3) uses *GSFCI*, the Goldman Sachs financial conditions index, (4) uses *VIX*, the VIX index from the Chicago Board Options Exchange, and (5) uses a vector of financial conditions indices that includes the four indices used in columns (1)–(4).

All series are quarterly. For each regression, we use the longest subsample inside our main 1962Q1–2022Q3 sample for which FCI_t and RP_t are both available,

Numbers in parenthesis are t-statistics, computed using Eicker–Huber–White standard errors.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

5 The VFCI and Common Risk Premia

In this section, we provide empirical evidence that the VFCI is a good explanatory variable for the Gilchrist, Yankov, and Zakrajšek (2009) bond spread (GZ) and the Shiller (2000) S&P 500 excess CAPE yield (ECY), two widely used measures of risk premia for corporate bonds and stocks, respectively. Gilchrist and Zakrajšek (2012) interpret GZ as a measure of "effective risk-bearing capacity of the financial sector", so it can serve not only as a measure of risk premia but also as an indicator of financial conditions.

Table 5 displays estimated coefficients and standard errors for analogous regressions that use ECY as a measure of risk premium. We see that the VFCI is a good explanatory variable of risk premia, with a coefficient that is significant at the 1 percent level (column (1)). And even though the NFCI and the VIX are also good predictors individually (columns (2) and (4)), only the VFCI is significant in a regression that includes all FCIs together as predictors (column (5)).

Table 5 displays estimated coefficients from linear regressions of the GZ on its lag and

the different FCIs we consider, with Eicker-Huber-White[11] standard errors in parentheses. Columns (1) through (4) show results from regressions that include a single FCI as independent variable, while column (5) includes all four FCIs as independent variables. When taken individually, the VFCI and the VIX have coefficients that are significant at the 1 percent level (columns (1) and (4)) while the NFCI (column (2)) and the GSFCI (column (3)) do not. When included together, only the VFCI remains significant.

We interpret these results not only as further evidence that the VFCI is a useful measure of risk premia and financial conditions, but also as an indication that it contains useful information not present in the other FCIs. Of course, many additional risk premium estimates have been proposed in the literature. We leave it to future research to explore further the asset pricing implications of the VFCI, including more formal cross-sectional asset pricing tests.

6 The VFCI and Macro-Financial Dynamics

In this section, we use a structural vector auto-regressive (SVAR) model to show that identified structural shocks to the VFCI have large and persistent effects on output and monetary policy. Positive one-standard-deviation VFCI shocks that reflect higher risk premia and tighter financial conditions lead to quantitatively large reductions in real GDP and the federal funds rate, with corresponding 90 percent error bands that do not include 0 for more than 20 quarters. This means that shocks to the VFCI are an important causal source of fluctuations for macroeconomic dynamics. We also show that positive one-standard-deviation shocks to the federal funds rate lead to a higher VFCI for 10 quarters, consistent with the extensive literature documenting that monetary policy shocks induce significant changes in risk premia across many asset classes.[12]

6.1 A Structural Vector Auto-Regression with Heteroskedasticity

The SVAR model is

$$B_0 y_t = B_1 y_{t-1} + ... + B_p y_{t-p} + C + \varepsilon_t, \tag{10}$$

where y_t is an $n \times 1$ vector of observed endogenous variables, B_0 is an $n \times n$ constant matrix that determines the simultaneous relationships among the n variables, B_j are $n \times n$ constant matrices of coefficients for each lag $j = 1, ..., p$ where p is the order of the SVAR, C is an

[11] Eicker (1967), Huber (1967), and White (1980)

[12] See the review article Drechsler, Savov, and Schnabl (2018) and citations therein.

$n \times 1$ vector of constants and ε_t is an $n \times 1$ vector of mean zero, independent and identically distributed structural shocks.

The reduced form of equation (10) is

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + D + u_t, \tag{11}$$

where A_j are constant coefficient matrices of the same size as the corresponding B_j, D is a vector of constants of the same size as C, and u_t is an $n \times 1$ vector of mean-zero reduced-form residuals.

Comparing equations (10) and (11), we see that the structural shocks ε_t are a linear combination of the reduced-form residuals u_t

$$\varepsilon_t = B_0 u_t. \tag{12}$$

6.2 VAR Variables

The $n = 4$ endogenous variables in our VAR specification are

$$y_t = [logGDP_t,\ logP_t,\ fedfunds_t,\ VFCI_t], \tag{13}$$

where *logGDP* is the logarithm of real GDP, *logP* is the logarithm the aggregate price level, *fedfunds* is the federal funds rate, and *VFCI* is the volatility financial conditions index.

As in the construction of the VFCI, all VAR series are quarterly from 1962Q1 to 2022Q3. All variables other than *VFCI* are constructed using FRED data. For *logY*, we use the same real GDP series that we use in the construction of the VFCI (FRED code GDPC1). For *logP*, we use the personal consumption expenditures price index that excludes food and energy (PCEPILFE). The federal funds rate, *fedfunds*, is the average over the current quarter of the monthly-frequency federal funds effective rate (FEDFUNDS). The *VFCI* is constructed in Section 3. Table 6 shows summary statistics.

6.3 Identification through Heteroskedasticity

We partition the entire sample period $t = 1, ..., T$ into M exogenously specified subperiods indexed by $m = 1, ..., M$, and let $m(t)$ be the function that maps time periods to their corresponding subperiod. We denote the diagonal variance-covariance matrix of the structural shocks by $\Lambda_{m(t)}$ and its i^{th} diagonal element by $\lambda_{i,m(t)}$. We assume $\Lambda_{m(t)}$ is constant within each subperiod but allow it to be different across subperiods. We denote by Λ_m the constant diagonal variance-covariance matrix for subperiod m. We impose the normalization that the

TABLE 6
Summary statistics for VAR variables

	Mean	Std. Dev.	Min	Max
logGDP	9.15	0.50	8.16	9.91
logP	4.01	0.62	2.86	4.82
fedfunds	0.05	0.04	0.00	0.18
VFCI	−0.23	0.37	−0.77	1.52

Notes: All series are quarterly from 1962Q1 to 2022Q3 (243 observations). *logGDP* is the logarithm of real GDP. *logP* is the logarithm of the price level, measured by the personal consumption expenditures price index that excludes food and energy. *fedfunds* is the federal funds rate, constructed as the average of the three monthly observations in the current quarter of the federal funds effective rate. *VFCI* is the volatility financial conditions index. The variables *logGDP*, *logP*, and *fedfunds* are from FRED. *VFCI* is the volatility financial conditions index, constructed in Section 3.3.

structural variance of each shock averages to one across subperiods:

$$\frac{1}{M}\sum_{m=1}^{M}\lambda_{i,m(t)} = 1. \tag{14}$$

By equation (12), the variance-covariance matrix of the reduced form residuals u_t, which we denote by $\Sigma_{m(t)}$, is related to $\Lambda_{m(t)}$ by

$$B_0\Sigma_{m(t)}B_0' = \Lambda_{m(t)} = \Lambda_m. \tag{15}$$

Since B_0 is constant, $\Sigma_{m(t)}$ is constant across subperiods, just as $\Lambda_{m(t)}$.

If the structural shocks for each pair of the n equations in the SVAR (10) have variances that differ in at least one subperiod, equations (14) and (15) together (locally) identify the n^2 parameters of B_0 up to row ordering and row sign changes.[13]

Identification "up to row ordering" means that even though each of the n estimated structural shocks is the structural shock to one of the n VAR variables, there is no identification regarding which shock corresponds to which variable, a consequence of the purely statistical nature of identification through heteroskedasticity. In Section 6.7, we assign each identified structural shock to one of the VAR variables using impulse response functions and economic intuition.

The first two columns of Table 7 show the volatility subperiods that we use. The most recent subperiod, which we label "Covid-19 pandemic", starts in 2020Q1 and ends in 2022Q3.

[13]See, for example, Lanne, Lütkepohl, and Maciejowska (2010).

In addition to the pandemic, this subperiod has high inflation and includes the war in Ukraine. The rest of the subperiods are identical to those determined by Brunnermeier et al. (2021), except that we extend their first and last subperiods since their 1973-2015 sample is shorter than ours.

TABLE 7
Volatility subperiods used for identification through heteroskedasticity

Subperiod	Description	Relative variance			
		logGDP	*logP*	*fedfunds*	*VFCI*
1962Q1–1979Q2	Oil crisis, stagflation	1.63	0.46	1.30	0.69
1979Q3–1982Q4	Volcker disinflation	1.23	1.72	3.32	0.85
1983Q1–1989Q4	S&L crisis defaults	0.42	0.64	0.60	0.96
1990Q1–2007Q4	Great Moderation	0.65	0.17	0.21	0.72
2008Q1–2010Q4	Financial crisis	1.18	0.60	0.49	1.78
2011Q1–2019Q4	ZLB, post-crisis recovery	0.32	0.13	0.07	0.87
2020Q1–2022Q3	Covid-19 pandemic	1.57	3.28	1.01	1.13

Notes: We take the first six volatility subperiods from Brunnermeier et al. (2021) and add a 2020Q1-2022Q3 subperiod labeled "Covid-19 pandemic" that has the Covid-19 pandemic, war in Ukraine, and high inflation as salient occurrences. The third column, labeled "Relative variance", shows the variance of each of the VAR variables in each subperiod relative to the average variance across subperiods, which we normalize to 1. These variances are posterior distribution medians from our Bayesian estimation procedure.

6.4 Distribution of Structural Shocks

We assume structural shocks ε_t are Student-t distributed. Using a t distribution has several advantages compared to using a normal distribution. First, the fat tails of the t distribution allow for a small number of isolated large shocks that would be too big to be consistent with normality even in high-volatility subperiods. For example, the federal funds rate increased around 600 basis points in 1980Q4 (6.8 standard deviations) and the VFCI increased by more than four standard deviations in 2020Q1.

Second, shocks that are not normally distributed can help identification.[14]

Third, Gouriéroux, Monfort, and Renne (2017) and Sims (2020) show that if the true distribution of structural shocks is fat-tailed and symmetric, likelihood-based estimation assum-

[14]See, for example, Karlsson, Mazur, and Nguyen (2023), Lanne and Luoto (2020), and Lanne, Meitz, and Saikkonen (2017).

ing a t-distribution is consistent under general conditions. For example, if the true volatilities are not constant within each subperiod, or if the subperiods themselves are misspecified but retain sufficient cross-subperiod variation in the estimated variances, then identification is still achieved, coefficient estimates are still consistent, and time paths of impulse response functions still have the same shape. The cost of these types of misspecification are potentially wider posterior density regions – making error bands seem larger than they really are – and potentially distorted variance decompositions.

6.5 Bayesian Estimation

We estimate the SVAR model using the same Bayesian procedure as in Brunnermeier et al. (2021), except that we modify the parameters of the Minnesota prior placed on the reduced form coefficients A_j by using a "tightness" of 3 (instead of 5) and a "decay" of 0.5 (instead of 1) to account for the quarterly frequency of our data (rather than the monthly frequency in Brunnermeier et al. (2021)).[15] We use a Gibbs sampling method with 10,000 draws to sample from the posterior distribution of all parameters, which also provides posterior distributions for impulse response functions.

6.6 Volatility of Structural Shocks

The last column of Table 7, labeled "Relative variance", reports posterior distribution medians for the variance of structural shocks in each of the different volatility subperiods. Given the normalization in equation (14), the numbers in Table 7 are volatility levels relative to the average of 1 across subperiods. One important takeaway is that the variance of the structural shocks differ substantially across volatility subperiods, supporting the identifying assumption of heteroskedasticity.

6.7 Impulse Responses and Interpretation of Shocks

Figure 4, shows impulse responses of the four SVAR variables to an increase of one standard deviation in each of the four identified shocks, where the shocks are drawn from a Student-t distribution with 2.5 degrees of freedom. In this and all subsequent IRF figures, IRFs are medians across posterior draws (the black line), with 68 percent (darker shade) and 90 percent (lighter shade) highest posterior density regions displayed as error bands. Given the normalization in equation (14), the IRFs are "averages" across the volatility subperiods.

[15] We use the Minnesota prior implemented through dummy observations and the same notion of "tightness" and "decay" as in Sims and Zha (1998).

Since B_0, B_j and C are constant (the same for all subperiods), the impact effect of shocks and the dynamic relations among the variables in y_t are time-invariant; impulse responses have the same shape across subperiods (and the same shape as the averages in Figure 4), although with a potentially different scale determined by the subperiod-specific variances of shocks from Table Table 7.

In Figure 4, we have assigned labels to the identified shocks, which, as mentioned earlier, is not provided by the purely statistical nature of the identification strategy. We now discuss the reasoning behind the labeling together with the economic intuition and implications of the results.

The leftmost column shows impulse responses to what we interpret as a real GDP shock or, more broadly, a demand shock. There are several reasons. First, despite not having imposed any short-term zero restrictions, the GDP shock has little effect on the VFCI and the price level on impact, against the interpretation of this shock as a VFCI or price-level shock. Second, although there is some initial response of the federal funds rate, it is in the same direction as the response of GDP. If the shock were a federal funds rate shock, one would expect higher federal funds rate – tighter monetary policy – to be accompanied by lower GDP. Third, the pattern of a high GDP throughout, prices that rise steadily over time, and a higher federal funds rate, are all consistent with a demand shock in a sticky price economy in which the central bank responds with higher interest rates when it observes a positive shock to output and inflation. Financial conditions as measured by the VFCI show neither a contemporaneous response to the GDP shock nor a large response in any of the 20 quarters shown in the figure. While we expect that, ceteris paribus, higher economic activity would loosen financial conditions – at least eventually – we also expect (and show more explicitly later) that higher interest rates tighten financial conditions. In the impulse responses of the figure, these two opposing forces approximately offset each other, resulting in a muted response of the VFCI. If anything, financial conditions can be seen to tighten slightly at the same time that the federal funds rate peaks.

The second column of Figure 4 shows responses to what we label an inflation shock. The main reason for this label is that the price level is the only variable that shows a large response to the shock. In addition, despite the large error bands, GDP goes down and the federal funds rate increases persistently, consistent with the interpretation and the reasoning in the last paragraph. The VFCI is essentially unresponsive to inflation, consistent with previous literature (see footnote 7).

The third column of Figure 4 shows responses to what we label a VFCI shock. This shock leads to positive response of the VFCI at impact that decays exponentially for around 7 quarters and then becomes essentially zero, a prototypical response to own-shocks for

autoregressive VAR variables. Real GDP decreases by around 0.4 percent for over 6 quarters, and remains persistently low, reaching close to a 0.5 percent decline over the 20 quarters plotted, with no signs of reversal. The price level declines slightly, escaping the 68 error band (but not the 90 percent band) only by the end of the 20 quarters, reaffirming the weak connection between inflation and financial conditions in our sample. Monetary policy responds to the VFCI shock by lowering the federal funds rate by around 20 basis points (in annualized terms) at the peak of the IRF that occurs around 7 quarters after the shock. The one standard deviation shock to the VFCI is therefore comparable in magnitude to a 25 basis point change in the federal fund rate. Since the SVAR is linear, a negative shock to the VFCI would result in the same impulse responses but with signs reversed. A negative VFCI shock would lead to a response of monetary policy that can be understood as "leaning against the wind" of looser financial conditions. Overall, the delayed buildup in the responses of output, the price level and the Federal funds rate points to a sluggish propagation of financial conditions to the real economy.

The right-most column of figure 4 displays responses to the shock that we label a federal funds shock or, more broadly, a monetary policy shock. The contractionary monetary policy shocks lead to a transitory yet persistent decline in output. The response of the price level exhibits the "price puzzle" common to small VAR specifications.[16] The VFCI responds strongly to the federal funds shock. The median estimated response is around 5 percent upon impact, increasing to around 7.5 percent over 3 quarters before dissipating after 8 quarters. The response of the VFCI to monetary policy shocks is consistent with empirical evidence in the literature

By construction, the VFCI is a measure of the price of risk. In Section 4, we argued it was also a financial conditions index. In both of these roles, the response of the VFCI to monetary policy shocks is consistent with empirical evidence in the literature. A higher price of risk in response to tighter monetary policy is one of the main takeaways of the vast literature originating in Kuttner (2001) and Gürkaynak, Sack, and Swanson (2004), with more recent studies in Nakamura and Steinsson (2018), Caldara and Herbst (2019), Cieslak and Vissing-Jorgensen (2020), among other. The tightening of financial conditions after a positive federal funds rate shock is documented in Gertler and Karadi (2015), Brunnermeier et al. (2021), and others.

[16] Originated in Sims (1992), reviewed in Ramey (2016)

7 Alternative Identification Strategies

In this section, we show that the impulse response functions obtained using identification through heteroskedasticity are very similar to those obtained using four other plausible identification strategies. We give a brief description of each strategy and provide more details in Appendix II.

Instrumental Variables

Our first alternative identification strategy is to use instrumental variables (also referred to as proxy variables, and as external instruments) for shocks to GDP, the federal funds rate, and the VFCI.

For the GDP instrument, we use the growth news shock constructed in Cieslak and Pang (2021), available between 1983Q1 and 2022Q3[17]. We convert the instrument to quarterly frequency by averaging the daily observations over the current quarter. Whenever we use this growth news shock, we estimate the VAR using GDP growth instead of log-GDP to be aligned with the nature of the shock, and inflation instead of log-prices to keep all variables stationary.

For the federal funds rate instrument, we splice two data series. Between 1969Q1 and 1994Q4, we use the monetary policy shock constructed in Romer and Romer (2004) using the "narrative approach", updated by Wieland and Yang (2020)[18]. From 1995Q1 to 2022Q3, we use the monetary policy shock constructed in Nakamura and Steinsson (2018) and convert the monthly series to quarterly frequency by averaging observations over the current quarter[19].

The external instrument for the VFCI shock uses the identifying assumption that a VFCI shock reduces the price level on impact. The instrument itself is the structural VFCI shock in an auxiliary Bayesian VAR that imposes the identifying assumption on the orthogonalized IRF.

Local Projections with Instrumental Variables

Our second alternative identification strategy is the instrumental variable local-projection (LP) method proposed by Jordà, Schularick, and Taylor (2015) using the same instruments as in the previous strategy. Despite the asymptotic equivalence between VAR-based and local-projection-based IRFs (Plagborg-Møller and Wolf (2021a)), they can differ in finite samples.

[17]We thank the authors, who provided the updated series.

[18]Downloaded from https://www.openicpsr.org/openicpsr/project/135741/version/V1/view on February 12, 2023. We use the series 'resid_full' in the file 'RR_monetary_shock_quarterly.dta', divided by 10.

[19]We thank Emi Nakamura and Miguel Acosta for providing an updated data series

Whether IRF or LP should be preferred depends on the setting and the researcher's goals. For example, IRF and LP have different bias-variance trade-offs (Li, Plagborg-Møller, and Wolf (2024)) and different robustness properties (Montiel Olea and Plagborg-Møller (2021)).

Recursive VAR

Third, we estimate a recursive VAR in which the federal funds rate and the VFCI are ordered last, reflecting the assumption that they respond contemporaneously to shocks to GDP and the price level, but that GDP and the price level do not respond contemporaneously to shocks to the federal funds rate or to the VFCI. We show results with the federal funds rate ordered third and the VFCI ordered last, although results are essentially identical if we reverse this order.

Sign restrictions

As our last alternative identification strategy, we impose sign restrictions on the impact effect of monetary policy and VFCI shocks. We assume that the price level and GDP must respond negatively to a positive monetary policy shock, and that the price level must respond negatively to a positive VFCI shock.

7.1 A Comparison of All Identification strategies

Figures 5 and 6 compare IRFs for all the identification strategies. Figure 5 focuses on the interactions between the VFCI and monetary policy while Figure 6 looks at VFCI and GDP. In both figures, each row corresponds to a different identification strategy. The first row, labeled "Vol-SVAR", shows impulse responses for our baseline SVAR specification in which shocks are identified by heteroskedasticity. These impulse responses are the same impulse responses already shown in Figure 4, which we include here for ease of comparison. The second row, labeled "SVAR-IV", uses instrumental variables to identify shocks. The third row, labeled "LP-IV" uses local projections and the same instruments as the SVAR-IV specification. The fourth row, labeled "Cholesky", shows IRF for the recursive VAR. The fifth row shows IRFs for the sign-restricted SVAR.

The IRFs in the heteroskedasticity-identified and the sign-restricted SVARs are estimated using Bayesian methods and correspond to medians across 10,000 draws from the posterior distribution. The other three identification strategies are estimated using frequentist methods. In each instance, the shock corresponds to a one standard deviation increase, and we plot the evolution of the variables over 20 quarters.

8 Estimating the VFCI within the VAR

Until now, we have first estimated the VFCI and then included it as an additional variable in the VAR. Yet, the VAR implies its own path for the volatility of GDP growth which may or may not be consistent with the one estimated in the construction of the VFCI.

In Figure 7, we show that estimating the VFCI using the implied volatility of GDP growth from a VAR with log GDP, log PCE, and the Federal Funds rate generates essentially the same index. This Internal VAR VFCI is constructed using the VAR reduced form residuals of log GDP as ε_{t+1} in equation 9. In other words, we replace the first step (equation 8) of the two-step estimation of heteroskedasticity with our reduced form VAR. The second step remains unchanged, using the same principal components of our financial variables to estimate the conditional volatility.

In addition, we compare the IRFs generated by this Internal VAR VFCI in Appendix D. Using a recursive identification strategy with either the VFCI or the Internal VAR VFCI ordered last generates matching responses to the VFCI shock.

9 Robustness

In this section, we present several variations in our model and estimation procedures to assess robustness of our results.

Appendix A shows that the VFCI is not materially different when we:

- replace real GDP by real aggregate consumption
- use all the financial variables listed in Table 1 as independent variables rather than their first four principal components,
- use five or six principal components in the construction of the VFCI instead of the baseline case of four,
- use more financial variables in the construction of the principal components that include oil prices, exchange rates,
- use the VIX of Berger, Dew-Becker, and Giglio (2019)
- the equity-based SDF of Kozak, Nagel, and Santosh (2020)

The robustness exercises for our main SVAR specification that identifies shocks through heteroskedasticity are described in detail in Appendix A, where we show that the magnitude,

persistence, error bands, and overall shape of the impulse responses in Figures 4 that involve the VFCI remain broadly unchanged when we:

- use stationary variables by replacing log GDP with GDP growth or an output gap, and the log price level with inflation,
- use $\exp(VFCI)$ (a measure of volatility) instead of $VFCI$ (a measure of log-volatility),
- use the alternative VFCI constructions detailed above
- use a normal distribution for structural shocks instead of the t distribution
- use 100,000 and 1,000,000 posterior draws in the MCMC chain rather than the 10,000 of our main specification
- vary the Minnesota prior tightness to 1, 2, or 5 (instead of the baseline of 3) and the decay to 0.3 and 0.7 (instead of the baseline of 0.5)
- use data only up to 2007Q4 that excludes the 2008 global financial crisis and Covid pandemic
- use time-varying VAR coefficients that can differ across subperiods instead of the constant ones in our main specification,

alternative specifications of the baseline SVAR 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).

First, real PCE can be used instead of real GDP to calculate the VFCI. Table 3 already showed that the regression of the GDP-based VFCI and the PCE-based VFCI give rise to very similar coefficients. In Figure 8, we show graphically that the two series are virtually indistinguishable.

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 six financial variables. It turns out that, due to 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.

Finally, we compute the VFCI for the Euro Area analogously to the construction of the VFCI but using real GDP for the Euro Area instead of real GDP for the United States, and the Composite Indicator of Systemic Stress[20] from the European Central Bank instead of the first four principal components of the financial variables in Table 1.

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

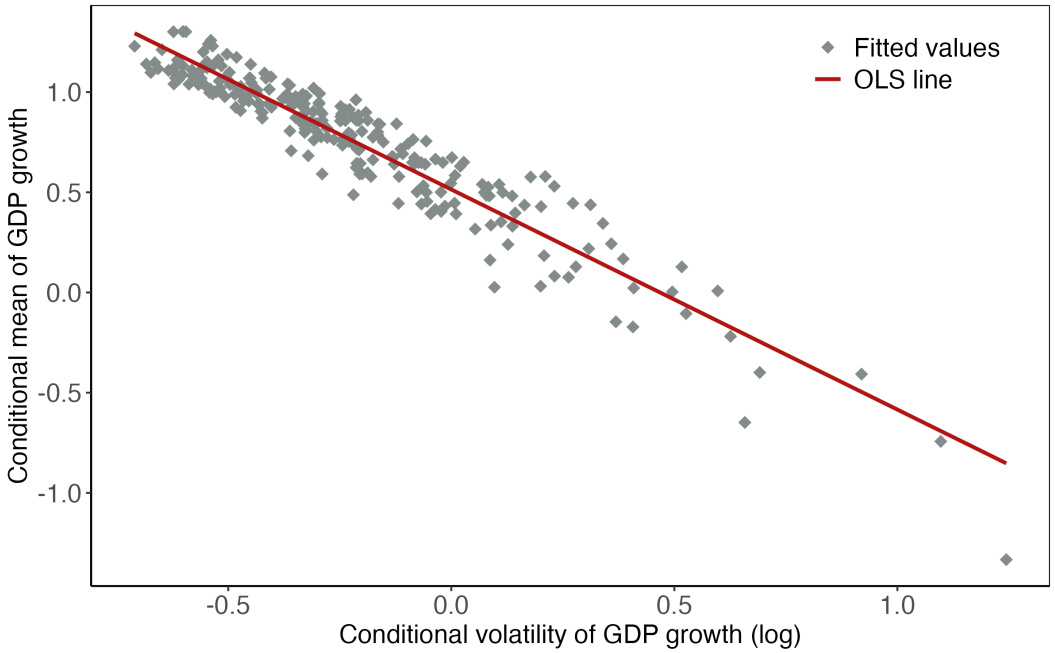
The Euro Area VFCI (EA-VFCI) does look materially different from the US-VFCI, but that is to be expected. We leave it for future research to examine the VAR evidence for Europe.

10 Conclusion

In this paper, we propose a new 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 exists. In contrast to other FCIs that are mostly atheoretical, the VFCI is the first FCI to be derived from solid theoretical underpinnings. The VFCI is correlated with other leading FCIs, but has notable differences. An important one is that it exhibits better explanatory power for stock and corporate bond risk premia. 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 strategies to study the causal impact of VFCI shocks on monetary policy and output, and vice versa. Across identification strategies, the baseline conclusions remain the same: a tightening of financial conditions based on the VFCI leads to an immediate easing of monetary policy and a persistent contraction in output. Conversely, contractionary monetary policy shocks lead to a tightening of financial conditions. In contrast, output shocks do not move the VFCI much, and inflation seems to be mostly unrelated to it. These results are encouraging, as they suggest a step forward in estimating financial conditions based on economic theory, with broad applicability and uses in policy-making. Further research could compute the VFCI for additional countries, conduct asset pricing tests, and embed the VFCI into structural macro-financial models.

FIGURE 2
Conditional mean and volatility of GDP growth



Notes: The scatter plot shows the log-conditional volatility of GDP growth, $VFCI_t = \hat{\delta} PC_t$, in the horizontal axis against the conditional mean of GDP growth, $\hat{\theta} PC_t$, on the vertical axis, where $\hat{\delta}$, $\hat{\theta}$ are the maximum likelihood estimate of δ, θ in the model

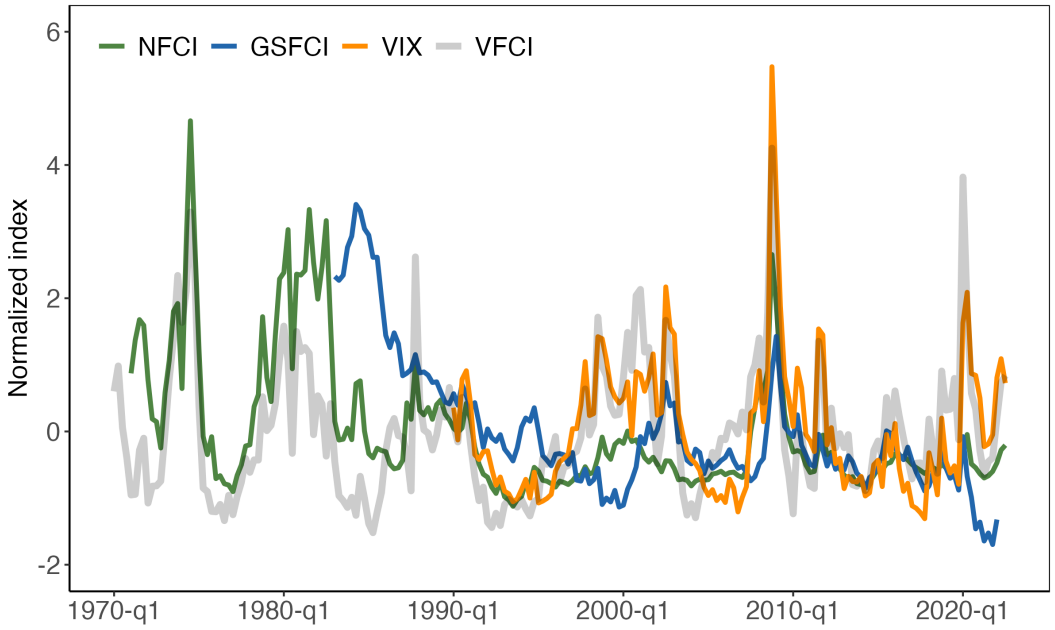
$$\Delta y_{t+1} = \theta PC_t + \varepsilon_t,$$
$$Var_t(\varepsilon_{t+1}^2) = \exp(2\delta PC_t),$$

in which Δy_{t+1} is real quarter-over-quarter GDP growth, PC_t is a vector with a 1 followed by the first four principal components *PC1–PC4* of the financial variables in Table 1, ε_t is zero-mean, i.i.d. normal, and θ, δ are vectors of parameters.

All series used are quarterly from 1962Q1 to 2022Q3. Each gray diamond corresponds to one of the quarters in the sample. The red line is the OLS line from a regression of $\hat{\theta} PC_t$ on a constant and $VFCI_t = \hat{\delta} PC_t$.

FIGURE 3

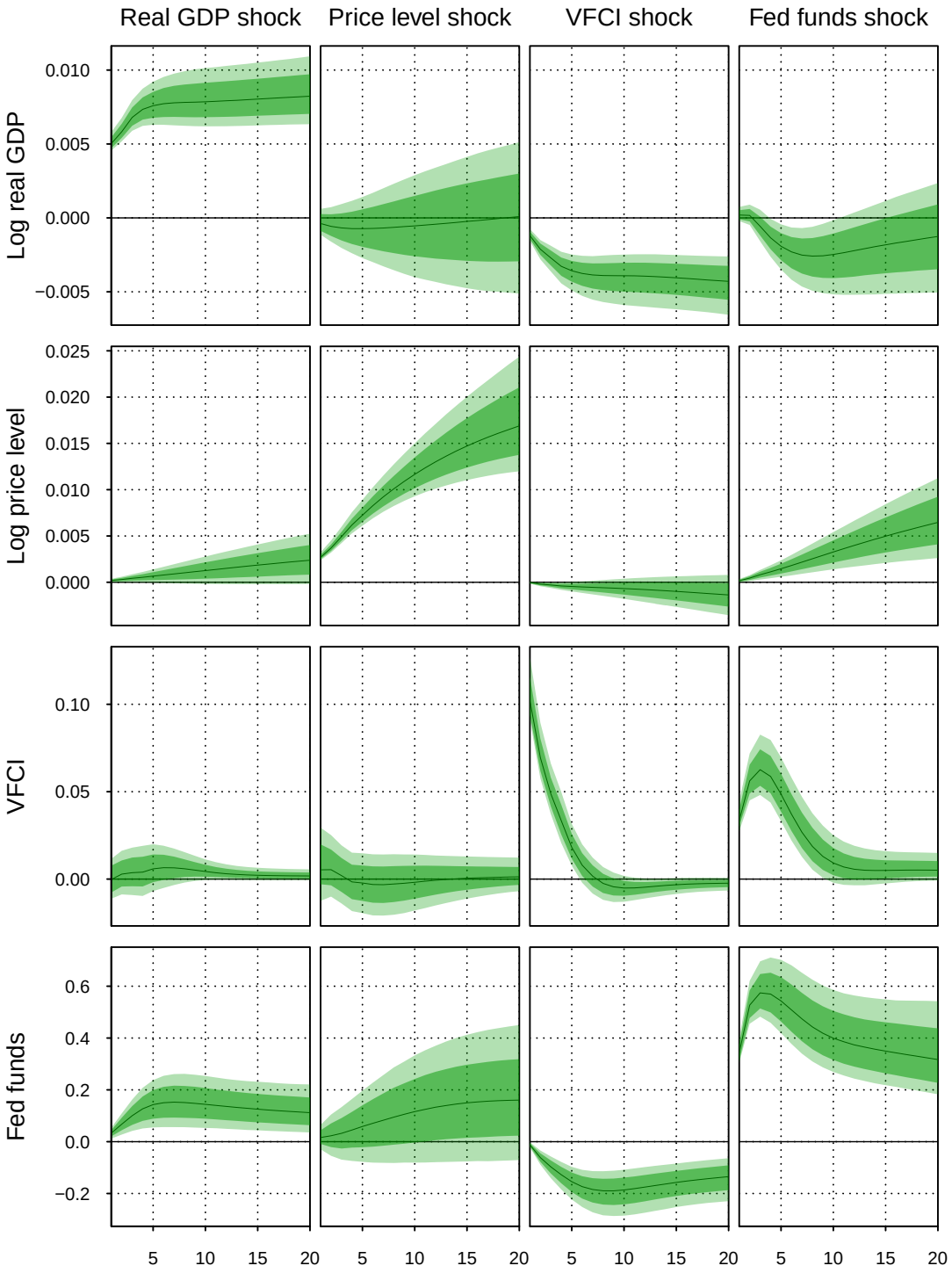
Comparison of different financial conditions indices (FCIs)



Notes: The green line plots *NFCI*, the Federal Reserve Bank of Chicago's national financial conditions index; the blue line plots *GSFCI*, the Goldman Sachs financial conditions index; the organge line plots *VIX*, the VIX index from the Chicago Board Options Exchange; the gray line plots *VFCI*, the volatility financial conditions index constructed in Section 3. All series are normalized to have zero mean and unit variance.

FIGURE 4

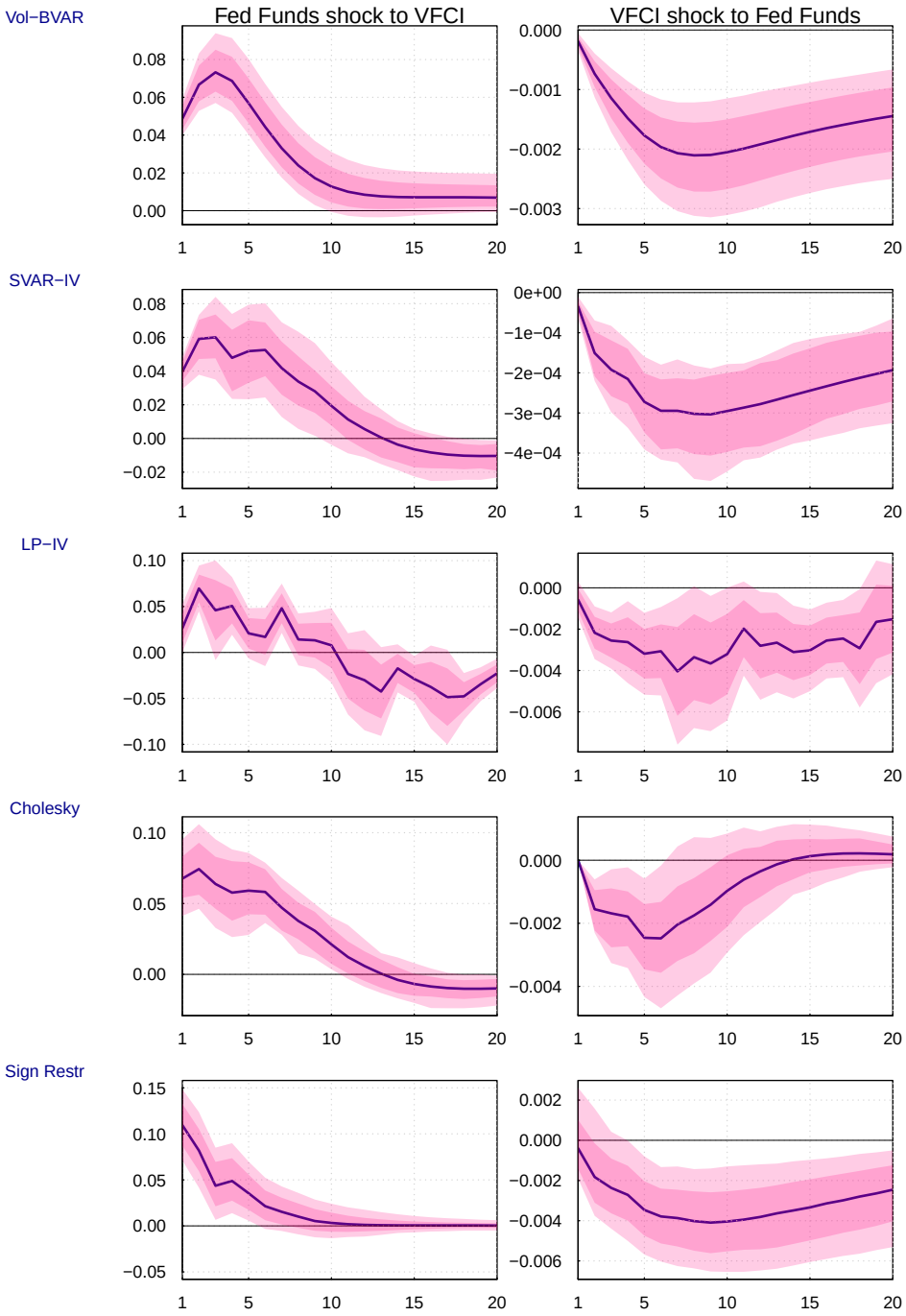
Impulse response functions with heteroskedasticity-identified shocks



Notes: Impulse response functions (IRF) using structural shocks identified through heteroskedasticity with 68 percent (dark shade) and 90 percent (light shade) posterior uncertainty regions. IRF scaled to an average subperiod (variance of shocks is the average across subperiods). VAR estimated using quarterly data from 1962Q1 to 2022Q3.

FIGURE 5

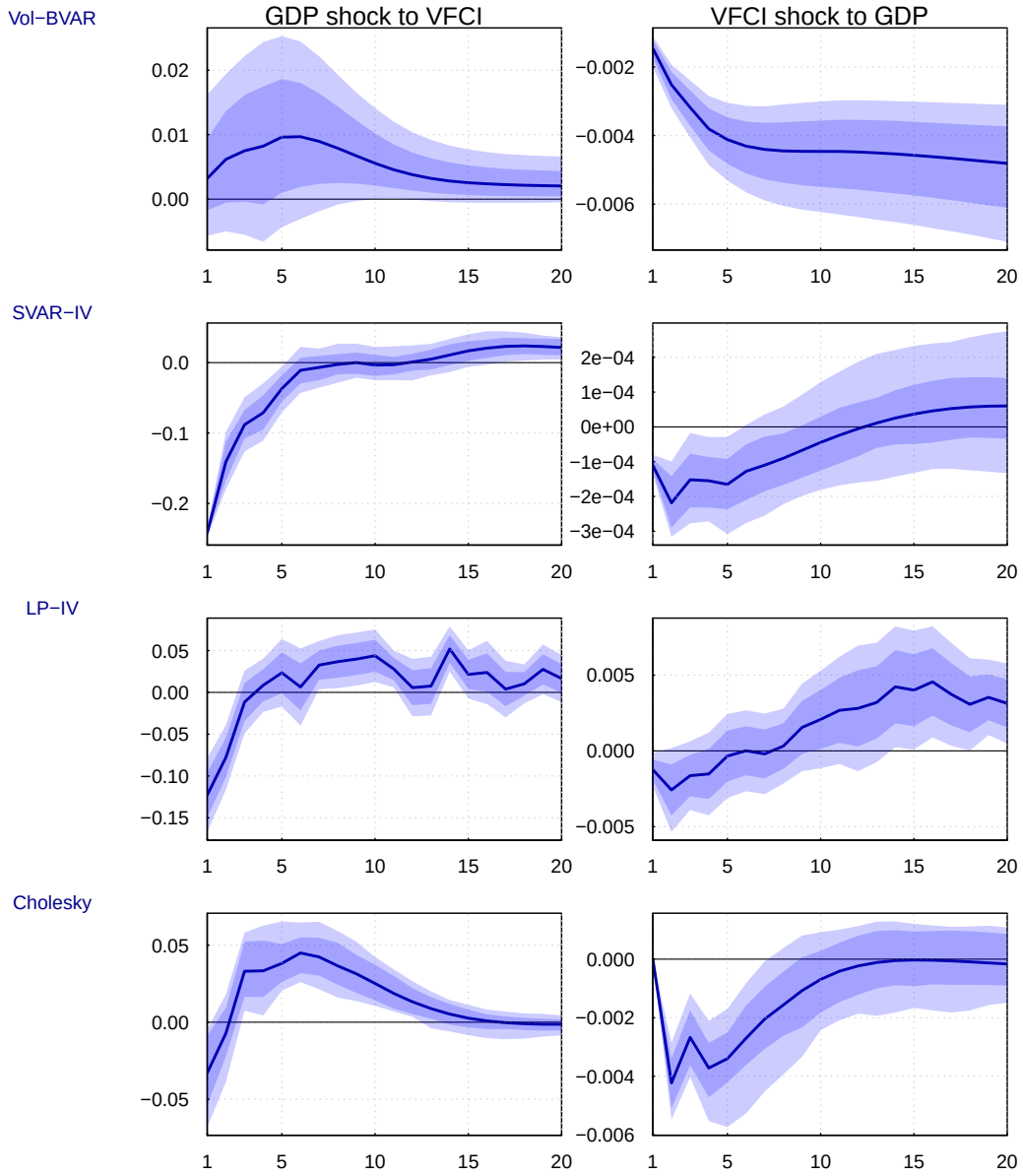
Comparison of IRFs across identification strategies: VFCI and monetary policy



Notes: IRF of the VFCI to a federal funds rate shock (left column) and of the federal funds rate to a VFCI shock (right column) for five different identification strategies (across rows), with 68 percent (dark shade) and 90 percent (light shade) posterior uncertainty regions. IRF scaled to an average subperiod (variance of shocks is the average across subperiods).

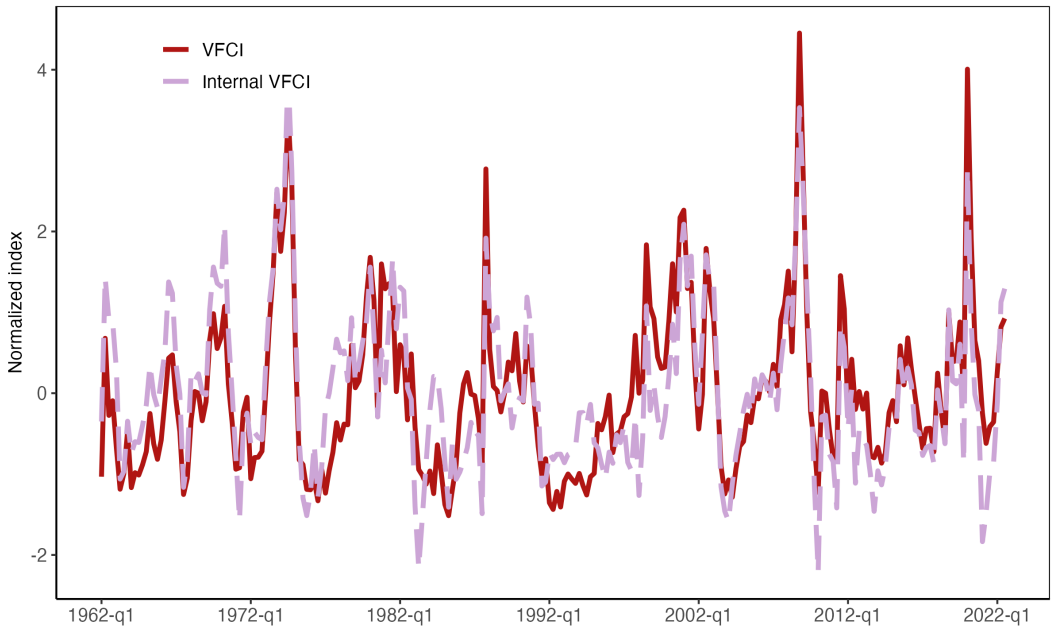
FIGURE 6

Comparison of IRFs across identification strategies: VFCI and output



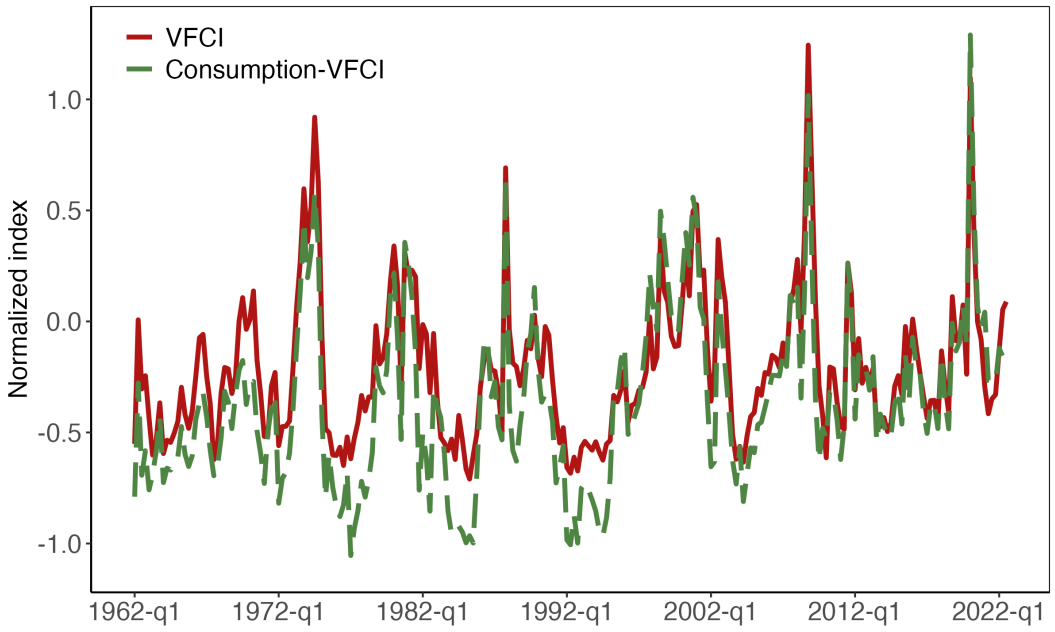
Notes: IRF of the VFCI to a GDP shock (left column) and of GDP to a VFCI shock (right column) for four different identification strategies (across rows), with 68 percent (dark shade) and 90 percent (light shade) posterior uncertainty regions. IRF scaled to an average subperiod (variance of shocks is the average across subperiods).

FIGURE 7
VFCI and Internal VAR VFCI



Notes: The red line plots the *VFCI*, the volatility financial conditions index, reproduced from Figure 1. The dotted purple line plots the *VFCI* consistent with a VAR (log real GDP, log personal consumption expenditure price index, and the federal funds rate) with four lags.

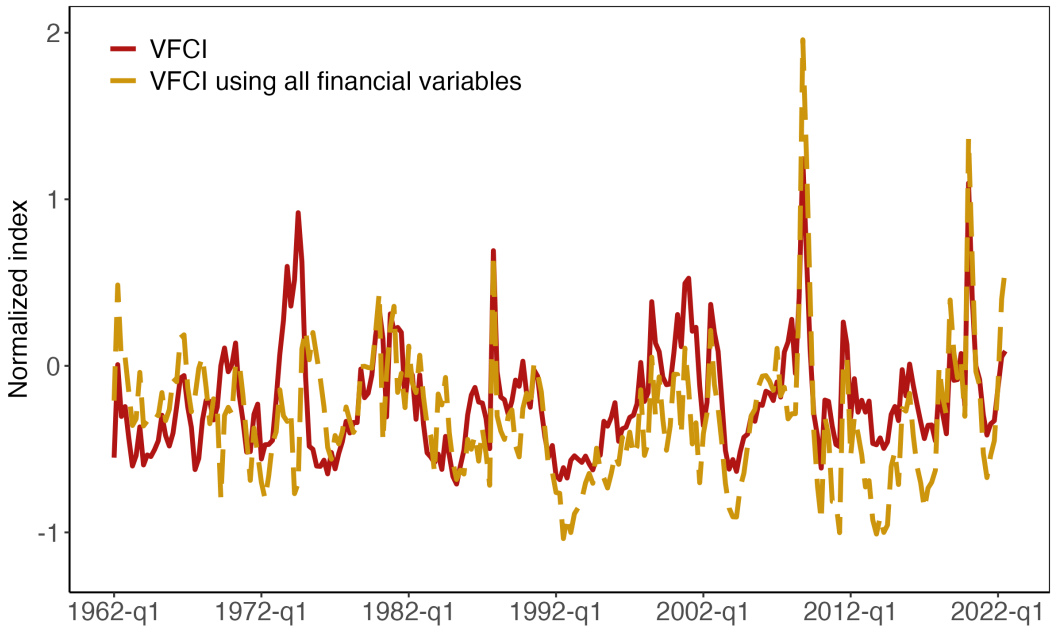
FIGURE 8
VFCI and consumption–VFCI



Notes: The red line plots the *VFCI*, the volatility financial conditions index, reproduced from Figure 1. The dotted green line plots the consumption–*VFCI*, constructed analogously to *VFCI* but using real aggregate consumption (seasonally adjusted real personal consumption expenditures) instead of real GDP.

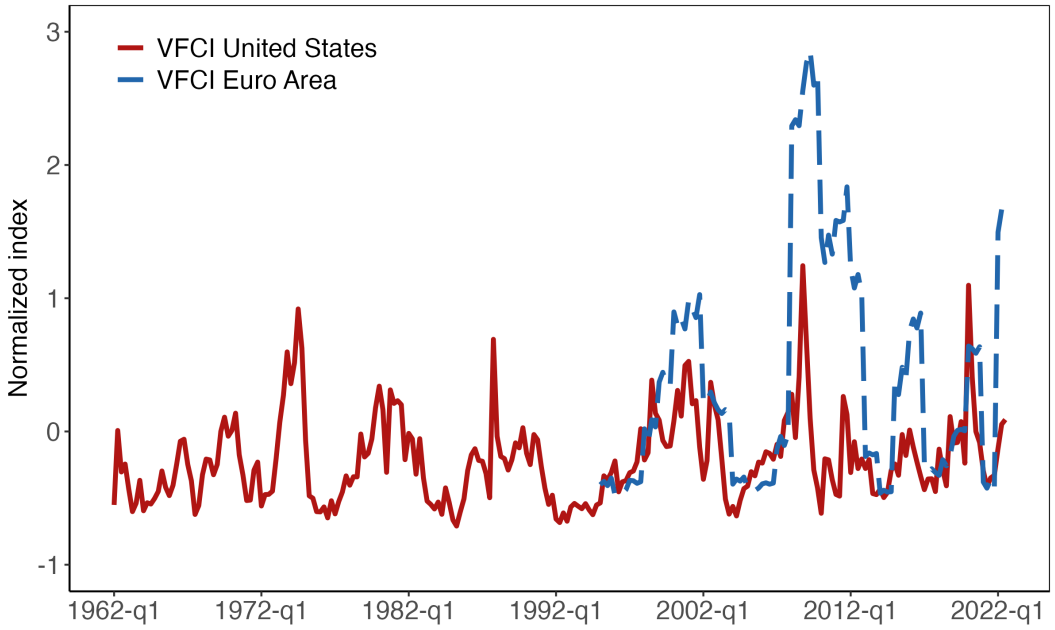
FIGURE 9

VFCI and VFCI constructed using all financial variables



Notes: The red line plots the *VFCI*, the volatility financial conditions index, reproduced from Figure 1. In the estimation of the VFCI, we use the first four principal components of the financial variables in Table 1 as independent variables. The dotted orange line plots an alternative *VFCI* constructed using all financial variables listed in Table 1 as independent variables rather than their first four principal components.

FIGURE 10
VFCI for the United States and Euro Area



Notes: The red line plots the *VFCI* for the United States, the volatility financial conditions index, reproduced from Figure 1. The dotted blue line plots the *VFCI* for the Euro Area, constructed analogously to *VFCI* but using real GDP for the Euro Area instead of real GDP for the United States, and the Composite Indicator of Systemic Stress (CISS) from the European Central Bank instead of the first four principal components of the financial variables in Table 1.

References

Adrian, Tobias, Nina Boyarchenko, and Domenico Giannone. 2019. "Vulnerable Growth." *American Economic Review* 109, no. 4 (April): 1263–89. https://doi.org/10.1257/aer.20161923.

Adrian, Tobias, Richard Crump, and Emanuel Moench. 2013. "Pricing the Term Structure with Linear Regressions." *Journal of Financial Economics* 110 (1): 110–138. https://doi.org/10.1016/j.jfineco.2013.04.009.

Adrian, Tobias, and Fernando Duarte. 2018. "Financial vulnerability and monetary policy," https://doi.org/https://ssrn.com/abstract=2891253.

———. 2020. *Financial Vulnerability and Monetary Policy,* January 11, 2020. https://ssrn.com/abstract=2891253.

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. https://doi.org/10.1257/mac.20180428.

Aruoba, S Borağan, Francis X Diebold, and Chiara Scotti. 2009. "Real-time measurement of business conditions." *Journal of Business & Economic Statistics* 27 (4): 417–427.

Bálint, Dániel Ágoston, and Martin Schweizer. 2022. "Making No-Arbitrage Discounting-Invariant: A New FTAP Version beyond NFLVR and NUPBR." *Frontiers of Mathematical Finance,* https://doi.org/10.3934/fmf.2021010.

Bansal, Ravi, Varoujan Khatchatrian, and Amir Yaron. 2005. "Interpretable Asset Markets?" *European Economic Review* 49 (3): 531–560. https://doi.org/10.1016/j.euroecorev.2004.09.002.

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. https://doi.org/10.1111/j.1540-6261.2004.00670.x.

Barro, Robert. 2006. "Rare Disasters and Asset Markets in the Twentieth Century." *Quarterly Journal of Economics* 121 (3): 823–866. https://doi.org/10.1162/qjec.121.3.823.

Berger, David, Ian Dew-Becker, and Stefano Giglio. 2019. "Uncertainty Shocks as Second-Moment News Shocks." *The Review of Economic Studies* 87, no. 1 (April): 40–76. ISSN: 0034-6527. https://doi.org/10.1093/restud/rdz010. eprint: https://academic.oup.com/restud/article-pdf/87/1/40/50282077/rdz010.pdf. https://doi.org/10.1093/restud/rdz010.

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. https://doi.org/10.2307/2109844.

Bianchi, Francesco, Martin Lettau, and Sydney Ludvigson. 2022. "Monetary Policy and Asset Valuation." *Journal of Finance* 77 (2): 967–1017. https://doi.org/10.1111/jofi.13107.

Bianchi, Francesco, Sydney C. Ludvigson, and Sai Ma. 2022. *Monetary-Based Asset Pricing: A Mixed-Frequency Structural Approach.* Working Paper, 30072, May. Accessed January 31, 2023. https://doi.org/10.3386/w30072. https://www.nber.org/papers/w30072.

Bidder, Rhys, and Matthew Smith. 2018. "Doubts and Variability: A Robust Perspective on Exotic Consumption Series." *Journal of Economic Theory* 175:689–712. https://doi.org/10.1016/j.jet.2018.02.007.

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 Ying Jiao, 71–144. Mathematical Lectures from Peking University. Springer Singapore.

Bollerslev, Tim. 1986. "Generalized Autoregressive Conditional Heteroskedasticity." *Journal of Econometrics* 31 (3): 307–327. https://doi.org/10.1016/0304-4076(86)90063-1.

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. https://doi.org/10.1016/j.jeconom.2015.02.031.

Brave, Scott, and Andrew Butters. 2011. "Monitoring Financial Stability: A Financial Conditions Index Approach." *Economic Perspectives* 35 (1): 22. https://www.chicagofed.org/publications/economic-perspectives/2011/1q-brave-butters.

Breeden, Douglas. 1979. "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities." *Journal of Financial Economics* 7 (3): 265–296. https://doi.org/10.1016/0304-405X(79)90016-3.

Breeden, Douglas, Michael Gibbons, and Robert Litzenberger. 1989. "Empirical Tests of the Consumption-Oriented CAPM." *Journal of Finance* 44 (2): 231–262. https://doi.org/http://dx.doi.org/10.1111/j.1540-6261.1989.tb05056.x.

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. https://doi.org/10.1146/annurev-financial-111914-041800.

Brunnermeier, Markus, Darius Palia, Karthik Sastry, and Christopher Sims. 2021. "Feedbacks: Financial Markets and Economic Activity." *American Economic Review* 111, no. 6 (June): 1845–79. https://doi.org/10.1257/aer.20180733.

Brunnermeier, Markus, and Yuliy Sannikov. 2014. "A Macroeconomic Model with a Financial Sector." *American Economic Review* 104 (2): 379–421. https://doi.org/10.1257/aer.104.2.379.

Caballero, Ricardo, and Alp Simsek. 2020. "A Risk-Centric Model of Demand Recessions and Speculation." *Quarterly Journal of Economics* 135 (3): 1493–1566. https://doi.org/10.1093/qje/qjaa008.

———. 2022. *A Monetary Policy Asset Pricing Model.* https://doi.org/http://dx.doi.org/10.2139/ssrn.4113332. https://ssrn.com/abstract=4113332.

Caldara, Dario, and Edward Herbst. 2019. "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs." *American Economic Journal: Macroeconomics* 11 (1): 157–92. https://doi.org/10.1257/mac.20170294.

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. https://doi.org/10.1086/250059.

———. 2000. "Explaining the Poor Performance of Consumption-Based Asset Pricing Models." *Journal of Finance* 55 (6): 2863–2878. https://doi.org/10.1111/0022-1082.00310.

Campbell, John, Stefano Giglio, Christopher Polk, and Robert Turley. 2018. "An Intertemporal CAPM with Stochastic Volatility." *Journal of Financial Economics* 128 (2): 207–233. https://doi.org/10.1016/j.jfineco.2018.02.011.

Chen, Nai-Fu, Richard Roll, and Stephen Ross. 1986. "Economic Forces and the Stock Market." *Journal of Business,* 383–403. https://doi.org/10.1086/296344.

Cieslak, Anna, Adair Morse, and Annette Vissing-Jorgensen. 2019. "Stock Returns over the FOMC Cycle." *Journal of Finance* 74 (5): 2201–2248. https://doi.org/10.1111/jofi.12818.

Cieslak, Anna, and Hao Pang. 2021. "Common Shocks in Stocks and Bonds." *Journal of Financial Economics* 142 (2): 880–904. ISSN: 0304-405X. https://doi.org/10.1016/j.jfineco.2021.06.008.

Cieslak, Anna, and Annette Vissing-Jorgensen. 2020. "The Economics of the Fed Put." *Review of Financial Studies* 34, no. 9 (October): 4045–4089. https://doi.org/10.1093/rfs/hhaa116.

Delbaen, Freddy, and Walter Schachermayer. 2006. *The Mathematics of Arbitrage.* Springer Science & Business Media.

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. https://doi.org/10.1162/REST_a_00225.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2018. "Liquidity, Risk Premia, and the Financial Transmission of Monetary Policy." *Annual Review of Financial Economics* 10 (1): 309–328. https://doi.org/10.1146/annurev-financial-110217-022833. eprint: https://doi.org/10.1146/annurev-financial-110217-022833. https://doi.org/10.1146/annurev-financial-110217-022833.

Drehmann, Mathias, and Mikael Juselius. 2014. "Evaluating Early Warning Indicators of Banking Crises: Satisfying Policy Requirements." *International Journal of Forecasting* 30 (3): 759–780. https://doi.org/10.1016/j.ijforecast.2013.10.002.

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

———. 2010. *Dynamic Asset Pricing Theory.* Princeton University Press.

Duffie, Darrell, and William Zame. 1989. "The Consumption-Based Capital Asset Pricing Model." *Econometrica : journal of the Econometric Society* 57 (6): 1279–1297. https://doi.org/10.2307/1913708.

Eicker, Friedhelm. 1967. "Limit Theorems for Regressions with Unequal and Dependent Errors." In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability,* 1:59–82. 1. Berkeley, CA: University of California Press.

Engle, Robert. 1982. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica : journal of the Econometric Society,* 987–1007. https://doi.org/10.2307/1912773.

Gabaix, Xavier. 2012. "Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance." *The Quarterly journal of economics* 127 (2): 645–700. https://doi.org/10.1093/qje/qjs001.

Gertler, Mark, and Peter Karadi. 2015. "Monetary Policy Surprises, Credit Costs, and Economic Activity." *American Economic Journal: Macroeconomics* 7 (1): 44–76. https://doi.org/10.1257/mac.20130329.

Gilchrist, Simon, 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. https://doi.org/10.1016/j.jmoneco.2009.03.017.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit Spreads and Business Cycle Fluctuations." *American Economic Review* 102 (4): 1692–1720. https://doi.org/10.1257/aer.102.4.1692.

Gouriéroux, Christian, Alain Monfort, and Jean-Paul Renne. 2017. "Statistical inference for independent component analysis: Application to structural VAR models." *Journal of Econometrics* 196 (1): 111–126. ISSN: 0304-4076. https://doi.org/https://doi.org/10.1016/j.jeconom.2016.09.007. https://www.sciencedirect.com/science/article/pii/S0304407616301749.

Gürkaynak, Refet S, Brian P Sack, and Eric T Swanson. 2004. "Do actions speak louder than words? The response of asset prices to monetary policy actions and statements." *The Response of Asset Prices to Monetary Policy Actions and Statements (November 2004).*

Hansen, Lars Peter, and Thomas J Sargent. 2010. "Wanting Robustness in Macroeconomics." In *Handbook of Monetary Economics,* 3:1097–1157. Elsevier.

Hansen, Lars Peter, and Kenneth Singleton. 1982. "Generalized Instrumental Variables Estimation of Nonlinear Rational Expectations Models." *Econometrica : journal of the Econometric Society,* 1269–1286. https://doi.org/10.2307/1911873.

———. 1983. "Stochastic Consumption, Risk Aversion, and the Temporal Behavior of Asset Returns." *Journal of Political Economy* 91 (2): 249–265. https://doi.org/10.1086/261141.

Hatzius, Jan, and Sven Jari Stehn. 2018. "The Case for a Financial Conditions Index." *Economic Research, Global Economics Paper* (July). https://www.goldmansachs.com/insights/pages/case-for-financial-conditions/report-the-case-for-financial-conditions-index.pdf.

He, Zhiguo, and Arvind Krishnamurthy. 2013. "Intermediary Asset Pricing." *American Economic Review* 103, no. 2 (April): 732–70. https://doi.org/10.1257/aer.103.2.732.

Holmström, Bengt, and Jean Tirole. 1998. "Private and Public Supply of Liquidity." *Journal of political Economy* 106 (1): 1–40. https://doi.org/10.1086/250001.

Huber, Peter J. 1967. "The Behavior of Maximum Likelihood Estimates under Nonstandard Conditions." In *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability,* 1:221–233. 1. Berkeley, CA: University of California Press.

Jordà, Oscar. 2005. "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review* 95, no. 1 (March): 161–182. https://doi.org/10.1257/0002828053828518.

Jordà, Oscar, Moritz Schularick, and Alan Taylor. 2015. "Betting the House." *Journal of International Economics* 96:2–18. https://doi.org/10.1016/j.jinteco.2014.12.011.

Jordà, Òscar, Moritz Schularick, and Alan Taylor. 2016. "The Great Mortgaging: Housing Finance, Crises and Business Cycles." *Economic policy* 31 (85): 107–152. https://doi.org/10.1093/epolic/eiv017.

Kabanov, Yuri, and Mher Safarian. 2009. *Markets with Transaction Costs: Mathematical Theory.* Springer Science & Business Media.

Karlsson, Sune, Stepan Mazur, and Hoang Nguyen. 2023. "Vector autoregression models with skewness and heavy tails." *Journal of Economic Dynamics and Control* 146:104580. ISSN: 0165-1889. https://doi.org/https://doi.org/10.1016/j.jedc.2022.104580. https://www.sciencedirect.com/science/article/pii/S0165188922002834.

Kashyap, Anil, and Jeremy Stein. 2022. *Monetary Policy When the Central Bank Shapes Financial-Market Sentiment.* https://doi.org/https://dx.doi.org/10.2139/ssrn.4304219. https://ssrn.com/abstract=4304219.

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy* 105 (2): 211–248. https://doi.org/10.1086/262072.

Kozak, Serhiy, Stefan Nagel, and Shrihari Santosh. 2020. "Shrinking the cross-section." *Journal of Financial Economics* 135 (2): 271–292. ISSN: 0304-405X. https://doi.org/https://doi.org/10.1016/j.jfineco.2019.06.008. https://www.sciencedirect.com/science/article/pii/S0304405X19301655.

Krishnamurthy, Arvind, and Tyler Muir. 2017. "How Credit Cycles across a Financial Crisis," https://doi.org/10.3386/w23850.

Kuttner, Kenneth N. 2001. "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market." *Journal of monetary economics* 47 (3): 523–544.

Lanne, Markku, and Jani Luoto. 2020. "Identification of Economic Shocks by Inequality Constraints in Bayesian Structural Vector Autoregression." *Oxford Bulletin of Economics and Statistics* 82 (2): 425–452. https://doi.org/https://doi.org/10.1111/obes.12338. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/obes.12338. https://onlinelibrary.wiley.com/doi/abs/10.1111/obes.12338.

Lanne, Markku, Helmut Lütkepohl, and Katarzyna Maciejowska. 2010. "Structural vector autoregressions with Markov switching." *Journal of Economic Dynamics and Control* 34 (2): 121–131. https://doi.org/10.1016/j.jedc.2009.08.002.

Lanne, Markku, Mika Meitz, and Pentti Saikkonen. 2017. "Identification and estimation of non-Gaussian structural vector autoregressions." *Journal of Econometrics* 196 (2): 288–304. ISSN: 0304-4076. https://doi.org/https://doi.org/10.1016/j.jeconom.2016.06.002. https://www.sciencedirect.com/science/article/pii/S0304407616301828.

Li, Dake, Mikkel Plagborg-Møller, and Christian K. Wolf. 2024. "Local projections vs. VARs: Lessons from thousands of DGPs." *Journal of Econometrics,* 105722. ISSN: 0304-4076. https://doi.org/https://doi.org/10.1016/j.jeconom.2024.105722. https://www.sciencedirect.com/science/article/pii/S030440762400068X.

López-Salido, David, Jeremy Stein, and Egon Zakrajšek. 2017. "Credit-Market Sentiment and the Business Cycle." *Quarterly Journal of Economics* 132 (3): 1373–1426. https://doi.org/10.1093/qje/qjx014.

Lucas Jr, Robert. 1978. "Asset Prices in an Exchange Economy." *Econometrica: Journal of the Econometric Society,* 1429–1445. https://doi.org/10.2307/1913837.

Ludvigson, Sydney. 2013. "Advances in Consumption-Based Asset Pricing: Empirical Tests." *Handbook of the Economics of Finance* 2:799–906. https://doi.org/10.1016/B978-0-44-459406-8.00012-3.

Mankiw, Gregory, and Matthew Shapiro. 1986. "Risk and Return: Consumption Beta versus Market Beta." *Review of Economics and Statistics* 68 (3): 452–459. https://doi.org/10.2307/1926022.

Matoussi, Anis, and Hao Xing. 2018. "Convex Duality for Epstein–Zin Stochastic Differential Utility." *Mathematical Finance* 28 (4): 991–1019. https://doi.org/10.1111/mafi.12168.

Mehra, Rajnish. 2012. "Consumption-Based Asset Pricing Models." *Annual Review of Financial Economics* 4 (1): 385–409. https://doi.org/10.1146/annurev-financial-102710-144825.

Mian, Atif, Amir Sufi, and Emil Verner. 2017. "Household Debt and Business Cycles Worldwide." *Quarterly Journal of Economics* 132 (4): 1755–1817. https://doi.org/10.1093/qje/qjx017.

Monoyios, Michael. 2022. "Duality for Optimal Consumption under No Unbounded Profit with Bounded Risk." *The Annals of Applied Probability* 32 (5): 3572–3613. https://doi.org/10.1214/21-AAP1767. https://doi.org/10.1214/21-AAP1767.

Montiel Olea, José Luis, and Mikkel Plagborg-Møller. 2021. "Local Projection Inference Is Simpler and More Robust Than You Think." *Econometrica* 89 (4): 1789–1823. https://doi.org/https://doi.org/10.3982/ECTA18756. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA18756. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA18756.

Nakamura, Emi, and Jon Steinsson. 2018. "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect." *Quarterly Journal of Economics* 133, no. 3 (January): 1283–1330. https://doi.org/10.1093/qje/qjy004.

Plagborg-Møller, Mikkel, and Christian K Wolf. 2021a. "Local projections and VARs estimate the same impulse responses." *Econometrica* 89 (2): 955–980.

———. 2021b. "Local Projections and VARs Estimate the Same Impulse Responses." *Econometrica : journal of the Econometric Society* 89 (2): 955–980. https://doi.org/10.3982/ECTA17813.

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

Romer, Christina, and David Romer. 2004. "A New Measure of Monetary Shocks: Derivation and Implications." *American Economic Review* 94, no. 4 (September): 1055–1084. https://doi.org/10.1257/0002828042002651.

Rubinstein, Mark. 1976. "The Valuation of Uncertain Income Streams and the Pricing of Options." *Bell Journal of Economics,* 407–425. https://doi.org/10.2307/3003264.

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. https://doi.org/10.1257/aer.102.2.1029.

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

Sims, Christopher A. 2020. "Svar identification through heteroskedasticity with misspecified regimes." *Princeton University.*

———. 1992. "Interpreting the macroeconomic time series facts: The effects of monetary policy." *European Economic Review* 36 (5): 975–1000. ISSN: 0014-2921. https://doi.org/https://doi.org/10.1016/0014-2921(92)90041-T. https://www.sciencedirect.com/science/article/pii/001429219290041T.

Sims, Christopher A., and Tao Zha. 1998. "Bayesian Methods for Dynamic Multivariate Models." *International Economic Review* 39 (4): 949–968. ISSN: 00206598, 14682354, accessed July 15, 2023. http://www.jstor.org/stable/2527347.

Skiadas, Costis. 2009. *Asset Pricing Theory.* Princeton University Press.

Stock, James, and Mark Watson. 2018. "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments." *Economic Journal* 128, no. 610 (May): 917–948. https://doi.org/10.1111/ecoj.12593.

Stock, James H., and Mark W. Watson. 2012. "Disentangling the Channels of the 2007–09 Recession." *Brookings Papers on Economic Activity* 2012 (1): 81–135. ISSN: 1533-4465, accessed January 31, 2023. https://doi.org/10.1353/eca.2012.0005. https://muse.jhu.edu/pub/11/article/486370.

Sundaresan, Suresh. 2000. "Continuous-Time Methods in Finance: A Review and an Assessment." *Journal of Finance* 55 (4): 1569–1622. https://doi.org/10.1111/0022-1082.00261.

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. https://doi.org/10.1016/j.jmoneco.2004.05.007.

Van Binsbergen, Jules, and Ralph Koijen. 2010. "Predictive Regressions: A Present-Value Approach." *Journal of Finance* 65 (4): 1439–1471. ISSN: 00221082, 15406261. https://doi.org/10.1111/j.1540-6261.2010.01575.x.

White, Halbert. 1980. "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity." *Econometrica: journal of the Econometric Society,* 817–838. https://doi.org/https://doi.org/10.2307/1912934. eprint: https://www.jstor.org/stable/1912934. https://www.jstor.org/stable/1912934.

Wieland, Johannes F., and Mu-Jeung Yang. 2020. "Financial Dampening." *Journal of Money, Credit and Banking* 52 (1): 79–113. https://doi.org/https://doi.org/10.1111/jmcb.12681. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jmcb.12681. https://onlinelibrary.wiley.com/doi/abs/10.1111/jmcb.12681.

Internet Appendix

The Internet Appendix conducts a set of robustness checks to test the main predictions of the identification schemes that monetary policy shocks have a causal impact on financial conditions, and that shocks to financial conditions causally affect monetary policy and output. The sensitivity analysis includes estimating subperiod-specific IRFs, estimating the models with a second financial variable, checking on alternate assumptions on stationarity and the distribution of error terms, using alternate calibration of Bayesian parameters, and reporting the VFCI in exponential terms.

Appendix I Robustness of Macro-Financial Dynamics

A Subperiod Specific IRFs

The baseline case reports IRFs that are the average across the seven volatility subperiods, as in Figure 4. Here, we relax the assumption that the economy responds in the same way across subperiods. Hence, the VAR dynamics are allowed to change along with the covariance matrix of shocks, implying that the economy reacts in different ways across time. In reporting the subperiod-specific IRFs here, as well as in the other robustness checks in the appendix, we calibrate the t degrees of freedom as 2.5 as in the baseline model, noting that the conclusions remain the same if this is varied. There are three main findings based on estimating the subperiod-specific dynamic causal effects.

First, the average causal effects remain robust to subperiod-specific estimation. Across all the seven subperiods and regardless of times of relative calm versus crises, we find that monetary policy shocks have a significant causal effect on financial conditions. Conversely, a tightening of financial conditions leads to a significant decline in real activity and triggers an accommodative monetary policy response across all subperiods. These results provide robust empirical evidence that the decision making of monetary policy makers has been causally affected by financial market activity, and vice versa, throughout recent U.S. macroeconomic history.

Second, monetary policy shocks have non-linear effects on financial conditions, with the amplification effect of shocks conditional on the extent of economic stress. For instance, the peak response of VFCI to a Fed Funds shock was above 12 percent during the Volcker Disinflation era (1979Q4-1982Q4) whereas it was less than 3 percent during two periods of relative calm –both the Great Moderation era (1990Q1-2007Q4) as well as the Zero Lower Bound era (2011Q1-2019Q4). This could reflect the adverse impact on financial market volatility due to the unprecedented spike in the Fed Funds rate during

the Volker era in a bid to bring inflation down to manageable levels. During both the Global Financial Crisis (2008Q1-2010Q4) as well as the recent Covid-19 Pandemic (2020Q1-2022Q3), the peak financial tightening was around 6 percent in response to a Fed Funds shock. Thus, compared to the two calmer time periods, financial conditions tightened by approximately double as much in response to monetary policy shocks during times of financial crises.

Third, monetary policy becomes somewhat more accommodative in response to financial tightening in times of economic crises. During the Great Moderation (1990Q1-2007Q4) and Zero Lower Bound (2011Q1-2019Q4) eras, for instance, the peak Fed Funds rate decline was below 0.2 points. During the Global Financial Crisis (2008Q1-2010Q4) and the Covid-19 pandemic (2020Q1-2022Q3) eras, however, the peak Fed Funds rate response was a bit stronger, at or above 0.2 percentage points. The results suggest that the implicit monetary policy rule in response to financial shocks has been fairly consistent over time, though the Fed has veered toward slightly greater accommodation during crises.

B Exponential VFCI and Stationarity in the Five Identification Schemes

Figures IA.8 and IA.9 use the exponential representation of VFCI, and present the dynamic causal effects of monetary policy and VFCI on each other, and on GDP and VFCI on each other. The results corroborate those in the paper, where the baseline VFCI is reported as the log market price of risk. The magnitude of responses is not significantly different in most cases, apart from the slightly stronger response in terms of financial loosening of exponential VFCI in response to positive GDP shocks.

Figures IA.10 and IA.11 present the results across the five identification schemes in stationary terms, with the models containing inflation, GDP growth, baseline VFCI, and the Fed Funds rate. In Figure IA.10, which reports the responses of VFCI to monetary policy shocks, and the Fed Funds rate to financial conditions shocks, it is noted that the magnitude and direction of the dynamic causal effects are very similar to the models estimated in levels. In Figure IA.11, the responses of VFCI and GDP growth to shocks to each other are also similar to those in the paper. However, unlike GDP in levels which displays a persistent decrease in response to financial conditions shocks in the heteroskedastic BVAR, GDP growth drops temporarily over the next year before starting to recover.

C Second Financial Variable

This section estimates the heteroskedastic BVAR with five variables instead of four as in the paper. We seek to analyze the robustness of the dynamic causal effects with the inclusion of a

second financial variable as suggested in Brunnermeier et al. 2021. In particular, we analyze a variety of cases, by including in turn separately the Excess CAPE Yield (ECY) of Shiller 2000, the Gilchrist and Zakrajšek 2012 corporate bond risk premium, the 3-month Libor-US Treasury spread (TED spread), and the NFCI of the Federal Reserve Bank of Chicago.

We find that the inclusion of the second financial variable does not change the implications of the baseline case with four variables. Including the fifth variable leads to similar responses, in terms of both significance and magnitude of the responses of monetary policy, output, and prices to VFCI shocks. VFCI also responds in a similar way to the structural shocks across all models. Therefore, the empirical results with one financial variable are found to hold robust.

D Additional BVAR Robustness

Gaussian Errors Assumption

Figures IA.20 and IA.21 estimate the heteroskedastic BVAR with Gaussian, instead of t-distributed, shocks. In general, the responses of monetary policy and GDP to VFCI shocks are somewhat more pronounced, as is the response of VFCI to all the structural shocks in the model. As the variance of the structural shocks differs substantially across the subperiods in our dataset, the baseline model of t-distributed shocks is more efficient. However, the conclusions remain the same regardless of the assumption on the distribution so that 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.

100,000 MCMC Draws

Figures IA.22 and IA.23 estimate the heteroskedastic BVAR with 100,000 draws instead of 10,000 draws as in the baseline model. The dynamic causal effects are almost identical, with slightly tighter posterior error bands in some cases. The robustness of the estimation when we increase the number of draws is useful to corroborate using 10,000 draws for the baseline models as it leads to faster estimation with the same conclusions on the impact and response of VFCI.

Pre-Global Financial Crisis and Covid-19 Crisis

Figures IA.24 and IA.25 estimate the heteroskedastic BVAR with the time period ending in 2007Q4, before the Global Financial Crisis and the Covid-19 crisis. The average causal effects

remain very similar, including the peak accommodative response of monetary policy to VFCI shocks and the tightening of VFCI in response to Fed Funds rate shocks. These results are not surprising in light of the results from the subperiod-specific estimation, which analyzed the causal effects specific to each time period and found that the although the responses were of different magnitudes, the conclusions were qualitatively the same. Thus, regardless of time period under consideration and whether or not crises are excluded, a VFCI shock, as a representation of tightening financial conditions, causes monetary policy to become more accommodative and real economic activity to fall. Conversely, contractionary monetary policy causes a tightening of financial conditions.

Estimating the VFCI within the VAR

Figure IA.26 compares IRFs for VARs using the baseline VFCI (column 1) and the VFCI estimated using the residuals of the three variable VAR of log Real GDP, log PCE, and the federal funds rate (column 2). In this figure, we identify the VFCI shock with a recursive ordering assumption, with the external or Internal VAR VFCI ordered last. The two are nearly identical, with a somewhat stronger response of the price level when using the Internal VAR VFCI.

Appendix II Alternative Identification Strategies

A 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

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

$$min_\alpha \Psi(\alpha) = \sum_{j \in J} \sum_{k \in JK} b(l_j) \frac{r(j, \alpha)(k)}{\sigma_j} \tag{IA.16}$$

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.

arias2018inference

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

$$\alpha = Ba \tag{IA.17}$$

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.

B Identification through SVAR-IV

To outline the SVAR-IV identification problem, consider the following reduced-form version of equation 10 for a vector of endogenous variables, $y(t)$

$$B(L)y_t = \eta_t \tag{IA.18}$$

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

$$\eta_t = H\varepsilon_t \tag{IA.19}$$

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 10 and IA.18 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 $H = C(L)^{-1}\Theta(L) = I + B_1 L + ...)(\Theta_0 + \Theta_L + ...) = \Theta_o +$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

$$E\varepsilon_{1,t} z_t' = \alpha \neq 0 \tag{IA.20}$$

$$E\varepsilon_{2:n,t} z_t' = 0 \tag{IA.21}$$

Equations IA.20 and IA.21 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 IA.20 and IA.21 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 IA.18 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.[21]

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.[22] A surprise increase in GDP growth leads to an immediate easing of financial conditions, but VFCI tightens in the following quarters as it reverts to the mean. The loosening of financial conditions in response to growth shock may be accorded to the plausibly better identification of these shocks using an external instrument.

C 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 2021b). The LP model can also be estimated using external instruments (Jordà,

[21] 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.

[22] 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)

Schularick, and Taylor 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 2021b. 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, and so on. 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 10, 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

$$y_{i,t+h} = \Theta_{h,i1} y_{1,t} + u^h_{i,t+h} \tag{IA.22}$$

where $u^h_{i,t+h} = \varepsilon_{t+h}, ..., \varepsilon_{t+1}, \varepsilon_{2:n,}, \varepsilon_{t-1}\varepsilon_{t-2,...}$. OLS estimation of IA.22 is not valid since $Y_{1,t}$ is correlated with $u^h_{i,t+h}$. However, IA.22 can be estimated if we use a suitable external instrument that satisfies the instrument relevant and exogeneity conditions, IA.20 and IA.21, along with a third condition

$$E\varepsilon_{t+j,t} z'_t = 0, j \neq 0 \tag{IA.23}$$

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 IA.22 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.

D 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, Morse, and Vissing-Jorgensen 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 respect to 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.

E 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 A. 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.

F Robustness of Identification through External Instruments and Sign Restrictions

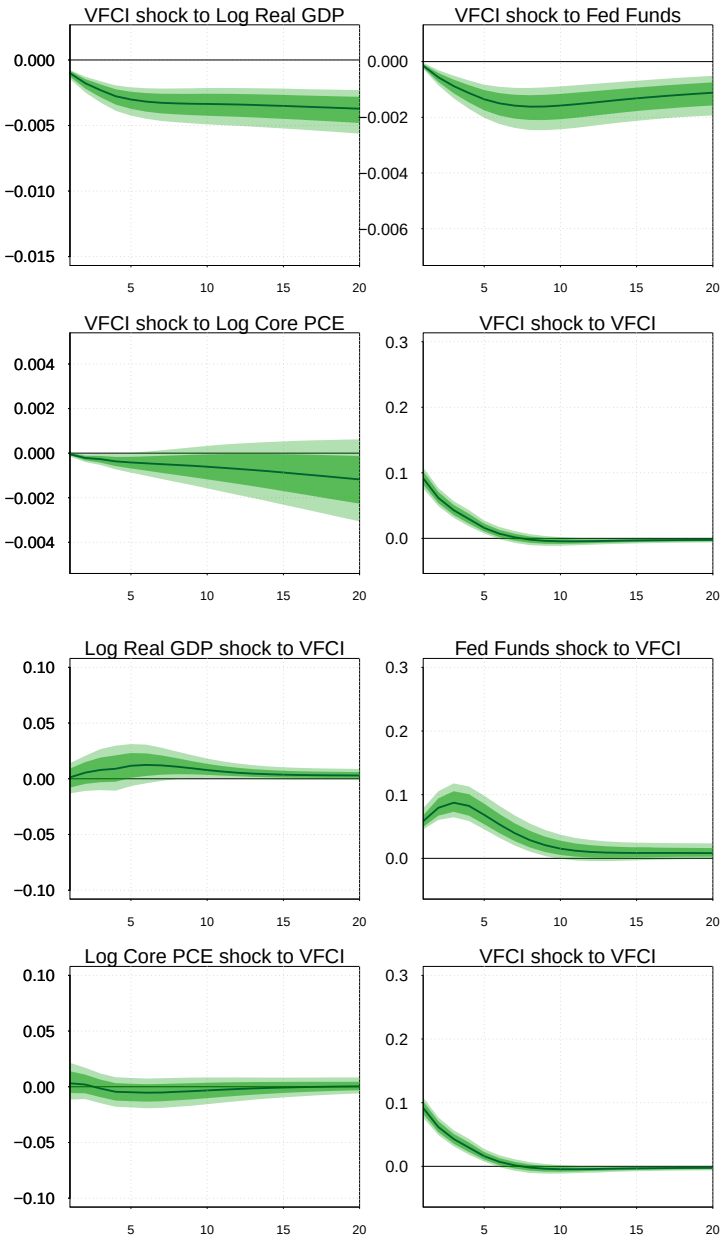
We perform sensitivity analysis by perturbing the baseline set of results for the LP-IV, SVAR-IV, and sign-restricted BVAR models. The causal impact of VFCI shocks on monetary policy and output, and of monetary policy shocks on VFCI, is checked for robustness as follows

- 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

The original conclusions are broadly robust to these changes.

FIGURE IA.1

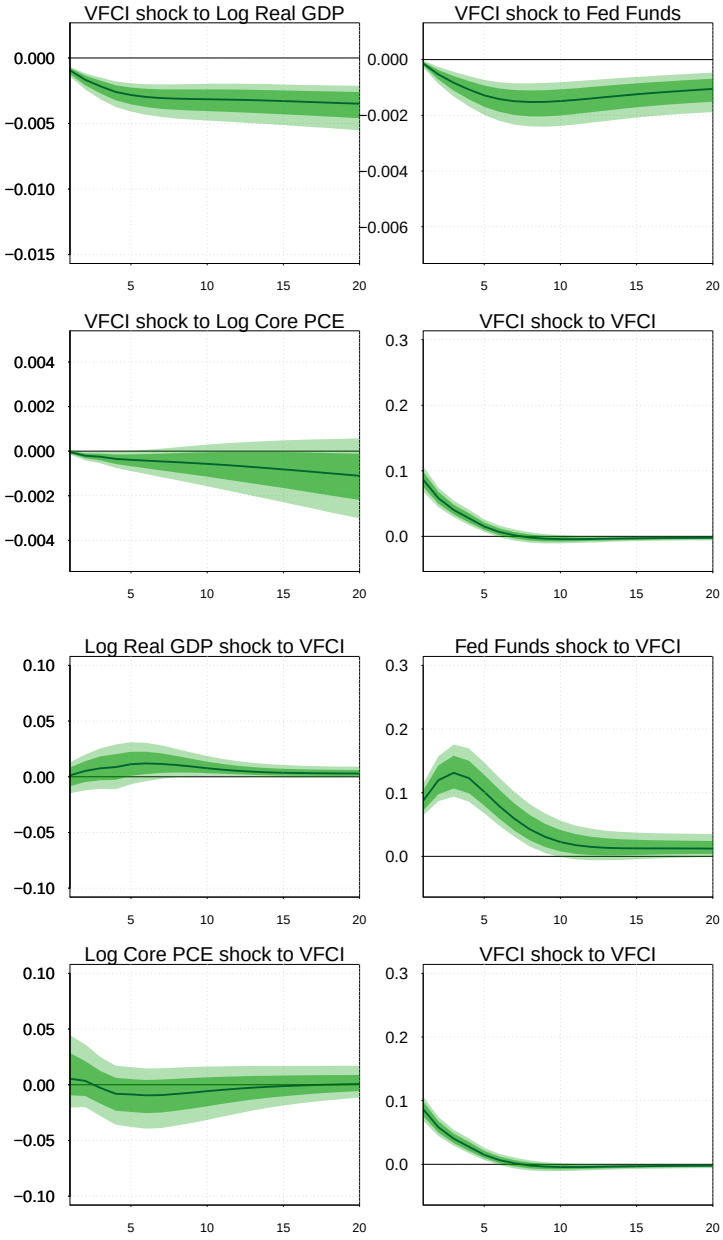
1962Q1-1979Q3 oil crisis and stagflation (subperiod 1) dynamics: VFCI Shocks and Responses



Notes: 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 IA.2

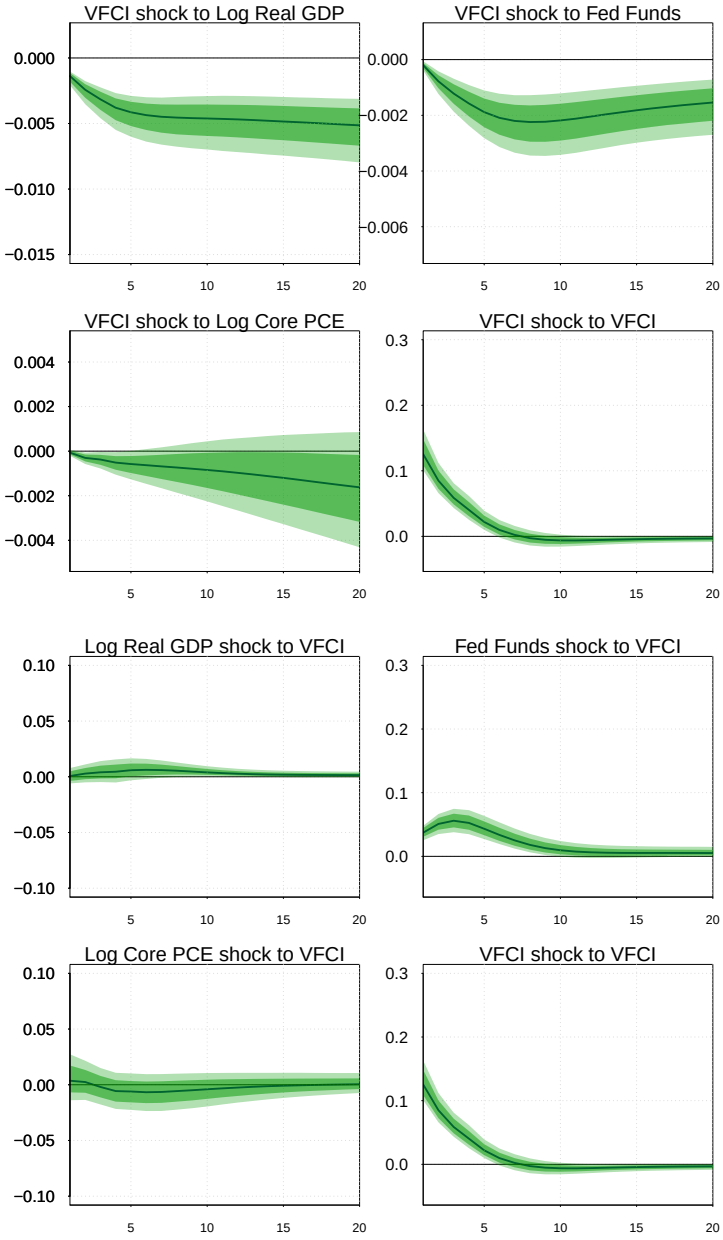
1979Q4-1982Q4 Volcker disinflation (subperiod 2) dynamics: VFCI Shocks and Responses



Notes: 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 IA.3

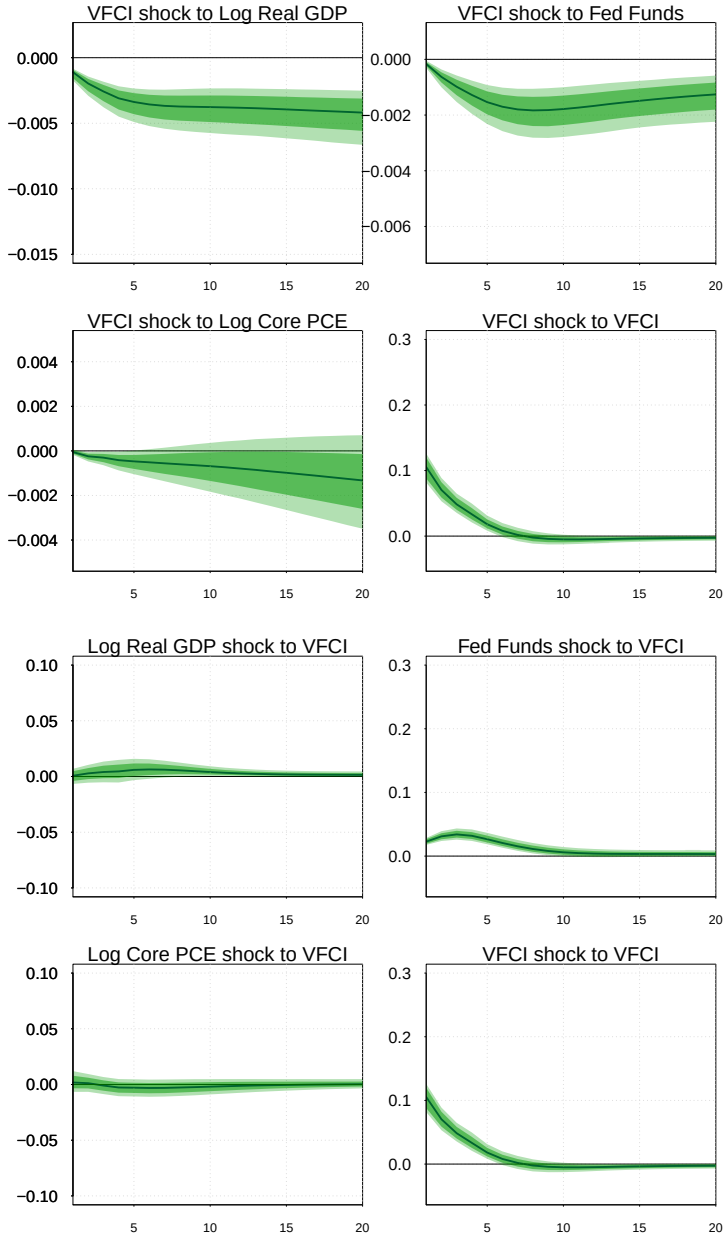
1983Q1-1989Q4 Major S&L crisis defaults (subperiod 3) dynamics: VFCI Shocks and Responses



Notes: 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 IA.4

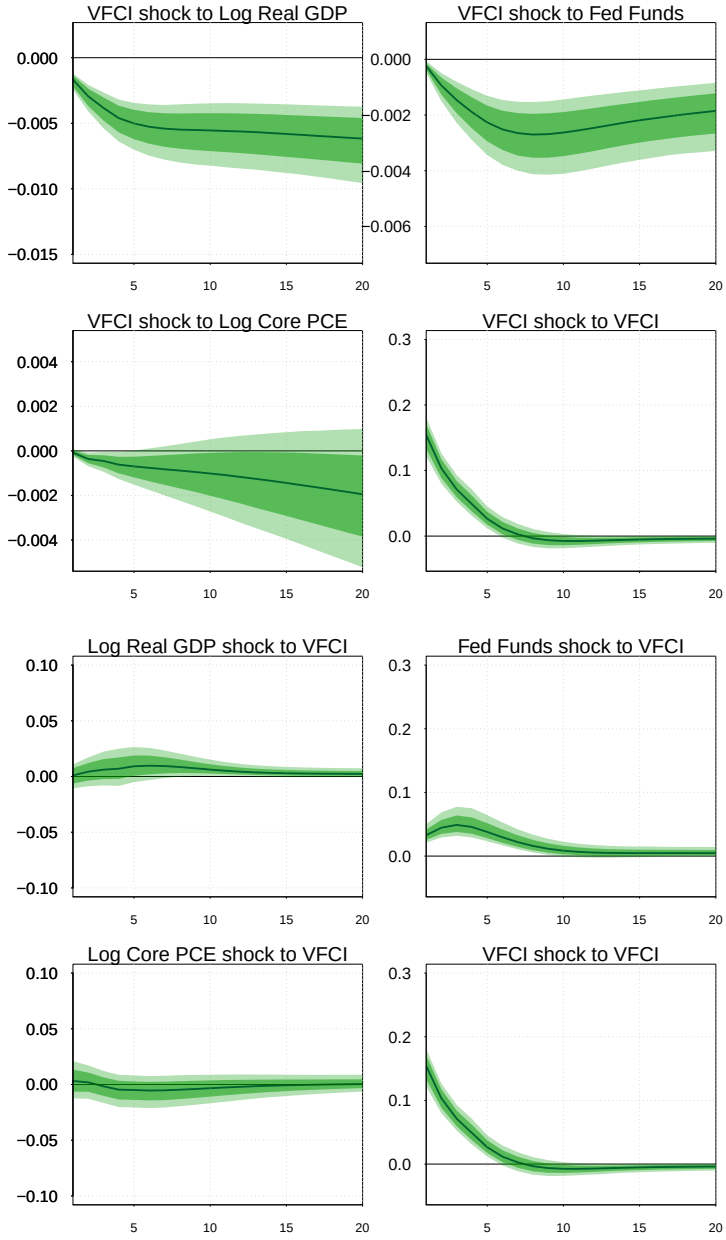
1990Q1-2007Q4 Great Moderation (subperiod 4) dynamics: VFCI Shocks and Responses



Notes: 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 IA.5

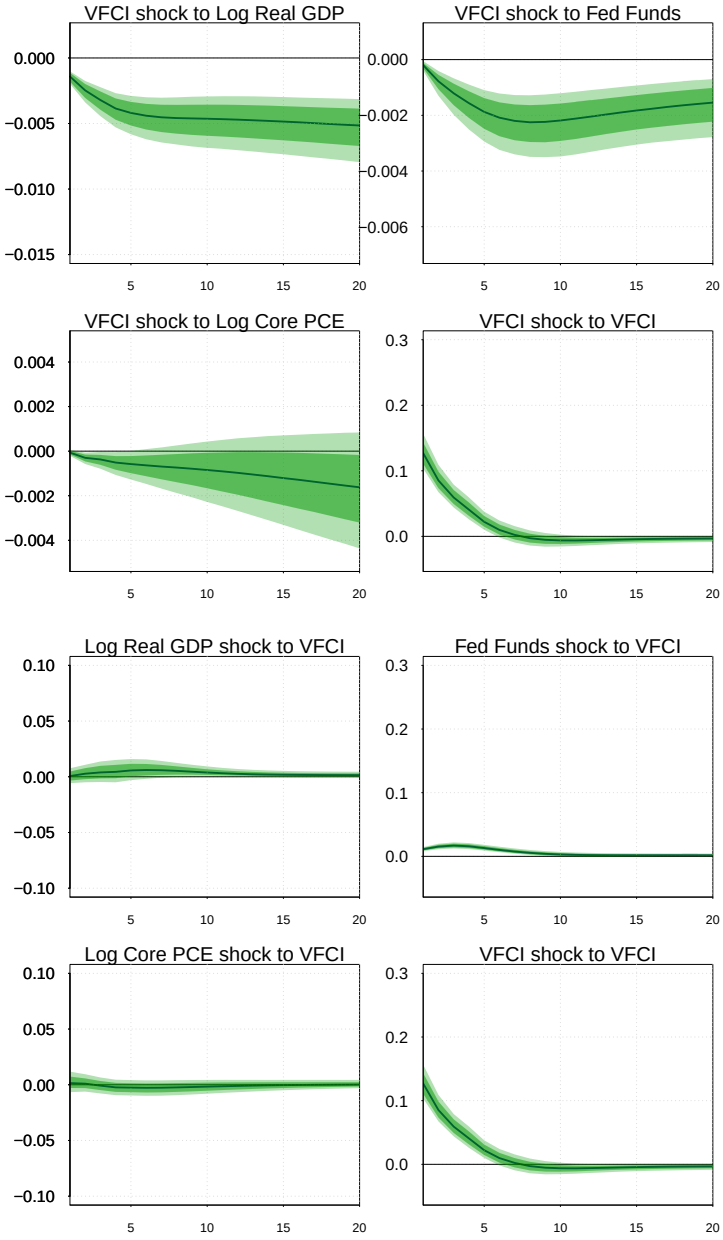
2008Q1-2010Q4 Financial crisis (subperiod 5) dynamics: VFCI Shocks and Responses



Notes: 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 IA.6

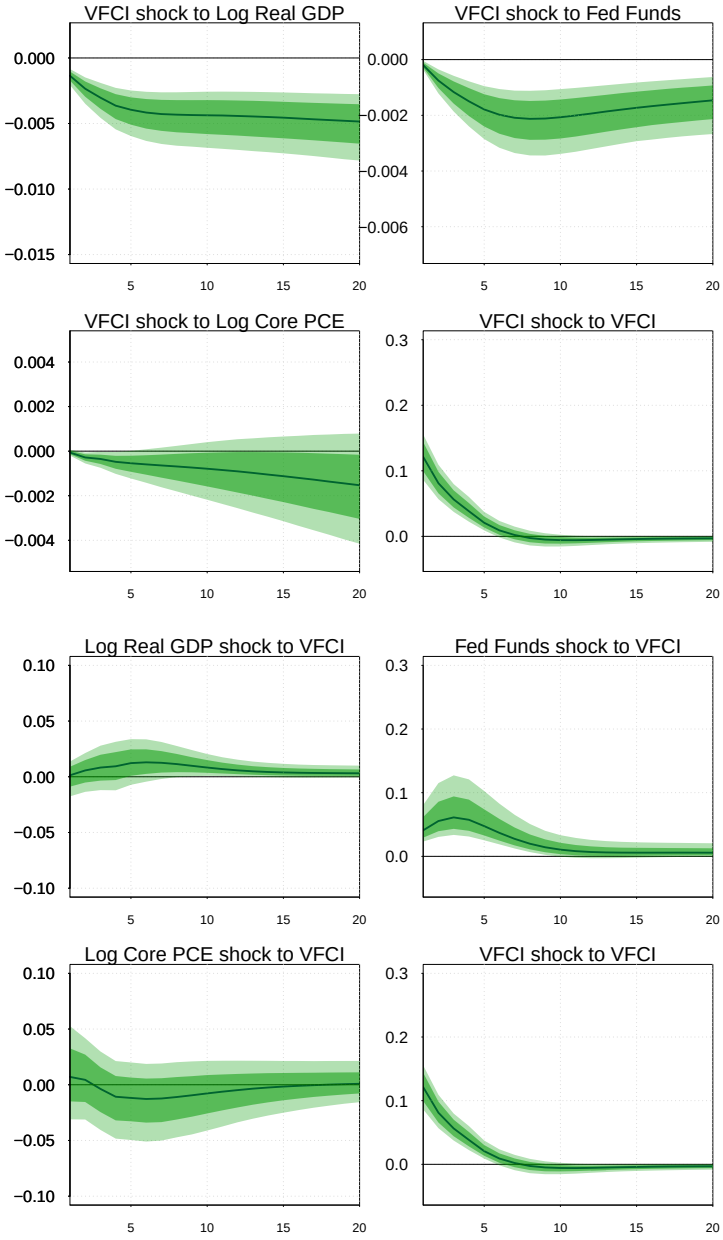
2011Q1-2019Q4 Zero Lower Bound, Recovery from crisis (subperiod 6) dynamics: VFCI Shocks and Responses



Notes: 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 IA.7

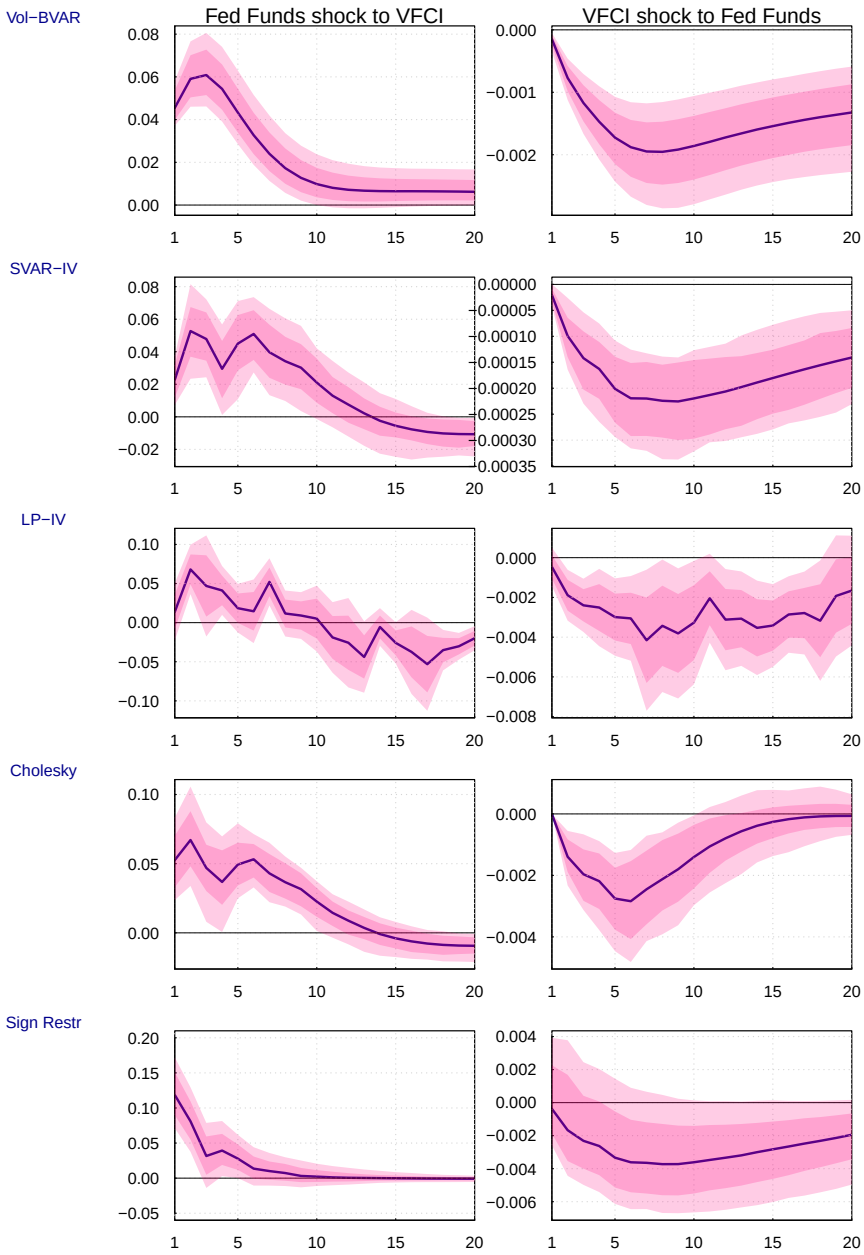
2020Q1-2022Q3 Covid-19 pandemic and war in Ukraine (subperiod 7) dynamics: VFCI Shocks and Responses



Notes: 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 IA.8

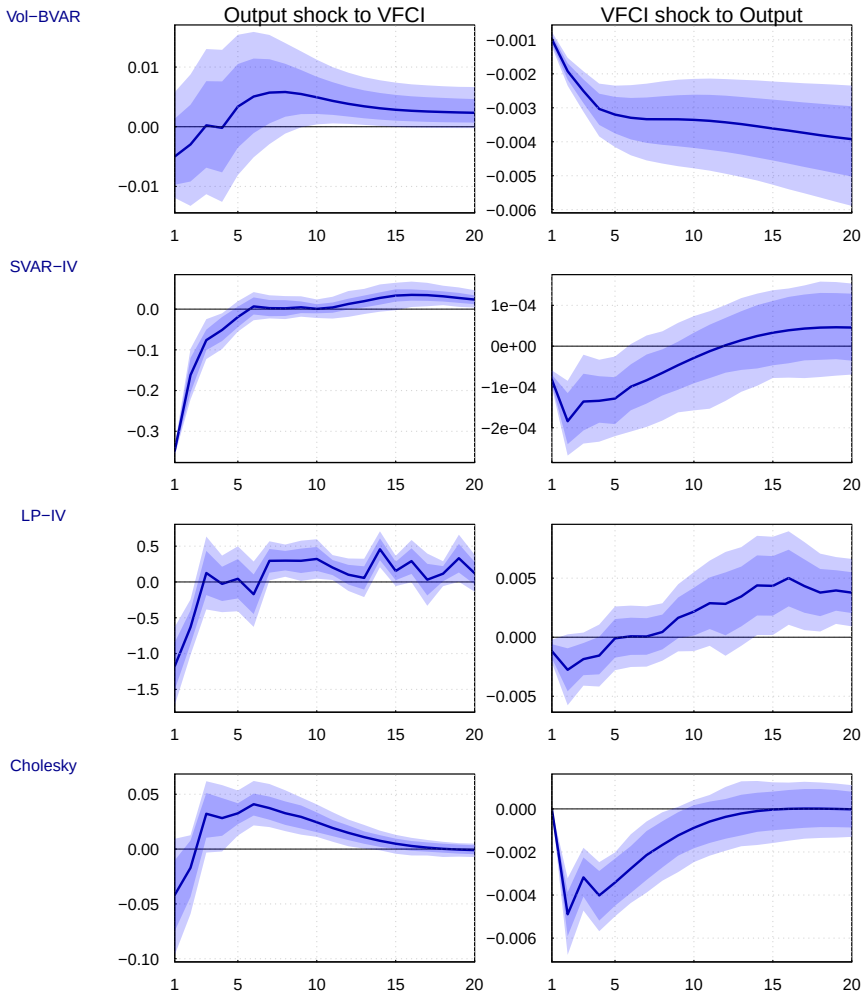
Exponential VFCI - Comparison of Impulse Responses Across Identification Schemes: VFCI and Monetary Policy



Notes: 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 68 percent (dark shade) and 90 percent (light shade) error bands.

FIGURE IA.9

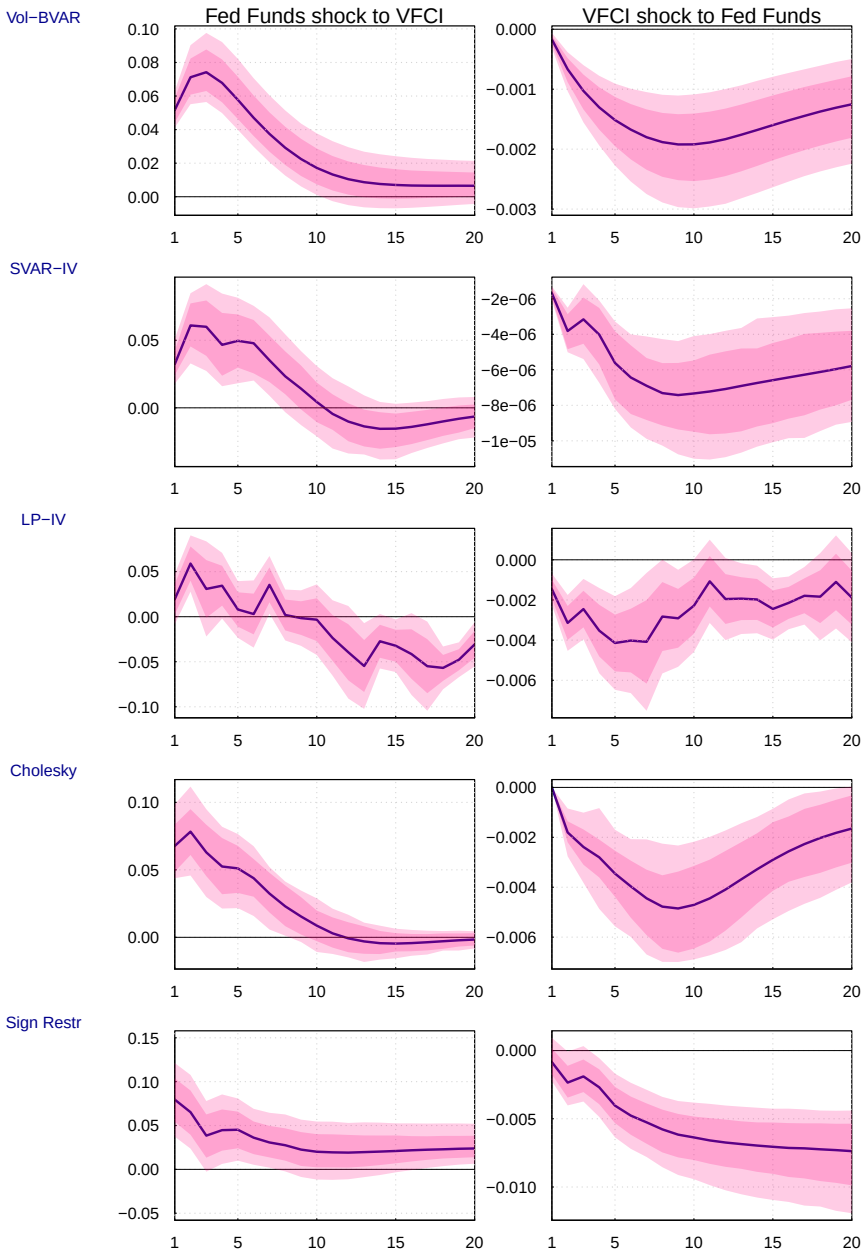
Exponential VFCI - Comparison of Impulse Responses Across Identification Schemes: VFCI and GDP



Notes: Impulse responses to a one standard deviation increase in the GDP and VFCI structural shocks identified through five different identification schemes over 20 quarters, with 68 percent (dark shade) and 90 percent (light shade) error bands.

FIGURE IA.10

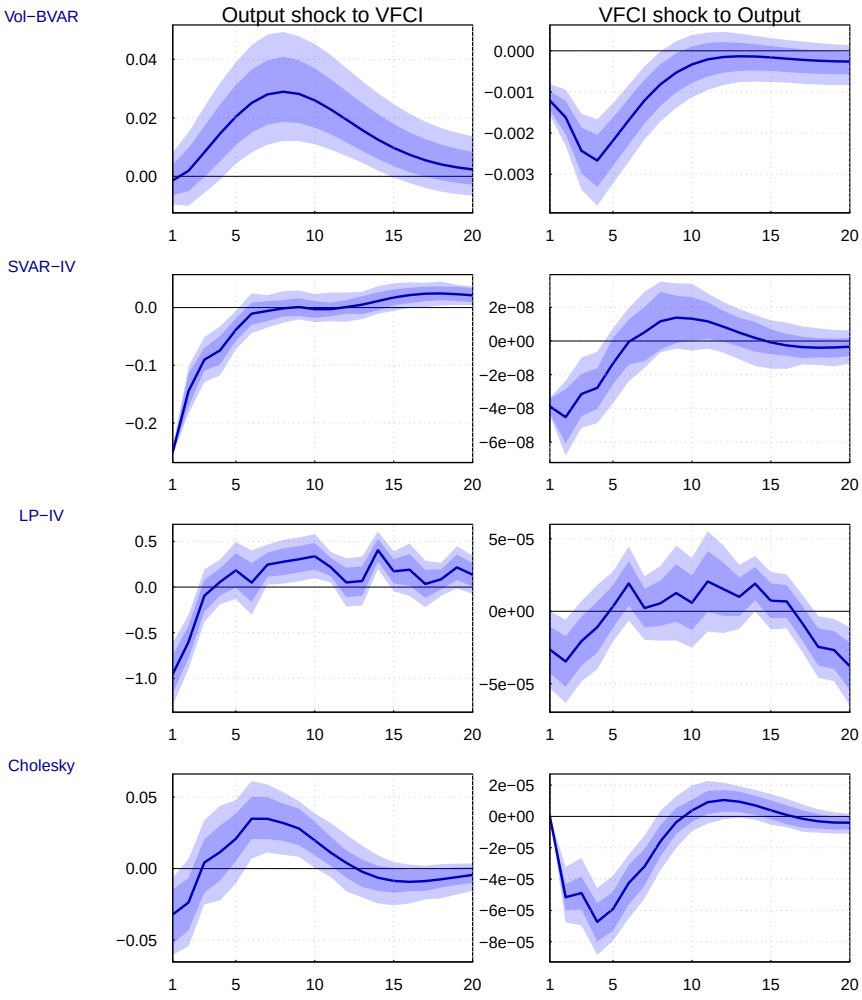
Stationary Models - Comparison of Impulse Responses Across Identification Schemes: VFCI and Monetary Policy



Notes: 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 68 percent (dark shade) and 90 percent (light shade) error bands.

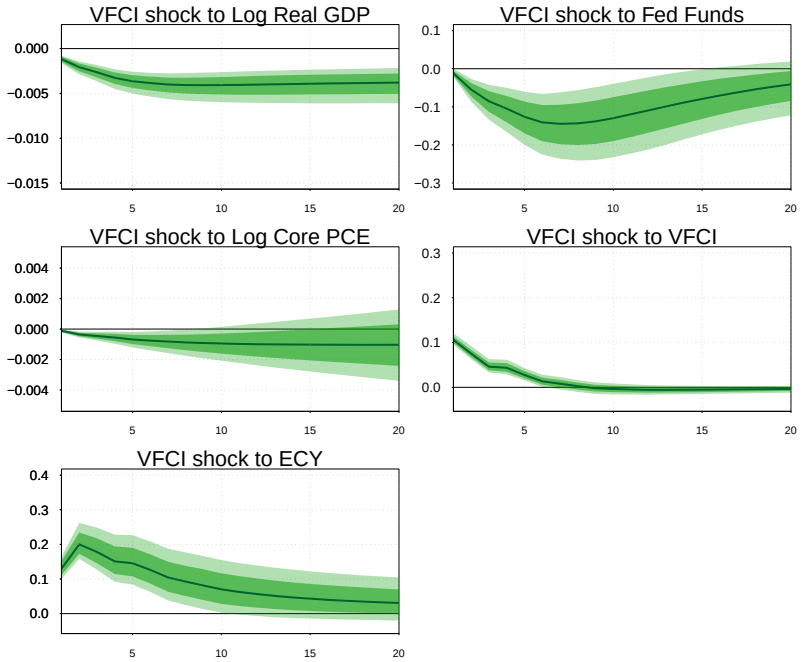
FIGURE IA.11

Stationary Models - Comparison of Impulse Responses Across Identification Schemes: VFCI and GDP



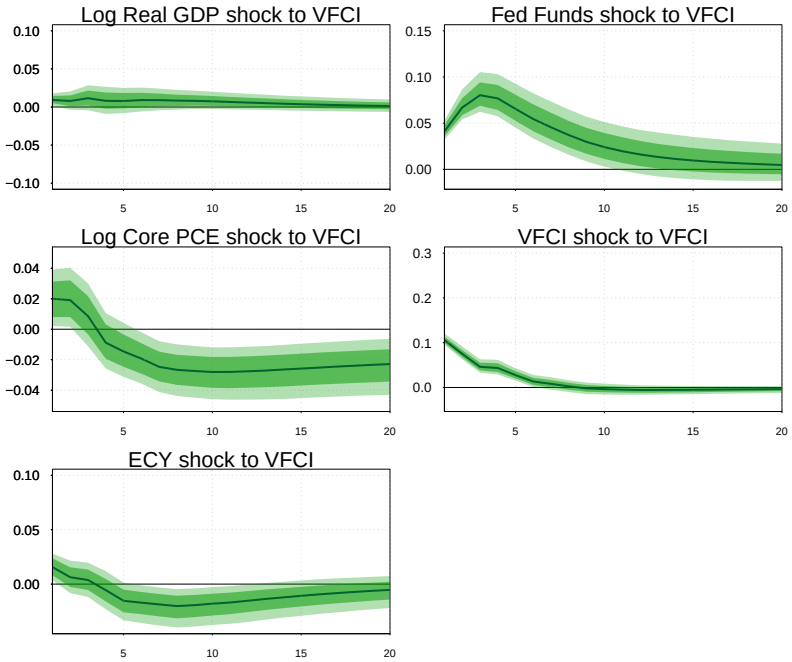
Notes: Impulse responses to a one standard deviation increase in the GDP and VFCI structural shocks identified through five different identification schemes over 20 quarters, with 68 percent (dark shade) and 90 percent (light shade) error bands.

FIGURE IA.12
IRFs: VFCI Shocks with ECY in the Model



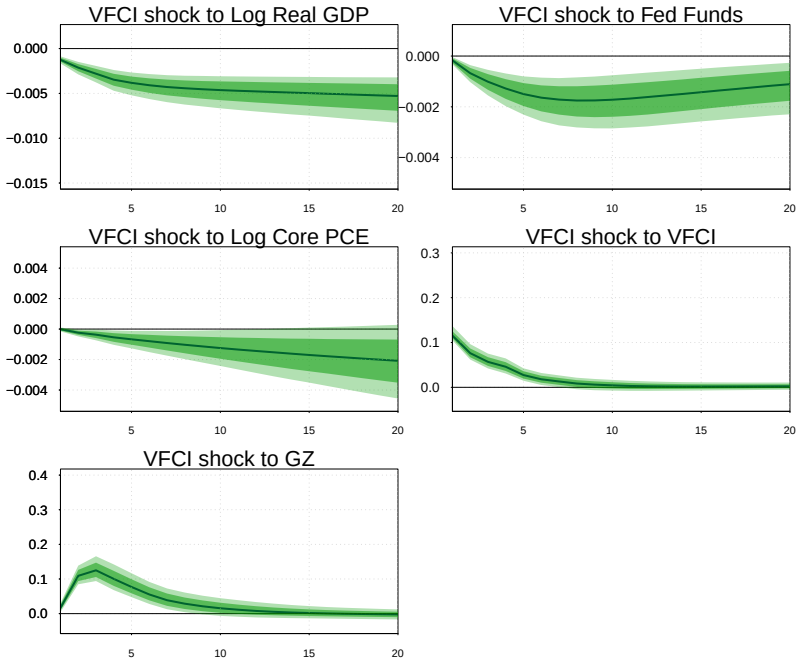
Notes: Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.13
IRFs: VFCI Responses with ECY in the Model



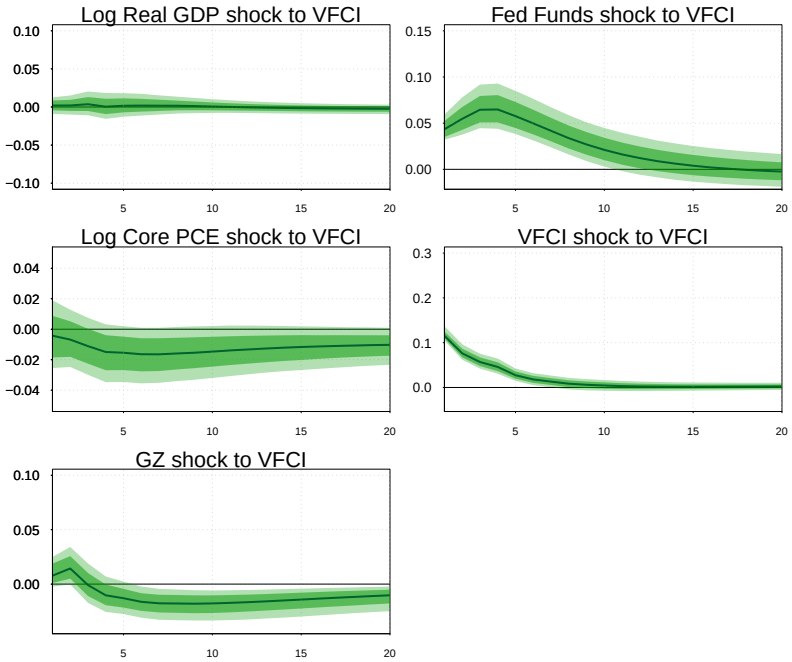
Notes: Impulse responses of VFCI to the four structural shocks in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.14
IRFs: VFCI Shocks with GZ in the Model



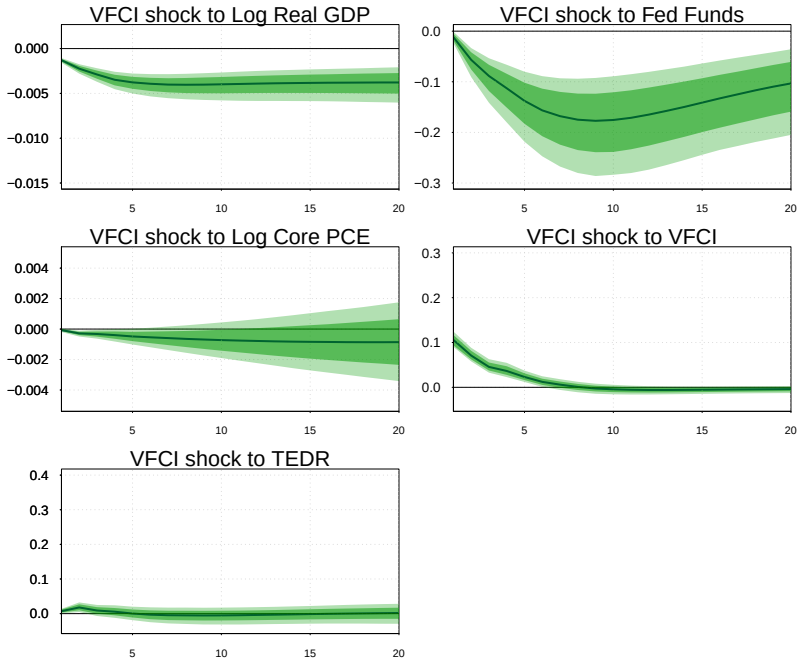
Notes: Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.15
IRFs: VFCI Responses with GZ in the Model



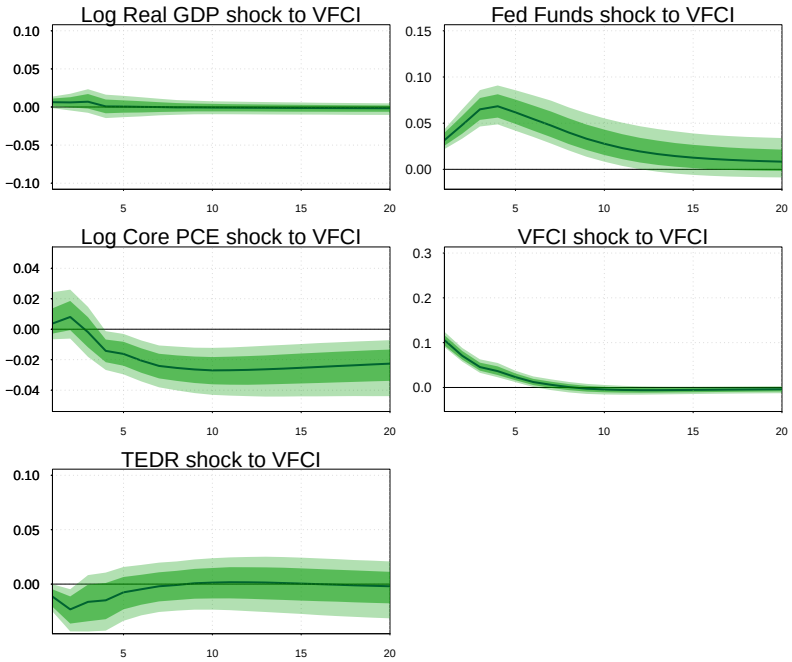
Notes: Impulse responses of VFCI to the four structural shocks in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.16
IRFs: VFCI Shocks with TEDR in the Model



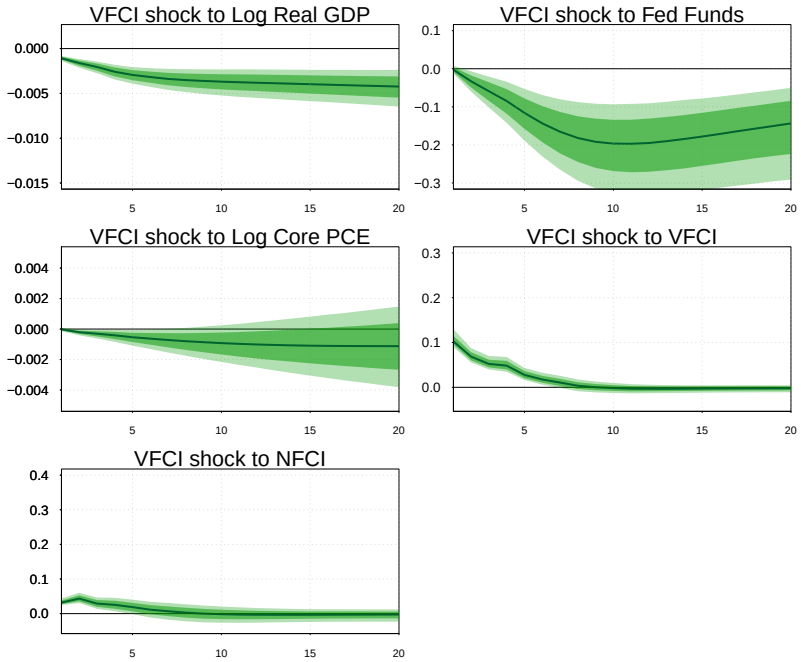
Notes: Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.17
IRFs: VFCI Responses with TEDR in the Model



Notes: 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.

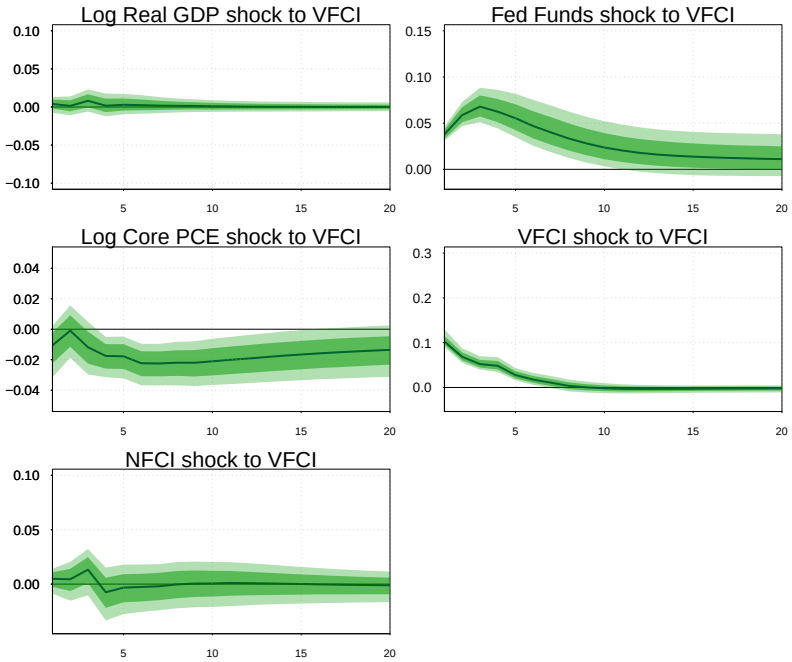
FIGURE IA.18
IRFs: VFCI Shocks with NFCI in the Model



Notes: 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.

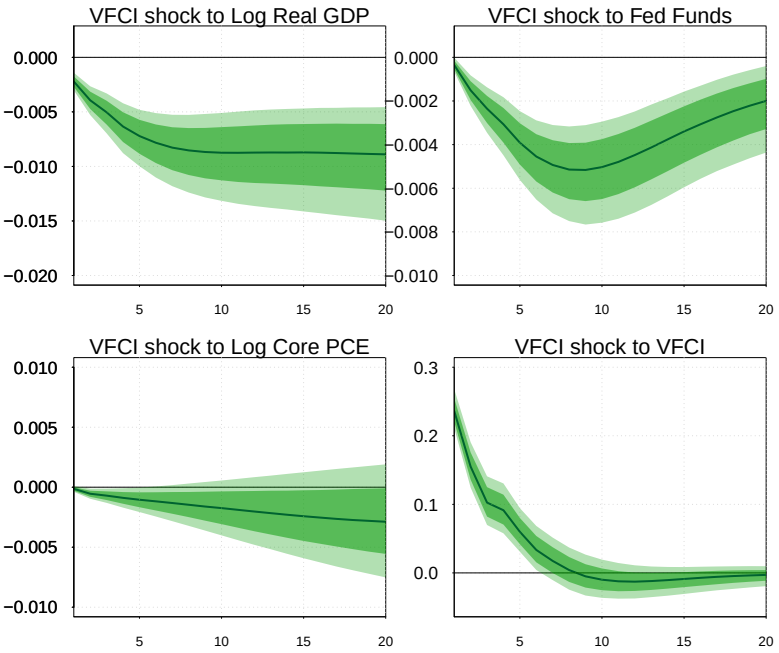
FIGURE IA.19

IRFs: VFCI Responses with NFCI in the Model



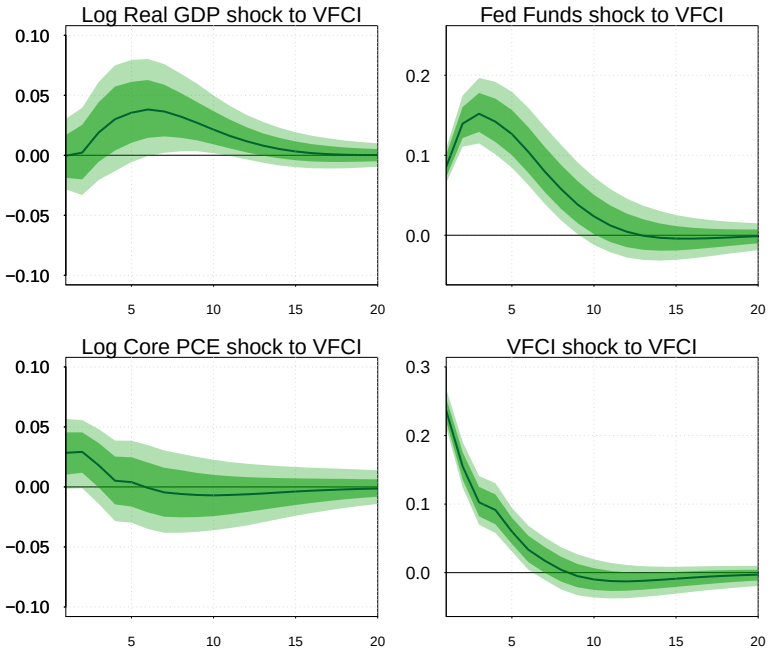
Notes: Impulse responses of VFCI to the four structural shocks in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.20
IRFs: VFCI Shocks with Normal Errors



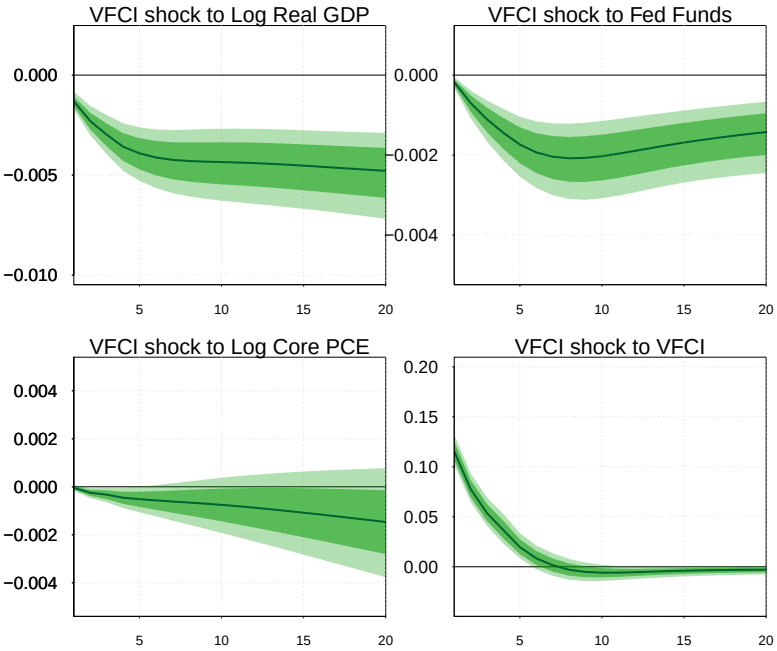
Notes: Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with Gaussian errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.21
IRFs: VFCI Responses with Normal Errors



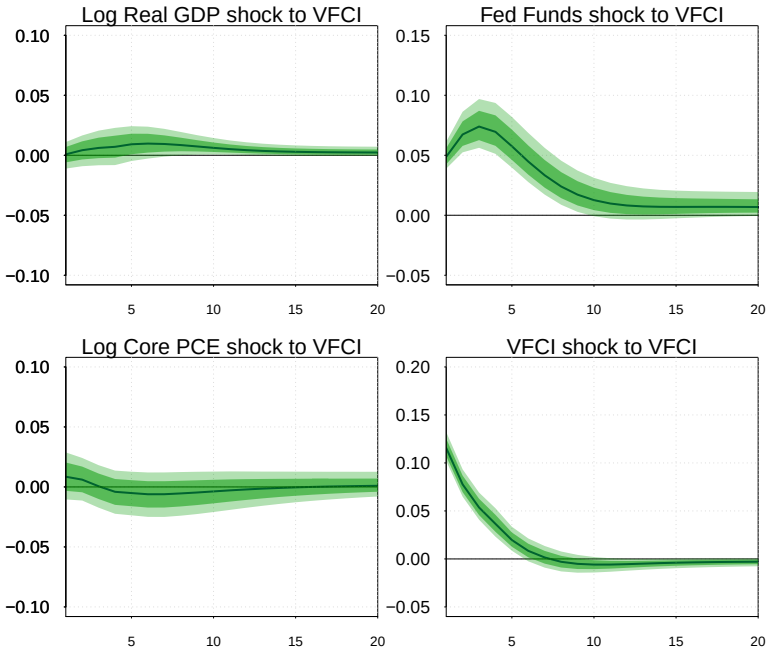
Notes: Impulse responses of VFCI to the four structural shocks in the volatility-identified BVAR model with Gaussian errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.22
IRFs: VFCI Shocks 100k Draws



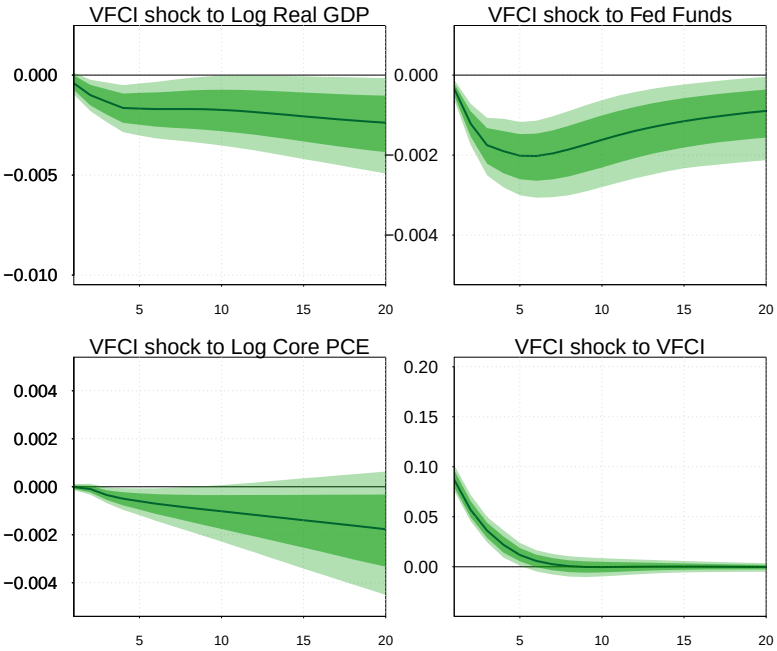
Notes: Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.23
IRFs: VFCI Responses 100k Draws



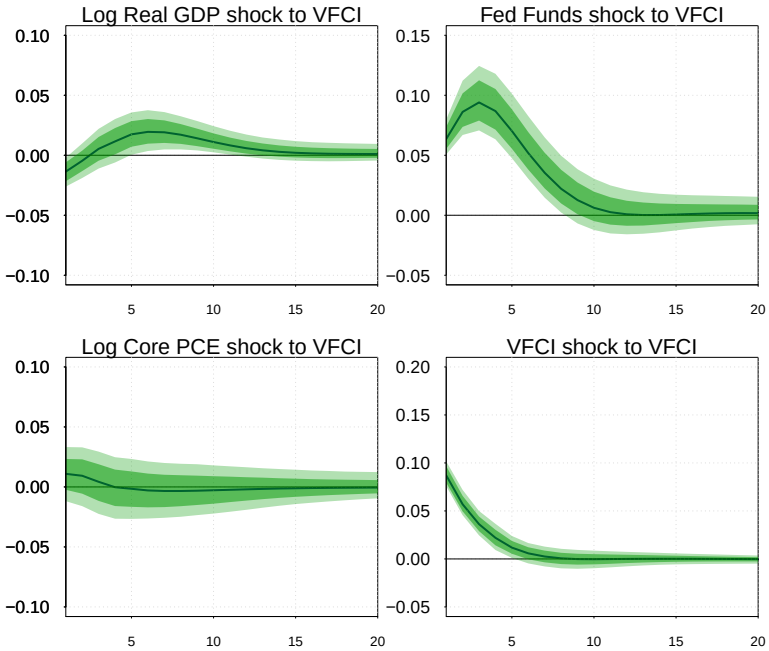
Notes: Impulse responses of VFCI to the four structural shocks in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.24
IRFs: VFCI Shocks Pre-Crises



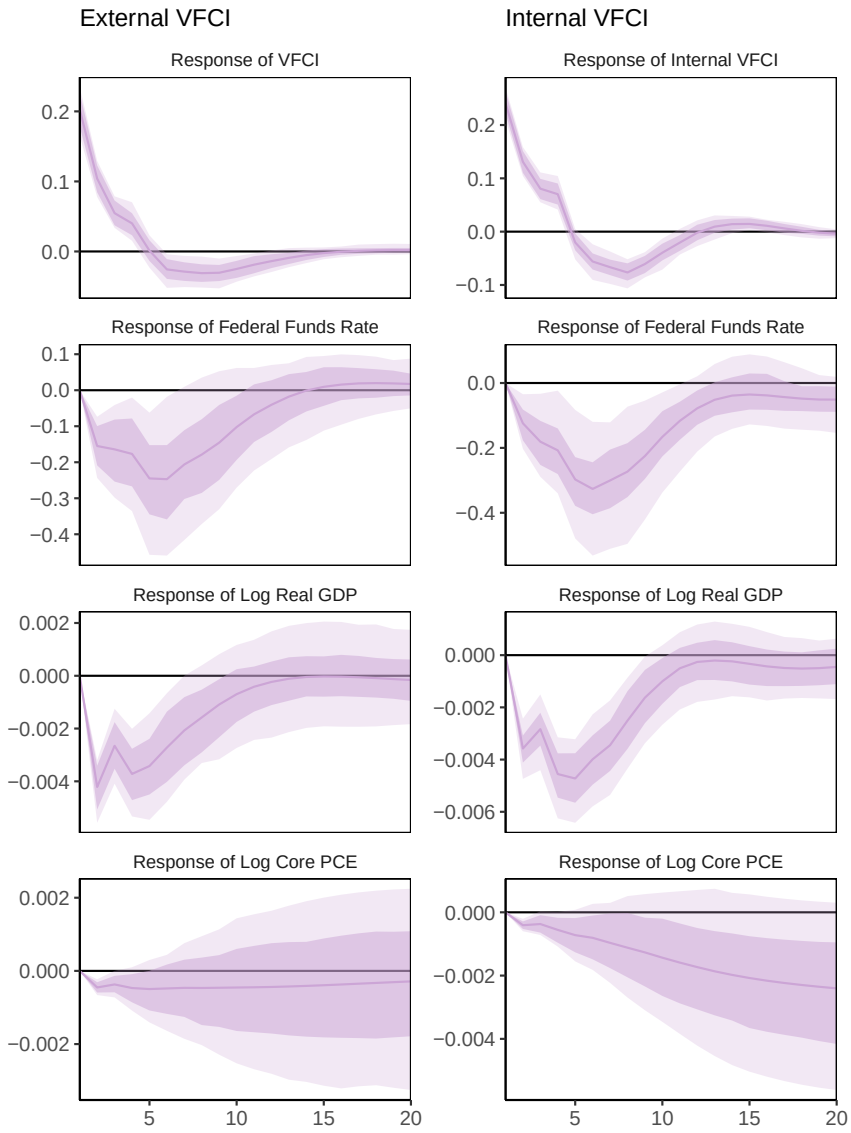
Notes: Impulse responses to the VFCI structural shock in the volatility-identified BVAR model with t-distributed errors over 20 quarters, with 68 percent (dark green) and 90 percent (light green) posterior error bands. Scaled to an "average" period with unit scale.

FIGURE IA.25
IRFs: VFCI Responses Pre-Crises



Notes: 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.

FIGURE IA.26
IRFs: VFCI and Internal VAR VFCI



Notes: Impulse responses to the VFCI structural shock over 20 quarters, with 68 percent (dark purple) and 90 percent (light purple) bootstrapped confidence intervals. The External VFCI is the baseline, with the Internal VFCI estimated using the reduced form residuals of a VAR (log Real GDP, log PCE, and the federal funds rate) and four lags. The IRFs are identified with a Cholesky ordering with the VFCI shock last out of the four variables.