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Beyond Financial Conditions: Measuring Structural Vulnerabilities in the U.S. Financial System

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Abstract

We introduce the Financial Vulnerability Index (FVI), a novel indicator of financial vulnerabilities in the U.S. Unlike financial condition indices, which measure current credit market conditions and spike during periods of financial turmoil, the FVI displays the gradual build-up of structural financial weaknesses and declines as such episodes materialize. We demonstrate that the FVI exhibits properties consistent with theoretical mechanisms of financial vulnerabilities. When the index is high, adverse shocks are substantially amplified, generating larger declines in consumption and investment. We provide new empirical evidence that monetary tightening is associated with gradual declines in the FVI, with this effect substantially delayed, taking a few years to fully materialize. Moreover, monetary policy transmission to prices depends on the state of financial vulnerabilities, with significantly stronger effects when vulnerabilities are low.

JEL: C53, E27, E44, G01

1 Introduction

Following the Global Financial Crisis, a consensus has strengthened around the view that structural weaknesses in the financial system can amplify exogenous shocks, with their impact on the real economy varying according to the intensity of these vulnerabilities. This understanding builds on both pre-crisis (Kiyotaki & Moore, 1997; Bernanke et al., 1999; Krishnamurthy, 2003) and post-crisis theoretical frameworks (He & Krishnamurthy, 2012; Brunnermeier & Sannikov, 2014).

Despite this extensive theoretical work, the empirical literature has focused primarily on measuring financial conditions–a concept related to current credit market tightness rather than structural weaknesses. This paper aims at filling this gap by introducing the Financial Vulnerability Index (FVI), which systematically measures structural financial vulnerabilities.

Figure 1 illustrates how the FVI's behavior differs fundamentally from financial condition indices (FCIs). The FVI (black line) builds up gradually in pre-crisis periods, peaks before crises materialize, and starts declining immediately before FCIs spike—reflecting the reduction of vulnerabilities through deleveraging, reduced risk appetite, and regulatory responses. In contrast, FCIs (red shaded area showing the range across multiple indices) spike during crises alongside the VIX (red line), which captures how investors price risk in real time, reflecting their coincident nature.

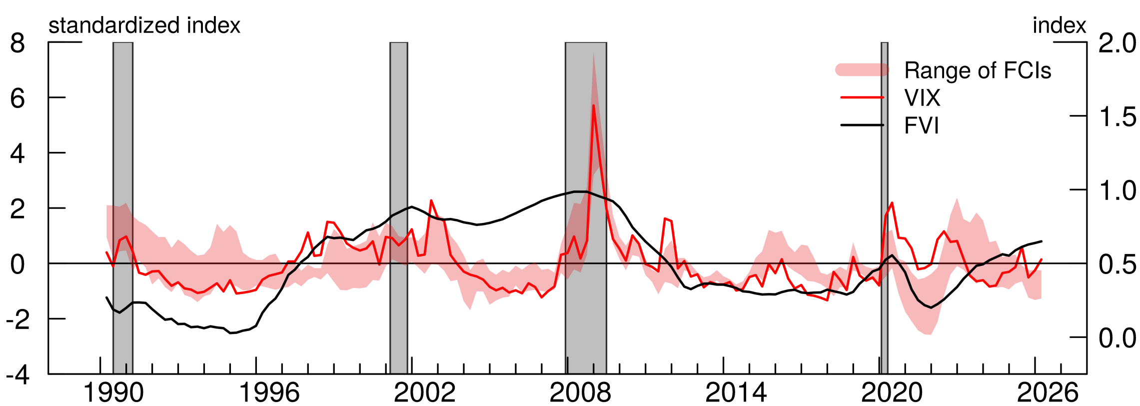


Figure 1: Financial Vulnerability Index and Financial Conditions Indices. Indices are shown as the standard deviation of their own historical distribution 1990-present. The Financial Conditions Indices included in the range of FCIs are: Goldman Sachs U.S. Financial Condition Index (GSUSFCI), Chicago National Financial Conditions Index (NFCI), Financial Conditions Impulse on Growth (FCI-G), Kansas City Financial Stress Index (KCFSI), and the St. Louis Financial Stress Index (STLFSI). On top of this range is the CBOE Volatility Index (VIX) in red and the Financial Vulnerability Index (FVI) in Black.

This divergent behavior stems from how we interpret financial indicators. Although many variables serve as inputs to both FCIs and the FVI, their interpretation often differs markedly.

Low volatility, tight credit spreads, and lenient collateral requirements signal favorable financial conditions, but encourage greater risk-taking and leverage accumulation—heightening vulnerabilities, a phenomenon reflecting the *volatility paradox* of Brunnermeier and Sannikov (2014) and Geanakoplos (2010)'s *leverage cycle*. However, this interpretative divergence across shared variables is not universal: certain metrics such as household, business, and financial leverage measures affect both financial conditions and vulnerabilities in the same direction, with both FCIs and the FVI rising as leverage increases.

Our methodological approach to the construction of the index can shed light on why our index differs from existing ones. First, we select variables based on the Federal Reserve's Financial Stability Report, leveraging the expertise of sector specialists whose mission is to understand whether the current financial system conditions can amplify shocks rather than measuring how easy is to access credit for households and firms. We then group variables according to four vulnerability categories—valuation pressures, household and business borrowing, financial leverage, and funding risk—and aggregate the variables using weights that depend on their ability to predict right-tail unemployment outcomes two years ahead, consistent with empirical evidence that the effect of financial shocks on real activity peaks at this horizon (Jordà et al., 2013; López-Salido et al., 2017; Aikman et al., 2025).[1,2] This process yields four subindices, one for each category. The FVI is a common factor capturing their co-movement, identifying the financial system as vulnerable when multiple categories simultaneously signal heightened risk.

The index depicts intuitively plausible vulnerability patterns: building up before the dot-com bubble and the Global Financial Crisis, declining as crises materialize, improving after pandemic household deleveraging, and rising before the 2023 regional banking stress. To identify which variables drive these patterns in our non-linear framework, we apply Shapley values (Shapley et al., 1953)—a decomposition method adopted for machine learning models (Borup et al., 2022). We further demonstrate the FVI's distinct temporal properties by characterizing vulnerability patterns during the Global Financial Crisis relative to the widely-used NFCI. Following Adrian et al. (2019), we estimate quantile regressions of future GDP growth. The FVI exhibits stronger relationships to medium-term tail outcomes (1.5 to 2 years ahead), while the NFCI exhibits stronger short-horizon relationships, confirming their complementary nature: the FVI as a measure of structural vulnerabilities, the NFCI as a coincident measure of financial stress.

[1]This four-category framework used in the Federal Reserve's Financial Stability Report is similar to categorical frameworks employed by the Bank of England, European Central Bank, IMF, and Bank for International Settlements. See e.g., Bank of England Financial Stability Report and IMF Global Financial Stability Report.

[2]This approach aligns with the FSR's stated mission: "*in an unstable financial system, adverse events are more likely to result in severe financial stress and disrupt the flow of credit, leading to high unemployment and great financial hardship.*" Financial Stability Report, May 2022.

We further examine whether the index exhibits amplification properties consistent with theoretical mechanisms of financial vulnerabilities. We estimate state-dependent local projections and show that when the FVI is high, adverse business cycle shocks generate deeper contractions in consumption and investment, consistent with the FVI capturing economically meaningful amplification mechanisms.

Having established the statistical and the macroeconomic properties of FVI, we investigate the response of our index to a monetary policy shock. How financial vulnerabilities respond to monetary policy is a largely unexplored empirical question, yet the answer can inform the debate about preemptive monetary tightening to address financial stability concerns.[3] We show that tightening has no impact effect, but is associated with gradual declines in the FVI over time, with sizable and significant effects after 2 years. This result is consistent with the view that preemptive monetary policy tightening may be associated with declining vulnerabilities, though these effects are considerably lagged. In contrast, the response of the NFCI shows an immediate and short-lived tightening in financial conditions, highlighting once again that the two indices capture fundamentally different concepts.

Finally, we explore how financial vulnerabilities interact with monetary policy by estimating state-dependent IRFs to a monetary policy shock when the FVI is high versus low. We find that when vulnerabilities are low, monetary policy transmission to prices is stronger, with the price level declining more in response to a tightening. We show that this result is mainly driven by the non-financial leverage subcomponent of the index, suggesting that when private leverage is already high, borrowing decisions become less sensitive to interest rate adjustments, thereby attenuating the overall effects of monetary policy on the economy.

Our work contributes to several strands of literature. First, we complement the financial conditions index literature (Brave et al., 2012; Hatzius et al., 2010; Koop & Korobilis, 2014; Ajello et al., 2023) by providing a vulnerability measure with distinct cyclical properties. While FCIs capture current financing ease, our vulnerability measure exhibits patterns associated with future tail risk. Second, we relate to the crisis indicator literature that identifies precursors to financial crises (Schularick & Taylor, 2012; Jordà et al., 2013). Our contribution lies in systematically integrating regulatory expertise with statistical methods to construct a comprehensive, replicable vulnerability measure. Third, we contribute to the growth-at-risk literature (Adrian et al., 2019) by demonstrating that financial vulnerabilities—not just current conditions—are critical determinants of macroeconomic tail risk. Finally, our state-dependent transmission results connect to research on financial accelerators and nonlinear macro-financial linkages (Bernanke et al., 1999; Brunnermeier

[3]See for example: Bernanke (2002, 2015); Yellen (2014); Svensson (2015, 2017, 2016); Gourio et al. (2018)

& Sannikov, 2014).

The remainder of the paper is organized as follows. Section 2 describes the data selection process. Section 3 presents the statistical model, the estimation strategy and briefly discusses the historical decomposition through Shapley values. Section 4 reports the historical evolution of the FVI and its components and characterizes its temporal patterns during the GFC compared to the NFCI. Section 5 examines whether the FVI exhibits amplification properties by analyzing state-dependent responses to adverse business cycle shocks. Section 6 investigates the responses of the index to a monetary policy shock and shows that FVI can significantly alter the transmission of monetary policy to prices. Section 7 concludes.

2 Data

We construct our dataset from the Federal Reserve's quarterly financial stability monitoring framework, which provides the analytical foundation for the semi-annual Financial Stability Report (FSR). The Federal Reserve conducts detailed vulnerability assessments across different dimensions of the financial system, with specialized monitoring of household and business leverage, banking sector vulnerabilities, dealer and non-bank financial intermediation, funding risks, asset valuations across multiple markets, and emerging vulnerabilities in areas such as private credit and new technologies. The number and scope of these monitoring areas evolve over time to reflect changes in the financial system structure and emerging risks.

These monitoring activities map to the four vulnerability categories emphasized in the FSR: *Valuation Pressures*, which incorporates measures from monitoring asset valuations across equity markets, corporate bonds, real estate (both residential and commercial), and leveraged credit markets. Variables include price-to-fundamental ratios, risk premia, credit spreads, and indicators of risk appetite in private credit markets. *Household and Business Borrowing*, which draws on monitoring household leverage, nonfinancial business leverage, and leveraged lending. This includes measures of debt relative to income or GDP, debt service burdens, lending standards from bank surveys, and the prevalence of riskier borrowing structures such as covenant-lite loans or high-risk consumer credit. *Financial Leverage*, which aggregates information from monitoring vulnerabilities across diverse financial intermediaries: banking system capital and leverage ratios, dealer balance sheet metrics, insurance sector vulnerabilities, housing GSE exposures, and measures of leverage in non-bank financial institutions. These variables capture the capacity of the financial sector to absorb losses and continue intermediating credit. *Funding Risk*, which combines measures from monitoring short-term funding and maturity transformation, securitization and risk transformation, foreign dollar funding vulnerabilities, asset management industry structures, and central counterparty exposures. Variables include runnable liabilities, maturity mismatches, repo market dynamics, and measures of liquidity risk across financial institutions.

We extract all time series appearing in charts and tables across four consecutive editions of the internal monitoring framework, yielding 342 non-overlapping series. Each series is counted once even if it appears in multiple editions or monitoring areas. This initial dataset represents the comprehensive set of financial indicators that are actively monitored by Federal Reserve staff for vulnerability assessment.

2.1 Variable Selection

From this initial set of 342 variables, we select a final dataset that avoids redundancy, ensures data quality, and appropriately weights different sectors of vulnerability assessment. The selection proceeds in two stages: expert consultation followed by statistical filtering.

We conduct structured interviews with Federal Reserve staff responsible for monitoring each area of financial stability. Areas covered by multiple analysts (for example, asset valuation monitoring includes separate expertise for equity markets, corporate bonds, government bonds, and international markets) involves consultations with all contributing experts. In total, we consulted with subject matter experts across all monitored vulnerability dimensions.

The consultation follows a semi-structured interview protocol designed to elicit both quantitative assessments and qualitative insights:

1. *Is this variable regularly monitored or issue-specific?* This distinguishes between core monitoring variables and those tracked only in response to specific events.

2. *How important is this variable for assessing vulnerabilities in your area?* Experts rate each variable on a three-point scale: 1 (not important), 2 (worth monitoring), 3 (very important).

3. *How do you use this variable in your analysis?* This open-ended question clarifies the role of each variable in the vulnerability assessment framework.

4. *Are there other variables that provide similar information?* For redundant indicators, we ask experts to identify which variable best capture the underlying concept.

We retain variables that receive an importance rating of 2 or higher, indicating they are worth monitoring for vulnerability assessment. When multiple variables capture similar concepts, we defer to subject matter expert judgment to select the most informative indicator. This consultation scales our dataset down from 342 to 176 variables.

The second stage of variable selection applies three statistical criteria to ensure data quality and conceptual coherence. First, we require at least 10 years of quarterly observations for each variable. This threshold ensures sufficient data for reliable quantile regression estimation while recognizing that some important vulnerability indicators (e.g., certain post-crisis regulatory metrics) become available only after the Global Financial Crisis.

Second, variables subject to definition changes that induc structural breaks are either truncated (retaining only the post-break segment if it exceeds 10 years) or excluded. For example, regulatory reporting changes that alter the construction of a financial ratio trigger truncation or exclusion depending on the resulting sample length.

Third, we ensure that each variable's predictive relationship with economic stress aligns with theoretical expectations about vulnerabilities. Subject matter experts first determine how each variable should relate to tail risk based on economic wisdom. For example, measures of household or business leverage should predict elevated tail risk, while measures of capital adequacy or liquidity buffers should predict lower risk. We then test these theoretical predictions empirically using quantile regression methods (detailed in Section 3). Variables whose estimated relationships with future high unemployment contradict expert interpretation are excluded, ensuring our final dataset captures theoretically coherent vulnerability measures. These three filters reduce our dataset from 176 to 39 variables.

2.2 Sample Construction

Following Basel III guidance on the credit-to-GDP gap, we detrend ratios of debt aggregates to income or GDP using a two-sided HP filter with smoothing parameter $\lambda = 400,000$ (the Basel III standard for quarterly data). Specifically, we detrend: (1) total nonfinancial debt to GDP (`cred_gdp`), (2) household mortgage debt to GDP (`mort_gdp`), (3) consumer credit held by riskier borrowers to disposable personal income (`concred_dpi`), and (4) gross short-term wholesale debt of the financial sector to GDP (`gross_debt_gdp`). In contrast, the other variables in our dataset are used in levels.

This selective approach to detrending balances three considerations. First, detrending reflects how practitioners actually monitor these ratios. Second, and for the same reason experts filter them this way, credit aggregates relative to income or output exhibit strong trends driven by financial deepening and structural change; detrending isolates the cyclical component most relevant for vulnerabilities. Third, other financial variables, particularly those reflecting regulatory regimes or market pricing mechanisms, are more naturally interpreted in levels.

Before estimation, we standardize each variable by subtracting its full-sample mean and dividing by its full-sample standard deviation. This normalization ensures that variables with different scales contribute comparably to the estimated factors. Our dataset spans 1990:Q1 to 2025:Q4. While most variables are available from the start of the sample, some series—particularly those related to post-crisis regulatory reforms or recently monitored vulnerabilities—begin later. We handle missing data as follows. In the first-stage quantile regressions that estimate variable weights (Section 3.1), estimation begins when each variable's data become available—no imputation is performed. In the second-stage dynamic factor model aggregation (Section 3.2), we employ the Expectation-Maximization algorithm of Bańbura and Modugno (2014), which accommodates missing observations in an unbalanced panel by conditioning factor estimates on available data at each point in time. This approach allows us to incorporate all 39 variables while respecting their actual availability.

Table A.1 in the appendix lists all 39 variables, their definitions, estimated weights as of June 2025, and their assignment to vulnerability categories.

3 Model

This section describes the statistical model, the estimation strategy and the historical decomposition of the index using shapley values.

We construct the FVI in two stages. First, we aggregate variables into four subindices, each corresponding to one of the areas of vulnerability tracked in the FSR. Second, we aggregate the four subindices into the aggregate FVI.

3.1 Construction of Subindices

We cluster variables into four groups ($j = 1, ..., 4$), according to the section of the FSR in which they appear: valuation pressures, nonfinancial leverage, financial leverage and funding risk. Accordingly, we construct a subindex for each category of vulnerability.

To construct the subindices, we employ the Quintile Factor Model proposed by Giglio et al. (2016). Let y_{t+h} be a target macroeconomic indicator observed h periods ahead and I_t the information set including the financial variables in the four groups, $\mathbf{x}_t^j$, and other observables $\mathbf{g}_t$. We assume that the α-th quintile of y_{t+h} can be written as a linear combination of four latent factors z_t^j, and observable variables $\mathbf{g_t}$:

$$Q_\alpha(y_{t+h}|I_t) = \delta \mathbf{z_t} + \kappa \mathbf{g_t} \tag{1}$$

where $\mathbf{z_t}$ is a vector collecting subindices values z_t^j at time t, while δ and κ are vectors of coefficients.

We further assume that the financial variables in group j, $\mathbf{x}_t^j = \{x_{1t}^j, ...x_{n_jt}^j\}$, depend linearly on the corresponding latent factor z_t^j:

$$\mathbf{x}_t^j = \theta^j z_t^j + \iota_t^j \tag{2}$$

where $\iota_t^j \sim \text{iid}(\mathbf{0}, \mathbf{\Sigma}_j)$ is a vector of idiosyncratic components with $\mathbf{\Sigma}_j$ being a diagonal covariance matrix, ensuring the components are mutually uncorrelated.

Relative to the setup of Giglio et al. (2016)—in which the α-th quantile, $Q_\alpha(y_{t+h}|I_t)$, is modelled as a function of a unique latent factor common to all variables—we express the conditional quantile as a combination of four distinct latent factors, each extracted from the corresponding group of variables, and control variables in $\mathbf{g_t}$.

We select the change in unemployment over h periods ahead as our target variable y_{t+h}, in alignment with the Federal Reserve's fundamental objective in monitoring financial stability—preventing economic downturns that lead to the disruption of the labor market.[4]

We choose $h = 8$, so to target changes in the unemployment rate 2 years ahead. We ground this decision on the empirical evidence that the effect of financial shocks on unemployment peaks after 8 quarters (Jordà et al. (2013),López-Salido et al. (2017),Aikman et al. (2025)). Furthermore, we choose $\alpha = 0.8$, focusing on the relationship between each variable and changes in unemployment above the 80^{th} percentile of its historical distribution. This choice balances the conceptual benefit of emphasizing extreme unemployment realizations and the efficiency cost of excluding too many observations.

Interpreted through the lenses of the model, a financial vulnerability is an unobserved component common to a group of financial variables $\mathbf{x}_t^j$. In turn, this component is a predictor of future realizations of unemployment which fall in a specific area of its distribution.

To estimate the factors z_t^j from variables in $\mathbf{x}_t^j$, we use the Partial Quintile Regression (PQR) estimator of Giglio et al. (2016), which extends the Partial Least Squares to the quantile regression framework. The estimation consists of two steps. First, for each variable i in the dataset, we estimate the following quantile regression (Koenker & Bassett, 1978):

$$y_{t+h} = \gamma_\alpha^i + \theta_\alpha^i \, x_{it} + \beta_{1,\alpha}^i \, NFCI_t + \beta_{2,\alpha}^i \, y_t + e_{t+h} \tag{3}$$

[4]

> *—In an unstable financial system, adverse events are more likely to result in severe financial stress and disrupt the flow of credit, leading to high unemployment and great financial hardship.—*
>
> Financial Stability Report, May 2022

where $y_{t+h} = u_{t+h} - u_t$—-with u_t being the unemployment rate—-and with the restriction

$$Q_\alpha(e_{t+h}|x_{it}, NFCI_t, y_t) = 0,$$

meaning that the α-th quantile of the error term conditional on all regressors equals zero. We include the NFCI and the contemporaneous 2-year change in unemployment as controls, broadly capturing the credit and the business cycles, but each serves a distinct purpose. Conditioning on the NFCI—a coincident measure of financial stress—ensures that θ^i_α isolates the *marginal* predictive content of each variable for future tail unemployment, over and above current financial conditions, rather than comovement with contemporaneous market stress. Conditioning on the current 2-year change in unemployment absorbs labor-market momentum and mean reversion, so that the estimated elasticities are not driven by the mechanical persistence of the unemployment process itself. The object of interest in the above regression are the coefficients θ^i_α, which capture the quantile semi-elasticities of large increases in unemployment 2 years ahead to each variable.

The second stage consists in estimating T cross-sectional covariance between each variable i in $\mathbf{x}^j_t$ and θ^i_α, separately for each subindex j. This covariance is an estimate of the latent factor z^j_t, which we obtain as a linear combination of the regressors weighted by their coefficients, θ^j.

In Table A.1, we report estimates of weights θ^i_α and their t-stats, as of June 2025.

3.2 Aggregate FVI

The second stage in the construction of the FVI aggregates the four subindices into the aggregate FVI using a Dynamic Factor Model (DFM):

$$\hat{\mathbf{z}}_\mathbf{t} = \mathbf{\Lambda} f_t + \zeta_\mathbf{t} \tag{4}$$

$$\zeta_\mathbf{t} = \mu\zeta_\mathbf{t-1} + \eta_\mathbf{t} \tag{5}$$

$$f_t = \rho f_{t-1} + \psi_t \tag{6}$$

Equation 4 models the estimated vector of subindices $\hat{\mathbf{z}}_\mathbf{t}$ as a linear combination of a single common factor f_t, with factor loadings $\mathbf{\Lambda}$, and four idiosyncratic components, $\zeta_\mathbf{t}$, which follow independent AR(1) processes, with autoregressive coefficients μ. The common factor also evolves as an AR(1) process with persistence parameter ρ. The innovation terms are normally distributed: $\eta_\mathbf{t} \sim N(0, \mathbf{\Sigma}_\eta)$ with $\mathbf{\Sigma}_\eta$ being a diagonal covariance matrix, and $\psi_t \sim N(0, \sigma^2)$. To estimate the parameters of the model we use the algorithm in Bańbura and Modugno (2014).

After estimating the FVI and its subcomponents, we assign a qualitative assessment to each index based on their value relative to their historical distribution. To do this, we first compute the probability integral transform of the indices and rescale them on an interval between 0 and 1. We then associate five qualitative assessments to each inter-quintile interval.We assign qualitative assessments based on the index's position within its historical distribution: values in the first quintile (0.00-0.20) indicate ”subdued” vulnerabilities; the second quintile (0.21-0.40) corresponds to ”low”; the third (0.41-0.60) to ”moderate”; the fourth (0.61-0.80) to ”notable”; and the fifth quintile (0.81-1.00) to ”elevated” vulnerabilities. These characterizations align with the terminology used in the FSR to facilitate direct comparison.

3.3 Historical Decomposition

The relevance of a financial index is determined not only by its ability to capture periods of heightened vulnerability, but also to identify their sources. To identify the main drivers of vulnerabilities over time, we decompose the FVI in the contribution of each variable. However, because our model is non-linear, this decomposition cannot simply be performed by looking at loadings and weights. We then leverage the concept of Shapley values, borrowed from cooperative game theory (Shapley et al., 1953) and recently used to interpret the predictions of machine learning forecasting models (see for example Borup et al., 2022 and Lenza et al., 2025).

We estimate Shapley values in two stages for both computational and conceptual reasons.

Computationally, calculating exact Shapley values becomes prohibitively expensive as the number of variables grows. With 39 variables in the FVI, accurate calculation would require 2^{39} model runs—roughly 550 billion evaluations. While parallel computing and strategic indexing can reduce redundant calculations, we estimate a runtime of 25-30 days, making this approach impractical for timely policy analysis.

Conceptually, a two-stage approach offers valuable insights. Decomposing contributions first at the subindex level (how each variable contributes to its subindex) and then at the aggregate level (how each subindex contributes to the FVI) enhances interpretability. This structure allows us to understand which variables drive vulnerability readings within each domain and how these domains combine to form the aggregate index. We can trace each variable's exact contribution to the FVI using proportional allocation: a variable's contribution equals its subindex's contribution to the FVI, weighted by the variable's proportional share of that subindex. This two-stage decomposition maintains computational efficiency while deepening our understanding of the index construction. We provide technical details in Appendix B.

4 Historical patterns and empirical properties

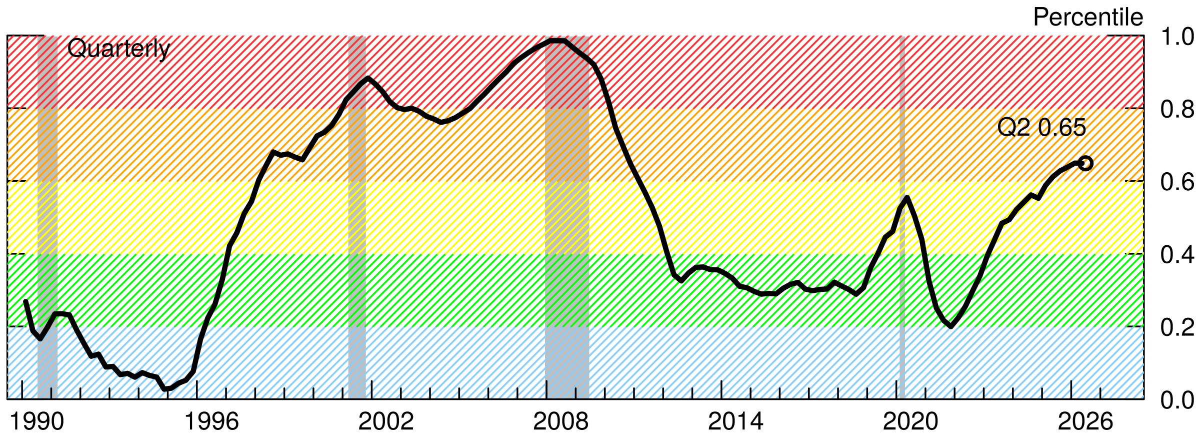
In this section we report the results of the estimation of FVI and its subcomponents and characterize its temporal patterns during the GFC.

Figure (2) reports the estimates of FVI and its subindices, highlighting the qualitative characterization corresponding to different percentiles using a heatmap.

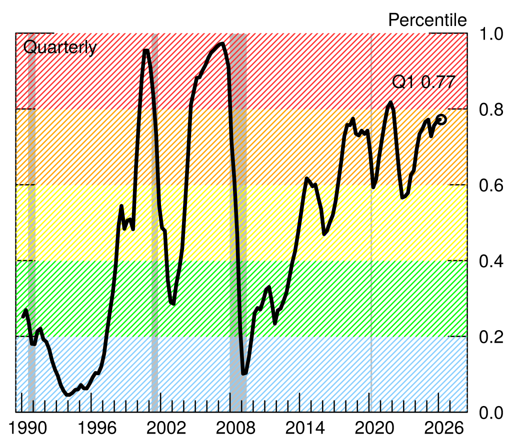
The FVI correctly captures the build-up of vulnerabilities before the GFC and their subsequent decline (2). While all subindices increased before the GFC (2b-2e), funding risk, financial and nonfinancial vulnerabilities were the ones decreasing the most in the aftermath of the crisis, reflecting the effects of new regulatory frameworks and the increased liquidity generated by the FED's asset purchases. Furthermore, the FVI captures heightened vulnerabilities in asset evaluation before the dotcom bubble and the rapid increase in vulnerabilities in financial leverage before the collapse of SVB and other regional banks in March 2023.

Figures (8),(9) and (10) in section B of the Appendix, report the historical decomposition of the aggregate FVI and its subinidices using Shapley values. For instance, the sharp decrease in Financial Leverage contributions reflects the implementation of Basel III regulatory frameworks (2013-2019), driven largely by improvements in tangible common equity and tier-1 capital ratios in response to heightened regulatory requirements. Similarly, Nonfinancial Leverage contributions declined significantly following the pandemic, reflecting strengthened household and business finances through reduced financial obligations and increased savings relative to income. Other notable patterns include the rising contribution of banks' duration gaps to Funding Risk prior to SVB's collapse in March 2023, and the elevated contribution of residential and commercial real estate prices to Asset Valuations before the 2008 crisis.

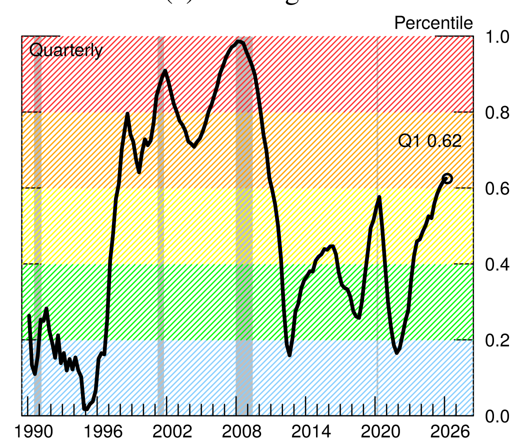
(a) Aggregate FVI



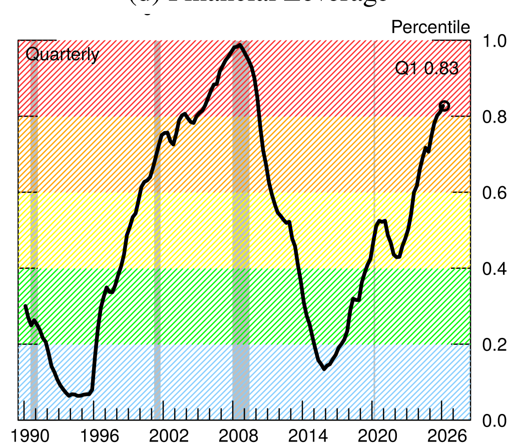
(b) Valuation Pressures



(c) Funding Risk



(d) Financial Leverage



(e) Households and Business Borrowing

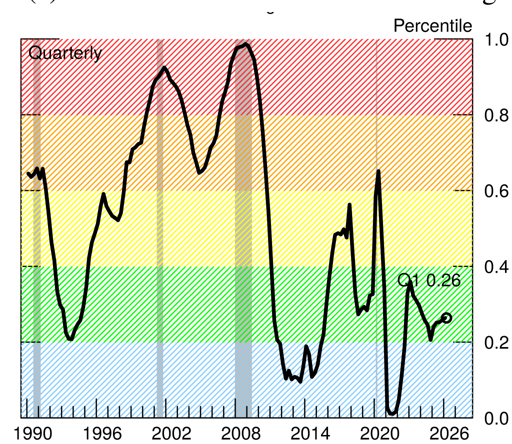


Figure 2: Heatmaps of aggregate FVI and its subindices. Red: 0.81-1 percentiles (Elevated); orange: 0.61-0.8 percentiles (Notable); yellow: 0.41-0.6 (Moderate); green: 0.21-0.4 (Low); blue: 0.01-0.2 (Extremely Subdued).

4.1 FVI and NFCI: Temporal Patterns During the GFC

One important aspect of our study is how FVI relates to existing financial condition indices (FCIs), which are popular indicators of financial markets tightness or stress. Figure (1) reports the FVI together with the range for five FCIs—the Chicago FED National Financial Condition Index (NFCI), the Kansas City Financial Stress Index (KCFSI), the Goldman Sachs Financial Condition Index (GSFCI), the Financial Condition Index Impulse to growth (FCI-G), the Sant Luis FED Financial Stress Index (STLFSI)—together with the VIX. While all FCIs show high correlation with each other and with the VIX, they have very low correlation with the FVI. This divergence stems from fundamental differences in their construction and purpose. FCIs are typically weighted averages of several indicators of current financial market conditions and often overweight higher-frequency variables which are closely related to measures of market price of risk, such as the VIX. A notable exception is the FCI-G Ajello et al. (2023) which weights the changes in seven financial variables based on their impact on output growth one year ahead, as predicted by the FRB/US. However, even this index is based on a limited number of variables, most of which capture financial markets stress. In contrast, the FVI weights a large number of variable, which go beyond high frequency financial variables, based on their relationship to future tail unemployment outcomes and exhibits patterns that may diverge from currently priced market risks. These conceptual differences between the FVI and FCIs suggest they may exhibit distinct temporal patterns in their relationships to future tail outcomes.

To characterize the temporal properties of the FVI relative to traditional financial condition indices, we compare how these indicators relate to the severe economic contraction observed during the Global Financial Crisis. We focus on comparing the FVI with the Chicago Fed's National Financial Conditions Index (NFCI), possibly the most used among financial stress indicators.

We follow the methodology in Adrian et al. (2019) and, conditional on FVI or NFCI, we estimate quantile regressions relating each index to future GDP growth and unemployment changes at horizons ranging from one to twelve quarters ahead. Specifically, for each horizon h and each conditioning variable, FVI or NFCI, we estimate:

$$Q_\tau(y_{t+h}|X_t) = \alpha_{\tau,h} + \beta_{\tau,h}X_t + \gamma_{\tau,h}y_t \tag{7}$$

where y_{t+h} represents either GDP growth or unemployment change over horizon h, X_t is either FVI or NFCI. We estimate this equation across multiple quantiles τ and fit the skewed t-distribution of Azzalini and Capitanio (2003), yielding conditional distributions for each target variable. Figure 3 reports the 4- and 8-quarter ahead densities for GDP growth conditional on FVI or NFCI for

2008:Q1 and 2008:Q4. The model conditional on FVI assigns higher density mass to the realized value of GDP growth at longer horizons. At shorter horizons, this pattern holds primarily for the onset of the crisis (2008:Q1), consistent with the different temporal dynamics: by the end of 2008, the NFCI already captured tightened financial conditions, resulting in higher probability assigned to tail events.

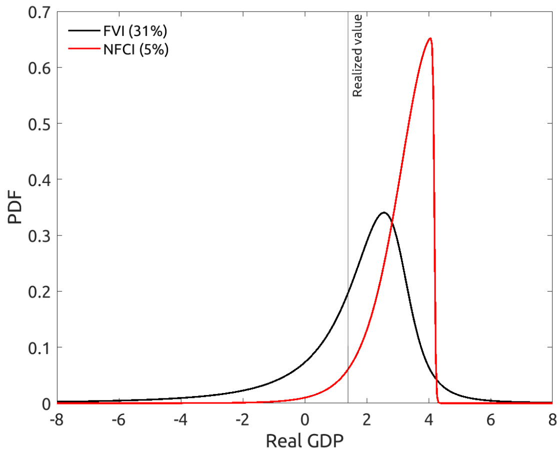
Table (1) provides a more systematic quantification of these patterns, reporting implied probabilities for the same two crisis dates across a broader set of horizons (1, 4, 6, and 8 quarters) and for both GDP growth and unemployment changes. The table reveals a clear temporal pattern: at shorter horizons (less than 4 quarters), the NFCI-conditional distributions assign higher probability to the realized outcomes, both for 2008:Q1 and 2008:Q4 and for unemployment or GDP growth. However, at medium and longer horizons (4+ quarters), the FVI-conditional distributions assign higher probability to unemployment and GDP outcomes, consistent with the FVI exhibiting stronger relationships to medium-term tail realizations.

Figure (4) complements this analysis by illustrating how the temporal contrast between the FVI and NFCI evolved over time during the GFC. The figure displays the conditional probability distributions for GDP growth at both 4-quarter and 8-quarter horizons, with the vertical line indicating the GFC trough (2008:Q4). The realized GDP contraction falls in a region where the FVI-conditional distribution assigns substantially higher probability compared to the NFCI-conditional distribution at longer horizons. This pattern is consistent with the FVI capturing structural vulnerabilities that exhibit stronger associations with medium-term tail outcomes, while the NFCI reflects coincident financial market conditions.

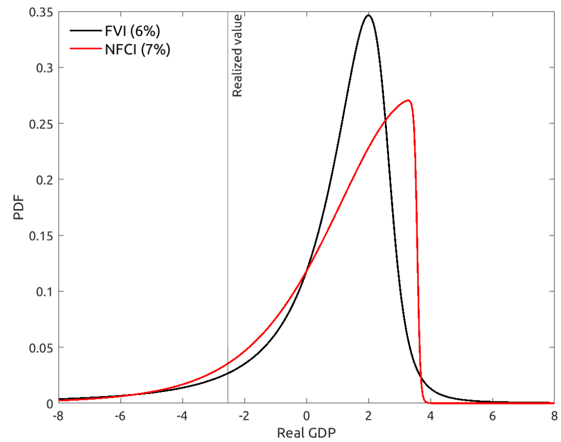
		GDP growth		Δ UR	
target	h	FVI	NFCI	FVI	NFCI
2008:Q1	1	0.07	0.13	0.49	0.73
	4	**0.31**	0.05	**0.39**	0.08
	6	**0.35**	0.07	**0.46**	0.10
	8	**0.33**	0.04	**0.56**	0.16
2008:Q4	1	0.00	0.03	0.00	0.00
	4	0.06	0.07	0.16	0.17
	6	**0.08**	0.00	**0.14**	0.01
	8	**0.10**	0.00	**0.17**	0.02

Table 1: Implied probabilities of GFC outcomes. Probabilities of GDP growth (left) or unemployment changes (right) being smaller or equal to their realized values for the targeted quarter (2008:Q1 or 2008:Q4). Results are based on a fitted skewed-t distribution estimated through quantile regressions.

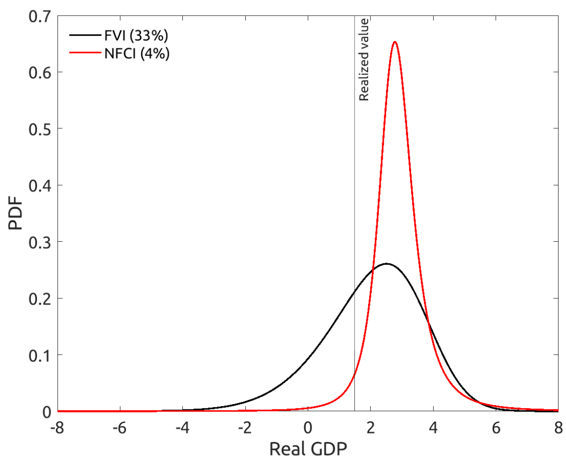
(a) 4-Quarter ahead forecast for 2008:Q1



(b) 4-Quarter ahead forecast for 2008:Q4



(c) 8-Quarter ahead forecast for 2008:Q1



(d) 8-Quarter ahead forecast for 2008:Q4

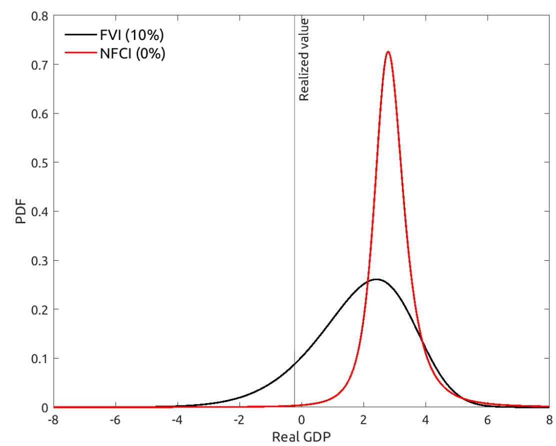
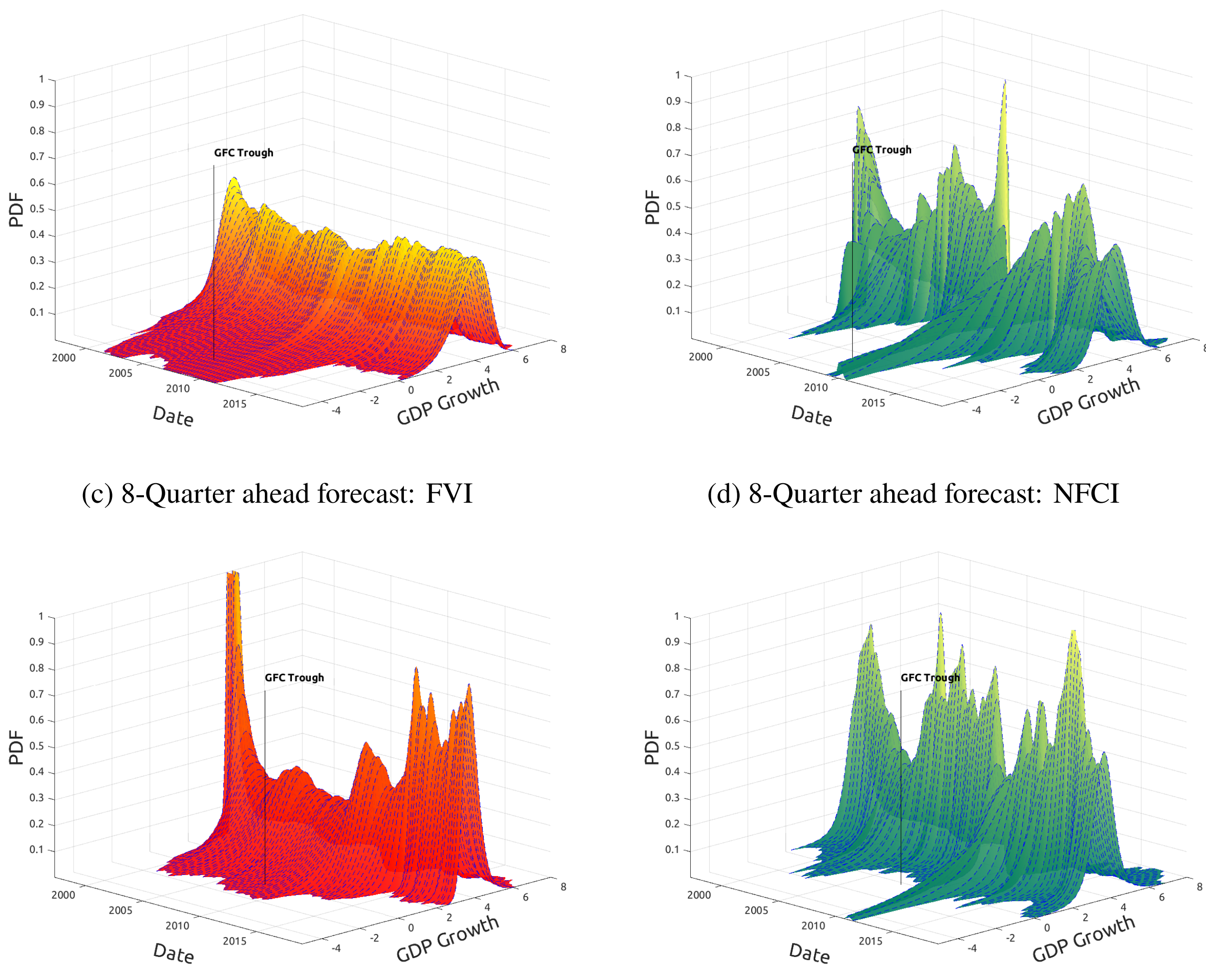


Figure 3: Fitted skewed-t distributional forecasts of GDP growth conditional on lagged GDP growth and FVI or NFCI. The vertical line represents the realization of GDP growth for the targeted quarter. Legend values in parenthesis report the estimated probabilities of GDP growth being smaller or equal to the realized value under the corresponding fitted distribution.



(a) 4-Quarter ahead forecast: FVI

(b) 4-Quarter ahead forecast: NFCI

(c) 8-Quarter ahead forecast: FVI

(d) 8-Quarter ahead forecast: NFCI

Figure 4: Fitted skewed-t distributional forecasts of GDP growth conditional on lagged GDP growth and FVI or NFCI. The fitted fitted skewed-t distribution is estimated through quantile regressions.

5 Amplification Properties: shock transmission and the FVI

The theoretical literature characterizes financial vulnerabilities as aspects that can significantly alter how shocks propagate through the economy. For example, when leverage is elevated or households and businesses face financial constraints, adverse economic shocks may generate more severe and persistent contractions Bernanke et al. (1999) Brunnermeier and Sannikov (2014).

In this section we examine whether the FVI exhibits the amplification properties described by theory for financial vulnerabilities.

To test this hypothesis, we estimate the following local projections for $h = 1, \ldots, 12$ by OLS:

$$\begin{aligned} y_{t+h} =& I_t\Big(\alpha_h^H + \beta_h^H \varepsilon_t + \sum_{p=1}^{P} \gamma_{h,p}^H \mathbf{X}_{t-p}\Big) + \\ & \big(1 - I_t\big)\Big(\alpha_h^L + \beta_h^L \varepsilon_t + \sum_{p=1}^{P} \gamma_{h,p}^L \mathbf{X}_{t-p}\Big) + \delta_h D_t + \nu_{t+h} \end{aligned} \tag{8}$$

where y_t is a dependent variable of interest, I_t is a dummy variable which takes value 1 if FVI is above 0.5 and $\mathbf{X}_{t-p}$ is a vector of control variables and D_t is a dummy variable capturing COVID dates (2020:Q1-Q4). Our sample goes from 1990:Q1 to 2025:Q4. Coefficients β_h^H and β_h^L capture the impulse responses at horizon h in the high and low vulnerabilities states, respectively.

We choose ε_t to be the business cycle shock, defined as the shock which explains most of the variance of real per-capita GDP at business cycle frequencies (6 to 36 quarters). We estimate this shock in a linear VAR on data from 1960:Q1 to 2025:Q4, following the methodology of Giannone et al. (2019), and subsequently applied by Angeletos et al. (2020). We normalize the shock to generate -1% impact response in per-capita GDP in the VAR model. This normalization corresponds to an impact response of -1.5% in real GDP when estimated with linear local projections on our shorter sample (1990:Q1 to 2025:Q4) and -1% impact response in both regimes when estimated with non-linear local projections.

The business cycle shock represents a dominant empirical driver of economic fluctuations and it is identified without imposing structural assumptions about whether it originates from demand, supply, productivity, or other specific mechanisms. This agnostic approach allows us to study how the FVI affects macroeconomic dynamics independently of the source of the negative shocks. In addition, as argued by Angeletos et al. (2020), this disturbance is unlikely to correspond a standard monetary policy shock, as it is associated with large fluctuations in output and employment but only muted inflation responses. Therefore, the analysis in this subsection differs conceptually from the one in the next section, which focuses on the non-linear effects of a monetary policy shock.

In figure 5, we report the responses of real consumption expenditure and investment in non-residential fixed long-term assets in response to a business cycle shock. We focus on this latter measure rather than aggregate investment for two reasons. First, it excludes inventory changes and residential construction that correlate strongly with the labor market indicators used in constructing the FVI, thus minimizing the identification problems. Second, long-term investment decisions are particularly sensitive to financial frictions and borrowing constraints because even small increases in borrowing costs get magnified over the longer duration of the investment horizon. In our estimates we control for four lags of the shock, the PCE deflator, unemployment, real GDP and the 1-year treasury yield.

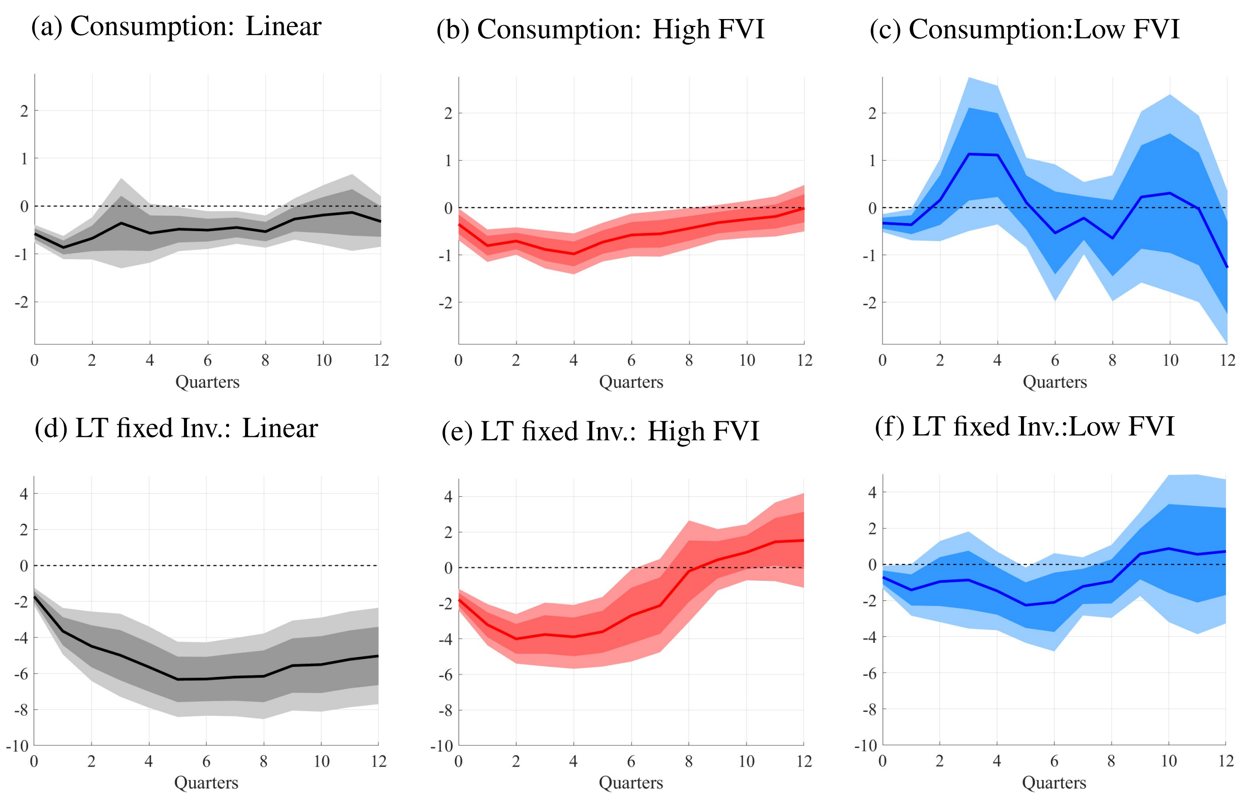


Figure 5: Responses of real consumption expenditure (first row) and fixed long-term investment (second row) to a business cycle shock, %: a), d) linear; b), e) high FVI; c), f) low FVI. Regimes are defined by FVI being above (high) or below (low) 0.5. Shaded areas represent the 90% (light) and 68% (dark) confidence bands.

Figure 5 reveals substantial state dependence in the transmission of business cycle disturbances. Consumption and long-term fixed investment decline more sharply in periods of high financial vulnerability (5b, 5e), with the amplification appearing particularly persistent for the dynamics of investment. When vulnerabilities are high, a business cycle shock which decreases real GDP by 1% on impact, generates a persistent response consumption and investment, which revert back to zero only after 2 years. These responses are sizable with consumption decreasing by 1% after one year and fixed investment by 4% after 2 quarters. Conversely, the responses to the same shock in the low vulnerability regime are more muted and become not significant after the first quarter. These results are robust across different definitions of regimes based on FVI'subindices. We report these responses for long-term fixed investment in figure (12).

We acknowledge an important consideration in interpreting these results: the FVI weights variables by their relationship to future unemployment tail outcomes. This feature does not, by itself, mechanically generate state dependence in the response to a structural shock. First, the index is a non-linear aggregation rather than a simple weighted average of the individual variables. Second, we study the responses of real GDP, consumption and long-term fixed investment—outcomes not targeted in the index construction. Third, our test concerns whether the *same shock* transmits differently across vulnerability regimes; such state dependence in the response is not built into how the index weights variables. Fourth, the weights target unemployment two years ahead, yet the amplification of GDP, consumption and investment emerges especially in the first quarter, so the immediate response cannot be a mechanical artifact of the weighting.

Our finding are consistent with the financial accelerator mechanism of Bernanke et al. (1999), whereby adverse shocks deteriorate private-sector balance sheets, increasing external financing premia and magnifying the contraction. Our result also aligns with the amplification mechanisms emphasized in Brunnermeier and Sannikov (2014), where highly leveraged financial intermediaries amplify negative disturbances through a forced deleveraging and reduction in their risk bearing capacity.

Overall, these findings are consistent with a core theoretical property of financial vulnerabilities: the amplification of adverse shocks to real activity. These amplification effects are economically meaningful, with consumption and investment displaying significantly larger responses in the high-vulnerability state. This validation establishes the FVI as a measure of structural weaknesses. By identifying conditions under which the economy becomes more vulnerable to disturbances, the FVI offers policymakers a tool for monitoring when the financial system might amplify shocks.

6 Responses to a Monetary Policy Shock

Having characterized the FVI's temporal properties and demonstrated its amplification patterns, in this section we turn to the interaction between monetary policy and financial vulnerabilities and explore two questions. First, we examine whether monetary policy affect financial vulnerabilities by looking at the responses of our index to a monetary policy shock. Second, we explore whether financial vulnerabilities affect the transmission of monetary policy by looking at the responses of inflation to a monetary policy shock across vulnerability regimes.

6.1 Responses of Vulnerabilities to a Monetary Policy Shock

In this subsection we examine the responses of financial vulnerabilities to a monetary policy shock. This remains a largely unexplored question as, to the best of our knowledge, financial vulnerabilities has not been systematically measured in the literature until now. At the same time, how financial vulnerabilities respond to monetary policy can inform the long-standing debate on the preemptive use of monetary policy tools to address financial stability concerns (Bernanke, 2002, 2015; Yellen, 2014; Svensson, 2015, 2017, 2016; Gourio et al., 2018).

We investigate how monetary policy affects financial vulnerabilities by estimating the dynamic responses of FVI to monetary policy shocks using the local projection method of Jordà (2005). For each horizon h, we estimate:

$$y_{t+h} = \alpha_h + \beta_h \varepsilon_t^{MP} + \sum_{p=1}^{P} \gamma_p^h \mathbf{X}_{t-p} + \delta_h D_t + \nu_{t+h} \tag{9}$$

where y_t is the FVI, ε_t^{MP} is the monetary policy shock from Bu et al. (2021), $\mathbf{X}_{t-p}$ is a vector of control variables, D_t is a dummy variable capturing COVID dates (2020:Q1-Q4) and coefficient β_h captures the impulse response at horizon h. Our sample spans from 1994:Q1 to 2025:Q4. We aggregate the shock to quarterly frequency by summing its realizations over each quarter. The Bu et al. (2021) shock series is particularly suitable for our analysis as it isolates monetary policy surprises while controlling for information effects that could confound identification. Our set of controls includes four lags ($P = 4$) of the monetary policy shock, the dependent variable, the 1-year Treasury yield, log PCE deflator, log real GDP, and unemployment rate.

In panel a) of figure 6, we report impulse responses of the FVI to a monetary tightening, together with the 68 and 90% confidence bands based on Newey-West standard errors. A 100 bps monetary tightening doesn't affect the FVI on impact, but generates a persistent response which decreases the index by approximately 25 percentile points after 2 years and 35 points after 3 years. This evidence suggests that a monetary tightening can significantly reduce vulnerabilities but this effect is considerably delayed, complicating the use of monetary policy as a tool to address imminent financial stability risks.

For comparison, panel b) of Figure 6 reports the response of NFCI. The same shock has a very different effect on this index, generating a tightening of financial conditions on impact. However, this response is short-lived, reverting to zero within 4 to 5 quarters. These contrasting patterns confirm

(a) Financial Vulnerability Index (FVI)

(b) National Financial Conditions Index (NFCI)

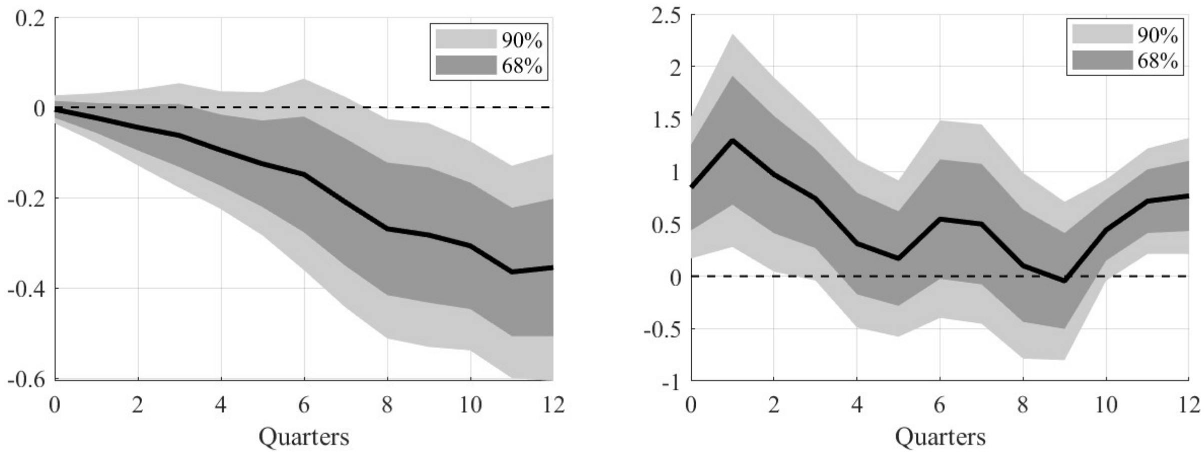


Figure 6: Responses to a 100 bps contractionary monetary policy shock: a) FVI (percentile points); b) NFCI (bps). Shaded areas represent the 90% (light) and 68% (dark) confidence bands.

once again the conceptual difference between financial vulnerabilities and financial conditions. The immediate increase in NFCI reflects how a policy tightening directly impact market conditions by increasing loan prices and restricting the availability of credit. Meanwhile, the gradual decline in FVI suggests that the same policy tightening slowly reduces vulnerabilities over time.

6.2 Monetary policy transmission across vulnerability regimes

Monetary policy may be affected by the financial system's underlying vulnerabilities. When vulnerabilities are elevated, traditional policy transmission could be impaired or, conversely, amplified through various channels (see for example Bernanke et al. (1999), Bernanke and Blinder (1988) Kashyap and Stein (1994), Bernanke and Gertler (1995), Kashyap and Stein (2000)).

We examine the interaction between monetary policy and financial vulnerabilities by studying the impulse responses to a monetary policy shock in high and low vulnerabilities regimes as captured by our index. To this end, we use the same empirical framework employed in (8) to take ε_t to be the Bu et al. (2021) monetary policy instrument and we include the same controls specified in section 5.1, namely four lags of the shock, the dependent variable, the 1-year Treasury yield, log real GDP, and unemployment rate.

Figure 7 reports the impulse responses of the PCE deflator to a 100 bps monetary tightening. Panel 7b plots the coefficients β_h^H, relative to the high FVI regime, while panel 7c reports coefficients β_h^L, relative to the low FVI regime. Panel 7a plots the linear responses, coefficients β_h in equation 6.1. A monetary tightening generates a negative and persistent response of prices, which is highly

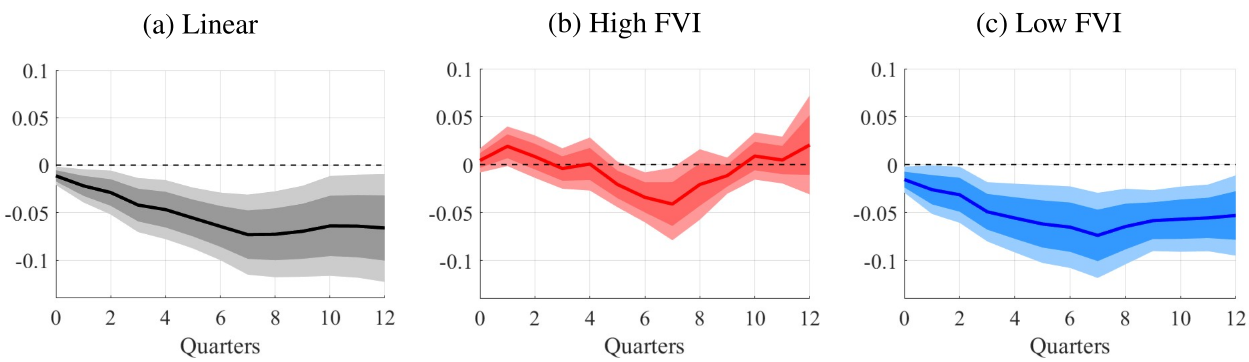


Figure 7: Responses of PCE deflator to a 100 bps contractionary monetary policy shock, log deviations: a) linear, b) high FVI, c) low FVI. Regimes are defined by FVI being above (high) or below (low) 0.5. Shaded areas represent the 90% (light) and 68% (dark) confidence bands.

state dependent. During periods of high financial vulnerabilities the transmission channel of monetary policy to prices is much less effective, with the response of prices being largely not significant. Conversely, when financial vulnerabilities are low, monetary policy has a significant negative effect on prices which displays similar dynamics and magnitudes to the linear case. This result is robust to several specification of the model, more lags, choice of controls and treatment of the COVID dates.

When decomposing the state-dependent response of inflation to monetary policy shocks across different vulnerability subindices (figure 11 in the Appendix), we find that household and business borrowing appears to be the primary driver of the observed state dependence. Monetary policy has virtually no effect on inflation when household and business borrowing is elevated (panel 11g), while producing a significant, persistent disinflationary response when such borrowing is low (panel 11h). This result is consistent with previous empirical evidence showing that monetary policy transmission is more effective when nonfinancial credit-to-GDP is above its long-term trend (Aikman et al. (2020)). The stark contrast in the responses among the two states—more pronounced than for other vulnerability components—suggests that nonfinancial sector leverage conditions may play a particularly critical role in determining monetary policy effectiveness on prices. One reason for this is that highly indebted households and businesses may be less responsive to interest rate changes at the margin. When private credit in the economy is already high and borrowers face existing debt service burdens, a further monetary tightening may have diminished effects on overall credit demand relative to when the private sector holds lower leveraged portfolios.This mechanism may explain why monetary policy's effectiveness becomes attenuated during periods of high nonfinancial sector vulnerabilities.

While inflation responses provide evidence of state dependence, the analysis of real activity warrants additional consideration. In principle, variables such as unemployment, real GDP and industrial production would be the natural candidates for the analysis of monetary policy transmission, as they are more directly affected by monetary policy shocks. At the same time, these variables are closely related to the target used to weight financial indicators in the construction of the index. As discussed above, this feature does not, by itself, generate state dependence in response to a structural shock. It does, however, warrant caution in interpreting evidence based on real activity. We therefore view the response of prices, which are not directly targeted in the construction of the FVI, as a cleaner test of state-dependent monetary policy transmission.

7 Conclusion

We introduce the Financial Vulnerability Index (FVI), a novel indicator of financial vulnerabilities in the U.S. Our approach combines quantile factor methods with Federal Reserve supervisory expertise, resulting in an index that exhibits temporal patterns consistent with structural financial vulnerabilities.

The FVI displays intuitively plausible patterns: building up before the Global Financial Crisis, dot-com bubble, and 2023 banking turmoil, declining as crises materialize, and showing patterns distinct from conventional financial conditions indicators. Our Shapley value decomposition enhances interpretability by revealing key vulnerability drivers over time and around these key events.

The distinct temporal properties of the FVI relative to traditional FCIs highlight their distinct nature. While FCIs capture immediate market stress with stronger relationships to short-horizon outcomes (under 1 year), the FVI exhibits stronger associations with medium-term tail realizations (1.5-2 years), consistent with its construction weighting variables by their relationships to future unemployment tail outcomes.

We demonstrate that the FVI exhibits properties consistent with theoretical mechanisms of financial vulnerabilities. Adverse economic shocks are substantially amplified in high-FVI periods, generating larger declines in consumption and investment, consistent with financial accelerator theories.

We then examine how monetary policy relates to financial vulnerabilities. Despite its importance in the debate about the preemptive use of monetary policy to address financial stability concerns, this empirical question has received limited attention due to the lack of direct measures of financial vulnerabilities. We document that monetary policy tightening is associated with gradual declines in the FVI over time, with stronger effects after 3 years, though establishing causality requires caution given the persistence of the index and long horizons involved.

The evidence that vulnerabilities amplify adverse shocks suggests that the state of the financial system may matter for monetary policy transmission as well. We therefore investigate whether monetary policy shocks transmit differently depending on whether the economy is in a high- or low-vulnerability regime. During periods of high vulnerability, monetary policy's ability to influence prices is significantly attenuated, especially when household and business borrowing is elevated. This suggests that highly indebted sectors may become less responsive to interest rate changes.

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Appendix A

A Data

Table 2 reports the list of variables used to construct the FVI with the subindex to which they belong, a description, their weight and their corresponding t-stat.

Table 2: Financial Vulnerabilities Index Variable Dictionary and Weights

Subindex	**Variable**	**Description**	**Weight**
Valuation Pressures	junk_share	Deep junk issuance share	**0.09** (1.82)
Valuation Pressures	cds_hist	5 yr spread for the North American Investment Grade index	**-0.34** (-3.19)
Valuation Pressures	epy_spread	12-month forward earnings-to-price ratio for the S&P 500 index less real yield on 10-year treasury	**-0.07** (-1.83)
Valuation Pressures	hpr	CoreLogic HPI (All tier with REO and Short Sales - National) divided by CPI-U: Rent of Primary Residence	**0.12** (5.99)
Valuation Pressures	pcre	Commercial real estate price index divided by PCE	**0.10** (5.22)
Valuation Pressures	swptn	Option-implied volatilities on the 10-year swap rates	**-0.10** (-3.53)
Valuation Pressures	vix	VIX (realized volatility from S&P 500 prior to 1990)	**-0.03** (-0.51)
Valuation Pressures	pb_ratio	Median of top BHC's Price to Book Ratios	**0.08** (1.57)
Funding Risk	lfl	Low-Friction Liquidity	**-0.18** (-7.97)
Funding Risk	stwf	Short Term Wholesale Funding	**0.10** (2.24)

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Table 2 – *Continued from previous page*

Subindex	**Variable**	**Description**	**Weight**
Funding Risk	prime_like	Prime-like investment vehicles	**0.07** (1.45)
Funding Risk	sigstress_runn	Significantly Stressed Runnables	**0.09** (3.92)
Funding Risk	loans_dep	Loans + HTM to deposit ratio	**0.09** (2.09)
Funding Risk	depth2	Market depth 2-year on-the-run Treasury securities	**-0.10** (-1.08)
Funding Risk	gross_debt_gdp	Gross short-term wholesale debt of financial sector to GDP	**0.11** (4.85)
HH & Business Borrowing	avgint_urspec	Average ratio of cost of capital to operational income (before depreciation) for HY and unrated firms	**0.02** (0.55)
HH & Business Borrowing	bus_savings	Nonfinancial corporate business net savings less net capital formation (including equity and REIT residential structures) all over GDP	**-0.07** (-3.39)
HH & Business Borrowing	concred_dpi	Consumer credit owned by riskier borrowers (ratio to DPI) divided by personal income	**0.07** (2.12)
HH & Business Borrowing	debt_growth	Nonfinancial business debt growth less inflation	**0.02** (0.76)
HH & Business Borrowing	cred_gdp	Total Nonfinancial Debt over GDP	**0.09** (4.11)
HH & Business Borrowing	hh_fin_ob	Household financial obligations to income ratio	**0.09** (3.66)
HH & Business Borrowing	hh_savings	Households and nonprofits net saving less net capital transfers and less capital formation over GDP	**-0.09** (-3.04)
HH & Business Borrowing	mort_gdp	Household and nonprofit home mortgages divided by GDP	**0.11** (3.88)

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Table 2 – *Continued from previous page*

Subindex	**Variable**	**Description**	**Weight**
HH & Business Borrowing	rap_concred	Incidence of rapid consumer borrowing by riskier borrowers	**0.07** (1.18)
HH & Business Borrowing	row_gnp	Before-tax domestic nonfinancial + ROW profits as a percentage of GNP	**-0.03** (-1.04)
HH & Business Borrowing	st_debt	75th percentile amount of short-term debt fraction for public firms -source Compustat	**0.02** (0.85)
HH & Business Borrowing	lend_std	Composite of banks lending standards from BFA	**0.14** (3.92)
Financial Leverage	matgap	The difference between the weighted average maturity of assets and liabilities for all commercial banks and thrifts	**0.04** (1.01)
Financial Leverage	net_debt_gdp	Net short-term wholesale debt of financial sector to GDP := (Net liabilities of Non-Monetary Authority, Non-Private Depository Institution financial sector over GDP)	**0.10** (4.44)
Financial Leverage	gross_dealer_gdp	Gross dealer borrowing to GDP	**0.11** (2.03)
Financial Leverage	risk_gsib	GSIB risk density	**0.05** (1.12)
Financial Leverage	net_borrowing	Primary dealer borrowing over financing	**0.16** (2.79)
Financial Leverage	nb_lev_ratio	Non-bank leverage ratio	**-0.04** (-1.75)
Financial Leverage	gsib_durgap	Duration gap (GSIBs weighted average)	**0.03** (0.56)
Financial Leverage	tce_ta	Tangible common equity to tangible assets – (BHC tangible equity to total tangible assets)	**-0.13** (-4.12)
Financial Leverage	tot_liabs	Total liabilities to GDP	**0.10** (3.23)

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Table 2 – *Continued from previous page*

Subindex	Variable	Description	Weight
Financial Leverage	y9c_av	Fire-sale vulnerability for BHCs	**0.15** (5.16)
Financial Leverage	hf_lev	NAV-weighted means of GNE / NAV (gross leverage) for qualifying hedge funds. Gross Notional Exposure / Net Asset Value	**0.20** (1.96)
Financial Leverage	lifeins_nontrad	FABS and FHLB advances over total liabilities held by life insurers	**0.13** (1.40)

Note: Table 1: FVI variables description and weights. Column 1: subindex the variable is contributing to; column 2: variable's acronym; column 3: variable description; column 4: variable's weight (bolded) and t-stat underneath, estimated using data up to June 2025. Variables that include stock of debt are detrended using a 2-sided HP-filter; "gross_debt_gdp", "concred_dpi", "cred_gdp" .

B Historical decomposition based on Shapley values

In machine learning, a Shapley value is the average contribution of a variable to a model prediction which is computed over all possible —coalitions— of other variables. We apply this concept in two steps. First, we estimate the Shapley values of each variable to the predicted level of each subindex. That is, we compute the contributions of each variable to the objective:

$$L_{z,t} = \hat{z}_t^j - \bar{z}_t \tag{10}$$

where $\hat{z}_t^j$ is the estimate of subcomponent j at time t and $\bar{z}_t$ is a reference value, corresponding to the *naif* prediction of the "empty model", i.e. the model with no variables. To decompose the level of the subindices, we take $\bar{z}_t$ to be 0 for every t. Conceptually, this assumption implies that without information, i.e. if none of the financial indicators is observed, the best prediction for the level of financial vulnerabilities is just zero.
Second, we estimate the Shapley values of each subindex to the predicted level of the aggregate Index. That is, we compute the contributions of each subindex to the objective:

$$L_{y,t} = \hat{Y}_t - \bar{Y} \tag{11}$$

where $\hat{Y}_t$ is the estimate of the aggregate FVI at time t and $\bar{Y}_t$ is the prediction of FVI from the —empty model—, where none of the subcomponent is observed. As before, we take $\bar{Y}_t = 0$ for each t.
We compute the contribution (the Shapley value) of variable x_{it}^j, to $\hat{z}_t^j$ can be computed as:

$$\phi_{it}^j = \sum_{Q \subseteq S_j \setminus \{i\}} \frac{q!\,(s_j - 1 - q)!}{s_j!} \left[\left(\hat{z}_t^j \middle| Q, x_{it}^j \right) - \left(\hat{z}_t^j \middle| Q \right) \right] \tag{12}$$

S_j is the set of all variables in subindex j and s_j is its cardinality. Q is a subset of S_j which excludes variable x_{it}^j and q is its cardinality. $\left(\hat{z}_t^j | Q\right)$ is the prediction of subindex j when only the variables in Q are included in the model. $\left(\hat{z}_t^j | Q, x_{it}^j\right)$ is the prediction of subindex j when the variables in Q and x_{it}^j are included.
According to the definition above, the Shapley value of a variable x_{it}^j is the weighted sum of the differences in the prediction $\hat{z}_t^j$ when x_{it}^j is added to a subset Q. The weights are inversely related to the number of available combinations of variables in Q. Notice that the estimate of ϕ_{it}^j can be computationally intensive as the number of variables in a subindex increases. Indeed, to obtain ϕ_{it}^j, we need to compute the difference in the prediction when including the variables in Q and x_{it}^j and when including Q only, for each possible Q.
In the same way, the contribution (Shapley value) of subindex $\hat{z}_t^j$ to $\hat{Y}_t$, call it ω_{jt}, can be computed by applying (12) and substituting x_{it}^j with $\hat{z}_t^j$, $\hat{z}_t^j$ with $\hat{Y}_t$.
An appealing property of Shapley Values is *efficiency*, which guarantees that all contributions sum up to the loss function. This property allows to exactly decompose the level of a subindex (or of FVI) into the

contributions of each variable (or each subindex):

$$L_{zt}^{j} \equiv \hat{z}_t^j = \sum_i \phi_{it}^j \tag{13}$$

$$L_{yt} \equiv \hat{Y}_t = \sum_j \omega_{jt} \tag{14}$$

Notice that, by combining these two decompositions, we could trace each variable's contribution through to the aggregate index. The contribution of variable i in subindex j to the FVI is given by proportional allocation:

$$\omega_{jt} \frac{\phi_{it}^j}{\hat{z}_t^j} \tag{15}$$

where the subindex contribution ω_{jt} is allocated proportionally to variable i's share of that subindex. By construction, these contributions sum to $\hat{Y}_t$:

$$\hat{Y}_t = \sum_j \sum_i \omega_{jt} \frac{\phi_{it}^j}{\hat{z}_t^j} \tag{16}$$

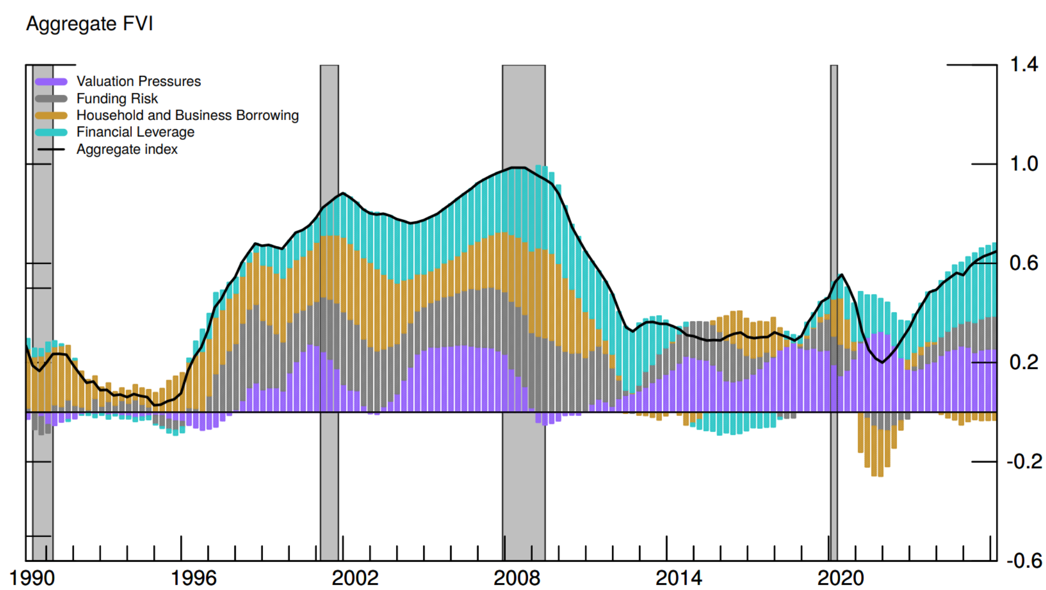
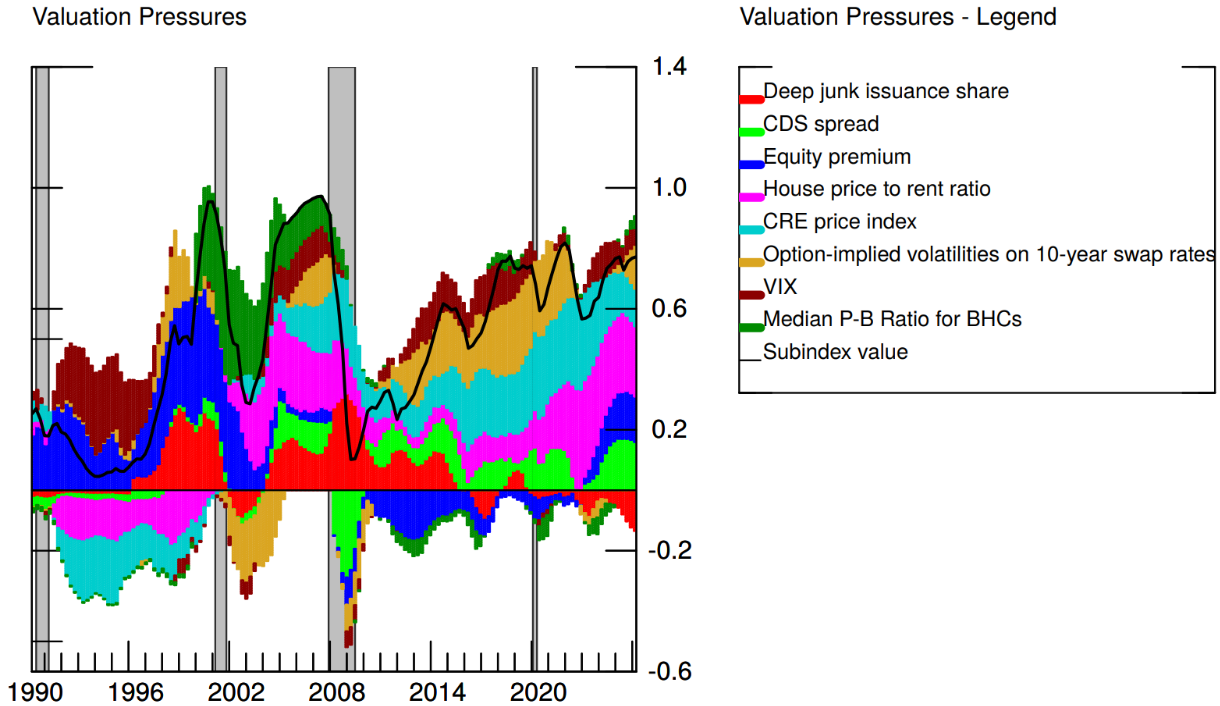


Figure 8: Shapley value decomposition of the FVI. Stacked areas show each subindex's contribution (Shapley value ω_{jt}) to the aggregate FVI over time.

(a) Valuation Pressures



(b) Funding Risk

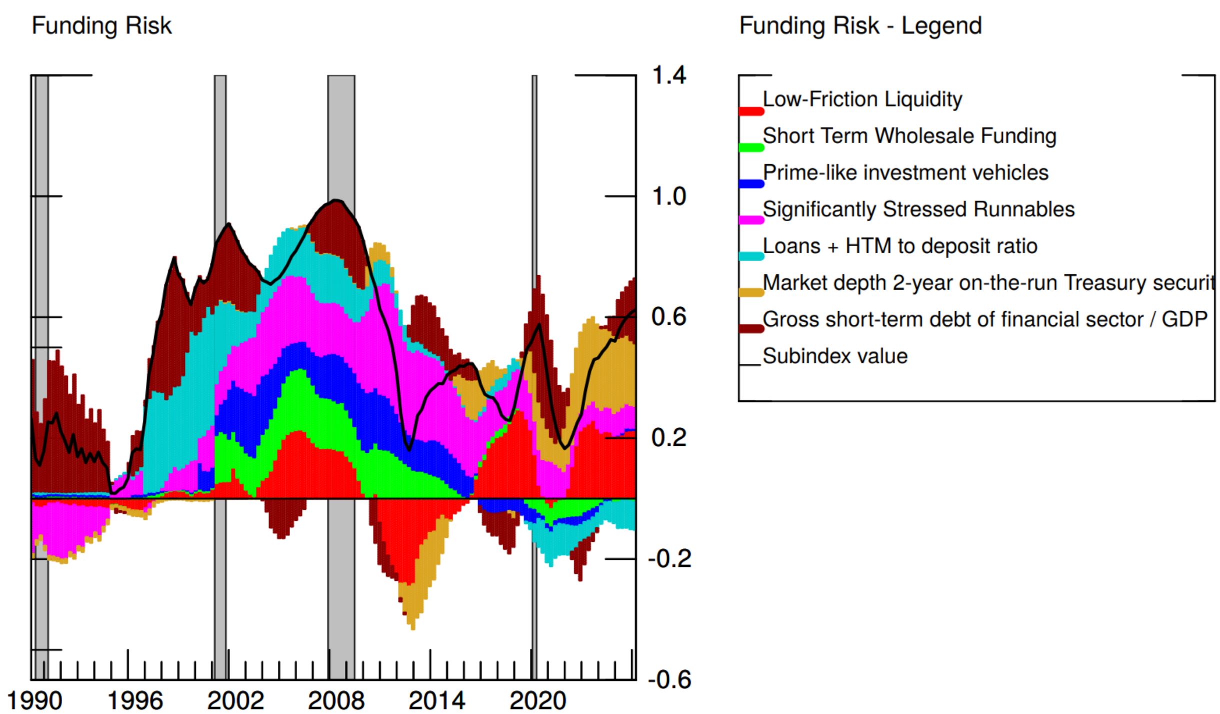
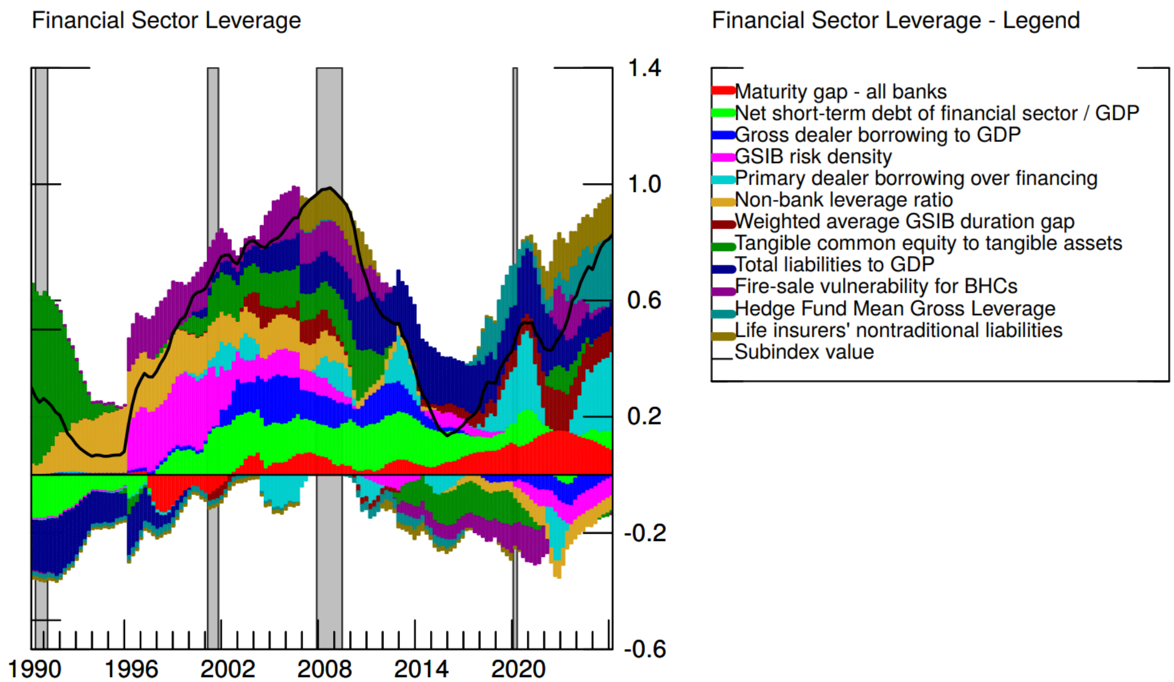


Figure 9: Shapley value decomposition of subindices - I. Stacked areas show each variable's contribution (Shapley value ϕ_{it}^{j}) to the aggregate FVI over time.

(a) Financial Leverage



(b) Households and Business Borrowing

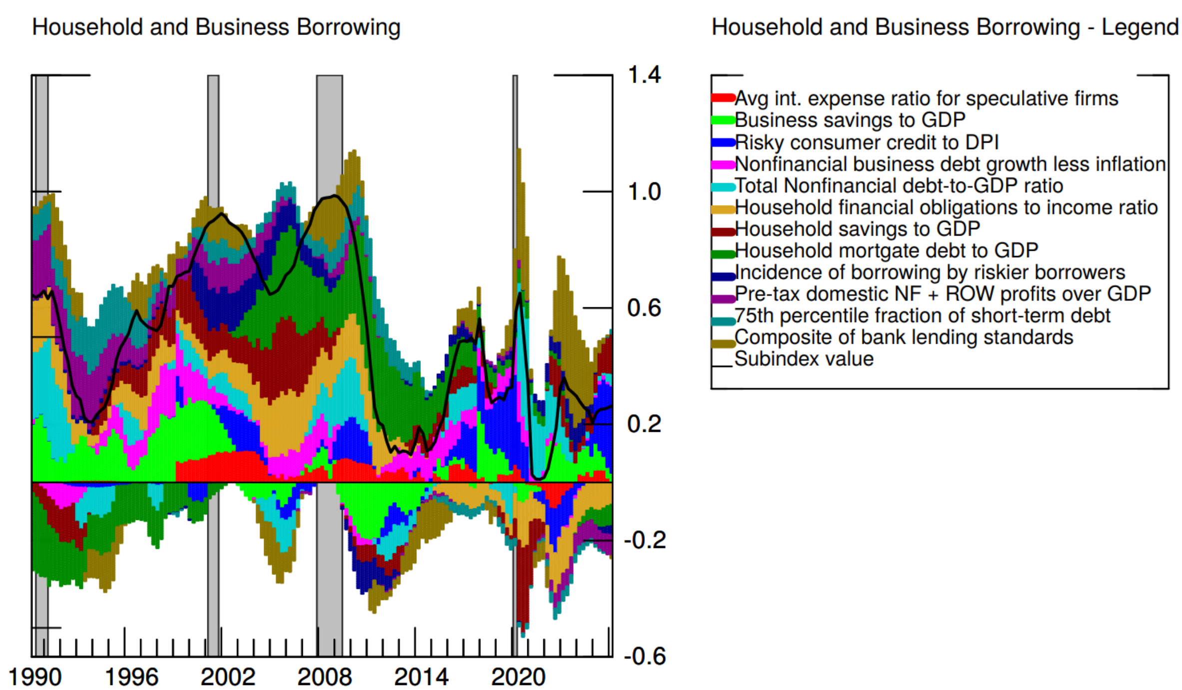


Figure 10: Shapley value decomposition of subindices - II. Stacked areas show each variable's contribution (Shapley value ϕ_{it}^{j}) to the aggregate FVI over time.

C Non-linear transmission of shocks: additional evidence

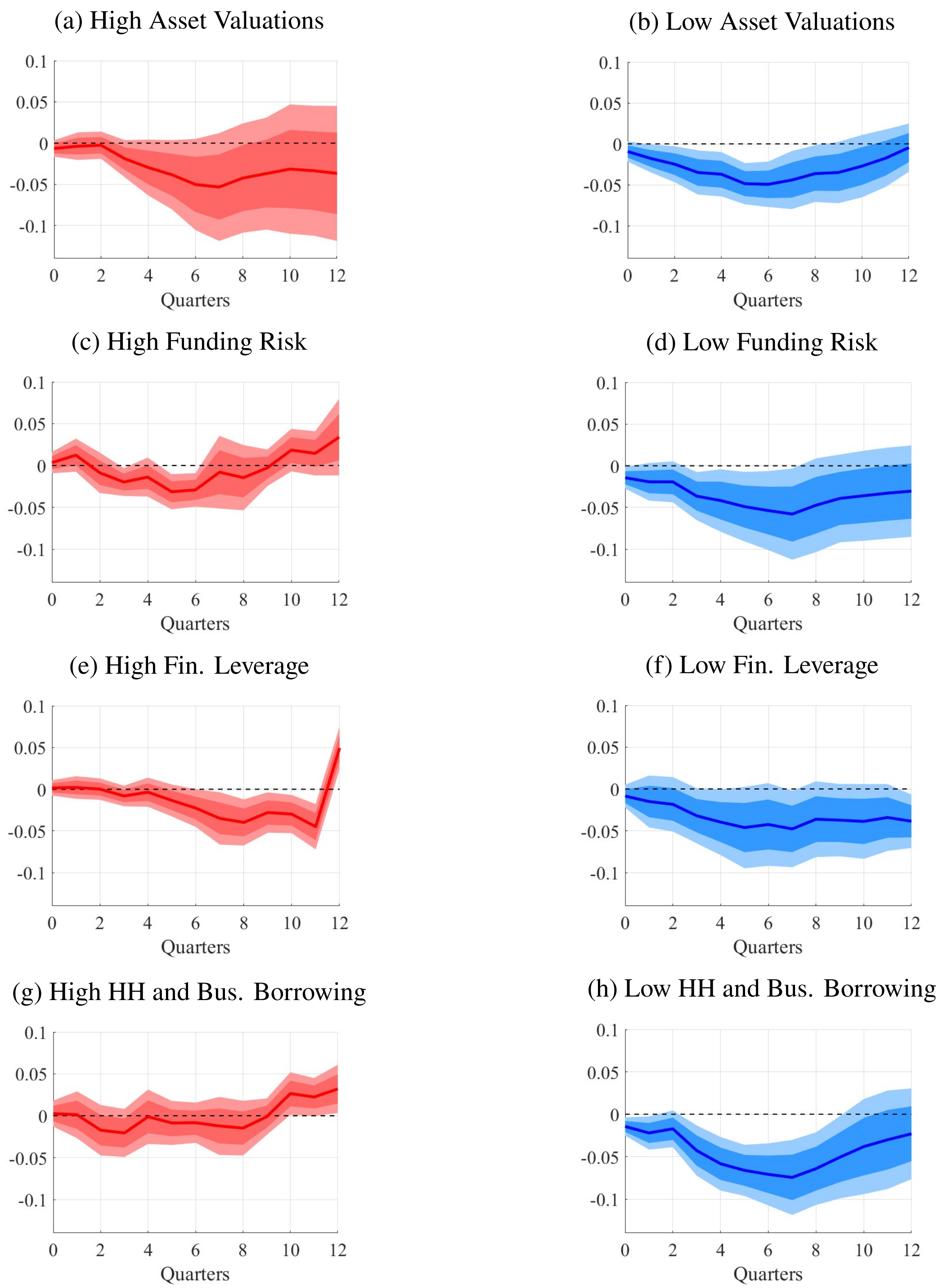


Figure 11: IRFs of PCE deflator to a 100 bps contractionary monetary policy shock, log deviations. Regimes defined on FVI subindices: a), b) Asset Valuations; c), d) Funding Risk ; e), f) Financial Leverage; g), h) HH and Business Leverage . Shaded areas are 90% (light) 68% (dark) confidence bands.

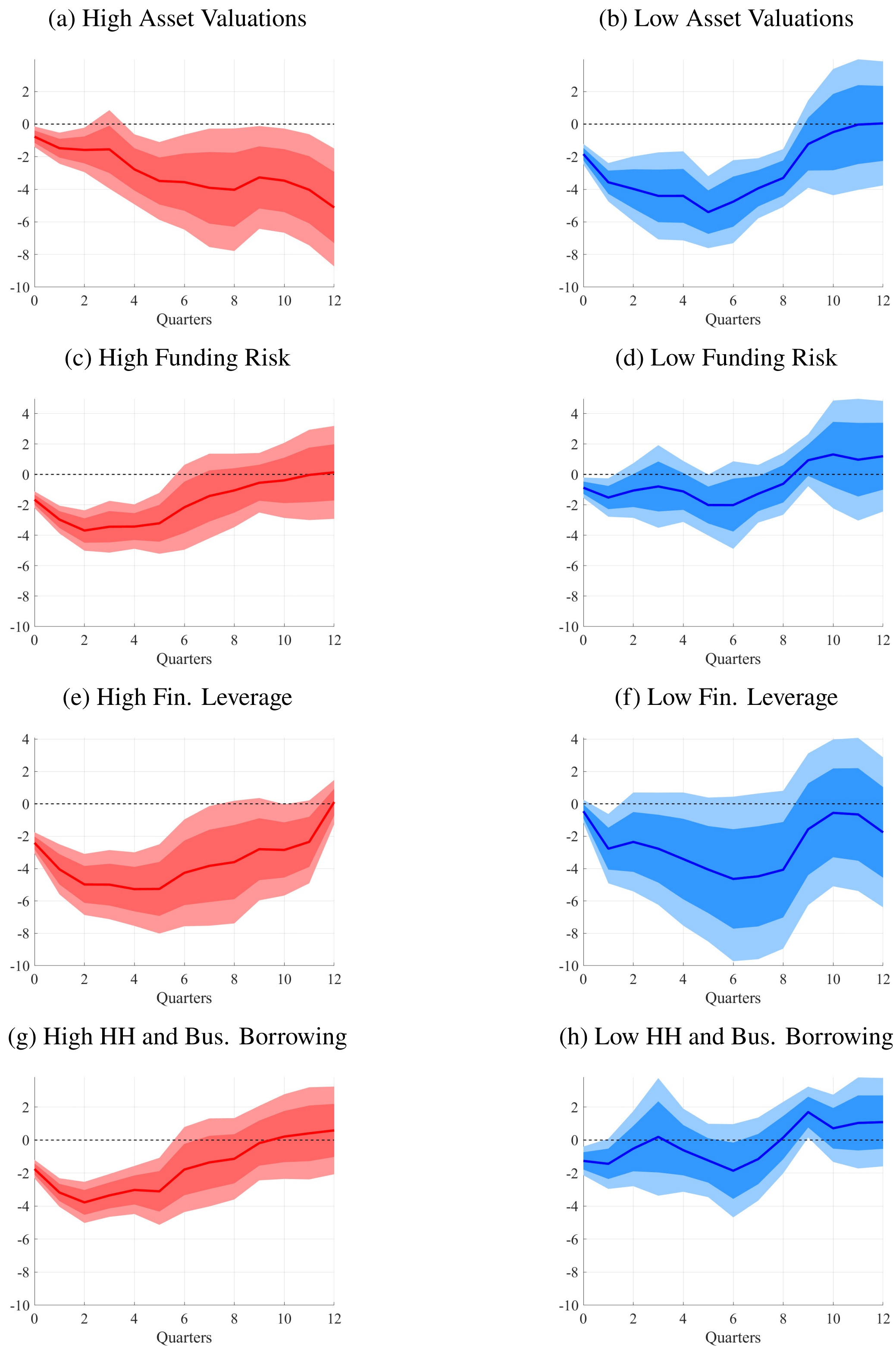


Figure 12: IRFs of fixed-investment to a negative business cycle shock, %. Regimes defined on FVI subindices: a), b) Asset Valuations; c), d) Funding Risk ; e), f) Financial Leverage; g), h) HH and Business Leverage. Shaded areas are 90% (light) 68% (dark) confidence bands.