MONETARY POLICY AND SYSTEMIC RISK

A Master's Thesis

by
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İhsan Doğramacı Bilkent University
Ankara
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To my mother

Monetary Policy and Systemic Risk

The Graduate School of Economics and Social Sciences
of
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by

UTKU ÇAM

In Partial Fulfillment of the Requirements for the Degree of
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Monetary Policy and Systemic Risk
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I certify that we have read this thesis and have found that it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Arts in Economics.

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ABSTRACT

Monetary Policy and Systemic Risk

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This thesis investigates how and through which channels conventional U.S. monetary policy affects systemic risk from February 1990 to February 2020. Systemic risk is measured with a market capitalization-weighted ΔCoVaR framework applied to U.S. Global Systemically Important Banks, directly linked to two emphasized channels: the credit cost channel and the risk-taking channel. The study employs structural vector autoregressions with external instrument identification, using high-frequency monetary policy surprises around FOMC announcements to isolate exogenous policy shocks. This strategy is benchmarked against traditional Cholesky identification across specifications, including industrial production, consumer prices, the federal funds rate, and financial indicators such as the excess bond premium, National Financial Conditions Index Risk, and the CBOE Volatility Index. External instruments perform better than Cholesky, eliminating price puzzles and generating stronger, theoretically consistent responses. A contractionary monetary policy shock reduces systemic risk, with ΔCoVaR falling by 0.12 percentage points on impact and reaching -0.60 percentage points within two months. These effects persist for nearly three quarters.

Variance decomposition shows that policy shocks account for up to 39% of systemic risk variation under external instruments, compared to less than 10% under Cholesky identification. Transmission occurs primarily through credit costs and risk-taking. The excess bond premium rises immediately after tightening, reflecting higher funding costs, while NFCIRISK and the VIX increase gradually, capturing broader market risk perceptions. Overall, contractionary policy shifts risk away from systemic exposures toward costlier credit and market risks, lowering interconnectedness while raising borrowing costs.

Keywords: Monetary Policy, Systemic Risk, Transmission Mechanisms, Tail Dependency

ÖZET

Para Politikası ve Sistemik Risk

Çam, Utku
Yüksek Lisans, İktisat Bölümü
Tez Danışmanı: Doç. Dr. Öğr. Üyesi Taner Yiğit

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Bu tez, 1990 Şubat ile 2020 Şubat arasındaki dönemde geleneksel ABD para politikasının sistemik riski hangi kanallar üzerinden ve nasıl etkilediğini incelemektedir. Sistemik risk, ABD Küresel Sistemik Öneme Sahip Bankalara uygulanan piyasa değeri ağırlıklı ΔCoVaR çerçevesiyle ölçülmekte olup iki temel kanalla doğrudan ilişkilidir: kredi maliyeti kanalı ve risk alma kanalı. Çalışma, FOMC duyuruları etrafındaki yüksek frekanslı para politikası sürprizlerini kullanarak dışsal politika şoklarını izole eden harici araç tanımlamasına dayalı yapısal vektör otoregresyonları uygulamaktadır. Bu yöntem, sanayi üretimi, tüketici fiyatları, federal fon oranı ve fazla tahvil primi, Ulusal Finansal Koşullar Endeksi Risk bileşeni (NFCIRISK) ile CBOE Volatilite Endeksi gibi finansal göstergeleri kapsayan geleneksel Cholesky tanımlamasıyla karşılaştırılmaktadır. Harici araçlar Cholesky'ye kıyasla daha iyi sonuç vermekte, fiyat bilmecelerini ortadan kaldırmakta ve daha güçlü, kuramsal olarak tutarlı tepkiler üretmektedir. Daraltıcı bir para politikası şoku sistemik riski azaltmakta, ΔCoVaR anında 0,12 yüzde puan düşmekte ve iki ay içinde -0.60 yüzde puana ulaşmaktadır. Bu etkiler yaklaşık üç çeyrek boyunca sürmektedir. Varyans ayrıştırması, politika şoklarının sistemik riskteki varyasyonun harici araçlar altında %39'una kadarını açıkladığını, Cholesky'de ise %10'un altında kaldığını göstermektedir. Aktarım esas olarak kredi maliyetleri ve risk alma üzerinden işlemektedir. Fazla tahvil primi sıkılaşma sonrasında hemen artarak daha yüksek finansman maliyetlerini yansıtırken, NF-CIRISK ve VIX kademeli olarak yükselmekte, daha geniş piyasa risk algılarını göstermektedir. Genel olarak daraltıcı politika, riski sistemik maruziyetlerden daha maliyetli kredi ve piyasa risklerine kaydırarak bağlantısallığı azaltmakta fakat borçlanma maliyetlerini yükseltmektedir.

Anahtar Kelimeler: Para Politikası, Sistemik Risk, Aktarım Mekanizmaları, Kuyruk Bağımlılığı

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CHAPTER 1

INTRODUCTION

Before 2008, central banks had a simple view that financial markets were efficient. Policy could stay narrow and target price stability and employment. Then the global financial crisis broke that view. Major intermediaries came close to failing. Policy actions were shown to feed back into bank balance sheets, credit markets, and risk-taking in ways that could put the whole system in danger (Brunnermeier, 2009). Attention moved from single institution failures to systemic risk: the chance that stress at one institution spreads through links and balance-sheet feedback (Bandt and Hartmann, 2000; Allen and Gale, 2000). A new question became central: how does monetary policy shape systemic risk, and through which channels? This question matters because policy now weighs price stability together with financial stability.

Traditional microprudential metrics could not account for joint dependencies or contagion. (Adrian and Brunnermeier, 2016) introduced CoVaR, the system's Value-at-Risk (VaR) conditional on one institution being under stress. ΔCoVaR is that institution's marginal contribution to system tail risk. It is estimated from quantile regressions that link system returns to institution outcomes and state variables. Multivariate volatility implementations preserve tail dependence (Girardi and Ergün, 2013). We read ΔCoVaR as a contagion-channel metric and, for simplicity, use "ΔCoVaR" and "systemic risk" interchangeably.

We emphasize the transmission process of monetary policy to systemic risk centers on two channels. While monetary policy has other transmission channels such as expectations, consumption, exchange rate, and asset prices, we found the credit cost channel and risk-taking channel more pivotal for systemic risk, since the credit cost channel affects the interconnectedness of the financial intermediaries through borrowing-lending activities, and the risk-taking channel affects the common risk exposures in the market. Moreover, these channels operate through intermediaries' balance sheets, especially VaR constraints of their balance sheets, which are by construction and fundamentally linked to our systemic risk measure ΔCoVaR.

First, the credit-cost channel. When the policy rate increases, discount rates rise, and asset prices fall. Intermediaries' net worth shrinks. With decreased equity, external funding becomes costly as collateral. Under financial frictions, lenders demand higher external risk premia and cut their supply of credit. Eventually, this leads to a decrease in the interconnectedness of financial intermediaries (Bernanke and Gertler, 1995; Bernanke et al., 1999). In data, this shows up as wider corporate bond spreads representing the external finance premium, excess risk premia over the standard term premium. (Gilchrist and Zakrajšek, 2012) decomposes corporate spreads into expected default and an excess bond premium (EBP) residual that captures time-varying risk appetite and intermediary balance-sheet capacity. Thus, EBP is a natural proxy for the external finance premia, and it is strongly countercyclical and spikes in crises, so it is a natural gauge of credit costs and funding conditions. Procyclical leverage and liquidity spirals can amplify these dynamics, turning small valuation hits into larger contractions in credit and market liquidity (Adrian and Shin, 2010; Brunnermeier and Sannikov, 2014; Dewachter and Wouters, 2014). Second, the risk-taking channel. Policy also shapes intermediaries' risk appetite, funding choices, and binding VaR and capital constraints. Prolonged periods of low interest rates encourage search-for-yield, higher leverage, and more correlated exposures by common risk exposures. Higher rates do the reverse. They compress risk-taking incentives of intermediaries, tighten balance-sheet constraints, and reduce common exposures across institutions (Borio and Zhu, 2012; Rajan, 2006; Martinez-Miera and Repullo, 2017; Dell'Ariccia et al., 2017).

To track these transmission channels together, we embed ΔCoVaR alongside EBP and the Chicago Fed's National Financial Conditions Risk Subindex (NFCIRISK). NFCIRISK summarizes market volatility, funding premia, and risk perceptions that are orthogonal to macro fundamentals by construction (Brave and Butters, 2011). Moreover, we replace NFCIRISK with the CBOE Volatility Index (VIX) to just account for the implied volatility as risk perceptions in financial markets, while EBP already captures the funding costs through balance sheet constraints rather than the market-based index NFCIRISK.

Our empirical design follows three steps. First, we construct a time-varying ΔCoVaR for U.S. Globally Systemically Important Banks (GSIBs). It is a forward-looking signal of how the system's conditional tail risk changes when an individual bank is distressed. Second, we estimate structural VARs with both recursive (Cholesky) and external instruments (proxy SVAR) identification. The proxy SVAR uses high-frequency federal funds future rate surprises (changes) around the narrow 30-minute window of FOMC announcements as instruments (Gertler and Karadi, 2015). This helps us to isolate policy-driven variation more cleanly, and we can argue that the instruments are orthogonal to other shocks than monetary policy shocks. Third, we trace the dynamic effects of identified policy shocks on macro variables and on EBP, NFCIRISK, and VIX. This decomposition allows us to see the complementary effects of the credit-cost channel and the risk-taking channel.

Three findings emerge. First, identification matters. Recursive identification can yield price puzzles and weak responses. The proxy SVAR isolates exogenous policy responses and delivers patterns that are theoretically plausible and quantitatively strong. Under external instruments, monetary policy shocks explain up to 39% of the variance in systemic risk, versus less than 10% under Cholesky identification. Second, a contractionary shock reduces systemic tail dependence. A 25bps tightening lowers ΔCoVaR by about 0.12 percentage points on impact, with effects lasting nearly three quarters. These responses are statistically and economically meaningful. Third, transmission runs primarily through financial markets rather than traditional macroeconomic variables. EBP, NFCIRISK, and VIX rise consistently with tighter credit conditions, increased volatility expectations, and diminished risk appetite. Taken together, the evidence shows policy tightening reallocates risk away from correlated systemic tail dependency toward higher-priced credits and market risk, reducing interconnectedness and contagion in the financial system.

The remainder of the thesis is organized as follows. Chapter 2 details data and variable construction, including ΔCoVaR estimation and VAR specifications. Chapter 3 presents the econometric framework: the ΔCoVaR quantile regressions and the proxy SVAR with forecast error variance decompositions. Chapter 4 reports the main results, from ΔCoVaR estimates to proxy SVAR responses and robustness checks with alternative policy indicators and instruments. Chapter 5 concludes with implications for monetary policy design and directions for future research.

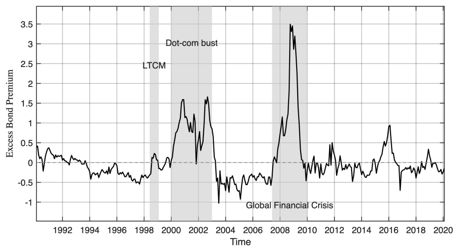
CHAPTER 2

DATA

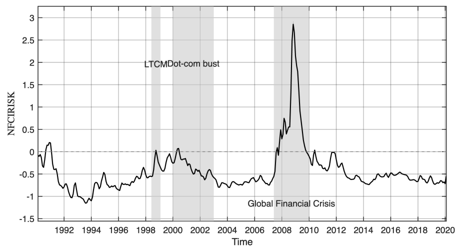
In this study, we employ monthly US macroeconomic and financial data spanning February 1990 to February 2020, sourced primarily from the Federal Reserve Economic Data (FRED) database. The VIX series begins January 2, 1990, representing the earliest date for reliable volatility index calculations. The TED spread data is discontinued as of January 21, 2022. Thus, we exclude the COVID-19 pandemic period beginning in March 2020 due to market disruptions, extraordinary policy interventions (unconventional monetary policy), and *insufficient post-pandemic normalization data* by early 2022. Thus, our VAR specifications eventually have monthly data from 1990:02 to 2020:02.

Economic activity is proxied by industrial production, which provides comprehensive coverage of output and allows us to use monthly data instead of employing GDP, which is released quarterly or relying on interpolation methods. The consumer price index represents inflation. Both are log-transformed and scaled by 100 to allow interpretation in approximate percentage changes. Monetary policy stance is measured by the federal funds effective rate and the 3-month treasury bill rate. We chose them because the federal funds rate is the main conventional policy instrument of the Fed, and the 3-month treasury bill rate is still strongly correlated with the federal funds rate and indicates the policy stance, but also includes some part of the Fed's forward guidance.

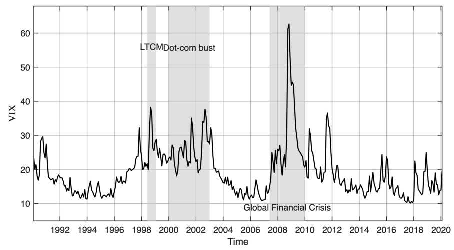
The excess bond premium, introduced by (Gilchrist and Zakrajšek, 2012), isolates the portion of corporate bond spreads not explained by expected defaults. It captures the extra yield investors demand for holding risky credit beyond fundamentals. Thus, it is a proxy for borrowers' risk appetite and the risk-bearing capacity of financial intermediaries. The excess bond premium is strongly countercyclical, spiking in crises, reflecting a withdrawal of intermediary balance sheet capacity. Empirically, it is closely tied to broker–dealer leverage and funding (credit) conditions, which supports the interpretation of it as a measure of credit market and funding conditions. The NFCIRISK, part of the Chicago Fed's National Financial Conditions Index (Brave and Butters, 2011), is designed to extract the unexpected financial stress component orthogonal to macroeconomic activity. Unlike the broad NFCI, the risk subindex isolates shocks to risk premiums, volatility, and market-based measures of uncertainty. Conceptually, it captures shifts in market-wide risk sentiment and funding conditions beyond what fundamentals predict, making it a complementary indicator to the excess bond premium. Moreover, we replace NFCIRISK with VIX in the 6-Variable VAR setup to account for the volatility risk perception in the markets, while excess bond premium already captures the credit conditions through the balance sheets of intermediaries. The three variables provide a sharper picture of monetary policy transmission to systemic risk. The following figures show the excess bond premium, NFCIRISK, and VIX time series plots from February 1990 to February 2022.



(a) Time Series of Excess Bond Premium (Feb 1990 - Feb 2022)



(b) Time Series of NFCIRISK (Feb 1990 - Feb 2022)



(c) Time Series of VIX (Feb 1990 - Feb 2022)

Moreover, the table below shows the pairwise correlations between EBP, NFCIRISK, VIX and ΔCoVaR.

Table 2.1: Pairwise Correlations Among the Risk Measures

	ΔCoVaR	EBP	NFCIRISK	VIX
ΔCoVaR	1.0000	-0.7516	-0.8385	-0.7719
EBP	-0.7516	1.0000	0.7560	0.7373
NFCIRISK	-0.8385	0.7560	1.0000	0.7803
VIX	-0.7719	0.7373	0.7803	1.0000

Note: See Appendix B for multicollinearity diagnostics.

On the monetary policy side, we use high-frequency monetary policy surprises reported by (Bauer and Swanson, 2023) and (Jarociński and Karadi, 2020), specifically unanticipated surprises (MPS_ORTH) and 3 months ahead federal funds futures rate surprises (FF4). The MPS_ORTH is constructed by regressing the 30-minute changes of the first four quarterly Eurodollar futures contracts (ED1–ED4) around the FOMC announcement on the set of six variables that have predictive power on the policy announcement and taking the residual from the regression. Similarly, the FF4 is constructed by taking the 3-month-ahead federal funds futures rate changes around the FOMC announcements. One advantage of the FF4 is that it captures the expectations for the policy rate at the next meeting, since the regular meeting horizon is six weeks. Therefore, we can say that it contains the near-term forward guidance effects as well. [1]

Lastly, we employ the ΔCoVaR as our systemic risk measure. The advantage of the ΔCoVaR is that it focuses on the marginal systemic risk contribution from a distressed institution to the system, unlike VaR, which focuses on losses of only a single component. Since it can be computed in both directions, from institution to system or system to institution, it allows for flexibility in identifying systemic risk contributing institutions and systemically vulnerable institutions. Therefore, it will enable directional analysis. However, we use only the institution to the system in our study. We follow mostly the same data of (Adrian and Brunnermeier, 2016) when estimating the ΔCoVaR. We use the change in the 3-month treasury yield, take the change of the 10-year constant maturity rate minus the 3-month treasury yield as the term spread, and take the change of the Moody's seasoned BAA corporate bond yield minus the 10-year constant maturity rate as the change in credit spreads. Moreover, we use the short-term TED spread, showing the credit risks of the banks, and market returns on S&P500. We use different measures for real estate excess return and equity market volatility. We obtain the daily industry returns from the data library of (Fama and French, 2023). Then, we compute the weekly real estate excess returns by subtracting the mean returns of the banking, insurance, and financial sectors from real estate sector returns and aggregating them to weekly returns by compounding them. For the equity market volatility, instead of computing 22-day rolling standard deviations of the returns of each market constituent, we use the implied volatility index (VIX) of S&P500. These were state variables for

[1] Near-term contracts like FF3 average the funds rate over the whole month, mixing pre- and post-meeting days. By contrast, FF4 covers mostly post-meeting days, giving a cleaner measure of the expected policy rate after the next FOMC decision.

the ΔCoVaR estimation. [2]

The following chapter focuses on the results of our empirical study. First, we present the results of the ΔCoVaR estimation process. Then, we compare Cholesky identification and proxy SVAR methods across different VAR specifications.

[2]See Appendix A. for detailed data dictionary.

CHAPTER 3

METHODOLOGY

This section outlines the econometric framework used to estimate the time-varying ΔCoVaR measure of systemic risk, following the approach of (Adrian and Brunnermeier, 2016), the proxy SVAR method used by (Gertler and Karadi, 2015), and the forecast error variance decomposition methodology.

3.1 The ΔCoVaR Framework

In words, ΔCoVaR quantifies the marginal contribution of a financial institution to system-wide distress by capturing changes in the system's conditional Value-at-Risk when the institution moves from a median state to a distress state. Now, we start by defining the Value-at-Risk (VaR). Let $R_{t,i}$ denote (loss) returns of institution i at time t. The VaR at quantile level $q \in (0, 1)$ is the smallest number $\text{VaR}^q_{t,i}$ such that the probability of losses not exceeding this value is q. Formally, VaR is defined as:

$$\Pr\left(R_{t,i} \leq \text{VaR}^q_{t,i}\right) = q \tag{3.1}$$

In other words, $\text{VaR}^q_{t,i}$ represents the q-quantile of the distribution of $R_{t,i}$ and is interpreted as the maximum expected loss over a given horizon with confidence level q. Higher values of $\text{VaR}_{t,i}^q$ correspond to higher tail risk. Now, before defining conditional VaR (CoVaR), let $R_{t,sys}$ denote the return loss of the financial system, measured as the value-weighted portfolio return of all institutions in the sample. The Conditional Value-at-Risk of the system given that institution i is in state $R_{t,i} = \text{VaR}_{t,i}^q$ is defined as

$$Pr(R_{t,sys} \leq \text{CoVaR}_{sys|i}^q | R_{t,i} = VaR_{t,i}^q) = q \tag{3.2}$$

Lastly, the marginal contribution of institution i to systemic risk is the difference between the system's CoVaR conditional on i's distress and the CoVaR conditional on i's median state. Formally, it is defined as

$$\Delta\text{CoVaR}_{t,sys|i}^q = \text{CoVaR}_{t,sys|i}^q - \text{CoVaR}_{t,sys|i}^{0.5} \tag{3.3}$$

Now we can proceed with the estimation process of ΔCoVaR. We estimate the ΔCoVaR following the methodology of quantile regressions developed by Adrian and Brunnermeier (Adrian and Brunnermeier, 2016). First, we run the following quantile regression with the desired quantile level q% and median level 0.5

$$R_{t,i} = \alpha_i^q + \gamma_i^q M_{t-1} + \varepsilon_{i,t}^q \tag{3.4}$$

with the lagged state variables M_{t-1} and obtain the estimate VaR of institution i at quantiles q and 0.5 as

$$\widehat{\text{VaR}}_{t,i}^q = \hat{\alpha}_i^q + \hat{\gamma}_i^q M_{t-1} \tag{3.5}$$

$$\widehat{\text{VaR}}_{t,i}^{0.5} = \hat{\alpha}_i^{0.5} + \hat{\gamma}_i^{0.5} M_{t-1} \tag{3.6}$$

Then, using the estimated $\widehat{\text{VaR}}^{q}_{t,i}$, we estimate the following regression

$$R_{t,sys} = \alpha^{q}_{sys|i} + \gamma^{q}_{sys|i} M_{t-1} + \beta^{q}_{sys|i} \widehat{\text{VaR}}^{q}_{t,i} + \varepsilon^{q}_{t,sys|i} \tag{3.7}$$

and obtain the estimated $\hat{\beta}^{q}_{sys|i}$. Then, we compute the ΔCoVaR as

$$\Delta\text{CoVaR}_t = \hat{\beta}^{q}_{sys|i}(\widehat{\text{VaR}}^{q}_{t,i} - \widehat{\text{VaR}}^{0.5}_{t,i}) \tag{3.8}$$

While the ΔCoVaR methodology provides a robust measure of systemic risk, analyzing its relationship with monetary policy presents significant econometric challenges. The main difficulty is distinguishing between exogenous monetary policy shocks and endogenous policy responses to changing economic and financial conditions. We follow the proxy SVAR approach used by (Gertler and Karadi, 2015) to identify exogenous monetary policy shocks. This framework combines a reduced-form vector autoregression (VAR) with an external instrument that isolates the unexpected component of policy innovations. We present the procedure in the following steps.

3.2 The Proxy SVAR Framework

Let Y_t denote the $n \times 1$ vector of endogenous variables, which we will explicitly mention in the data section. The structural form VAR of order p is specified as

$$AY_t = a + \sum_{j=1}^{p} C_j Y_{t-j} + \varepsilon_t \tag{3.9}$$

where A is the $n \times n$ structural matrix, C_j is the $n \times n$ coefficient matrices, and $\varepsilon_t \sim$ i.i.d. $(0, I_n)$ is the vector of structural shocks. To recover reduced form residuals, we convert the structural form VAR to reduced form VAR by multiplying both sides by A^{-1} and obtain the following form

$$Y_t = c + \sum_{j=1}^{p} B_j Y_{t-j} + u_t, \quad u_t \sim (0, \Sigma), \quad \Sigma = \mathbb{E}[u_t u_t'] \tag{3.10}$$

Here $B_j \in \mathbb{R}^{n\times n}$ and u_t are reduced form residuals. Let $S = A^{-1}$ for notational purposes. Then, we have $B_j = A^{-1}C_j$ and the relationship between reduced form residuals and structural shocks is $u_t = S\varepsilon_t$. Under normalization of $\mathbb{E}[\varepsilon_t\varepsilon_t'] = I_n$, we have $\Sigma = SS'$. Let the policy indicator be the variable with index p, and ε_t^p denote the structural policy shock. Then, $s \in \mathbb{R}^n$, the p-th column of S, is the impact vector. Let e_p be the selection vector, 1 in the p-th position, and zero elsewhere. Since $u_t = S\varepsilon_t$, we have $s = Se_p$. Thus, to identify the impulse response of the policy indicator, we only need to identify this single column s, not the full S matrix. Now, we have

$$Y_t = c + \sum_{j=1}^{p} B_j Y_{t-j} + s\varepsilon_t^p + \text{(other shocks)} \tag{3.11}$$

To identify the column vector s, the framework employs an instrumental variable (IV) approach. Let $Z_t \in \mathbb{R}^m$ be a vector of external instruments and assume that the relevance and exogeneity assumptions hold, $\mathbb{E}[Z_t\varepsilon_t^p] = \phi \neq 0$ and $\mathbb{E}[Z_t\varepsilon_t^q] = 0$ for all $q \neq p$ hold. Now, we estimate the reduced-form VAR by OLS and obtain the residuals u_t. Then, we denote the policy indicator residual as u_t^p and u_t^q for any $q = p$. We regress u_t^p on Z_t as first-stage regression

$$u_t^p = Z_t'\pi + \nu_t \tag{3.12}$$

and obtain $\hat{u}_t^p = Z_t'\hat{\pi}$. For the second-stage, we instrument u_t^p with Z_t for each $q \neq p$ by

$$u_t^q = \beta_q \hat{u}_t^p + \xi_t \tag{3.13}$$

and obtain $\hat{\beta}_q = \frac{\hat{s}_q}{s_p}$ for each $q \neq p$. Then, let $\hat{b} = [\hat{\beta}_1, \dots, \underbrace{\hat{\beta}_{q=p}}_{1}, \dots, \hat{\beta}_n]' \in \mathbb{R}^n$, so that $\hat{b}_p = \hat{\beta}_{q=p} = 1$ and $\hat{b}_q = \frac{\hat{s}_q}{s_p}$ for all $q \neq p$. By definition, we have $\hat{s} = \hat{s}_p \hat{b}$. Notice that, any column s of S satisfies $s'\Sigma^{-1}s = 1$. Then, we can recover

$$\hat{s}_p \pm \frac{1}{\sqrt{\hat{b}'\hat{\Sigma}^{-1}\hat{b}}}, \qquad \hat{s} = \hat{s}_p \hat{b}, \qquad \hat{s}_q = \hat{s}_p \, \hat{\beta}_q \tag{3.14}$$

We can identify $\hat{s}_p$ up to a sign convention, thus we choose $\hat{s}_p > 0$ if Cov$(Z_t, u_t^p) > 0$, otherwise $\hat{s}_p < 0$.

Now, consider the vector moving average form of the reduced-form system as

$$Y_t = \mu + \sum_{h=0}^{\infty} \Theta_h u_{t-h} \tag{3.15}$$

where $\Theta_0 = I_n$ and n is the number of variables, and Θ_h is recursively defined as

$$\Theta_h = \sum_{h=0}^{p} B_j \Theta_{h-j} \tag{3.16}$$

for all $h \geq 1$. Then, we can compute the impulse response of each variable i to a one standard deviation monetary policy shock at horizon h is

$$\text{IRF}_i(h) = e_i' \Theta_h s_p \tag{3.17}$$

where Θ_h is the reduced-form moving average coefficients.

3.3 Forecast Error Variance Decomposition

Forecast Error Variance Decomposition (FEVD) measures how much each structural shock contributes to the uncertainty in forecasting variables within a VAR system across selected time horizons. Unlike impulse response functions, which track how individual shocks affect variables over time, FEVD takes a broader approach by breaking down the total variability of each variable into components attributable to different shocks.

Using the reduced-form vector moving average equation (3.15), the H step ahead forecast error in time t is

$$Y_{t+H} - E_t Y_{t+H} = \sum_{h=0}^{H-1} \Theta_h u_{t+H-h} \tag{3.18}$$

Now, for each variable i, the total forecast error at horizon H is

$$\mathrm{Var}_i(H) = e_i' \left(\sum_{h=0}^{H-1} \Theta_h \Sigma \Theta_h' \right) e_i \tag{3.19}$$

The policy shock's variance contribution to the total forecast error variance is

$$Var_{i,p}(H) = \sum_{h=0}^{H-1} (e_i' \Theta_h s)^2 \tag{3.20}$$

Finally, the proportion of the policy shock's variance contribution relative to the total forecast error variance for variable i is

$$\mathrm{FEVD}_{i,p}(H) = \frac{\sum_{h=0}^{H-1} (e_i' \Theta_h s)^2}{e_i' \left(\sum_{h=0}^{H-1} \Theta_h \Sigma \Theta_h' \right) e_i} \times 100 \tag{3.21}$$

This equation yields the percentage of forecast error variance in variable i caused by the policy shock at horizon H. FEVD allows us to quantify the relative contribution of the shocks to the variation in the other variables and to see the time-varying dynamics of the importance of the shock.

In summary, this chapter outlined the empirical strategy for estimating ΔCoVaR, a proxy SVAR framework for the identification of monetary policy shocks through external instruments, the procedure for estimating impulse responses, and the FEVD computation process. The next chapter turns to the description of the dataset, where we present the macroeconomic and financial variables employed in the analysis and discuss their transformations and sources.

CHAPTER 4

RESULTS

4.1 ΔCoVaR Estimation Results

We begin the results chapter by presenting the estimation outcomes for ΔCoVaR, our primary measure of systemic risk. We estimate the weekly ΔCoVaR at the 5% quantile level for the set of US Global Systemically Important Banks (G-SIBs), aggregate end-of-month values, and take their weighted mean by market capitalization for computing a single time series of ΔCoVaR. Table 4.1 lists the eight U.S. G-SIBs, however we exclude Goldman Sachs from the estimation of ΔCoVaR because their initial public offerings were in the year 1999.

Table 4.1: List of US Global Systemically Important Banks (G-SIBs)

No.	**Financial Institution**	**Ticker**	**Exchange**
1	Bank of America	BAC	NYSE
2	Bank of New York Mellon	BK	NYSE
3	Citigroup	C	NYSE
4	Goldman Sachs	GS	NYSE
5	JP Morgan Chase	JPM	NYSE
6	Morgan Stanley	MS	NYSE
7	State Street	STT	NYSE
8	Wells Fargo	WFC	NYSE

First, we run (3.4) regression with financial market returns for each financial institution with a 5% quantile level and 50% median level. Then, we compute an aggregated system-level return using the market capitalization of the financial institutions as weights. Then, we run (3.7) regression with computed system returns and estimated VaR values for institutions again at the 5% quantile level. Finally, using (3.8), we compute ΔCoVaR. In this section, we present mean regression results across institutions from ΔCoVaR estimation process with 5% quantile level.

Table 4.2: VaR Regression (5% Quantile) — Fixed Effects

	Coefficient	t-statistics	p-value
Constant	-0.00274	-1.297	0.195
Δ 3 Month Yield	0.03358**	2.621	0.009
Δ Term Spread	0.03470***	4.231	<0.001
TED Spread	-0.01537***	-7.214	<0.001
Δ Credit Spread	0.02227*	1.592	0.111
SP500 Returns	1.23960***	45.154	<0.001
Real Estate Excess Returns	-0.00262***	-8.548	<0.001
VIX	-0.00214***	-19.193	<0.001

See Appendix C for detailed computation.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4.2 shows VaR regression results at the 5% quantile level. The S&P 500 returns, with a coefficient of 1.23, indicating that equity market performance is the primary driver of extreme losses, suggesting that during periods of broad market decline, the portfolio experiences amplified downside risk as expected. Credit market conditions also play a crucial role, as evidenced by the negative TED spread coefficient, which indicates that increased credit stress and liquidity concerns are associated with more severe tail losses. Interest rate factors demonstrate mixed effects: both changes in 3-month yields and term spreads show positive relationships with VaR, suggesting that interest rate volatility contributes to tail risk. The negative coefficient on VIX presents a counterintuitive finding that suggests higher implied volatility is associated with less severe tail losses. Real estate excess returns show a small negative relationship with tail risk, indicating that stronger real estate performance provides modest protection against extreme losses.

Table 4.3 shows the CoVaR regression results at the 5% quantile level, demonstrating how systemic risk factors influence tail risk conditional on banking

Table 4.3: CoVaR Regression (5% Quantile) — Fixed Effects

	Coefficient	t-statistics	p-value
Constant	-0.00185*	-1.697	0.090
Δ 3 Month Yield	0.01544***	2.634	0.008
Δ Term Spread	0.02094***	5.244	<0.001
TED Spread	-0.00774***	-7.873	<0.001
Δ Credit Spread	0.00449	0.735	0.463
SP500 Returns	0.69156***	36.751	<0.001
Real Estate Excess Returns	-0.00142***	-9.417	<0.001
VIX	-0.00101***	-18.716	<0.001
$\widehat{VaR}^q$	0.50075***	45.232	<0.001

See Appendix C for detailed computation.
* p<0.10, ** p<0.05, *** p<0.01

sector distress. $\widehat{\text{VaR}^q}$ with a coefficient of 0.45, suggesting that individual tail risk exposure in the banking sector substantially amplifies tail risk in the financial system. This finding underscores the interconnected nature of financial markets and the role of the interconnected transmission mechanism for systemic risk. Consistent with the unconditional VaR results, S&P 500 returns remain highly significant with a coefficient of 36. However, although the magnitude is lower than in the standard VaR model, it indicates that equity market performance remains important. The TED spread coefficient remains negative, confirming that credit stress increases conditional tail losses. Interest rate factors maintain positive relationships with conditional VaR, while the counterintuitive negative coefficients on VIX and real estate excess returns persist. These results show the importance of individual tail risk exposure in determining system-wide tail risk. In Table 4.4 and 4.5, we show the descriptive statistics of estimated ΔCoVaR and state variables used in the estimation.

Table 4.4: Descriptive Statistics of ΔCoVaR Measures

	Mean	Median	Std. Dev.	Min	Max
ΔCoVaR(1%)	-3.3862	-2.9289	1.4527	-12.3840	-1.6403
ΔCoVaR(5%)	-2.1809	-1.9485	0.8359	-7.2308	-1.1638
ΔCoVaR(10%)	-1.5655	-1.3737	0.6409	-5.5477	-0.7926

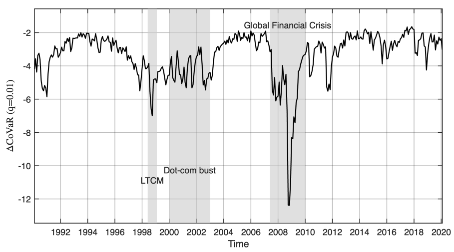
Notes: ΔCoVaR measures are reported at the 1%, 5%, and 10% quantile levels. Values are weekly and expressed in percentage points.

Table 4.5: Descriptive Statistics of State Variables

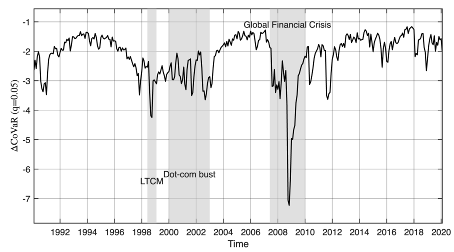
	Mean	Std. Dev.	Min	Max
Δ 3M Yield	-0.0045	0.0817	-0.9800	0.5900
Δ Term Spread	0.0006	0.1108	-0.8700	0.8600
TED Spread	0.4641	0.3595	0.0700	4.0800
Δ Credit Spread	0.0001	0.0677	-0.4400	0.7200
VIX	19.4690	7.8885	9.3400	74.6200
Real Estate Excess Returns	-0.1046	2.4878	-18.9170	11.1370
Market Return	0.0023	0.0230	-0.1937	0.1166

Notes: The spreads and spread change variables are on a weekly basis, while returns are in weekly percentage points.

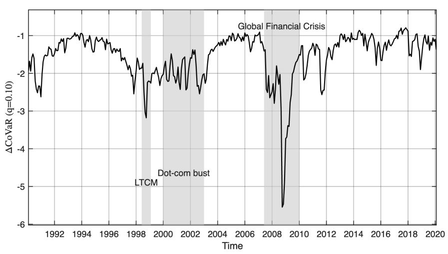
The ΔCoVaR statistics show systemic risk spillovers are consistently negative across all quantile levels. The spillover effects are most pronounced at extreme quantiles, with ΔCoVaR at the 1% level averaging -3.39 percentage points compared to -2.18 percentage points at the 5% level and -1.57 percentage points at the 10% level. The substantial variation in these measures reflects the highly volatile nature of systemic risk transmission over the sample period. The following figures show the time-series graphs of ΔCoVaR in three quantile levels.



(a) ΔCoVaR at the 1% quantile



(b) ΔCoVaR at the 5% quantile



(c) ΔCoVaR at the 10% quantile

Figure 4.1: Time series of ΔCoVaR measures at different quantile levels.

Notes: ΔCoVaR values are monthly aggregations for a cleaner look and expressed in percentage points.

The following Figure 4.1 shows how the volatility of systemic risk has changed over time. The line stays around zero most of the time, meaning financial system risk was relatively stable. During major crises, the line drops sharply, showing systemic risk contributions declined and became unstable. The most significant fall happened during the global financial crisis of 2007–2009, when uncertainty and spillover risks across institutions were at their highest. There are also minor dips during the LTCM rescue in 1998, the dot-com bust in the early 2000s, and the COVID-19 pandemic in 2020. In short, this graph shows us the isolated systemic risk contribution behavior during some of the recent financial crises.

4.2 Proxy SVAR Results

This section presents the empirical results of the proxy SVAR analysis. The main objective is to assess how unanticipated monetary policy shocks propagate through the real economy and financial markets, emphasizing their implications for systemic risk and idiosyncratic risks. Throughout our analysis, we use the literature standard of 12 monthly lags. First, we present our 4-Variable baseline proxy SVAR model specification with industrial production, consumer price index, federal funds effective rate, and ΔCoVaR. We multiply ΔCoVaR by 100 to be able to interpret it easily in percentage points. We identify the structural monetary policy shocks to our policy indicator, the federal funds effective rate, using MPS_ORTH to discover the unanticipated part of the monetary policy shock. The impulse responses we present in this study reflect a 25bps positive shock to the policy indicators. Table 4.6 shows the first-stage regression statistics for this specification, and we observe a robust F-statistic above the threshold 10, recommended by (Stock et al., 2002). Although it is an ad hoc threshold, our instrument is seemingly strong.

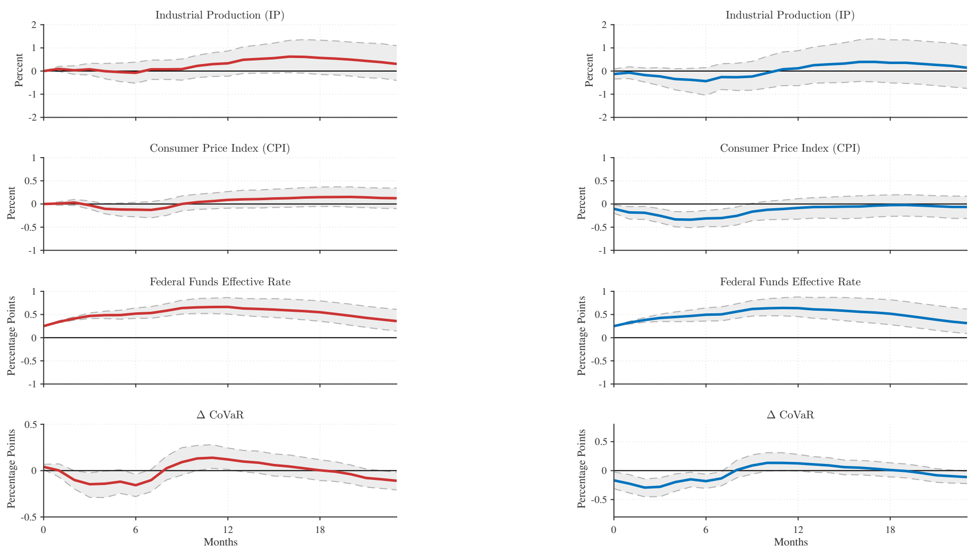
First, we compare the results of our baseline 4-Variable VAR specification in

Table 4.6: First-Stage Regression Statistics: 4-Variable VAR

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
MPS_ORTH	0.439***	0.129	3.398	0.0008
R-squared	0.0405			
F-statistic	14.68*** (0.0002)			
Robust F-statistic	11.54			
Observations	349			

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

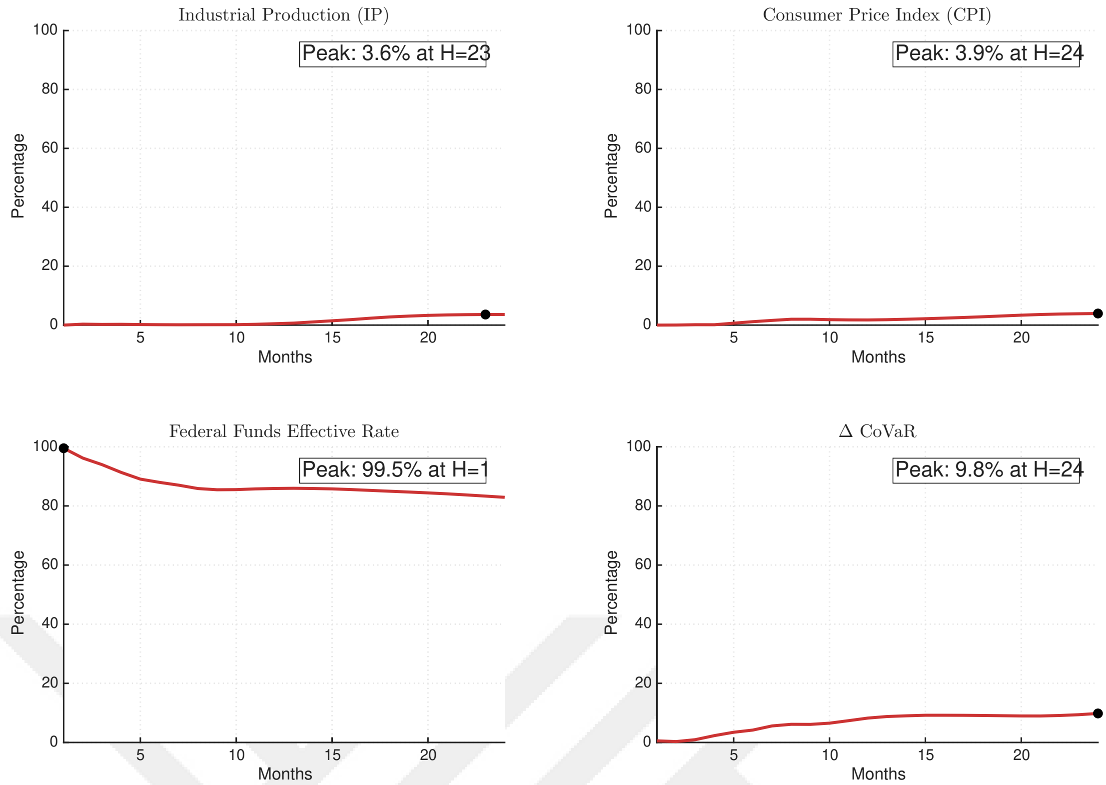
terms of Cholesky identification and proxy SVAR method to see whether the proxy SVAR method works well compared to classical Cholesky identification. In Cholesky identification, we assume the FED responds to industrial production and the consumer price index contemporaneously. Then, the systemic risk variable ΔCoVaR responds to the contractionary monetary policy shock and the shock to other variables contemporaneously. Formally, we specify the VAR setup as $Y_t = [logIP_t, logCPI_t, FFR_t, \Delta CoVaR]'$. We use the same ordering, although it does not matter in proxy SVAR, and identify the monetary policy shock on the policy indicator FFR_t with MPS_ORTH for unanticipated changes in the monetary policy.



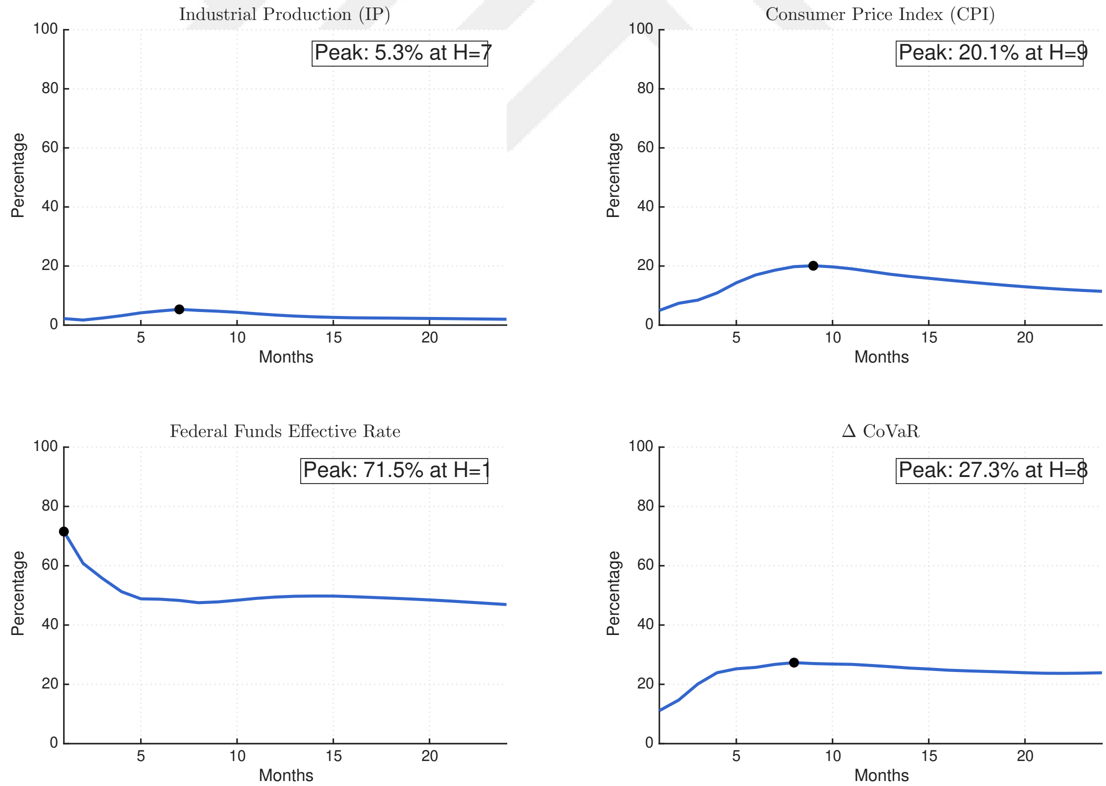
(a) Cholesky Identification (b) Instrumental Variable Identification

Figure 4.2: Impulse Responses of 4-Variable VAR

In Figure 4.2, we compare the impulse responses of both Cholesky identification on Panel (a) and proxy SVAR on Panel (b). Proxy SVAR significantly outperforms Cholesky identification in capturing theoretically consistent monetary policy transmission effects, particularly resolving key empirical puzzles like the price puzzle. Both identification schemes show statistically insignificant responses in industrial production over 24 months. This reflects common challenges with monthly output data where responses arrive with delays, and countervailing economic shocks compress the observable response. However, the methods diverge dramatically in treating price dynamics and systemic risk. Under Cholesky identification, consumer prices remain statistically insignificant throughout the entire horizon, indicating the presence of the well-known price puzzle where contractionary monetary policy appears to increase rather than decrease prices due to information effects that offset conventional transmission channels of monetary policy. The federal funds rate increases and maintains significance over 24 months, and peaks at 0.66 percentage points around month 12, consistent with contractionary policy. Notice that ΔCoVaR exhibits an increasing behavior under Cholesky. It initially increases significantly but minimally by 0.04 percentage points on impact, contradicting theoretical expectations, before becoming significant from months 3 and 6 and reaching a peak decrease of -0.15 percentage points at month 6. In contrast, proxy SVAR resolves the price puzzle entirely, showing consumer prices declining significantly by 0.10% on impact, reaching their lowest response of -0.33% decrease at month 5, and maintaining significance until month 9, a response that aligns with theoretical predictions for contractionary monetary policy. The federal funds rate response is a bit more muted compared to Cholesky identification, peaking at 0.64 percentage points around month 12, which reflects the fact that proxy SVAR can only identify shocks to the policy rate up to the strength of the instrumental variable. Most importantly, ΔCoVaR demonstrates theoretically consistent behavior under proxy SVAR, decreasing significantly by 0.17 percentage points on impact and maintaining significance until month 7, with a lowest level of -0.30 percentage points at month 2. This response indicates that contractionary monetary policy immediately decreases contributions of financial institutions to systemic risk, with effects persisting for nearly three quarters, providing evidence that policy shocks propagate through the financial system.



(a) Cholesky Identification



(b) Instrumental Variable Identification

Figure 4.3: Forecast Error Variance Decomposition (FEVD) of 4-Variable VAR

In Figure 4.3, we introduce the plots of forecast error variance decomposition

(FEVD) of Cholesky identification and proxy SVAR to see the proportional effect of the monetary policy shock on the VAR variables. One crucial distinction with proxy SVAR is that we can only plot the variance decomposition of the monetary policy shock since we only identify the associated column in the structural shock matrix. The remaining variance proportions can be seen as the composite of other shocks. For convenience, we plot only the monetary policy shock contribution to match the proxy SVAR format in Cholesky identification. Both methods confirm that monetary policy shocks explain minimal variation in industrial production, consistent with established literature showing limited real effects of policy shocks. However, the proxy SVAR demonstrates marginally higher explanatory power on impact. Cholesky identification shows no explanatory power for policy shocks on price movements. At the same time, proxy SVAR reveals that monetary policy accounts for up to 20% of consumer price variation at its peak, with this explanatory power declining gradually over the forecast horizon, aligning with theoretical expectations about monetary transmission to prices. Federal funds rate decomposition illustrates the fundamental differences between identification approaches. Cholesky identification begins at 99.5% explanatory power on impact due to its recursive structure that assumes policy shocks have immediate full effects on the policy rate itself. At the same time, proxy SVAR shows 71.5% explanatory power on impact, declining to approximately 50% over the forecast horizon. This reflects the instrument strength in identifying policy shocks. Cholesky identification shows virtually little explanatory power for policy shocks in systemic risk variation throughout the forecast horizon, indicating a failure to capture the risk-taking channel of monetary policy. In contrast, proxy SVAR maintains substantial explanatory power for policy shocks in ΔCoVaR variation across the entire horizon, providing clear evidence that correctly identified monetary policy innovations significantly influence systemic risk dynamics.

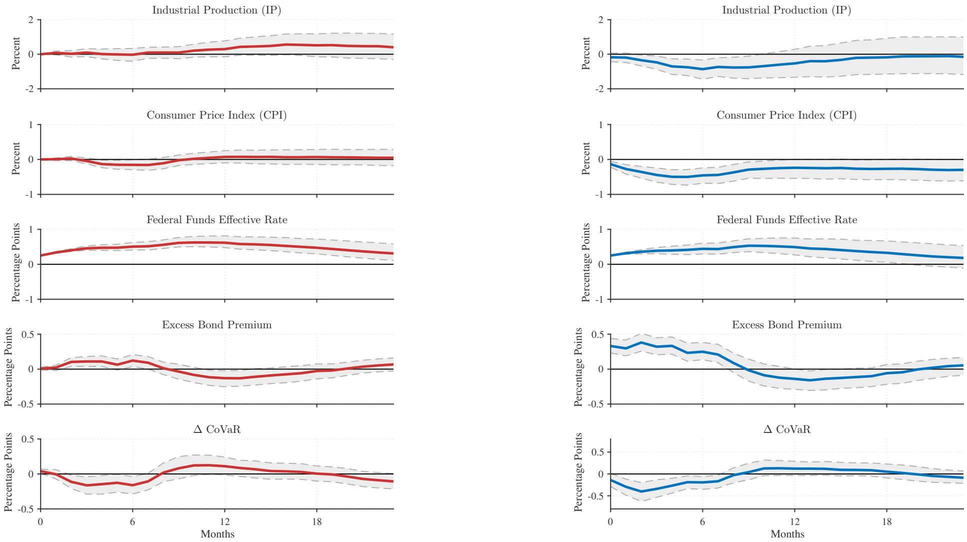
Compared to the Cholesky identification, the proxy SVAR delivers a more credible account of the monetary policy shock by eliminating the price puzzle, producing a consistent decline in consumer prices, and capturing a more realistic and persistent response of systemic risk. The Cholesky identification fails to explain the variation in systemic risk by the federal funds rate dynamics. On the other hand, the proxy only generates stronger and persistent effects on ΔCoVaR and attributes a larger share of price variance and systemic risk to monetary policy shocks. These results highlight that the proxy SVAR provides a sharper identification of policy shocks, yielding interpretations more aligned with theoretical foundations and empirical evidence. To employ the mentioned strengths of the proxy SVAR, we extend our baseline 4-Variable model with excess bond premium to account for credit costs and see the effects of the credit cost channel of the monetary policy. Table 4.7 shows that the robust F-statistic of the first-stage regression of our 5-Variable model is again above the threshold 10. Thus, the weak instrument problem is relatively not a concern.

Table 4.7: First-Stage Regression Statistics: 5-Variable VAR

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
MPS_ORTH	0.436***	0.124	3.518	0.0005
R-squared	0.0417			
F-statistic	15.15*** (0.0001)			
Robust F-statistic	12.38			
Observations	349			

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

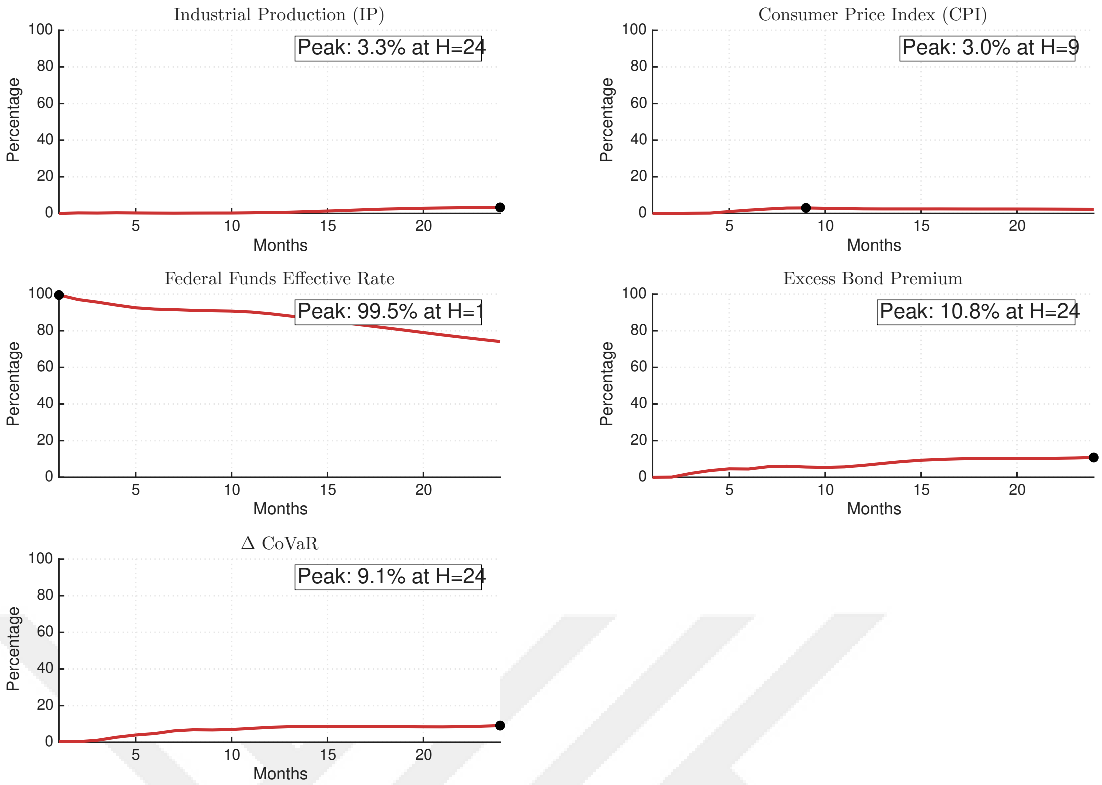
We add excess bond premium to our baseline model in percentage change terms and construct a 5-Variable VAR. Similar to the baseline 4-Variable VAR, we employ MPS_ORTH as the external instrument for the federal funds rate. With the inclusion of excess bond premium, we can isolate the non-default component of corporate bond spreads to capture pure investor risk attitude and the effects of financial frictions. It also allows us to investigate how monetary policy shocks transmit through borrowing-lending incentives and credit cost conditions of financial intermediaries.



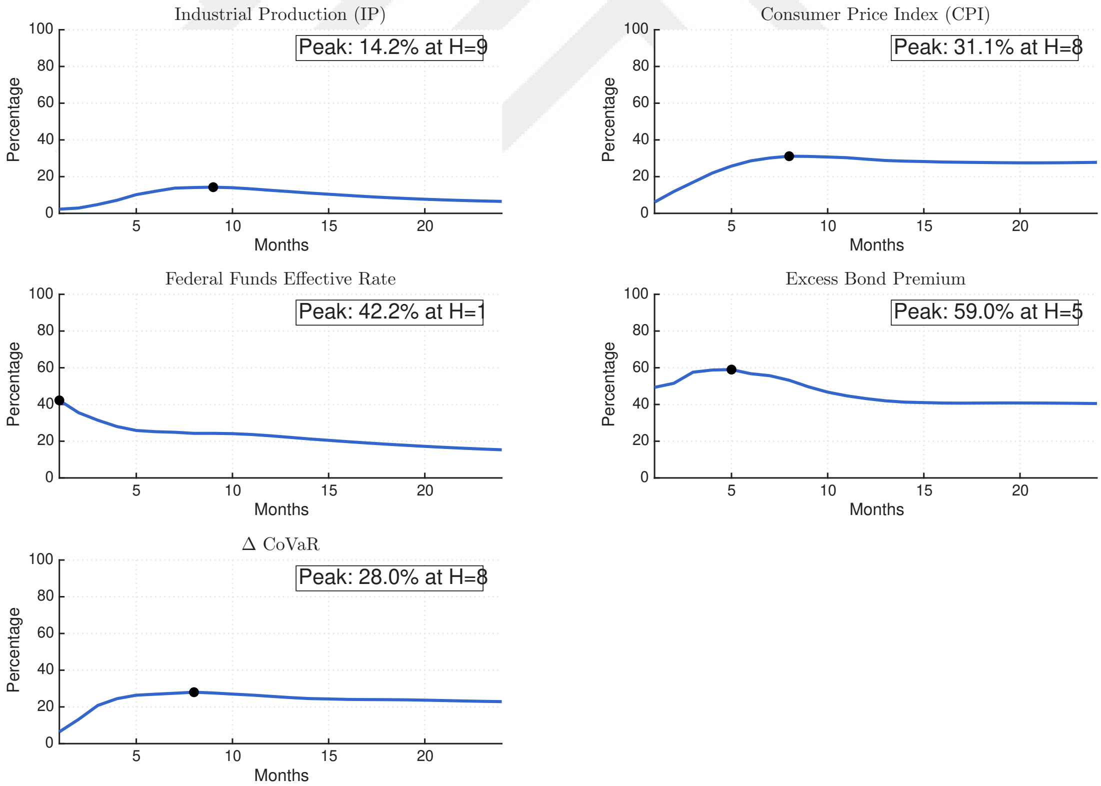
(a) Cholesky Identification (b) Instrumental Variable Identification

Figure 4.4: Impulse Responses of 5-Variable VAR

In Figure 4.4, we see a similar difference between the Cholesky identification and proxy SVAR approach, where Cholesky underestimates the effects and yields results that are proportionally less significant than the results in proxy SVAR. Moreover, the 5-Variable model amplifies these differences, showing more favorable differences between the Cholesky and proxy SVAR. In the 4-Variable model, industrial production remains statistically insignificant throughout the horizon under both identification methods. However, the 5-Variable model under proxy SVAR reveals significant output effects, with industrial production declining by 0.34% in month 2 with a delayed response and continuing to fall to -0.86% through month 6, maintaining significance until month 10. Consumer price responses show substantial differences across specifications. In the 4-Variable model, prices decline by 0.10% on impact under proxy SVAR, reaching a minimum of -0.33% at month 5. The 5-Variable model shows a similar response but presents a greater persistence, with prices falling by 0.48% by month 5 and stabilizing around -0.24% from baseline relative to pre-shock levels throughout the horizon. This evidence shows that credit market conditions contribute to more prolonged disinflationary pressures following contractionary policy. The federal funds rate responses differ notably between the models. The 4-Variable model shows a higher increase in the policy indicator in comparison to the 5-Variable specification. However, the latter one, the federal funds rate, responds in a more persistent way. In the 4-Variable model, systemic risk decreases by 0.17 percentage points on impact, with a lowest at -0.30 percentage points at month 2, and maintains significance until month 7. The 5-Variable model shows ΔCoVaR decreasing by 0.14 percentage points on impact and reaching a similar lowest point of 0.40 percentage points at month 2. However, the crucial difference is the synchronized movement between ΔCoVaR and excess bond premium, with both variables exhibiting nearly identical response patterns and timing. The inclusion of excess bond premium provides direct evidence of the credit cost channel operating as a transmission mechanism of monetary policy. This synchronization validates the theoretical framework linking the credit cost channel to systemic risk.



(a) Cholesky Identification



(b) Instrumental Variable Identification

Figure 4.5: Forecast Error Variance Decomposition (FEVD) of 5-Variable VAR

The FEVD of the extended model with EBP is presented in Figure 4.5. The

Cholesky identification fails again to properly isolate exogenous monetary policy shocks from endogenous central bank responses to economic conditions. Both identification methods confirm that monetary policy shocks explain a limited proportion of industrial production fluctuations, consistent with established empirical literature reporting limited effects of monetary policy shocks on real variables. However, proxy SVAR demonstrates superior performance, with explanatory power reaching 14.2% at month 9, compared to Cholesky identification, demonstrating virtually negligible contribution throughout the forecast horizon. The most pronounced divergence between methods occurs in the consumer price index. Cholesky identification explains only 3% of the variation in consumer prices. In contrast, proxy SVAR demonstrates that monetary policy shocks account for up to 31.1% of consumer price variation at month 6, with explanatory power gradually declining a tiny amount over the forecast horizon. The federal funds rate decomposition illustrates fundamental structural differences between identification approaches. Cholesky identification begins at 99.5% explanatory power at month 1, reflecting its recursive assumption that monetary policy shocks have immediate, complete effects on the policy indicator itself. This high initial value represents a methodological distinction rather than an economic meaning. Proxy SVAR shows 42.2% explanatory power initially, declining to approximately 20% over the forecast horizon, indicating a significant proportion of the unanticipated variation in the federal funds rate. The excess bond premium reveals the advantage of proxy SVAR in capturing monetary policy transmission mechanisms. Cholesky identification shows minimal explanatory power, reaching only 10.8% at month 24, suggesting weak and delayed credit effects of monetary policy. Conversely, proxy SVAR demonstrates robust and persistent monetary policy influence on credit conditions, with explanatory power peaking at 59.0% at month 6 before gradually declining. This difference indicates that properly identified monetary policy shocks significantly affect credit spreads beyond fundamental default risk. Cholesky identification explains merely 9.1% of ΔCoVaR variation at its peak, suggesting minimal monetary policy effects on systemic risk. In contrast, proxy SVAR shows substantial explanatory power of 28.0% at month 6, providing clear evidence that monetary policy shocks significantly influence the variation in contributions of financial institutions to systemic risk.

The variance decomposition results prove that Cholesky identification severely underestimates monetary policy's role in explaining the variation of macroeconomic and financial variables. We observe four important findings. First, the Cholesky identification method fails to properly isolate exogenous monetary policy innovations from endogenous central bank responses to macroeconomic and financial variables, leading to significant downward bias in estimated policy effects. Second, the price puzzle disappears under proxy SVAR, indicating that external instruments successfully identify policy shocks that generate theoretically consistent price responses. Third, the reactions of financial variables show the most significant behaviors under proxy SVAR, suggesting that monetary policy transmission operates particularly strongly through financial channels that recursive methods fail to capture. Lastly, the strong explanatory power of monetary policy for both credit cost and systemic risk under proxy SVAR provides empirical support for the credit cost channel of monetary policy, confirming that policy decisions significantly influence systemic risk through risk perceptions of financial intermediaries.

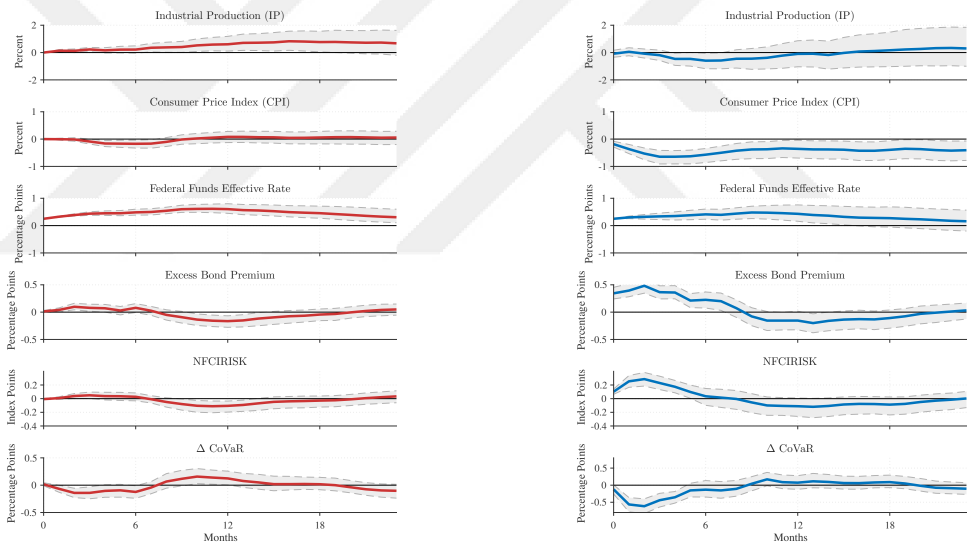
Now, we introduce NFCIRISK to construct our 6-Variable model. While excess bond premium measures how much more borrowers must pay above expected default risk, i.e., the balance sheet constraints of lenders, NFCIRISK measures the system-wide market risk sentiments about volatility and funding that can still amplify systemic risk. The NFCIRISK index is standardized to have a mean of zero and a standard deviation of one over the sample period. Again, we use MPS_ORTH as our instrument for the policy indicator.

Table 4.8: First-Stage Regression Statistics: 6-Variable VAR

Variable	Coefficient	Std. Error	t-statistic	p-value
MPS_ORTH	0.403***	0.113	3.549	0.0004
R-squared	0.0382			
F-statistic	13.82*** (0.0002)			
Robust F-statistic	12.60			
Observations	349			

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

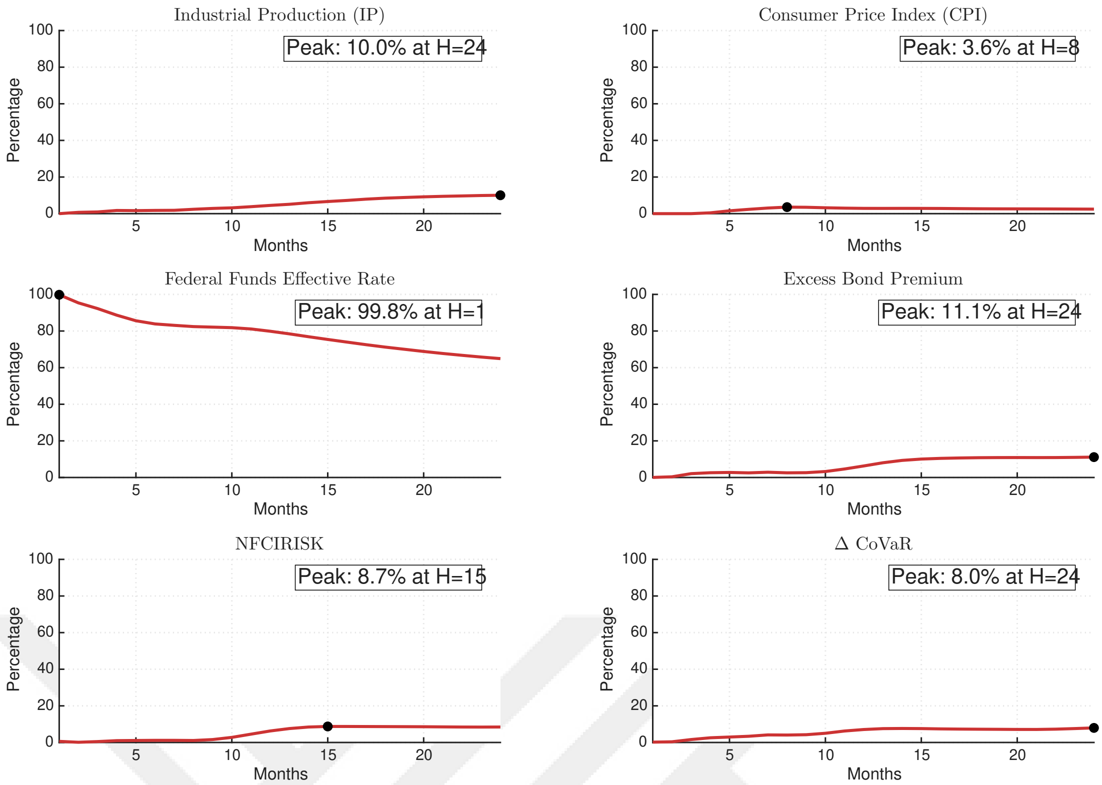
Table 4.8 presents the first-stage regression statistics for the extended proxy SVAR model with EBP and NFCIRISK. Consistent with our previous results, the robust F-statistic exceeds the conventional threshold of 10, indicating that weak instrument bias is unlikely to be a concern in this specification.



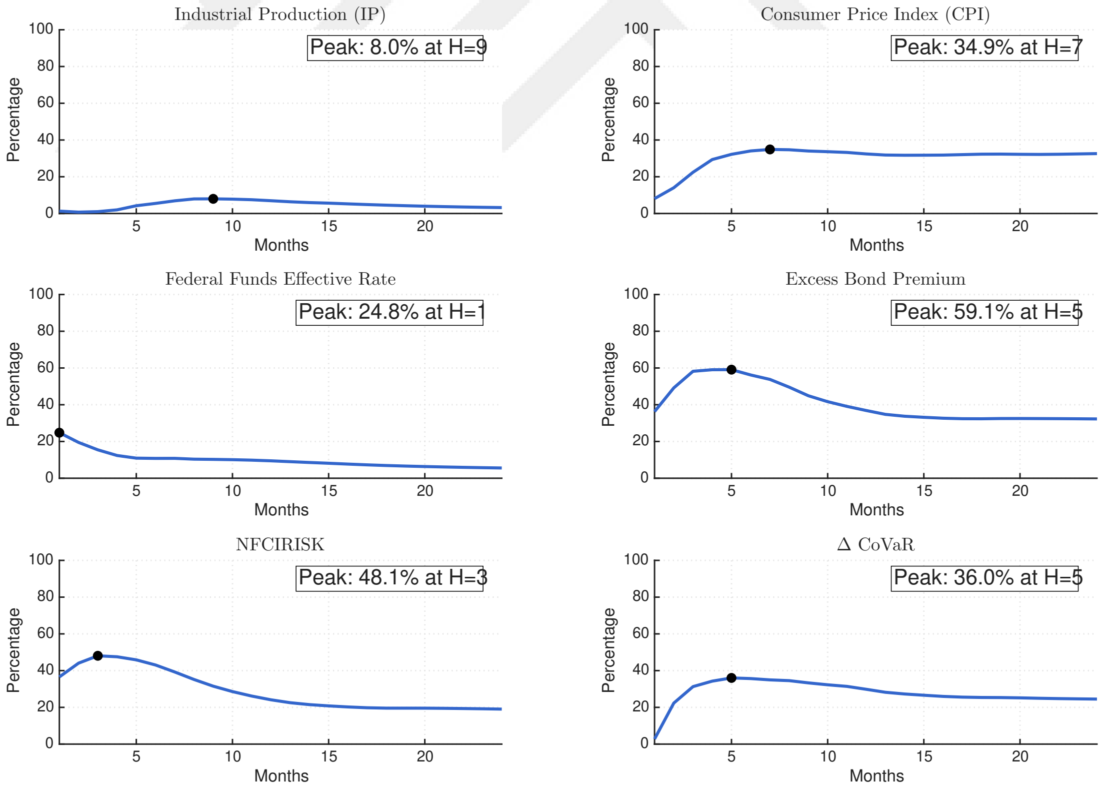
(a) Cholesky Identification (b) Instrumental Variable Identification

Figure 4.6: Impulse Responses of 6-Variable VAR

In Figure 4.6, Cholesky identification yields relatively insignificant and muted impulse responses compared to proxy SVAR again. Cholesky identification produces results that directly contradict established monetary theory. Most critically, industrial production responds positively and significantly for 19 months, reaching a peak increase of 0.86% at month 16. This result contradicts the basic theoretical foundation that contractionary monetary policy should reduce economic output. Before returning to baseline, consumer prices show only a minimal decline around months 4 and 7, indicating virtually no disinflationary effects from the supposed contractionary shock. At the same time, excess bond premium and NFCIRISK show counterintuitive negative responses, with EBP significant only between months 10 and 14 and declining by 0.17 percentage points. Most concerning, ΔCoVaR shows almost no statistically significant response throughout the forecast horizon. On the other hand, proxy SVAR presents theoretically consistent and economically meaningful results across all variables. Industrial production responds appropriately to contractionary policy, declining significantly between months 4 and 7 with a peak decrease of 0.57%, demonstrating the expected real effects of monetary tightening. Consumer prices exhibit persistent disinflationary effects, declining throughout the forecast horizon with the largest decrease of 0.62%, and stabilizing around 0.36% below baseline after 9 months. The federal funds rate increases by over 0.45 percentage points for 15 months, confirming sustained policy tightening. Excess bond premium increases immediately by 0.34 percentage points on impact, peaks at 0.47 percentage points in month 2, then gradually declines until month 7. Similarly, ΔCoVaR decreases by 0.12 percentage points on impact and reaches its lowest by -0.60 percentage points around month 2. The synchronized movement of excess bond premium, NFCIRISK, and ΔCoVaR shows us that contractionary monetary policy simultaneously tightens credit conditions, increases market-wide risk appetite, and decreases systemic risk, aligning the risk-taking channel theory predicts. This behavior of excess bond premium, NFCIRISK, and ΔCoVaR reveals that contractionary monetary policy operates through credit cost and risk-taking channels.



(a) Cholesky Identification



(b) Instrumental Variable Identification

Figure 4.7: Forecast Error Variance Decomposition (FEVD) of 6-Variable VAR

In Figure 4.7, we introduce the plots of FEVD for our 6-variable VAR specification.

This plot again indicates the superiority of proxy SVAR. Industrial production shows minimal variation to monetary policy shock under both methods, with Cholesky explaining only 10.0% at month 24 and proxy SVAR reaching 8.0% at month 9. Both results confirm that monetary policy shocks account for a small proportion of output. Consumer prices demonstrate the highest difference between the two identification methods. Cholesky identification shows virtually no explanatory power with a peak of 3.6% at month 3. In contrast, proxy SVAR shows that policy shock explains 34.9% of consumer price variation at month 7, maintaining substantial explanatory power around 30% throughout the forecast horizon. This significant difference confirms that external instrument identification successfully captures the disinflationary effects of contractionary monetary policy that Cholesky identification misses. Again, the federal funds rate's variance decomposition points out the structural differences between identification approaches. Cholesky begins at 99.8% due to its recursiveness assumption of immediate policy shock effects, declining to approximately 60% over time. Proxy SVAR initially shows 24.8% explanatory power, reflecting the instrument's strength while acknowledging that other factors influence policy rate movements. One important thing to note is that the more variables there are, the less initial explanatory power the shock variable has in proxy SVAR, since the total variance comprises more variables. Excess bond premium shows minimal monetary policy influence under Cholesky with a peak of 11.1% at month 24, suggesting weak credit cost effects. Proxy SVAR yields a robust explanatory power reaching 59.1% at month 3, indicating that properly unanticipated policy shocks significantly affect credit spreads beyond fundamental default risk. NFCIRISK shows the most dramatic contrast among financial variables. Cholesky identification explains only 8.7% at peak, while proxy SVAR shows a significant 48.1% explanatory power at month 3. Lastly, for ΔCoVaR, Cholesky shows minimal effect, while proxy SVAR demonstrates substantial explanatory power of 36.0% at month 3.

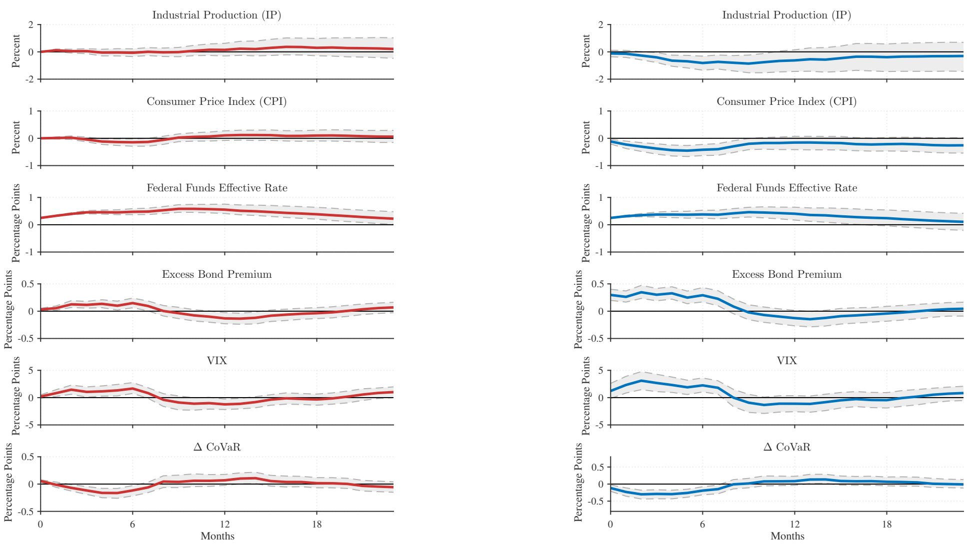
Lastly, we replace NFCIRISK with VIX in our 6-Variable model. Since EBP accounts for the funding costs through the balance sheet constraints, we emphasize capturing only the volatility as risk perception in the market, rather than capturing both funding costs and risk perceptions in the market. Through this specification, we aim to decompose the effects of the transmission channels separately. Since we already employed the VIX in the estimation of ΔCoVaR, we change the market volatility state variable to 22 days rolling standard deviations of the equity returns in the quantile regressions.

Table 4.9: First-Stage Regression Statistics: 6-Variable VAR with VIX

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
MPS_ORTH	0.416***	0.114	3.646	0.0003
R-squared	0.0401			
F-statistic	14.53*** (0.0002)			
Robust F-statistic	13.30			
Observations	349			

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

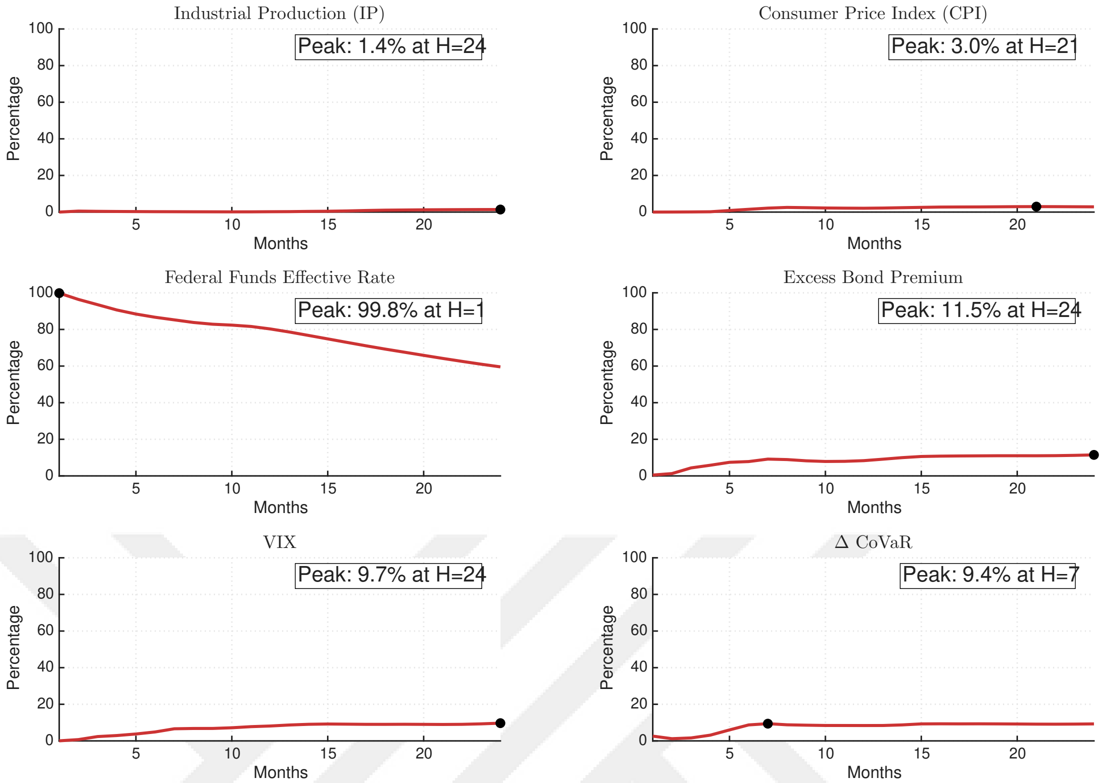
Table 4.9 shows the first stage regression statistics again with a robust F-statistic above 10, as in the previous model specifications.



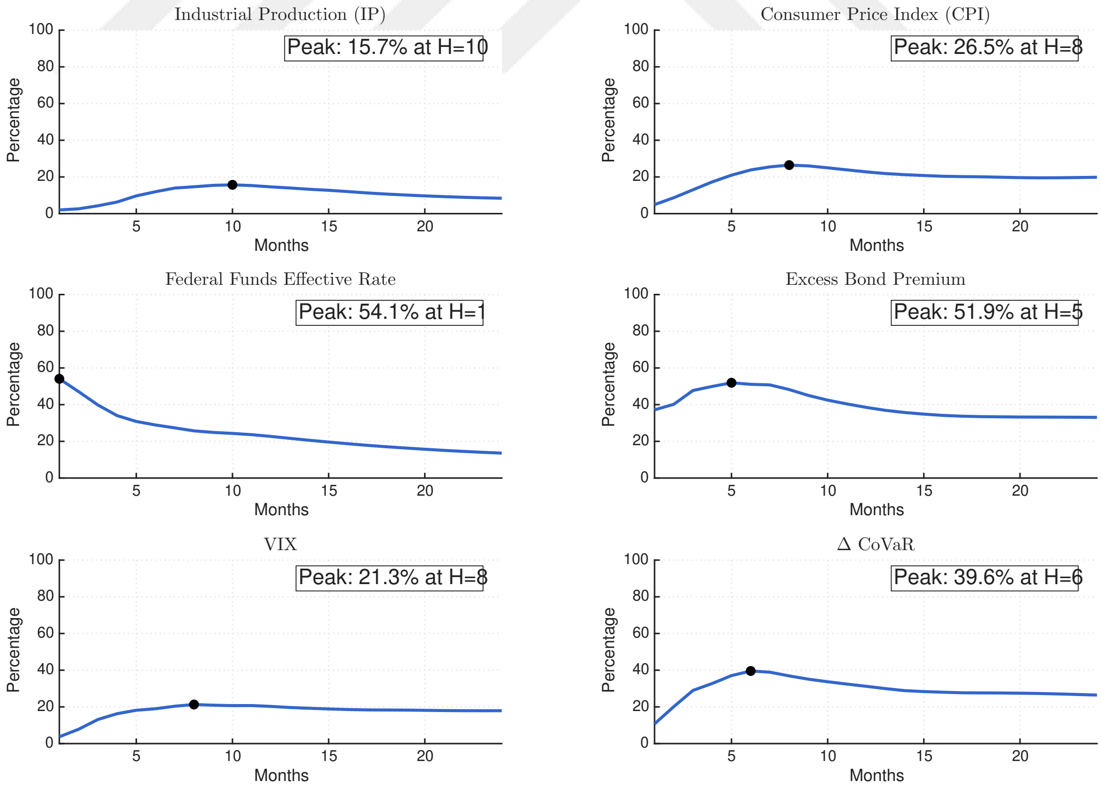
(a) Cholesky Identification (b) Instrumental Variable Identification

Figure 4.8: Impulse Responses of 6-Variable VAR with VIX

Figure 4.8 presents the impulse responses from the 6-Variable VAR with VIX, revealing again significant differences between identification methods that show the patterns observed with NFCIRISK. Under Cholesky identification, the results again contradict fundamental monetary theory. Industrial production shows no significant response to contractionary monetary policy, failing to capture the expected real effects of policy tightening. Consumer prices decline by only 0.15% in month 6, indicating minimal disinflationary impact. The excess bond premium increases modestly by 0.15 percentage points in month 6, while VIX rises by just 1.70 percentage points in the same period. Most notably, ΔCoVaR shows a limited response of -0.16 percentage points in month 5. In contrast, proxy SVAR delivers theoretically consistent and economically meaningful results across all variables. Industrial production responds appropriately to contractionary policy, declining significantly with a peak decrease of 0.85% in month 9, demonstrating the expected contractionary effects on real economic activity. Consumer prices exhibit a more pronounced disinflationary response, declining by 0.46% in month 6, indicating effective transmission through the price level. The excess bond premium increases more substantially by 0.34 percentage points in month 2, showing immediate tightening in credit markets. VIX responds twice as strongly, rising by 3.02 percentage points in month 2, reflecting heightened market uncertainty and risk aversion. Finally, ΔCoVaR shows a stronger and more immediate response, declining by 0.30 percentage points in month 2. Since the excess bond premium already captures funding costs through balance sheet constraints, incorporating VIX allows us to isolate market volatility and risk perception effects separately. This specification enables cleaner decomposition of transmission channels by avoiding overlap between risk measures, while NFCIRISK allows us to observe the combined effects of the channels. The synchronized responses of excess bond premium, VIX, and ΔCoVaR under proxy SVAR demonstrate that contractionary monetary policy operates through tightening credit conditions, increasing market volatility, and reducing systemic risk, consistent with the risk-taking channel and credit cost channel of monetary transmission.



(a) Cholesky Identification



(b) Instrumental Variable Identification

Figure 4.9: Forecast Error Variance Decomposition (FEVD) of 6-Variable VAR with VIX

Figure 4.9 presents the forecast error variance decomposition for the 6-Variable VAR with VIX, again demonstrating the limited explanatory power of Cholesky identification relative to proxy SVAR. Under proxy SVAR, contractionary monetary policy shocks explain substantial portions of variations in key variables. Industrial production shows 15.7% explanatory power at month 10, indicating moderate real effects of policy surprises. Consumer prices demonstrate strong policy influence with 26.5% of variation explained at month 8. The federal funds rate shows 54.1% explanatory power at month 1, reflecting the explanatory power of unanticipated changes in the policy decisions. Excess bond premium exhibits robust policy influence with 51.9% of variation explained at month 5, demonstrating significant transmission through credit channels. VIX shows 21.3% explanatory power at month 8, indicating that monetary policy shocks substantially affect market volatility and risk perception. Finally, ΔCoVar shows considerable policy influence with 39.6% of variation explained at month 6, confirming the credit cost channel and the risk-taking channel by an increase in the explanatory power of the policy shock.

In this section, structural monetary policy shocks are identified with the external instrument MPS_ORTH on the federal funds effective rate, within monthly VARs that include industrial production, consumer prices, excess bond premium, NFCIRISK replacement with VIX, and most importantly, the systemic risk proxy ΔCoVaR. Instrument strength exceeds conventional thresholds in first-stage diagnostics. In summary, we found the following results. Impulse responses align with standard transmission logic and are materially stronger than under Cholesky identification. In the first extended model, a contractionary shock raises excess bond premium immediately and durably. Moreover, ΔCoVaR falls on impact by around 0.13 percentage points and reaches its lowest within two months by -0.40 percentage points. It moves simultaneously with excess bond premium, which provides us with evidence that tighter intermediary credit conditions transmit into lower systemic tail dependence. In the 6-Variable VAR, NFCIRISK summarizes unexpected movements in risk premia, volatility, and liquidity that are orthogonal to contemporaneous macro conditions. We use it as a market-wide risk conditions index complementary to the credit cost focus with excess bond premium. Adding it preserves these patterns and shows a concurrent increase in risk conditions in the market. Moreover, we replace NFCIRISK with VIX to decompose the effects of the credit cost channel and risk-taking channel, since excess bond premium already captures the funding conditions through balance sheet constraints. The results remain robust to this replacement and strengthen the evidence for separate effects of the risk-taking channel and the credit cost channel. In FEVD, we observe that the proxy SVAR identification reallocates ΔCoVaR's variation toward the transmission channel variables and away from the policy rate's direct component, consistent with credit-cost transmission mechanisms. In the 6-Variable VAR specifications, policy shocks explain a larger share of ΔCoVaR in comparison to the 5-Variable VAR specification, presenting strong evidence for both of the transmission mechanisms. In conclusion, a contractionary monetary policy shock tightens intermediary credit cost conditions, increases market-wide risk perception and liquidity conditions, resulting in more incentives for financial intermediaries to hold safer assets, and decreases borrowing-lending activities, finally, a decrease in systemic risk.

In the following section, we introduce robustness checks by considering an alternative policy indicator and instrument. These checks ensure that our findings are not a result of a particular model specification. Importantly, we maintain our focus exclusively on the proxy SVAR framework. [1] The reason is twofold. First, the external instruments approach provides a credible interpretation of monetary policy shocks by employing high-frequency surprises around policy announcements. This allows us to isolate policy innovations from endogenous responses to macroeconomic or financial conditions. Second, our Cholesky

[1] See Appendix D. for Cholesky results.

identification produced weaker and, at times, counterintuitive dynamics such as price puzzles, while the proxy SVAR consistently generated economically coherent impulse responses that align with the established literature. Moreover, the Cholesky identification relies on overly restrictive timing assumptions. For these reasons, the subsequent robustness checks are all conducted within the proxy SVAR environment, which offers a more reliable setting for tracing the transmission of monetary policy to systemic risk.

4.3 Robustness Checks

In this section, in addition to the federal funds rate, we consider the 3-month Treasury bill rate as an alternative policy indicator. The short-term bill rate closely tracks the immediate stance of monetary policy and also includes near-term expectations. On the instrument side, we employ the FF4 for capturing the policy rate expectations about the next FOMC meeting. Compared to instruments measuring contemporaneous effects of FOMC announcements, FF4 is more sensitive to revisions in the expected path of the policy rate, allowing us to capture forward guidance effects more effectively. We test whether our main findings are robust to different measures of the policy stance and to the Fed's influence over the term structure of interest rates.

We specify the 5-Variable VAR with industrial production, consumer price index, 3-month Treasury bill rate, excess bond premium, and ΔCoVaR. This specification provides a clean testing opportunity to determine whether our results are robust to using a market-based short-term rate as a policy indicator.

Table 4.10: First Stage Regression Statistics: 5-Variable VAR (GS3, FF4)

Variable	Coefficient	Std. Error	t-statistic	p-value
FF4	0.580***	0.178	3.245	0.0013
R-squared	0.0514			
F-statistic	18.86*** (<0.0001)			
Robust F-statistic	10.53			
Observations	349			

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

Table 4.10 shows the first-stage regression statistics, and FF4 is a reasonably strong instrument for the 3-month Treasury bill.

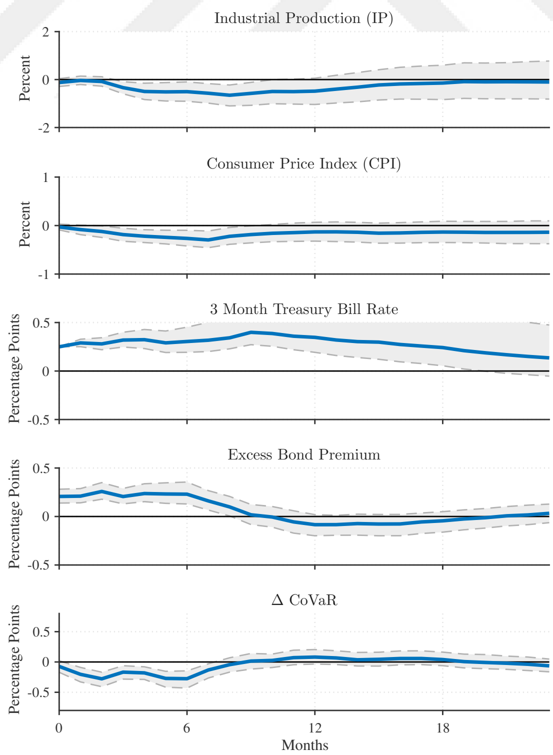


Figure 4.10: Impulse Responses of 5-Variable VAR (GS3, FF4)

Figure 4.10 presents the impulse responses from our first robustness check.

Industrial production exhibits a modest short-term decline, reaching a maximum contraction of 0.65%. This response is consistent with the expected effects of contractionary monetary policy shocks on output, which compress production activity. Consumer prices decline similarly in the short term, bottoming out at approximately -0.28% in month 7. Notably, we again observe no price puzzle under the proxy SVAR framework. The 3-month Treasury bill rate increases by 0.25 bps on impact, peaks at 0.40 bps in month 9. The excess bond premium rises sharply upon impact, reaching a peak of approximately 0.26 percentage points before gradually declining and reverting to pre-shock levels by month 8. This pattern indicates tightening constraints on the lending capacity of financial intermediaries and provides clear evidence of the credit cost channel. The change in ΔCoVaR decreases modestly on impact by 0.07 percentage points but reaches its lowest of approximately -0.28 percentage points in month 2. This demonstrates that systemic risk decreases immediately following a contractionary policy shock, consistent with the transmission of tighter funding conditions and elevated risk premia throughout the financial system. The simultaneity of excess bond premium and ΔCoVaR responses highlights that systemic risk materializes very quickly once the risk-bearing capacity of intermediaries is reduced.

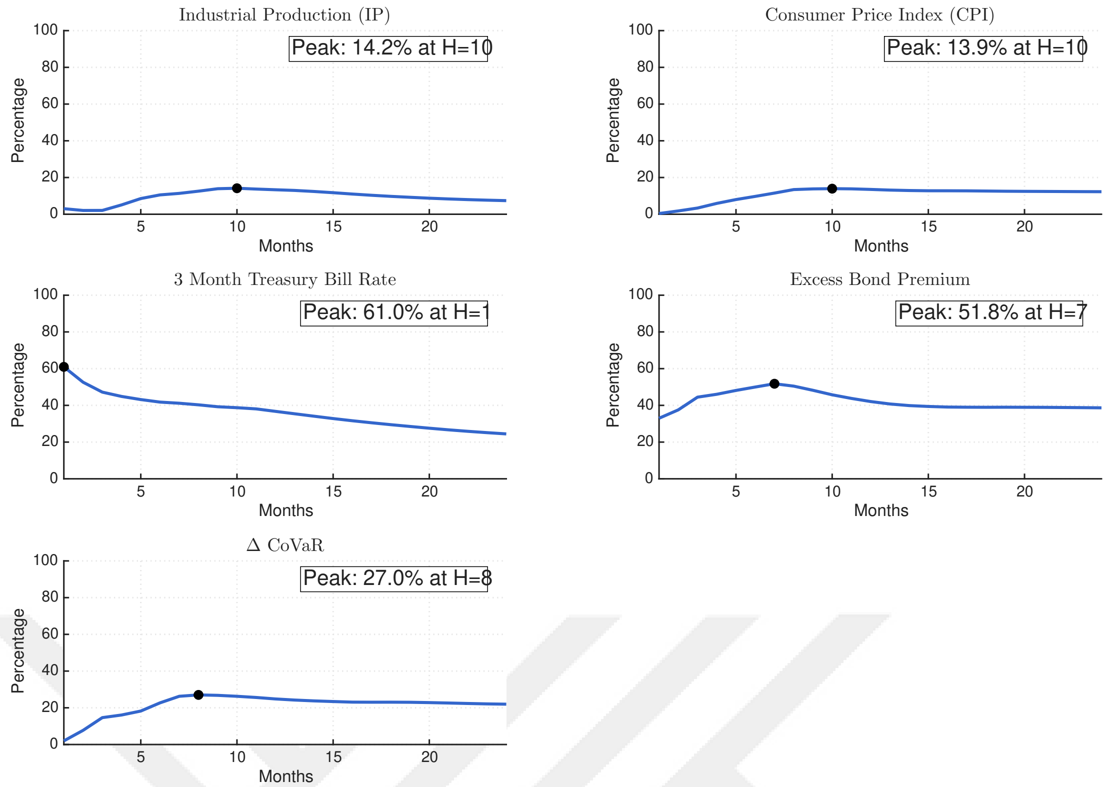


Figure 4.11: Forecast Error Variance Decomposition (FEVD) of 5-Variable VAR (GS3, FF4)

Figure 4.11 presents the FEVD results from the 5-variable VAR model incorporating GS3 as policy indicator and FF4 as external instrument. Industrial production shows the lowest contribution from monetary policy shocks among other variables, with the peak explanatory power reaching 14.2% at the 10-month horizon before gradually declining. This suggests that while monetary policy influences real economic activity, other structural shocks account for the majority of industrial production fluctuations. The consumer price index exhibits a similar pattern, with monetary policy shocks explaining a maximum of 13.9% of price level variance at the same horizon as industrial production. The relatively low contribution indicates that price dynamics are predominantly driven by non-monetary factors, consistent with the gradual transmission of monetary policy to prices. The excess bond premium displays significant sensitivity to monetary policy innovations, with shocks explaining 51.8% of variance at the month 7 horizon. This finding underscores the importance of the credit channel in monetary transmission, as policy changes directly affect risk premia and financial intermediation costs. Finally, ΔCoVaR shows moderate responsiveness to monetary policy shocks, reaching a peak contribution of 27.0%.

Now, we include NFCIRISK in the previous 5-Variable VAR specification. NFCIRISK measures broader shifts in financial market conditions, including unanticipated changes in funding conditions, volatility, and liquidity that are orthogonal to underlying macroeconomic fundamentals, while excess bond premium captures credit cost increases driven by financial intermediary balance sheet constraints. The inclusion of NFCIRISK allows us to analyze the complementary effects of the transmission channels.

Table 4.11: First Stage Regression Statistics: 6-Variable VAR (GS3, FF4)

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
FF4	0.580***	0.163	3.560	0.0004
R-squared	0.0560			
F-statistic	20.64*** (0.0000)			
Robust F-statistic	12.67			
Observations	349			

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

Table 4.11 presents the first-stage regression statistics for the 6-variable VAR model using the 3-month Treasury bill as the policy indicator. The robust F-statistic of 12.67 indicates that our instrument FF4 is strong in identifying monetary policy shocks, satisfying the standard threshold of 10 for valid instrumental variable selection.

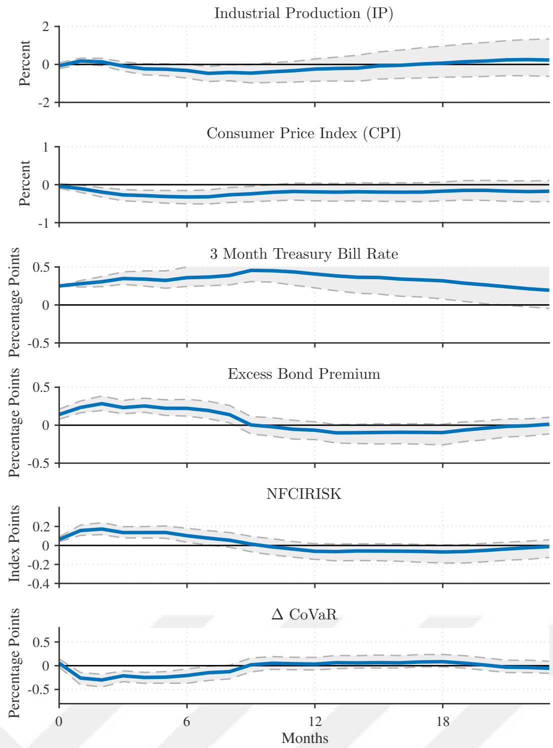


Figure 4.12: Impulse Responses of 6-Variable VAR (GS3, FF4)

The impulse responses represented in Figure 4.12 present consistent patterns with our previous specifications. The inclusion of NFCIRISK produces meaningful changes in real variable responses. Industrial production exhibits a smaller fall of 0.47%, while consumer prices display nearly identical behavior in both specifications. This similarity suggests that real economy transmission channels remain robust regardless of the market-wide risk conditions. The excess bond premium exhibits a similar peak magnitude around 0.28 percentage points. The inclusion of NFCIRISK reveals that broader financial market risk conditions respond more gradually than intermediary-specific credit constraints, with NFCIRISK peaking at 0.17 index points around month 2. In the 6-Variable VAR, systemic risk reaches the lowest point with a similar magnitude of -0.30 percentage points. This specification demonstrates that both of the transmission mechanisms are robust to policy indicators and instruments, i.e., near-term forward guidance.

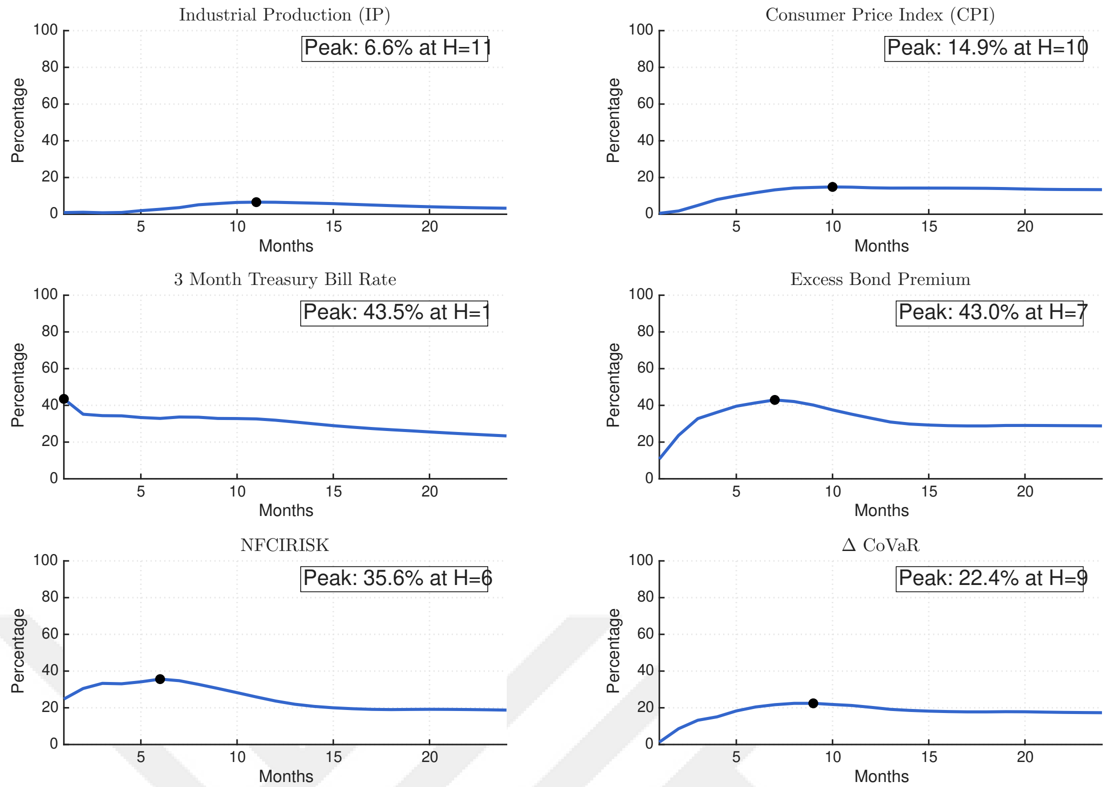


Figure 4.13: Forecast Error Variance Decomposition (FEVD) of 6-Variable VAR (GS3, FF4)

The FEVD plots represented in Figure 4.13 show that industrial production shows a decrease in explanatory power of policy shock from 14.2% to 6.6% at the 10-month horizon, while the consumer price index exhibits a slight increase from 13.9% to 14.9% at the same horizon. These changes suggest that NFCIRISK captures some of the variation previously attributed to monetary policy shocks in explaining output fluctuations. The most striking differences emerge in the financial variables. The 3-month government bond rate shows a significant fall from 61.0% to 43.5%. The excess bond premium displays a more moderate adjustment, with its peak contribution declining from 51.8% at the 7-month horizon to 43.0% at the same period. Importantly, NFCIRISK itself shows substantial sensitivity to monetary policy innovations, with shocks explaining 35.6% of its variance at the 6-month horizon. This finding suggests that monetary policy significantly influences broader financial market risk conditions beyond the specific credit channel captured by excess bond premium. ΔCoVaR exhibits a decrease from 27.0% to 22.4% at the 8-month horizon. Unfortunately, there is no clear way of identifying this decrease, whether by the increase of total variance by inclusion of variables or the irrelevance of NFCIRISK. However, in the main results, we observe an increase in the explanatory power of policy shocks on the variation of ΔCoVaR. Therefore, we conclude that it is caused by the increase in the total variance.

Now, we replace VIX wıth NFCIRISK in the previous 6-Variable VAR specification. The inclusion of VIX allows us to decompose the transmission channels. Specifically, this model allows us to distinguish whether decreases in systemic risk following monetary tightening primarily result from contractions in intermediary credit supply or from changes in market risk appetite and volatility.

Table 4.12: First Stage Regression Statistics: 6-Variable VAR with VIX (GS3, FF4)

Variable	**Coefficient**	**Std. Error**	**t-statistic**	**p-value**
FF4	0.540***	0.171	3.151	0.0018
R-squared	0.0462			
F-statistic	16.86*** (0.0001)			
Robust F-statistic	9.93			
Observations	349			

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

Table 4.12 shows the first stage regression statistics of the 6-Variable VAR with a robust F-statistic very close to the threshold of 10. Therefore, we arguably do not need to be concerned about the weak instrument problem here.

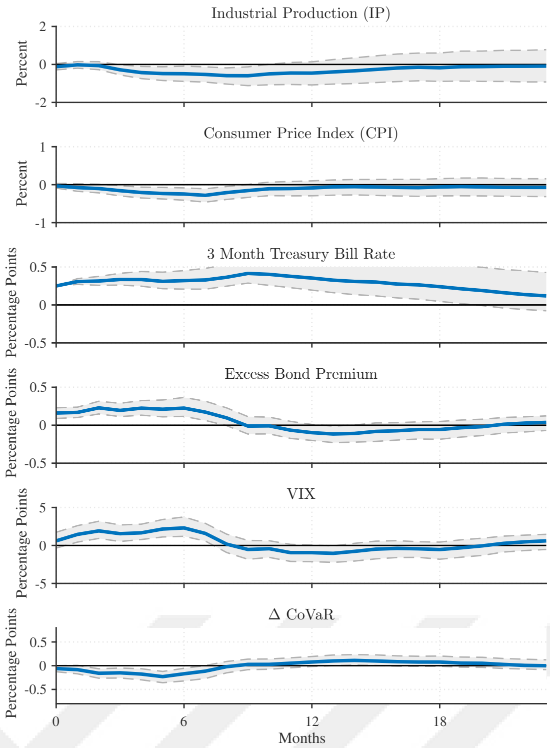


Figure 4.14: Impulse Responses of 6-Variable VAR with VIX (GS3, FF4)

Figure 4.14 shows the impulse responses of the 6-Variable VAR with VIX. Industrial production shows a highest decline of 0.59% at month 9, consistent with the delayed response of macroeconomic variables. Similarly, consumer prices have a highest decline of 0.28% in the month 7. Excess bond premium exhibits a peak of 0.22 percentage points in the second month, and VIX shows the highest increase of 2.33 percentage points in month 5, while ΔCoVaR reaches its lowest by declining 0.22 percentage points in month 5. Near-term forward guidance delayed the response of the market volatility and ΔCoVaR, while response patterns remained robust to the policy indicator and instrument change.

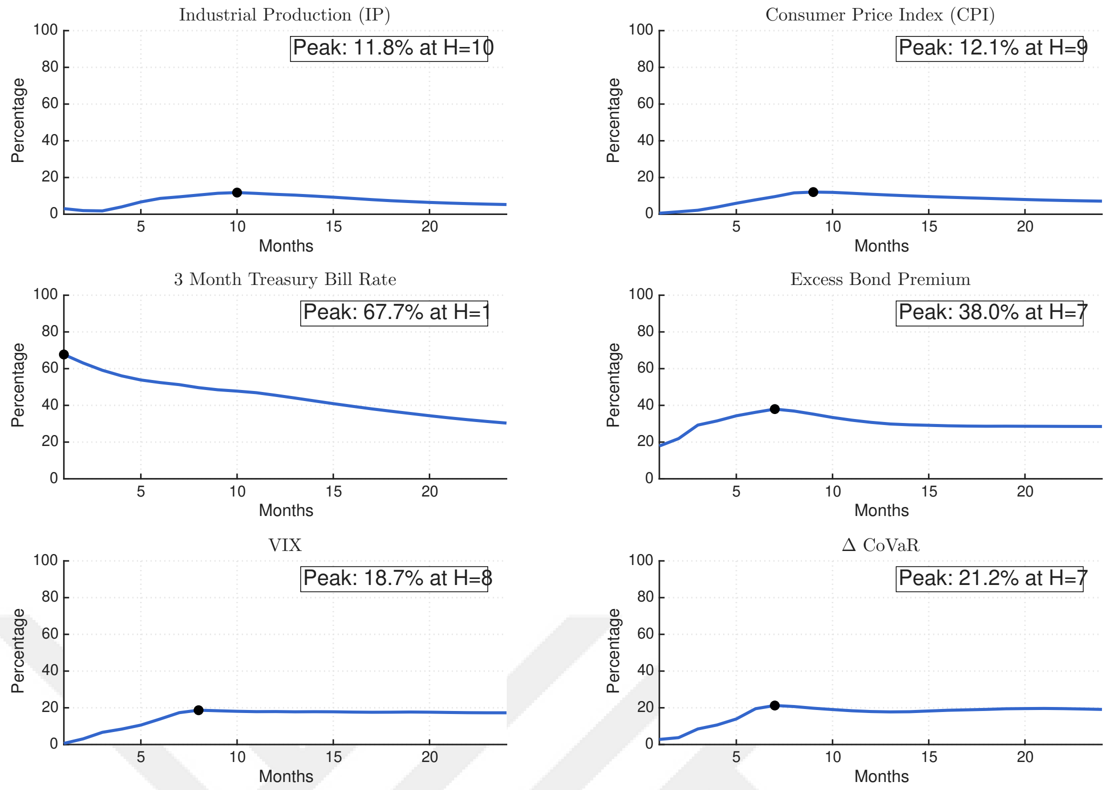


Figure 4.15: Forecast Error Variance Decomposition (FEVD) of 6-Variable VAR with VIX (GS3, FF4)

Figure 4.15 presents the variance decomposition for the 6-Variable VAR with VIX, revealing how the substitution of NFCIRISK with VIX affects the explanatory power of monetary policy shocks. Industrial production shows a slight decrease in policy shock explanatory power, falling from 14.2% to 11.8% at the 10-month horizon. This modest decline suggests that VIX captures some variation in output fluctuations that was previously attributed to monetary policy effects. Consumer prices exhibit a comparable pattern, with explanatory power declining slightly from 14.9% to 12.2% at the 9-month horizon. The financial variables reveal more pronounced differences between the two model specifications. The excess bond premium shows reduced policy influence, with peak explanatory power declining from 51.8% to 38.0% at the 7-month horizon. This decrease suggests that when market volatility is captured separately through VIX rather than combined with funding costs in NFCIRISK, the credit channel appears somewhat less dominant. VIX itself demonstrates substantial sensitivity to monetary policy innovations, with shocks explaining 18.7% of its variance at the 8-month horizon. This finding indicates that monetary policy significantly influences market volatility and risk perception. ΔCoVaR shows explanatory power of the policy shock by 21.2% at the 7-month horizon, representing a slight decrease from the 27.0% observed with NFCIRISK. This reduction likely reflects the increase in total variance from including an additional variable rather than the diminished relevance of systemic broad market risk funding risk perceptions.

These robustness checks confirm the results of our main findings while providing additional insights into the transmission mechanisms of monetary policy to systemic risk. The results demonstrate that our conclusions are not dependent on the specific choice of policy indicator, as both the federal funds rate and 3-Month Treasury bill specifications produce quantitatively similar impulse responses and forecast error variance decomposition patterns.[2] The consistent identification of the credit cost channel through EBP, and the transmission to systemic risk through ΔCoVaR remain robust across specifications. The inclusion of NFCIRISK and VIX in the expanded framework enhances our understanding by revealing that monetary policy affects systemic risk through both financial intermediary credit constraints and broader market-wide risk conditions. In the following chapter, we summarize these empirical findings and discuss their implications.

[2]See Appendix D. for Cholesky identification impulse responses and FEVD plots.

CHAPTER 5

CONCLUSION

This thesis investigates how monetary policy affects systemic risk through transmission channels using a structural vector autoregression framework with Cholesky identification and external instruments identification on monthly US data from 1990:02 to 2020:02. Our empirical strategy addresses the fundamental identification challenge of distinguishing exogenous policy shocks from endogenous central bank responses by employing orthogonalized monetary policy surprises around FOMC announcements as external instruments. The results demonstrate that contractionary monetary policy generates substantial and immediate effects on systemic risk, with ΔCoVaR reaching trough effects of -0.28 to -0.60 percentage points within two months. These effects persist for six to eight months, indicating that monetary policy decisions create lasting changes in systemic risk. Simultaneously, we observe significant macroeconomic responses consistent with theoretical predictions: industrial production declines reach a trough of -0.86% at six months, while consumer prices fall persistently by -0.50% at peak response, with disinflationary effects remaining significant for nearly a year. The proxy SVAR approach successfully resolves empirical puzzles such as the price puzzle that the Cholesky identification fails to. The decomposition of transmission mechanisms reveals how monetary policy affects systemic risk through two distinct but simultaneous channels. The credit cost channel operates through financial intermediary balance sheet constraints, captured by the excess bond premium peaks at 0.37 to 0.47 percentage points within two months. This channel reflects increased credit costs and tight funding conditions of financial intermediaries, with the excess bond premium isolating the portion of corporate bond spreads that exceeds expected default risk. The risk-taking channel operates through broader financial market conditions, as measured by two key indicators: NFCIRISK and VIX. These metrics capture unexpected shifts in market-wide risk premia, volatility expectations, and liquidity conditions. Specifically, NFCIRISK increases by approximately 0.28 percentage points, reflecting the complementary effects of the risk-taking channel, while VIX rises by about 3.03 percentage points, capturing the separate effects of the risk-taking channel. The synchronous movement of both transmission channels with systemic risk, with all variables peaking within two months of policy shocks, demonstrates that monetary policy affects financial risk conditions through multiple pathways operating simultaneously rather than sequentially. Variance decomposition analysis quantifies the substantial role of monetary policy in driving systemic risk dynamics, with policy shocks explaining up to 59% of excess bond premium variation, 48% of NFCIRISK variation, 21.3% of VIX variation, and most importantly, 22% to 39% of systemic risk variation at their respective peaks. Higher explanatory power of policy shocks emerges when transmission channel proxies are explicitly included in model specifications, demonstrating that monetary policy becomes more important for systemic risk when the mechanisms through which it operates are properly identified and measured.

Future research can extend the framework to incorporate unconventional monetary policy tools, which would enhance understanding of how quantitative easing affects systemic risk through similar transmission channels. This could inform us about the design of unconventional policy tools to uncover the effects on systemic risk while achieving central banking objectives. Moreover, developing a cross-industry comparative framework would illuminate how institutional differences in financial systems affect the strength and timing of monetary policy transmission to systemic risk. Variations in financial system structure across different sectors could provide identification for understanding which sectoral features amplify or dampen the transmission channels.

This research makes several distinct contributions to the monetary economics and systemic risk literature. First, we provide an empirical decomposition of monetary policy transmission to systemic risk through both credit cost and risk-taking channels using external instrument identification. While previous studies mainly focused on the effects of monetary policy on systemic risk, we identified the transmission mechanisms with variance decompositions to some extent. Second, our comparison between the Cholesky identification and external instrument approaches provides clear evidence that the identification strategy fundamentally affects monetary policy transmission mechanisms for systemic risk.

CHAPTER 6

APPENDIX

A. Data

The following tables summarize the data sources and transforms.

Table 6.1: VAR Variables

Variable	**Transformation/Units**	**Source**
Industrial Production: Total Index (INDPRO)	$\log \times 100$	FRED
Consumer Price Index (CPIAUCSL)	$\log \times 100$	FRED
Federal Funds Rate (FEDFUNDS)	Percent	FRED
3-Month Treasury Bill Rate (TB3MS)	Percent	FRED
Excess Bond Premium (EBP)	Percentage points	(Favara et al., 2016)
Chicago Fed National Financial Conditions Risk Subindex (NFCIRISK)	Index	FRED
CBOE Volatility Index (VIX)	Index (Percentages)	FRED
ΔCoVaR	Percentage points	Author's calculations
MPS_ORTH	Percentage points	(Bauer and Swanson, 2023)
FF4	Percentage points	(Jarociński and Karadi, 2020)

Notes: We compute ΔCoVaR with returns on the left tail (5%). Thus, a decrease in ΔCoVaR means an increase in systemic risk. We multiply it by -100 so that we can express it in percentage points and ease of interpretation in impulse responses.

Table 6.2: Variables Used in ΔCoVaR Estimation

Variable	Transformation/Units	Source
Bank Equity Returns	Percentage change	CRSP
System Returns	Percentage change	Constructed from equity returns
Δ 3 Month Treasury Yield	Percentage points	FRED
Δ Term Spread	Basis points	FRED
TED Spread	Percent	FRED
Δ Credit Spread	Basis points	FRED
CBOE Volatility Index (VIX) (22-day rolling average of std. dev. of equity returns)	Level	FRED
Real Estate Excess Returns	Percentage change	(Fama and French, 2023)
Market Return (S&P 500)	Percentage change	Bloomberg

Notes: Δ denotes first differences. Basis points are 10^{-2} percentage points. Percentage change refers to simple returns. Term spread is the difference between the 10-year constant maturity rate and the 3-month treasury yield. Credit spread is the difference between Moody's Seasoned Baa Corporate Bond Yield and the 10-year constant maturity rate.

B. Multicollinearity Diagnostics

We assess multicollinearity using the Variance Inflation Factor (VIF),

$$\mathrm{VIF}_j = \frac{1}{1 - R_j^2}, \qquad \text{Tolerance}_j = \frac{1}{\mathrm{VIF}_j},$$

where R_j^2 is from regressing regressor j on the remaining regressors. For the four variables, we obtain

- ΔCoVaR: VIF $= 4.0467$ (Tolerance $= 0.2471$), $\sqrt{\mathrm{VIF}} = 2.01$, $R_j^2 \approx 0.753$.
- EBP: VIF $= 2.8382$ (Tolerance $= 0.3523$), $\sqrt{\mathrm{VIF}} = 1.69$, $R_j^2 \approx 0.647$.
- NFCIRISK: VIF $= 4.1938$ (Tolerance $= 0.2385$), $\sqrt{\mathrm{VIF}} = 2.05$, $R_j^2 \approx 0.762$.
- VIX: VIF $= 3.1452$ (Tolerance $= 0.3179$), $\sqrt{\mathrm{VIF}} = 1.77$, $R_j^2 \approx 0.682$.

Conventional rules of thumb view VIFs below about 5 (tolerances above ≈ 0.20) as acceptable, with substantive concerns typically arising near $\mathrm{VIF} > 10$ (tolerance < 0.10). Our values indicate moderate correlation among the measures, implying modest standard-error inflation (by factors ≈ 1.6–2.1) rather than coefficient bias. Because EBP, NFCIRISK, and VIX capture distinct transmission channels, we retain all four variables and interpret estimates with the expected slightly wider confidence intervals.

C. Computation of Mean Regression Tables

For each institution $i = 1, \ldots, k$, we recover standard errors and use them for weighting from their regressions as follows.

$$\hat{se}_i = \frac{|\hat{\beta}_i|}{t_i}, \qquad w_i = \frac{1}{\hat{se}_i^2}$$

Then, we compute fixed-effect (FE) pooled coefficients as

$$\hat{\beta}_{FE} = \frac{\sum_{i=1}^{k} w_i \hat{\beta}_i}{\sum_{i=1}^{k} w_i}$$

The FE z-statistics are computed as

$$z_{FE} = \frac{\hat{\beta}_{FE}}{\hat{se}_{FE}}$$

Lastly, we compute the p-values as

$$p_{FE} = 2(1 - \Phi(|z_{FE}|))$$

where $\Phi(\cdot)$ is the CDF of standard normal distribution. This pooling treats institution-level estimates as approximately independent.

D. Figures

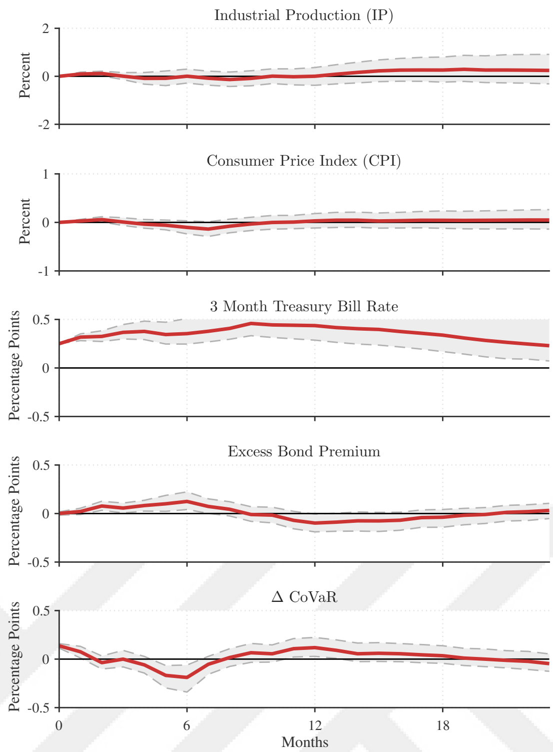


Figure 6.1: Impulse Responses of 5-Variable VAR (GS3, Cholesky)

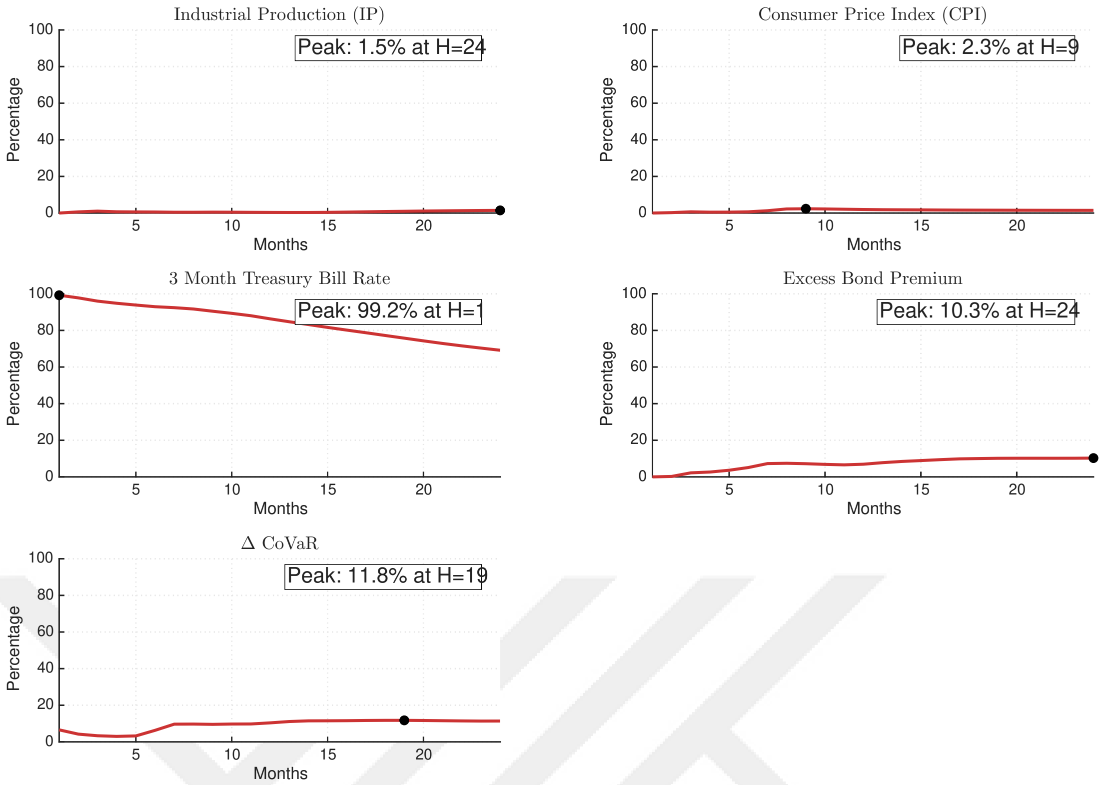


Figure 6.2: Forecast Error Variance Decomposition (FEVD) of 5-Variable VAR (GS3, Cholesky)

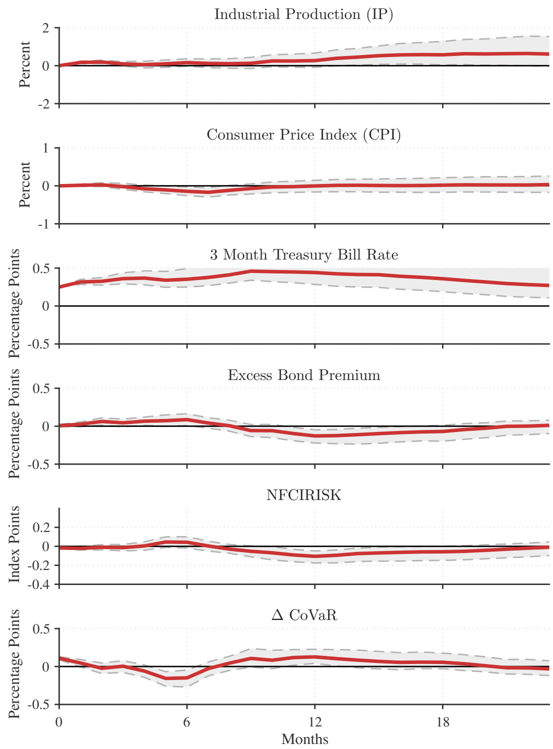


Figure 6.3: Impulse Responses of 6-Variable VAR (GS3, Cholesky)

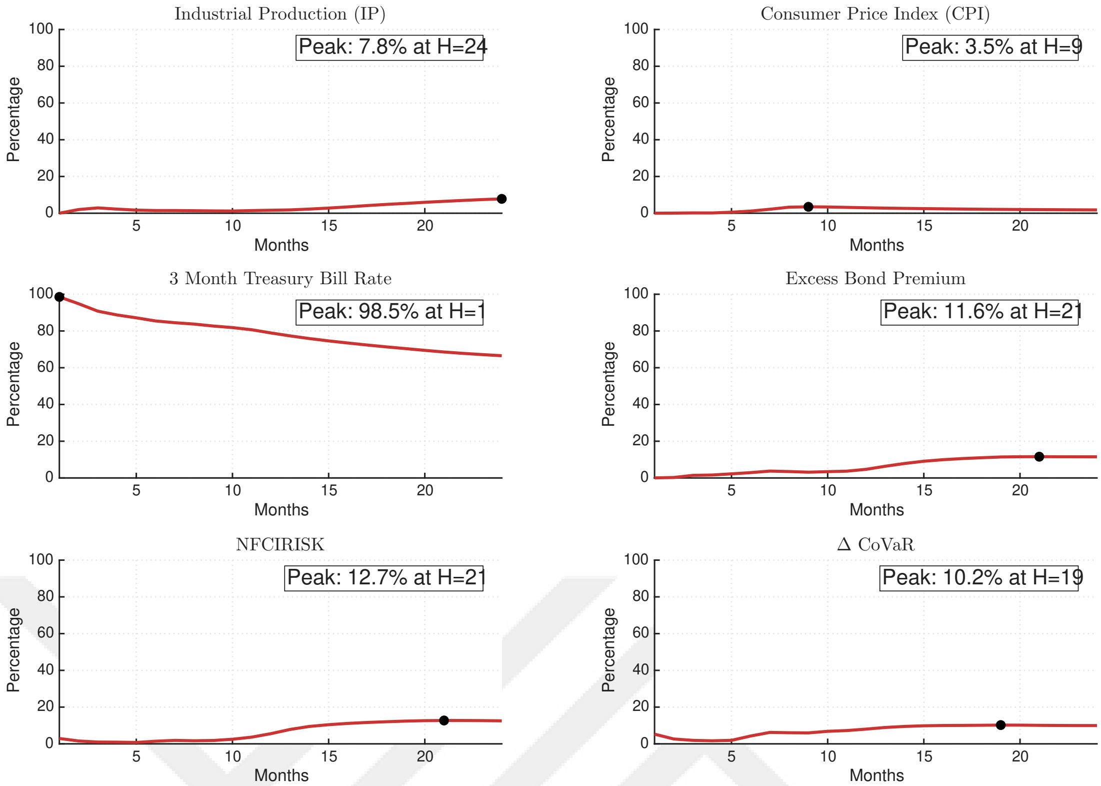


Figure 6.4: Forecast Error Variance Decomposition (FEVD) of 6-Variable VAR (GS3, Cholesky)

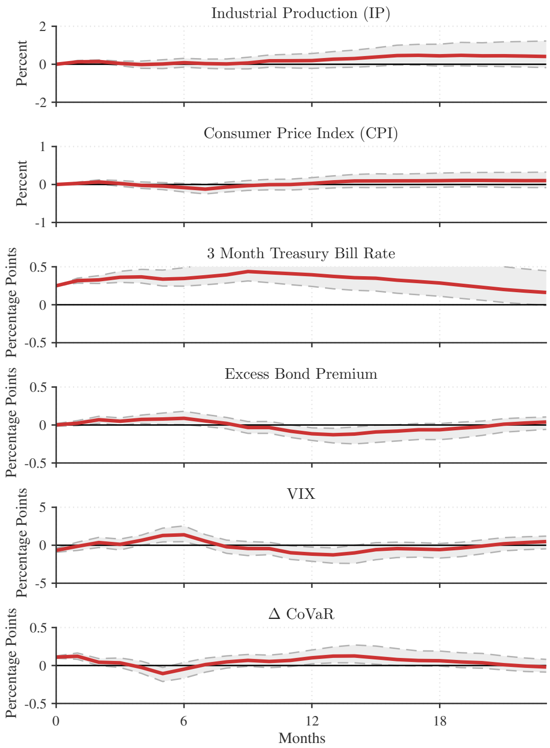


Figure 6.5: Impulse Responses of 5-Variable VAR with VIX (GS3, Cholesky)

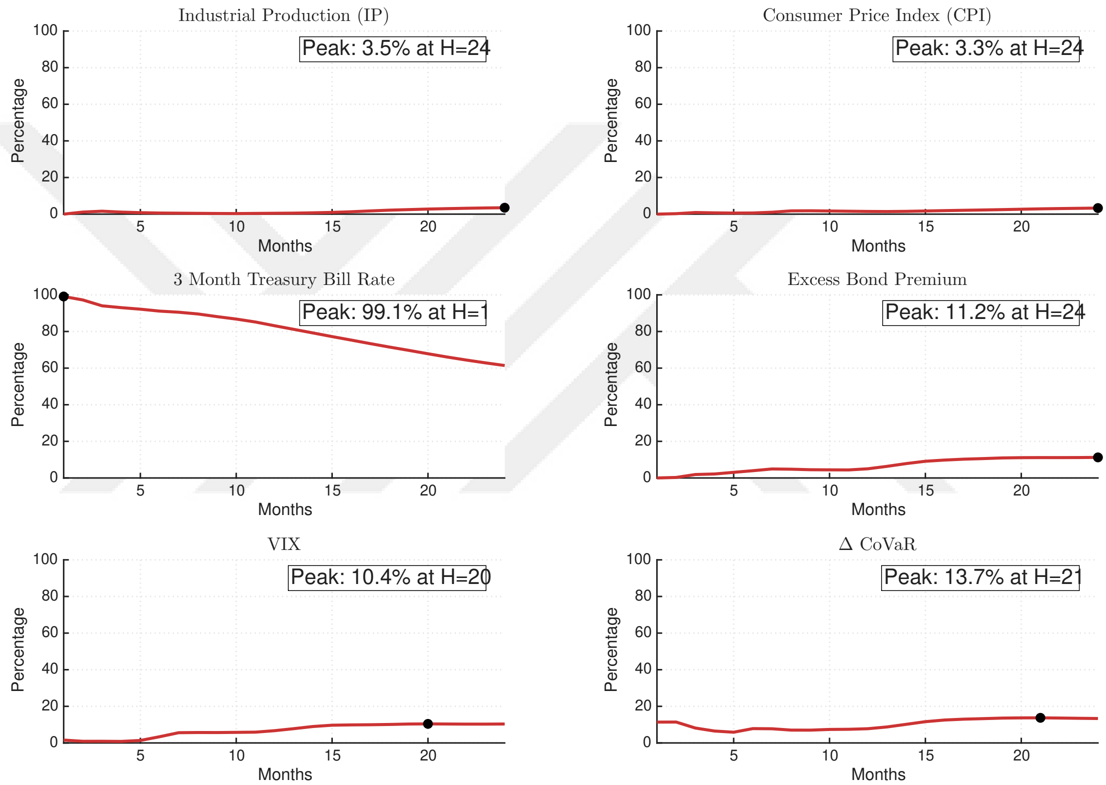


Figure 6.6: Forecast Error Variance Decomposition (FEVD) of 6-Variable VAR with VIX (GS3, Cholesky)

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