Three Essays on Financial Economics

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This study presents three essays on financial economics. In the first essay, we examine how monetary policy shocks affect risk aversion and uncertainty, as well as how risk aversion and uncertainty spread across financial markets. Although a recent study shows that monetary policy influences risk aversion and uncertainty in global stock markets, there are no studies on risk aversion and uncertainty spillover across stock, currency, and commodity markets. Following the method of Bekaert et al. (2013), we decompose the implied volatility indexes (VIX's) for the SP500, U.S. exchange rate, gold and crude oil into risk aversion and uncertainty. The decomposition requires estimating the expected volatility of the returns in each of these markets. We measure volatility with realized variance and estimate expected volatilities with regularized vector autoregression (VAR). Using a structural VAR, we show that monetary policy shocks affect uncertainty in the four markets and risk aversions in the stock and gold markets. We also show that risk aversion spreads, particularly from gold to other markets. We show uncertainties spread to all markets. Our findings are useful for both investors trying to make investment decisions in these markets and monetary policymakers trying to stabilize these markets.

In the second essay, we examine monetary policy and illiquidity connectedness across financial markets. Although illiquidity is a critical risk factor that explains financial market and real-economy outcomes, studies on illiquidity connectedness and the impact of monetary policy on illiquidity connectedness in financial markets are scarce. We use the Diebold and Yilmaz (2012, 2014) connectedness index to analyze illiquidity connectedness. We fit a SVAR to examine the relationship between monetary policy shocks and illiquidity connectedness. Our finding shows that the dynamic illiquidity connectedness in financial markets is substanc-
tial. Our study shows that, while bond markets are net illiquidity shock transmitters during noticeable financial and economic crises, other financial markets are net illiquidity shock receivers. Further, our study shows that tight monetary policy increases illiquidity connectedness in financial markets. The study contributes to literature devoted to understanding systemic risk by quantifying illiquidity connectedness in financial markets. Our research sheds new light on a potential mechanism for monetary policy transmission. By identifying assets vulnerable to illiquidity shocks, our study offers investors insight into dynamic portfolio diversification and monitoring opportunities.

In the third essay, we extend the work of Kilian and Park (2009) in two fundamental ways to examine the impact of oil shocks on stock returns. First, we use a data-driven identification approach to identify a SVAR to estimate the effect of oil price shocks on stock returns. Second, we incorporate both stock returns and monetary policy into the model. Our finding shows that the heteroskedastic innovation approach can successfully identify SVAR. The study findings also show that oil-specific demand shocks significantly affect real stock returns. The findings are useful for authorities concerned with the stability of the stock and oil markets and add to the literature on identifying a SVAR using data information content.
THREE ESSAYS ON FINANCIAL ECONOMICS

by

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CHAPTER 1
MONETARY POLICY, RISK AVERSION AND UNCERTAINTY SPILLOVER ACROSS MARKETS

1.1 Introduction

Monetary policy easing contributes to real economic activity and financial market stability. Expansionary monetary policy induces investors to take more risks by reducing uncertainty in the financial market and stimulating the real economy. In contrast, low risk appetite and high uncertainty in financial markets induce investors and consumers to spend less. This leads to lower output and employment. Financial market instability also spills over from one market to another through uncertainty and risk channels. To counteract this, it has recently been observed that the Federal Reserve always steps into any crisis and supplies liquidity. This Federal Reserve monetary policy pattern, known as the "Bernanke Put", makes investors willing to assume more risk. The fact that the Fed is so quick to intervene and provide stimulus makes risk-averse investors less risk-averse, and this can make markets unstable. However, empirical investigations that link monetary policy, uncertainty, and risk aversion across markets are scarce. In this study, we examine the effect of monetary policy on uncertainty and risk aversion across the stock, currency, and commodity markets. Additionally, we also examine uncertainty and risk aversion spillover in these markets for the period 2008 to 2020.

Bekaert et al. (2013) decompose stock implied volatility index (SVIX) into an expected volatility component and a variance risk premium component. The SVIX measures the
risk-neutral expected stock market return variance for the U.S. SP500 index. They specify a forecasting model to estimate stock return expected volatility, which is a proxy of uncertainty. The variance risk premium, which is a proxy of risk aversion, is the difference between the squared SVIX and the uncertainty measure. Bekaert et al. (2013) show that expansionary monetary policy reduces U.S. stock market uncertainty and risk aversion for the period 1990 to 2010. Their study focuses on the effect of monetary policy on uncertainty and risk aversion in a single market. Several recent studies have used the two components of the SVIX in finance research. Bekaert et al. (2021) examine the effect of U.S., euro area, and Japanese monetary policy on uncertainty and risk aversion in the stock markets of these countries. Their finding shows that there is no effect of monetary policy on risk aversion in the stock markets of these countries. Furthermore, their study shows that there is significant uncertainty and risk aversion spillover across the U.S., euro area, and Japanese stock markets. However, they do not examine the effect of monetary policy shock on uncertainty and risk aversion in multiple markets within the same country.

Some studies extend the work of Bekaert et al. (2013) to the period following the great financial crisis. For example, Hahn et al. (2017) show that while expansionary unconventional monetary policy reduces both uncertainty and risk aversion in U.S. stock market, conventional monetary policy does not influence uncertainty or risk aversion in U.S. stock market during the zero lower bound (ZLB) period. Jang (2020) shows that expansionary monetary policy has a positive effect on U.S. stock market uncertainty and risk aversion for the period from 1991 to 2015. Furthermore, Yun (2020) decomposes the Korea Composite Stock Price Index (KOSPI) 200 VIX into stock uncertainty and risk aversion to show that stock risk aversion in Korea predicts KOSPI200 returns. The findings of these studies contradict each other. Furthermore, neither of these studies considers the effect of monetary policy on uncertainty and risk aversion across multiple markets. They also fail to examine the uncertainty and risk aversion spillover across financial markets.
In this study, we examine the effect of monetary policy on risk aversion and uncertainty in a wider group of markets. Our study contributes to the literature in three ways. First, we extend the work of Bekaert et al. (2013) to multiple markets to examine the effect of monetary policy shocks, risk aversion, and uncertainty spillover across the markets. In their study, they focus only on the interaction between monetary policy stance, U.S. stock market uncertainty, and risk aversion. Previous studies implicitly presume that the stock market serves as a representative of financial markets. However, since various financial assets serve different purposes from the point of view of investors, we include the currency, gold, and oil markets in our study. By expanding this study to include the currency, gold and oil markets, we can examine the effect of monetary policy on the propagation of uncertainty and risk aversion across these markets for the period 2008 to 2020. By doing so, we examine whether the effect of monetary policy on U.S. stock market uncertainty and risk aversion persists in the unconventional monetary policy period. We also test if the effect of monetary policy on currency and commodity markets uncertainty and risk aversion is similar. Furthermore, we examine whether there is uncertainty and risk aversion spillover effect across these markets. We consider commodity markets because investors and portfolio managers increasingly use commodities to diversify their portfolios. In this regard, Mensi et al. (2020) argue that to reduce the effect of the increasing integration of regulatory and financial markets, investors and portfolio managers are considering commodities to enhance their portfolio diversification. Monetary policy shocks create uncertainty in commodity markets, in particular in the oil market. We use the oil market as a representative of the industrial commodity markets. Monetary policy shocks create uncertainty in the precious metal markets, especially in the gold market. Conventionally, gold as a safe haven serves as a hedging asset against inflation and market turmoil. If monetary policy shocks alter the perception of risk, the shock should affect the gold market. Monetary policy shocks also affect the international flow of capital and may destabilize international markets through currency exchange fluctuations. Investing in
currency helps investors as a hedge, as monetary policy shocks cause fluctuations in inflation and alter the value of foreign exchange.

Second, we use a multivariate forecasting model to estimate the expected uncertainty in each market. We use a multivariate forecasting model because we are required to construct estimates of four different expected uncertainties. Previous studies used univariate models to estimate stock return expected volatility to measure uncertainty. In this study, we consider multiple markets and employ a multivariate model to estimate the expected volatilities of SP500, currency, gold, and oil returns. Following Nicholson et al. (2017), we use a regularized VAR to estimate the expected volatilities for multiple markets. The regularized VAR is a machine learning approach that allows for a very large number of predictors, which is not possible with a conventional VAR. The regularized VAR does not suffer from the high-dimensional curse and performs better in prediction relative to a conventional VAR.

Third, we find strong evidence of a transmission mechanism of monetary policy shocks via uncertainty and risk aversion across markets. Identifying the effect of monetary policy on uncertainty and risk aversion can help monetary policy authorities stabilize financial markets. This study can help investors make optimal decisions about their investments by providing information on how uncertainty and risk aversion spill over across these four markets. Our main finding shows that monetary policy has a significant effect on the four markets’ uncertainty, and on the stock and gold markets’ risk aversion. We also show that there is significant uncertainty and risk aversion spillover across these markets. In particular, uncertainty spillover from the currency market to stock market uncertainty; from the gold market to other markets’ uncertainties. However, there is weaker evidence of risk aversion spillover from the stock and oil markets. Further, we show that there is a significant uncertainty spillover across stock, currency, and gold markets. To the best of our knowledge, our study is the first to show uncertainty-risk aversion and risk aversion-uncertainty spillover across the financial markets.
1.2 Estimation Strategy

In this section, we explain our estimation method. In the first section, we detail how we estimate the expected volatility using a multivariate model. We also describe how to decompose markets’ observed VIX’s into unobserved uncertainty and unobserved risk aversion components. In the second section, we explain how we model the effect of monetary policy on uncertainty and risk aversion, and uncertainty and risk aversion spillover across stock, currency, and commodity markets.

1.2.1 Decomposing VIX’s into uncertainty and risk aversion

Following Bekaert et al. (2013), we decompose the observed squared VIX’s into an unobserved uncertainty measure and an unobserved risk aversion measure. That is $VIX^2_{it} = UC_{it} + RA_{it}$, where $VIX^2_{it}$ represents the risk-neutral expected return volatility of asset $i$ in month $t$, $UC_{it}$ is the expectation of the realized volatility of the returns in market $i$ for 30 days and $RA_{it}$ is a measure of risk aversion in market $i$ in month $t$. Our strategy is to econometrically estimate uncertainty and calculate risk aversion as

$$RA_{it} = VIX^2_{it} - UC_{it}.$$  \hspace{1cm} (1.1)

The daily $VIX^2_{it}$s are obtained from the Chicago Board Options Exchange (CBOE).

To estimate expected volatility, we measure volatility with the realized volatility of each market computed from intraday prices for stock, currency, gold and oil. We use spot market prices for stocks, currency, and gold. We use future market prices for oil. Studies use futures prices for industrial commodities such as oil because futures markets for these commodities are more liquid than spot markets (Andersen et al., 2007; Corsi et al., 2010). The high-frequency data for asset prices is from Bloomberg Terminal. To understand the daily realized
variance-covariance matrix for the four asset returns, suppose that the log prices $s_t$ of the assets follow the standard continuous-time diffusion process given by

$$ds_t = \mu_t dt + \Omega_t dB_t$$  \hspace{1cm} (1.2)$$

where $B_t$ denotes a standard four-dimensional Brownian motion, the process for the $4 \times 4$ positive definite diffusion matrix, $\Omega_t$, is strictly stationary, and the time interval is normalized to unit, that is, $Q = 1$ for one trading day. Given the $s_t$, the return on the asset $i$ on day $t$ is given by

$$r_{t+Q}^i = s_{t+q} - s_{it}, \quad i = 1, \ldots, 4.$$  \hspace{1cm} (1.3)$$

Conditional on the realization of the sample path of $\mu_t$ and $\Omega_t$, the distribution of the continuously compounded $Q$-period returns, $r_{t+Q}, Q \equiv s_{t+Q} - s_t$, is then

$$r_{t+Q} | \sigma\{\mu_{t+\tau}, \Omega_{t+\tau}\}_{\tau=0}^Q \sim N\left(\int_0^Q \mu_{t+\tau} d\tau, \int_0^Q \Omega_{t+\tau} d\tau\right),$$  \hspace{1cm} (1.4)$$

where $\sigma\{\mu_{t+\tau}, \Omega_{t+\tau}\}_{\tau=0}^Q$ denotes the $\sigma$-field generated by the sample paths of $\mu_{t+\tau}$ and $\Omega_{t+\tau}$ for $0 \leq \tau \leq Q$. The daily realized variance-covariance matrix ($\Sigma_t$) for the four asset returns is then given by

$$\Sigma_t = \sum_{j=1}^{Q/\Delta} r_{t+j\Delta, \Delta} r_{t+j\Delta, \Delta}',$$  \hspace{1cm} (1.5)$$

where $Q/\Delta$ in our case is the number of sub-periods of 5 minutes in each day (Shephard and Sheppard, 2010); $r_{t,j} = (r_{t,j}^1 \ldots r_{t,j}^4)'$ is the vector of returns for the four assets over the $j^{th}$ sub-period, $j=1, \ldots, Q/\Delta$ in day $t$. By the theory of quadratic variation, under weak regularity conditions Andersen et al. (2001) show that

$$\Sigma_t - \int_0^Q \Omega_{t+\tau} d\tau \rightarrow 0$$  \hspace{1cm} (1.6)$$
for all \( t \) as the sampling frequency of the returns increases, or \( \Delta \to 0 \). Thus, \( \Sigma_t \) is a consistent nonparametric estimator of the integrated volatility of asset returns.

### 1.2.2 Estimating expected volatilities

We measure uncertainty in markets with expected volatility of the asset return. Following Bekaert et al. (2021), we estimate the expected volatility and risk aversion by decomposing the VIX’s of the four markets. They estimate the expected volatility of a single asset class. In particular, they estimate expected volatility based on a univariate model that forecasts the realized volatility in each market only using lagged values of realized volatilities and lagged values of VIX of that market. They do not use realized volatilities and VIX’s from other markets as information set in their univariate model. In this study, we use a multivariate model that uses the realized volatility of other markets and the realized covariance between markets as the information set to estimate the expected volatility for the four markets. The expected volatility measures uncertainty in the respective markets.

To measure uncertainty (UC) for each market, it is necessary to estimate multivariate expected volatilities. We use a machine learning approach to estimate expected volatilities for the four markets. The conventional VAR suffers from a high-dimensionality problem and performs poorly in out-of-sample prediction. To solve this problem, previous studies use a few predictors in the VAR models. However, the regularized VAR does not suffer from the high-dimensionality problem. The regularized VAR solves the high dimensionality problem by shrinking the coefficients of the less important variables towards zero. In this study, we compare the performance of the out-of-sample predictions of a regularized VAR to that of a conventional VAR. We use the BigVAR model developed by Nicholson et al. (2017) to estimate multivariate expected volatility. Using a BigVAR model, we evaluate the performance of out-of-sample predictions of the regularized VAR against the conventional
VAR. The BigVAR uses out-of-sample mean-square forecast error (MSFE) to evaluate the performance of the regularized VAR against the conventional benchmark VAR.

Following Nicholson et al. (2017), we estimate the expected volatilities for the four markets using the regularized VAR. The BigVAR handles many endogenous and exogenous variables that a conventional VAR cannot handle. BigVAR uses a machine learning approach to estimate expected volatilities for the four markets. The BigVAR uses a variety of regularized methods, which include the least absolute shrinkage and selection operator (lasso), ridge, and elastic net algorithms. BigVAR adds a penalty term to the conventional VAR. The penalty term shrinks the coefficients of the less important variable toward zero. The regularized VAR minimizes:

$$\min_{v,\Phi,B} \sum_{t=1}^{T} ||y_t - v - \sum_{i=1}^{q} \Phi_i y_{t-i} - \sum_{\zeta=1}^{s} B_{\zeta} x_{t-\zeta}||_F^2 + \lambda (p_y(\Phi) + p_x(B)), \quad (1.7)$$

where $||A||_F = \sqrt{\sum_{i,\zeta} A_{i,\zeta}^2}$ denotes the Frobenius norm of a matrix $A$, which reduces to the $L_2$ norm when $A$ is a vector, the $y_t$ is $kx1$ vector of realized variances (RV’s) of markets, $v$ is $kx1$ intercept vector, $\Phi_i$ is $kxk$ matrix of coefficients, $x_t$ is $mx1$ vector of realized covariances and VIX’s of the markets, $B_\zeta$ is $KxM$ coefficients of the exogenous variables, $\lambda \geq 0$ is penalty parameter which is determined by evaluating the MSFE. $\lambda$ is also known as the tuning parameter. When lambda is small, the result is basically the least squares estimates. As lambda increases, shrinkage occurs so that variables that are at zero can be excluded. $p_y(\Phi)$ is a penalty function on endogenous coefficients, and $p_x(B)$ is a penalty function on exogenous coefficients.

The BigVAR model considers a variety of penalty structures. It efficiently estimates a VAR with a high-dimensional time series with many exogenous variables. Following Nicholson et al. (2017), the penalty structures in Table 1.1 can apply to (1.7). The emphasis of each of these penalty structures is as follows.
**The Basic VARX-L:** The Basic VARX-L incorporates no structure resulting in penalties of the form of inducing sparsity in the coefficient matrices of endogenous and exogenous by zeroing individual entries.

**The Lag Group VARX-L:** This penalty structure groups the endogenous coefficients according to their matrix of lagged coefficients in each lag and partitions each series of exogenous components into its own group. This structure implies that, for each endogenous series, a coefficient matrix at lag $\iota$ is entirely non-zero or completely zero. Similarly, the relationship between an exogenous and endogenous series at lag $j$ will be nonzero for all endogenous series or identically zero.

**The Sparse Lag Group VARX-L:** To overcome the too restrictive nature of a group penalty structure, the sparse group lasso allows for within-group sparsity through a convex combination of lasso and group lasso penalties. It does this using an additional penalty parameter, $\alpha$, which controls the sparsity within the group. The $\alpha \in [0,1]$ shows that even if, as a group, the coefficient matrix is active, it can set the individual coefficient to zero. As $\alpha$ approaches 0, the penalty structure resorts to either a Lag VARX-L or the Own/Other structure.

**The Own/Other Group VARX-L:** This penalty structure partitions each lag matrix of endogenous coefficients into separate groups by assigning the endogenous penalty structure on diagonal elements and off-diagonal entries. With this structure, the diagonal entries of each coefficient matrix that represent regression in a series’ own lags are more likely to be nonzero than the off-diagonal entries, which represent lagged cross dependence with other components.

**The Sparse Own/Other Group VARX-L:** This structure combines the Sparse Lag VARX-L and Own/Other Group VARX-L penalty structures to allow for both within group sparsity and lagged own effects (diagonal) and lagged other (off-diagonal) effects.
The **Endogenous-First VARX-L**: This penalty structure considers a nested structure that can consider the relative importance between endogenous and exogenous predictor series based on a priori importance ranking among endogenous and exogenous variables. In such a scenario, it may be desirable for exogenous variables to enter a forecasting model only if endogenous variables are also present at a lag $\tau$.

The BigVAR divides the study periods (T) into three parts. The first part of the study period (1 to T1) is for initialization. The second part (T1+1 to T2) of the study period is for the selection of penalty parameters. And the third part (T2+1 to T) is for the out-of-sample prediction. The out-of-sample prediction uses rolling cross-validation to compute the MSFE. The default for the T1 period is 1 to T/3, for T2 is T1+1 to 2T/3 of the period and the rest is for the out-of-sample prediction. As a benchmark, we compare the forecast performances of the BigVAR models with a conventional VAR selected by the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). We also compare the forecast performances of the BigVAR models to a vector random walk model that uses its own lagged volatility as the optimal predictor and a vector white noise model that uses the sample mean as the optimal predictor. The algorithm uses MSFE to compare BigVAR models with these benchmark models.

We use the estimated expected volatility from this BigVAR model to measure markets uncertainty. We also use these estimated volatilities of the markets to decompose VIX’s into uncertainty and risk aversion measures. Risk aversion is the difference between respective markets squared VIX’s and expected volatilities. Thus, the forecasts from the BigVAR model represent expected volatility. We use the expected volatility for the uncertainty variables $UC_{it}$, $i=1, \ldots, 4$ in (1.1). Bekaert et al. (2021) estimate expected volatilities with forecasts from univariate models using only lagged values of realized volatility and lagged values of the VIX from that market. They do not use realized volatilities and VIX’s from other markets as part of the information set. In this study, we use a multivariate model that
uses realized volatility from other markets and realized covariances between markets as part of the information set. Given the volatility forecasts which serve as the four uncertainty measures, we compute the four risk aversion measures \( RA_t \) from (1.1).

1.2.3 Monetary policy, risk aversion, and uncertainty

To examine the dynamics between monetary policy, uncertainty, and risk aversion, we use a conventional structural vector autoregressive (SVAR). We follow Bekaert et al. (2013) to impose restrictions on the VAR to identify the system based on a Cholesky ordering. Let now \( y_t = [ipi_t, asset_t, ras_t, ucs_t]' \) be a 10 x 1 vector of observables endogenous variables where \( ip_i \) is industrial production index, \( asset_t \) is the total Federal Reserve asset, \( ras_t \) is the four-risk aversion measures, and \( ucs_t \) is the four uncertainty measures of the markets in month \( t \). Suppose that \( y_t \) follows the VAR (p), and we specify the model process as follows.

\[
Ay_t = \Pi_0 + \Pi_1 y_{t-1} + \ldots + \Pi_p y_{t-p} + \varepsilon_t, \tag{1.8}
\]

where \( A \) is a 10 x 10 full rank matrix and \( E(\varepsilon \varepsilon') = I \). The \( \varepsilon_t \) is a vector of structural shocks to the system. The reduced form of the VAR is

\[
y_t = \delta_0 + \delta_1 y_{t-1} + \ldots + \delta_p y_{t-p} + C\varepsilon_t, \tag{1.9}
\]

where is \( \delta'_i s \) are \( A^{-1} \Pi'_i s \); and \( C \) is \( A^{-1} \). The optimal lag length is 1 based on the BIC.

We first order the industrial production index, then the monetary policy, the four risk aversions, and the four uncertainties. This order reflects that risk aversions and uncertainties respond contemporaneously to monetary policy. The industrial production index responds to monetary policy through lags. However, all variables in the model respond to each other through lags. Previous studies also order monetary policy after IPI but before risk aversion.
and uncertainties (Bekaert et al., 2013; Hahn et al., 2017; Jang, 2020). This imposes 45 exclusion restrictions on the contemporaneous matrix $A$ and makes $A$ a lower triangle matrix. Based on these restrictions, we examine the effect of monetary policy on uncertainty and risk aversion across markets using impulse response functions (IRFs). The IRFs show the path of response of typical variables in the system to shocks to variables in the system. In this paper, we are interested in the IRFs of risk aversions and uncertainties to shocks to total Federal Reserve assets. We are also interested in the risk aversions and uncertainties spillover across these markets.

1.3 Descriptions of Variables and Data

Conducting monetary policy became challenging after the global financial crisis as the Federal funds rate approached the zero lower bound. Due to this invariability of the federal funds rate, the main monetary policy instrument became the total assets of the Federal Reserve (Asset). Total asset is the standard measure of an unconventional monetary policy’s stance after the global financial crisis. For example, Gambacorta et al. (2014) use total assets to examine the effectiveness of unconventional monetary policy during the global financial crisis. The total Federal Reserve assets are the value of the total Federal Reserve assets in millions of U.S. dollars. In this study, we used seasonally adjusted monthly data for total assets for the period from September 2008 to November 2020 from the Board of Governors of the Federal Reserve System (U.S.). The Augmented Dickey-Fuller test shows that total assets are not stationary in levels. We use the first difference of the logarithm to make the total assets stationary.

We use VIX’s form CBOE. In 1993, CBOE Global Markets, Incorporated introduced the CBOE Volatility Index (SVIX Index), which was originally designed to measure the markets expectation of 30-day volatility implied by at-the-money SP100 Index (OEX Index) options
prices. The SVIX Index soon became the premier benchmark for U.S. stock market volatility. Studies often consider the SVIX as the ‘fear gauge.’ The CBOE and Goldman Sachs updated the SVIX Index in 2003 to reflect a new way of measuring expected volatility, which is still widely used by financial theorists, risk managers, and volatility traders. The new SVIX is based on the SP500 Index (SPX), the core index for U.S. equities, and estimates the expected volatility by aggregating the weighted prices of SPX puts and calls over a wide range of strike prices. Following the same method for SP500 SVIX, CBOE introduced commodity and currency indexes and began calculating one currency volatility index (XVIX) and two commodity volatility indices in 2008. CBOE XVIX is based on CurrencyShares Euro Trust (FXE) options; CBOE Gold Volatility Index (GVIX) is based on SPDR Gold Shares (GLD) options, and CBOE Crude Oil Volatility Index (OVIX) is based on United States Oil Fund, LP (USO) options.

We constructed the returns of each asset from data on high-frequency asset prices. The source of data for asset spot prices and future prices is Bloomberg Terminal. We used five-minute sub-periods of the logarithm of prices of assets to compute the returns. Other studies also use returns constructed from logarithmic prices of five minutes to construct RVs (Bouri et al., 2021). Using five-minute interval prices to construct realized variance-covariances overcomes the bias that might arise from the microstructure aspect of the high-frequency data.

We use IPI to control for fluctuations in economic activity. The industrial production index measures the real output of all relevant establishments in the U.S., regardless of their ownership, but not those in U.S. territories. We used seasonally adjusted monthly data for the industrial production index for the period from September 2008 to November 2020 from the Board of Governors of the Federal Reserve System (U.S.). The IPI is not stationary in levels, therefore; we use the difference of the log of IPI.
1.4 Empirical Results

We discuss the findings of the study in this section. In the first section, we present an estimation of the stock, currency, gold, and oil markets’ uncertainty and risk aversion. In the second section, we present the effect of monetary policy on uncertainty and risk aversion in these markets. We also present and discuss uncertainty and risk aversion spillover across these markets.

1.4.1 Uncertainty and risk aversion across markets

We present descriptive statistics and a contemporaneous correlation matrix for daily RVs and VIX’s in Table 1.2 and Table 1.3. Figures 1.1 and 1.2 show time series plots of the daily RV’s and VIX’s for the four markets from July 2008 to November 2020. From these tables and figures, we observe that daily oil RV and OVIX oil have higher mean values relative to the other three. Further, there are episodes in which all RVs and VIX’s move together. Daily RV’s and VIX’s across the four markets exhibit similar patterns during the great financial crisis and COVID-19 pandemic episodes. However, they have unique patterns during other periods. In particular, daily RV’s and VIX’s across markets rise during the great financial crisis and COVID-19 pandemic periods. The strongest contemporaneous correlation of 0.84 is between SVIX and GVIX.

We include lags of the four RV’s, six realized covariances (RCV’s), and four VIX’s in the estimations of expected volatility in the regularized VAR. We include realized covariances (RCVs) in the estimation of the multivariate expected volatilities for the markets following the recommendations of empirical observations (Andersen et al., 2007). Previous studies consider SVIX as additional predictors in predicting future stock market volatility (Bekaert and Hoerova, 2014; Bekaert et al., 2013). These respective VIX’s are SVIX, XVIX, GVIX, and OVIX. Our dependent variables are the daily RV’s of the four market returns that rep-
resent over 30 days’ return volatilities. Because the values of VIX’s are in annual percentage, after squaring, we rescale VIX’s by 1/120000 to make them comparable with monthly RV’s. Further, all VIX’s and RV’s are stationary in levels based on the Augmented Dickey-Fuller test. We also standardize all series to have mean zero and unit variance. Standardization of variables is required, as regularized regressions are not scale-invariant. Standardization in regularized regressions is a general assumption that all variables are on the same scale. If the variables are not on the same scale, the penalty term favors the variable with a high magnitude. Based on unrestricted VAR optimal lag selection, we use 9 lags.

Evaluation of estimated models shows that regularized VAR’s have better prediction performance compared to benchmark VAR models. Table 1.4 presents the evaluation of the estimations of the BigVAR model. Basic VARX-L penalty structure results in the best regularized VAR. The Basic VARX-L has an out-of-sample MSFE of 4.83, which is lower than other benchmark models. All BigVAR estimates significantly outperform conventional VAR estimates. The out-of-sample MSFE for the two conventional VAR models based on AIC and BIC lag selection is 68.3 and 5.84. The optimal value for the shrinkage parameter is large for Endogenous First VARX-L, which shrinks about 21% of the coefficients toward zero; however, its out-of-sample MSFE is larger than the out-of-sample MSFE of Basic VARX-L. The value of the optimal shrinkage parameter for Basic VARX-L is large (160.50)) and only 8.41% of the coefficients are active. However, it performs better in out-of-the-sample prediction compared to the other models. The other BigVAR models are also closer to the Basic VARX-L model in terms of out-of-sample prediction performance. The Conditional Mean relatively performs closer to the BigVAR models. On the basis of the above results, we predict expected volatilities for the four markets with the Basic VARX-L BigVAR model.

We further examine the sparsity plot of the coefficients in Figure 1.3 for the estimated VARX-L BigVAR model. The sparsity plot shows the magnitudes of the coefficients for forecasting the four volatilities for the stock, currency, gold, and oil markets. The coefficients
are for the four lagged volatilities, six covariances, and four VIXs of the four markets. The shades represent the magnitudes of the coefficients. The magnitudes of the coefficients are blue, medium-light-blue magenta, light-blue magenta, very light-blue magenta, and white, in that order. We list the covariances in the following order: stock and currency; stock and gold; stock and oil; currency and gold; currency and oil; and gold and oil markets. We list the VIX’s in the following order: SVIX, XVIX, GVIX, and OVIX. From the sparsity plots, we find three observations. First, there is volatility spillover across the markets. Second, cross-market volatility covariances matter in predicting volatilities across markets. And third, VIX’s of the markets also matter in predicting volatilities across markets. Now we examine each equation.

Considering the first rows of Figure 1.3 which represent the stock market return expected volatility equations, we observe that at lower lag orders, its own lag volatilities and the other three markets’ lag volatilities affect stock market return volatility. At lower lag orders, the lags of covariances and VIX’s of the four markets also predict stock market return volatility. However, the effects of lags of covariances are more pronounced with BigVAR models that add more structures to the model.

The second rows of the sparsity plots in Figure 1.3 represent equations for currency market return expected volatility. At lower orders, lags of stock market volatility and gold market volatility predict currency market return realized volatility. The effect of the own lags of currency market return volatility decreases as the lag order increases. For models with more structures, lag covariances and lag VIX’s have larger effects on currency market return volatility. The effect of lag OVIX on all four markets’ volatility is persistently large, and larger for currency market return volatility.

From the third row in Figure 1.3, we observe its own lag and lag stock market volatility persistently predict gold market volatility. The coefficients of lag currency and oil market volatility are negligible. For the best model, it is only the own VIX lag that affects gold
market volatility, especially for the Basic VARX-L model. However, in the rest of the models, we observe that other VIX’s lags also affect gold market volatility.

The last rows of Figure 1.3 represent the oil market’s expected volatility equations. For this volatility equation, the coefficients of lag volatilities, lag covariances, and lag VIX’s of the other three markets are small. For the best model, both lags of oil market volatility and lags of OVIX do not seem to matter for other markets’ volatility predictions.

Using the forecasts of the best BigVAR model mentioned above to represent uncertainty, we construct risk aversions by subtracting predicted volatilities from squared VIX’s. We multiply the predicted volatilities by their standard deviation and add their mean to obtain the expected volatilities in an unstandardized form to make them comparable to the VIX’s scale because projections of expected volatilities from the BigVAR model are standardized. As we examine the effect of monetary policy on risk aversion and uncertainty across markets at a monthly frequency, we aggregated the estimated volatilities to a monthly frequency. We present plots of the monthly expected volatilities in Figure 1.4. These expected volatilities are measurements of uncertainties in the markets. The uncertainty plots show that the uncertainties are high in the markets during the great financial crisis and the COVID-19 pandemic periods compared to other periods. However, there is an anomaly regarding the magnitudes of market uncertainties. The currency market uncertainty exhibits lower magnitudes compared to other markets, whereas the oil market exhibits a higher magnitude of uncertainty relative to other markets.

We plot risk aversion, which is the difference between squared VIX and expected volatility in Figure 1.5. The plots of risk aversion, to some extent, exhibit distinct patterns. However, the entire market appears to experience a spike in risk aversion during both the global financial crisis and the COVID-19 pandemic periods. In terms of magnitude, the plots show that the oil market risk aversion is higher relative to other markets.
1.4.2 Monetary policy, risk aversion, and uncertainty

To examine the effect of monetary policy on uncertainty and risk aversion across markets, we aggregate daily uncertainty and risk aversion to a monthly frequency. Following Bekaert et al. (2013), we use the end-of-month values of market uncertainty and risk aversion for a monthly frequency. Before running SVAR, we conducted the stationarity test for each included variable. The total Federal Reserve assets and the industrial production index are not stationary in levels. Therefore, we use the first difference of the natural logarithm of total Federal Reserve assets and the industrial production index in SVAR. Markets risk aversions and uncertainties variables are stationary in levels.

We base the result of the study on IRFs. The dashed lines of the IRFs show the lower and upper bounds of confidence intervals (CI) for the point estimates. We construct the 90% confidence intervals (CI) from 1000 bootstrap simulations. Solid lines are point estimates. On the basis of the Cholesky ordering, we build the IRFs. We first order the index of industrial production first, then monetary policy. Risk aversion and uncertainty come last in our ordering. The Cholesky ordering shows that markets risk aversions and uncertainties contemporaneously respond to IPI and monetary policy (Asset). The industrial production index and monetary policy respond to market risk aversions and uncertainties through lags. Based on BIC, we use lag 1 as the optimal lag length.

Figure 1.6 shows the dynamic relationship between the four market uncertainties and monetary policy. Figure 1.6 panels A-D show the IRFs of stock, currency, gold, and oil market uncertainties to one standard deviation positive shock to monetary policy. A positive shock to total Federal Reserve assets reduces uncertainties in the stock, currency, gold, and oil markets. This study confirms previous studies showing that a negative shock to real interest rate reduces uncertainty in the U.S. stock market (Bekaert et al., 2013; Hahn et al., 2017). In this study, we show that expansionary monetary policy also reduces uncertainties in the
currency, gold, and oil markets. To our knowledge, these findings are new to the literature. That expansionary monetary policy affects uncertainties in these three markets similarly to it does in the stock market may imply that monetary policy authorities can stabilize the whole financial markets simultaneously. Further stock, commodity, and currency investors could gain insight into how monetary policy alters uncertainties in these markets, which could help them make optimal investment decisions.

In Figure 1.7, we present the dynamic responses of markets’ risk aversions to the one standard deviation positive shock to monetary policy. Panels A-D of Figure 1.7 show the IRFs of the stock, currency, gold, and oil markets risk aversions to the one standard deviation positive shock to monetary policy. A positive shock to the total Federal Reserve asset after briefly reducing risk aversions increases risk aversions in the stock and gold markets. Expansionary monetary policy shocks reduce risk aversion in the currency market and become significant after 4 months lag. A positive shock to the total Federal Reserve asset after briefly increasing risk aversions reduces risk aversions in the oil markets. Although the monetary policy instruments, study periods, and markets are different, the findings of this study confirm the empirical findings for the stock market in U.S. (Bekaert et al., 2013; Hahn et al., 2017).

1.4.3 Uncertainty and risk aversion spillover across markets

Figures 1.8-1.11 show uncertainty spillover effects across the four markets. We use IRFs to examine how shocks to uncertainty in a given market spill over to other markets. In Figure 1.8, panels A-D show IRFs of uncertainty in the stock, currency, gold, and oil markets to one standard deviation positive shock to stock market uncertainty. A positive shock to stock market uncertainty increases uncertainties in all markets until lag 1. The effect of stock market shock declines after lag 1. The spillover effects of stock market uncertainty are
persistent and remain significant until lag 10 in stock and gold, lag 3 in currency, and lag 5 in oil markets.

In Figure 1.9, panels A-D show the IRFs of the stock, currency, gold and oil markets uncertainties to the one standard deviation positive shock to currency market uncertainty. Currency market uncertainty affects stock and oil markets similarly. A positive shock to currency market uncertainty reduces uncertainties in these markets and increases uncertainties until it levels off to zero. The currency market uncertainty spills over to the gold market uncertainty until lag 1.

In Figure 1.10, panels A-D show the IRFs for the responses of the stock, currency, gold, and oil markets uncertainties to the one standard deviation positive shock to gold market uncertainty. A positive shock to gold market uncertainty increases stock, currency, and currency markets uncertainties until lag 3. The spillover effect of gold market uncertainty is significant until lag 12 in the stock and currency markets. However, the effect of a shock to gold uncertainty on the oil market uncertainty is not significant.

In Figure 1.11, panels A-D show the IRFs for the responses of stock, currency, gold, and oil markets uncertainties to the one standard deviation positive shock to oil market uncertainty. A positive shock to oil market uncertainty increases stock, currency, and gold markets uncertainties after lag 3. However, the effect of oil market uncertainty shock in these markets is insignificant.

Markets uncertainties also spill over to markets risk aversion. Figures 1.12-1.15 show the IRFs of the four markets risk aversion to the one standard positive shock to the four markets uncertainties. In Figure 1.12, panels A-D depict the risk aversions of the stock, currency, gold, and oil markets to a one standard deviation positive shock to stock market uncertainty. The shock of stock market uncertainty spills over to stock, currency, and oil market risk aversions. The shock to the stock market uncertainty reduces risk aversions until lag 2 in stock and currency markets, and until lag 3 in the oil market. After these lags,
it increases risk aversions in these markets. However, there is no significant stock markets uncertainty spillover to gold market risk aversion.

In Figure 1.13, panels A-D show the IRFs of stock, currency, gold, and oil markets risk aversions to the one standard deviation positive shock to the currency market uncertainty. Shock to the currency market uncertainty spills over to all markets risk aversions. Shock to the currency markets increases risk versions in stock, currency, and gold market until lag 2. After lag 2 the effect of shock in the stock market reduces risk aversion in these markets. However, a shock to uncertainty in the currency market initially reduces risk aversion in the oil market.

In Figure 1.14, panels A-D show the IRFs of stock, currency, gold, and oil markets risk aversions to the one standard deviation positive shock to the gold market uncertainty. Uncertainty shock in the gold market also significantly spills over to all markets’ risk aversion. The shock of uncertainty in the gold market increase risk aversion in the stock and oil market after lag 2 while it increases risk aversion in currency and gold markets until lag 2.

In Figure 1.15, panels A-D show the IRFs of stock, currency, gold, and oil markets risk aversions to the one standard deviation positive shock to the oil market uncertainty. Although shock to the oil market initially increases risk aversion in stock, currency, and gold market its effect is not significant.

Figures 1.16-1.19 show the IRFs of the four markets’ risk aversion to the one standard positive shock to the four markets’ risk aversions. In Figure 1.16, panels A-D show the IRFs of stock, currency, gold, and oil markets risk aversions to the one standard deviation positive shock to the stock market risk aversions. The finding of the study shows there is no significant risk aversion spillover from the stock market to currency, and gold markets risk aversions. A positive shock to stock market risk aversion initially increases oil market risk aversion until lag 3. After lag 3, a shock to stock market risk aversion significantly reduces oil market risk aversion.
In Figure 1.17, panels A and B, show the responses of the stock and currency markets risk aversion to the one standard deviation positive shock to currency market risk aversion. Shock to currency market risk aversion significantly and positively affects stock and oil market risk aversion until lag 2. A positive shock to currency market risk aversion increases stock market risk aversion after lag 2. A positive shock to currency market risk aversion increase oil market risk aversion until lag 2. However, the effect of a currency shock on gold market risk aversion is insignificant.

In Figure 1.18, panels A-D show the IRFs for the responses of the stock, currency, gold and oil markets to the one standard deviation positive shock to gold market risk aversion. A positive shock to gold market risk aversion increases stock and oil markets risk aversions until lag 2. Shock to gold market risk aversion increases currency market risk aversion after lag 2.

In Figure 1.19, panels A-D show the IRFs of stock, currency, gold, and oil markets risk aversions to the one standard deviation positive shock to oil market risk aversion. The oil market’s risk aversion does not spill over to the rest of the markets.

Market risk aversions also spill over to market uncertainties. Figures 1.20 -1.23 present IRFs of uncertainties due to shock to the market risk aversions. Figure 1.20 shows that shocks to stock market risk aversion increase uncertainties in all markets. The effect of shocks to risk aversion in the stock market on uncertainties remains significant until lag 4 in the stock, currency and oil markets and until lag 3 in the gold market. Figure 1.21 shows that there is no significant risk aversion spillover from currency to uncertainties in the stock, gold, and oil markets. In Figure 1.22, we observe that shocks to risk aversion in the gold market increase uncertainty in the stock market after lag 2 and decrease after lag 3. Shocks to risk aversion in the gold market significantly reduce uncertainty in the currency market until lag 1. However, a shock to risk aversion in the gold market increases uncertainty in the oil market until lag 3. In Figure 1.23 shocks to risk aversion in the oil market significantly
spill over to uncertainties in other markets. Shock to the oil market risk aversion reduces uncertainties in other markets until lag 1.

1.5 Conclusion

In this study, we look at how monetary policy affects market uncertainty and risk aversion. Furthermore, we look at how risk aversion and uncertainty spread among markets. We show, using structural VAR and Cholesky ordering, that expansionary monetary policy consistently reduces uncertainty in the stock, commodity, and currency markets in the United States. There is also evidence that monetary policy expansion reduces risk aversion in these financial markets. However, after lag 3, the impact of monetary policy on risk aversion in the currency and oil markets becomes significant. Furthermore, the study’s findings show that there is a significant and persistent spillover of uncertainty from the stock, currency, and gold markets to other markets. The spillover of uncertainty from the oil market to other markets is weak. There is no uncertainty spillover from the gold market to the oil market. Furthermore, there is a significant uncertainty spillover, particularly from the gold market to risk aversion in other markets.

The findings of the study also show that there is a significant risk aversion spillover from the gold market to other markets. Stock market risk aversion has a significant spillover to only oil market risk aversion, with no spillover to other markets. Currency market risk aversion only spills over into stock market risk aversion. There is significant risk aversion spillover from the stock, gold, and oil markets to other markets. The currency market’s risk aversion has a significant spillover effect on the oil market’s uncertainty.

Our study differs from previous studies in two ways. First, to measure uncertainties, we estimate multivariate expected volatility in contrast to previous studies. Second, unlike previous studies, we use regularized VAR, which employs a machine learning approach to
estimate expected market volatility. Regularized VAR performs better than conventional VAR in estimating expected volatility based on out-of-sample MSFE.

Our findings corroborate some previous findings on the effect of monetary policy on stock market uncertainty and risk aversion. To our knowledge, no previous research has examined the impact of monetary policy on market uncertainty and risk aversion in the context of commodities and currencies. Because expansionary monetary policy affects uncertainties in these three markets in the same way that it affects the stock market, monetary policymakers have the opportunity to stabilize the entire financial market at the same time. Additionally, investors in stocks, commodities, and currencies could gain insight into how monetary policy affects uncertainty in these markets, which could help them make better investment decisions.
1.6 References


1.7 Appendix
<table>
<thead>
<tr>
<th>Structure</th>
<th>$p_y(\Phi)$</th>
<th>$p_x(B)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic VARX-L</td>
<td>$\sqrt{\sum_{l=1}^{p} \Phi_l^2}$</td>
<td>$|B|_F$</td>
</tr>
<tr>
<td>Lag Group VARX-L</td>
<td>$(1 - \alpha) \sqrt{\sum_{l=1}^{p} \Phi_l^2} + \alpha |\Phi|_F$</td>
<td>$|B|_F + \alpha |\Phi|_F$</td>
</tr>
<tr>
<td>Sparse Lag Group VARX-L</td>
<td>$(1 - \alpha) \sqrt{\sum_{l=1}^{p} \Phi_l^2} + \alpha |\Phi|_F$</td>
<td>$|B|_F + \alpha |\Phi|_F$</td>
</tr>
<tr>
<td>Own/Other Group VARX-L</td>
<td>$(1 - \alpha) \sqrt{\sum_{l=1}^{p} \Phi_l^2} + \alpha |\Phi|_F$</td>
<td>$|B|_F + \alpha |\Phi|_F$</td>
</tr>
<tr>
<td>Endogenous-First VARX-L</td>
<td>$(1 - \alpha) \sqrt{\sum_{l=1}^{p} \Phi_l^2} + \alpha |\Phi|_F$</td>
<td>$|B|_F + \alpha |\Phi|_F$</td>
</tr>
</tbody>
</table>

Notes: The BigVAR penalty functions are adapted from Nicholson et al. (2017). The first column shows the structure of the BigVAR model, the second column is the penalty function on endogenous variables, and the third is penalty function on the exogenous variables of the model. The $\Phi_{on}$ and $\Phi_{off}$ denote the diagonal and off-diagonal elements of coefficient matrix $\Phi$. The $\alpha \in [0, 1]$ is an additional penalty that allows to control within-group sparsity in the sparse group setting or the trade off between the ridge and lasso penalty in the elastic net setting.
Table 1.2: Daily summary statistics of RV’s and VIX’s.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>RV in stock market (RVSP)</td>
<td>0.447</td>
<td>1.26</td>
<td>0.145</td>
<td>0.00367</td>
<td>27.7</td>
</tr>
<tr>
<td>RV in currency market (RVDOLLAR)</td>
<td>0.110</td>
<td>0.166</td>
<td>0.0597</td>
<td>0.00198</td>
<td>2.91</td>
</tr>
<tr>
<td>RV in gold market (RVGOLD)</td>
<td>0.347</td>
<td>0.587</td>
<td>0.171</td>
<td>0.00791</td>
<td>7.12</td>
</tr>
<tr>
<td>RV in oil market (RVOIL)</td>
<td>2.28</td>
<td>22.5</td>
<td>0.652</td>
<td>0.0126</td>
<td>1100</td>
</tr>
<tr>
<td>Squarer SVIX</td>
<td>0.420</td>
<td>0.571</td>
<td>0.231</td>
<td>0.0698</td>
<td>5.70</td>
</tr>
<tr>
<td>Squared XVIX</td>
<td>0.102</td>
<td>0.0890</td>
<td>0.0736</td>
<td>0.0142</td>
<td>0.731</td>
</tr>
<tr>
<td>Squared GVIX</td>
<td>0.355</td>
<td>0.358</td>
<td>0.258</td>
<td>0.0657</td>
<td>3.12</td>
</tr>
<tr>
<td>Squared OVIX</td>
<td>1.58</td>
<td>3.09</td>
<td>0.943</td>
<td>0.179</td>
<td>88.1</td>
</tr>
</tbody>
</table>

Notes: The table shows the daily summary statistics of RV’s and VIX’s of four markets from July 2008 to November 2020. We compute the daily RV’s of reruns from five minutes intraday asset prices.

Table 1.3: Correlation matrix RV’s and VIX’s.

<table>
<thead>
<tr>
<th></th>
<th>RVSP</th>
<th>RVDOLLAR</th>
<th>RVGOLD</th>
<th>RVOIL</th>
<th>SVIX</th>
<th>XVIX</th>
<th>GVIX</th>
<th>OVIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>RVSP</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RVDOLLAR</td>
<td>0.36</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RVGOLD</td>
<td>0.56</td>
<td>0.46</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RVOIL</td>
<td>0.09</td>
<td>0.03</td>
<td>0.07</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SVIX</td>
<td>0.73</td>
<td>0.44</td>
<td>0.53</td>
<td>0.14</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>XVIX</td>
<td>0.43</td>
<td>0.54</td>
<td>0.44</td>
<td>0.05</td>
<td>0.73</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GVIX</td>
<td>0.59</td>
<td>0.47</td>
<td>0.61</td>
<td>0.09</td>
<td>0.84</td>
<td>0.80</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>OVIX</td>
<td>0.34</td>
<td>0.18</td>
<td>0.22</td>
<td>0.46</td>
<td>0.51</td>
<td>0.27</td>
<td>0.37</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes: Table shows the correlation matrix of RV’s and VIX’s of the four markets. The RVSP, RVDOLLAR, RVGOLD and RVOIL are RV’s of stock, currency, gold, and oil returns. The SVIX, XVIX, GVIX and OVIX are VIX’s of the stock, currency, gold, and oil returns.
Table 1.4: Comparison of the BigVAR models’ and conventional VAR prediction performance.

<table>
<thead>
<tr>
<th>Model</th>
<th>OMSFE</th>
<th>IMSFE</th>
<th>TMSFE</th>
<th>SP</th>
<th>CUR</th>
<th>GLD</th>
<th>OIL</th>
<th>Lambda</th>
<th>FAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic VARX-L</td>
<td>4.8348</td>
<td>1.6804</td>
<td>0.6831</td>
<td>0.7059</td>
<td>0.6528</td>
<td>0.9176</td>
<td></td>
<td>160.4983</td>
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<td>0.7042</td>
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<td>Endogenous-First VARX-L</td>
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<td>1.2412</td>
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Notes: OMSFE is out-of-sample MSFE; IMSFE is in sample MSFE; the total sample MSFE is for all equations, and each equations; FAC is the fraction of active coefficients.
Figure 1.1: Plots of daily realized variances.

Notes: The daily plots of the RV’s for the four markets for the period from July 2008 to November 2020.
Notes: The daily plots of the VIX’s for the four markets for the period from July 2008 to November 2020.
Figure 1.3: Sparsity patterns produced by BigVAR penalty structures in estimating expected volatilities.

Notes: The optimal lag length for the endogenous and exogenous variables are 9 and 1 based on BIC. The shaded areas are active coefficients. Each row corresponds the coefficients for forecasting the four volatilities in the order stock, currency, gold, and oil markets. Each column corresponds to the coefficients at specific lag. The shading shows the magnitude of the coefficients. The magnitudes of coefficients in order from high to low are blue, medium light blue magenta, light blue magenta, very light blue magenta, and white. The order of the covariances are covariances between stock and currency; stock and gold; stock and oil; currency and gold; currency and oil; and gold and oil markets. The order of the lags of the VIX’s are SVIX, XVIX, GVIX, and OVIX.
Figure 1.4: Plots of monthly expected volatilities for the four markets.

Notes: Values are based on end-of-the-month in monthly frequency.
Figure 1.5: Plots of monthly risk aversion for the four markets.
Figure 1.6: Effect of monetary policy shocks on uncertainties.

Notes: For this and following figures, estimated orthogonal impulse-response functions (black lines) are based on Cholesky ordering and 90% bootstrapped confidence intervals (red dashed lines) with 1 lag (selected by BIC), based on 1000 replications. The $\text{Ind asset}$ is first difference of log of total Federal Reserve asset which is our monetary policy variable. The UCSM, UCCM, UCGM and UCOM are uncertainty in stock, currency, gold, and oil markets. The RASM, RACM, RAGM and RAOM are risk aversion in stock, currency, gold, and oil markets.
Figure 1.7: Effect of monetary policy shocks on risk aversions.

Figure 1.8: Uncertainties spillover from stock market to others.
Figure 1.9: Uncertainties spillover from currency market to others.

Figure 1.10: Uncertainties spillover from gold market to others.
Figure 1.11: Uncertainties spillover from oil market to others.

Figure 1.12: Uncertainties spillover from stock market to others risk aversion.
Figure 1.13: Uncertainties spillover from currency market to others risk aversion.

Figure 1.14: Uncertainties spillover from gold market to others risk aversion.
Figure 1.15: Uncertainties spillover from oil market to others risk aversion.

Figure 1.16: Risk aversion spillover from stock market to others.
Figure 1.17: Risk aversion spillover from currency market to others.

Figure 1.18: Risk aversion spillover from gold market to others.
Figure 1.19: Risk aversion spillover from oil market to others.

Figure 1.20: Risk aversion spillover from stock market to other uncertainties.
Panel A: Impulse RACM, Response UCSM  
Panel B: Impulse RACM, Response UCCM  
Panel C: Impulse RCSM, Response UGSM  
Panel D: Impulse RACM, Response UCOM

Figure 1.21: Risk aversion spillover from currency market to other uncertainties.

Panel A: Impulse RAGM, Response UCSM  
Panel B: Impulse RAGM, Response UCCM  
Panel C: Impulse RAGM, Response UGSM  
Panel D: Impulse RAGM, Response UCOM

Figure 1.22: Risk aversion spillover from gold market to other uncertainties.
Figure 1.23: Risk aversion spillover from oil market to other uncertainties.
CHAPTER 2
MONETARY POLICY AND ILLIQUIDITY CONNECTEDNESS
ACROSS FINANCIAL MARKETS

2.1 Introduction

Recently, financial market illiquidity has gained interest in the academic and policy arena. This is the case because financial market illiquidity is one of the important risk factors that explain asset returns and economic activity. As was clear from the 2007-2009 financial crisis, illiquidity spills across financial markets. During the subprime mortgage crisis, the illiquidity of the housing mortgage market spread to other financial markets. For the period December 31 2006 to February 27 2009, evidence in the U.S. shows that gross index returns tumbled by about 45% (Bartram and Bodnar, 2009). To ease the effect of financial market illiquidity risk, monetary policy authorities pursued different monetary policy actions. In January 2008, the Fed cut its discount rate by the largest amount since 1984 to address the liquidity crisis in financial markets. As conventional monetary policy became ineffective due to the zero lower bound (ZLB), the Fed used unconventional monetary policy to provide financial markets with additional liquidity. These unconventional monetary policies included sequences of quantitative easing (QE) between 2008 and 2014 to purchase illiquid financial assets to provide financial markets with more liquidity. The Fed also used forward guidance through monetary policy communication to alter financial decisions of market agents by providing information on the future trajectory of interest rates. This forward guidance was an attempt to avoid surprises that could distort the smooth functioning of financial markets. More
recently, after the COVID-19 pandemic crisis in March 2020, the Fed announced another QE in which it would purchase 700$ billion in U.S. Treasury and mortgage-backed assets (MBA).

Studies show that, in addition to liquidity provisions, monetary policy actions alter the behavior of investors in financial markets. Demirer et al. (2021) examine the role of monetary policy in connectedness patterns of speculative activities in financial markets. Demirer et al. (2021) find that an expansionary monetary policy stance is associated with greater spillover effects in speculative activities in financial markets. They argue that loose monetary policy allows speculators to enjoy inexpensive financing for their speculative positions, thus contributing to greater interaction of speculative activities across financial markets.

Further studies also examine the determinants of connectedness of the realized volatility of commodities (Bouri et al., 2021), connectedness of industry-level credit (Shahzad et al., 2018), and extreme return connectedness in energy investments (Saeed et al., 2021). Youssef et al. (2021) examine the dynamic connectedness between stock markets in the presence of the COVID-19 pandemic to show that there is a significant link between economic policy uncertainty and stock indexes across countries. Their study finds that global stock markets tend to collectively move in the same direction during periods of pressure and high economic uncertainty.

In addition to volatility, financial markets are linked through illiquidity. For instance, bond and stock markets are linked through illiquidity, which signifies the hypothesis of flight to quality or flight to liquidity. The flight to quality or flight to liquidity describes the behavior of investors that when one market is risky, investors shift their investments to less risk and/or less illiquid markets. Using a conventional VAR, Goyenko and Ukhov (2009) show that a positive shock to stock illiquidity decreases bond market illiquidity in U.S. Further, they show that a positive shock to bond illiquidity increases stock market illiquidity in U.S. Smimou and Khallouli (2016) show the existence of stock illiquidity spillovers across
European countries. There is also empirical evidence that shows that illiquidity is a more important channel than volatility in the propagation of shocks in the stock markets (Xu et al., 2018). Most previous studies focus on the liquidity connectedness of a particular asset across countries. For example, Inekwe (2020) attempts to show that stock markets across European countries are connected through liquidity. Furthermore, existing studies focus on the effect of monetary policy on the level of asset liquidities. Fernández-Amador et al. (2013) show that monetary policy affects the liquidity of the stock market in Germany, Italy, and France. Their study does not consider illiquidity spillover or illiquidity connectedness across Germany, Italy, and France. Goyenko and Sarkissian (2014) show that contractionary monetary policy increases bond illiquidity. Marozva and Makina (2020) shows that contractionary monetary policy reduces illiquidity in the stock market in South Africa. These studies focus on the stock or bond markets and do not consider the effect of monetary policy on illiquidity across multiple markets. These studies also do not examine how monetary policy affects illiquidity connectedness in financial markets.

Given this background, in this study we examine illiquidity connectedness across stock, currency, commodity, and different bond markets for the period from 1999 to 2021 in U.S. We also examine the effect of monetary policy on illiquidity connectedness across financial markets. The closest study to our study is by Liew et al. (2022) who examine the dynamics and determinants of liquidity connectedness across financial asset markets in an emerging country, Malaysia. In their study, they consider four markets: stock, currency, bond, and money markets. Our study differs from their study in the following aspects. First, due to the high frequency of intraday data unavailability, they use liquidity measures that are different from the Amihud (2002) illiquidity measures that we use in this study. Second, we consider gold and oil as additional financial markets. Third, in addition to using a single government bond, we also disaggregated the bond market into short, medium and long-term bonds because these bonds have different maturities and liquidities. Fourth, we consider
U.S. financial markets. We believe that the financial market environment in a highly developed economy like the U.S. and an emerging economy like Malaysia is not similar. Fifth, we examine the effect of monetary policy on illiquidity connectedness in these financial markets. They did not consider the direct effect of monetary policy on liquidity connectedness. Instead, they examine only U.S. monetary policy uncertainty among other determinants of liquidity connectedness.

We focus on seven broadly different asset classes because we believe that illiquidity is connected across the entire financial structure of the U.S. economy. If this is the case, illiquidity in one asset class can spread to other asset classes. As a result, a large illiquidity shock in one financial market can represent a systemic risk by destabilizing the entire financial system and having a severe negative impact on the real economy. In this paper, we establish that connection. Further, we show that monetary policy can affect the degree of connectedness. A monetary policy stimulus reduces the connectedness of illiquidity between asset types. Our results show a possible new transmission mechanism by which a monetary policy stimulus stabilizes the economy by reducing illiquidity connectedness throughout the financial structure.

The outline of the paper is as follows. We first discuss how to measure illiquidity in financial markets. We use the Amihud (2002) illiquidity index to measure illiquidities in the stock, currency, gold, oil, and bond markets. We use the Diebold and Yilmaz (2012, 2014) index to measure total, directional and pairwise illiquidity connectedness in financial markets. Using the Diebold and Yilmaz (2012, 2014) connectedness index, we quantify total, directional, and pairwise illiquidity connectedness among the five financial markets in static and dynamic frameworks. Then, using a structural vector autoregression (SVAR), we examine the effect of monetary policy on illiquidity connectedness in financial markets. Our main findings show that there is substantial illiquidity connectedness. The directional illiquidity connectedness analysis shows that while bond markets are net illiquidity shock
transmitters most of the time, the stock, currency, gold, and oil markets are net illiquidity shock receivers. Further, our study shows that tight monetary policy exacerbates illiquidity connectedness in financial markets.

2.2 Estimation Strategy

In this section, we explain our estimation methodology. In section 2.2.1, we discuss how we measure illiquidity in financial markets. We discuss how we estimate illiquidity connectedness in financial markets in section 2.2.2. We also describe directional, non-directional, static, and dynamic illiquidity connectedness. In section 2.2.3, we explain how we model the effect of monetary policy on total illiquidity connectedness in financial markets.

2.2.1 Measuring illiquidity in financial markets

We measure daily illiquidity in each market using the Amihud (2002) illiquidity index. Illiquidity measures for stock, commodity and currency markets can be calculated using the index Amihud (2002) as

\[ \text{ILLQ}_i^t = \frac{|r_i^t|}{V_i^t}, \]  

where \( \text{ILLQ}_i^t \) is the illiquidity index for asset \( i \) on day \( t \), \( r_i^t \) is the return of asset \( i \) on day \( t \), and \( V_i^t \) is the volume of transaction of asset \( i \) on day \( t \). The illiquidity measures for the bond market are computed as

\[ QS_j^t = \frac{\text{ASK}_j^t - BID_j^t}{\frac{1}{2}(\text{ASK}_j^t + BID_j^t)}, \]  

where \( QS_j^t \) for \( j = 1, 2, 3 \) is the average quoted spread of the bond \( j \) on day \( t \), ASK\(_j^t\) and BID\(_j^t\) are the ask and bid prices of the bond \( j \) on day \( t \). We consider separate measures for short, medium and long-term bonds. Short-term bonds are treasury bills with maturities
ranging from a few days to 52 weeks. Medium bonds are Treasury notes that are issued with maturities of 2 to 10 years. Long-term bonds are Treasury bonds that mature in 20 or 30 years. We use bonds maturing in three and six months for the short-term bond market. We use bonds maturing in three and five years for the medium-term bond market; and bonds maturing in 10 and 30 years for the long-term bond market illiquidity. To construct the illiquidities, we average the bond illiquidities for the respective short, medium and long-bond markets. In the illiquidity connectedness analysis, we use all three of the short-, medium-, and long-term bond market illiquidities series.

2.2.2 Illiquidity connectedness in financial markets

To examine illiquidity connectedness in financial markets, we follow Diebold and Yilmaz (2012, 2014). The Diebold and Yilmaz (2012, 2014) connectedness index uses the generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) to derive a measure of connectedness. They base the construction of the connectedness on the GFEVD conditional on a specified time horizon. They propose two measures of connectedness: total connectedness and directional connectedness. Total connectedness shows the overall connectedness of markets based on market outcomes, such as illiquidity. Connectedness can be a single static measure or a time-varying measure based on the data generating process. The directional connectedness has two parts: the 'FROM' connectedness and the 'TO' connectedness. The FROM connectedness measure shows the proportion of the forecast error caused by the rest of the market. The TO connectedness shows the contribution of the single market to the whole market. The directional connectedness can also be examined by considering net directional connectedness which is the difference between TO and FROM connectedness. The positive and negative values of the net directional connectedness show that the market is a net illiquidity transmitter and a net illiquidity receiver. The net directional connectedness also shows vulnerability of a given market due to shocks to the other markets. In general,
while illiquidity spillover focuses on the responses of a single market to the shocks to a single market in the system, we can think of illiquidity connectedness as a time-varying illiquidity spillover. In our case, the total illiquidity connectedness measures the overall market’s connectedness in illiquidity. Directional illiquidity measures either spillover from a single market to all other markets or illiquidity spillover from all the rest of the markets to a single market.

To derive illiquidity connectedness in financial markets, consider a covariance stationary K-variable VAR(p)

\[ y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t, \tag{2.3} \]

where \( \varepsilon \sim (0, \Sigma) \) is an identically and independently distributed (i.i.d.) disturbance vector. The moving average (MA) representation is

\[ y = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}. \tag{2.4} \]

The \( K \times K \) coefficient matrices \( A_i \) obey the recursion \( A_i = \Phi_1 A_1 + \Phi_2 A_{t-2} + ... + \Phi_p A_{t-p} \), with \( A_0 \) being an \( K \times K \) identity matrix and with \( A_i = 0 \) for \( i < 0 \). The dynamics of the system can be understood from MA coefficients, impulse response functions (IRFs), or variance decompositions (VDCs). We use the variance decomposition of H-step-ahead error variance in predicting \( y_t \) due to shocks to \( y_j \), \( \forall j \neq i \) for each i.

Now following Diebold and Yilmaz (2012, 2014), the total and directional connectedness are computed from the generalized variance forecast error decomposition. The generalized H-step-ahead forecast error variance decomposition is

\[ d_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \tag{2.5} \]
where $\Sigma$ is the variance matrix for the error vector $\varepsilon_t$, $\sigma_{jj}$ is the standard deviation of the error term for the $j^{th}$ equation, and $e_i$ is the selection vector, with one as the $i^{th}$ element and zeros elsewhere. By normalizing the variance decomposition by the row sum, the illiquidity spillover index due to shock in $j$’s market is given by

$$
\tilde{d}^g_{ij}(H) = \frac{d^g_{ij}(H)}{\sum_{j=1}^{N} d^g_{ij}(H)}.100 .
$$

(2.6)

The total illiquidity spillover index (total connectedness) is

$$
ILLQCI = C^g(H) = \frac{\sum_{j=1,i\neq j}^{N} \tilde{d}^g_{ij}(H)}{\sum_{i,j=1}^{N} d^g_{ij}(H)}.100.
$$

(2.7)

The directional illiquidity spillover index (directional connectedness) from others to market $i$ is

$$
C^g_{i.}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{d}^g_{ij}(H)}{\sum_{i,j=1}^{N} d^g_{ij}(H)}.100.
$$

(2.8)

The directional illiquidity spillover index from market $i$ to other markets is

$$
C^g_{.i}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{d}^g_{ji}(H)}{\sum_{i,j=1}^{N} d^g_{ji}(H)}.100.
$$

(2.9)

The total connectedness and the directional illiquidity connectedness can be easily understood from the "connectedness table" shown in Table 2.1. Suppose $d^g_{ij}(H)$ denotes the generalized $ij^{th}$ H-step variance decomposition, that is, the fraction of variable $i$’s $H-$step error variance due to shocks to $j$, where $i, j = 1, 2...N, i \neq j$. The upper left $N \times N$ block of the connectedness table can be represented by $DH = [d^H_{ij}]$. The DH denotes the variance decomposition. The off-diagonals of DH represent the pairwise-directional illiquidity connectedness. In this case, all illiquidity connectedness measures are based on the non-own variance decomposition.
2.2.3 Monetary policy and illiquidity connectedness in financial markets

To examine the effect of monetary policy on financial market illiquidity connectedness, we use a SVAR. Suppose our variables are given in the vector \( Z_t = (\Delta IP I_t, \Delta CPI_t, \Delta SR_t, ILLQCI_t)' \), where \( \Delta IP I \) is change in industrial production index, \( \Delta CPI \) is the inflation rate, \( \Delta SR \) is the change in shadow rate which measures monetary policy stance, and \( ILLQCI \) is illiquidity connectedness index. Following the standard literature on the monetary transmission mechanism in the U.S. economy [Strongin (1995), Bernanke and Mihov (1998), Christiano et al. (1996), Leeper et al. (1996)], we order \( \Delta IP I \) and \( \Delta CPI \) before \( \Delta SR \). Following Goyenko and Ukhov (2009) we order \( ILLQCI \) after \( \Delta SR \). This ordering implies that the illiquidity connectedness responds instantly to monetary policy shocks, while \( \Delta IP I \) responds to \( \Delta CPI \), \( \Delta SR \) and \( ILLQCI \) only through lags. The optimal lag length is a one month lag. Ignoring the constant, a SVAR is given by

\[
AZ_t = \Phi Z_{t-1} + \varepsilon_t, \tag{2.10}
\]

where \( A \) is a 4 x 4 full rank matrix and \( E(\varepsilon_t \varepsilon_t') = I \). Our interest is the dynamic responses to structural shocks \( \varepsilon_t \). The reduced-form VAR is given by

\[
Z_t = BZ_{t-1} + C\varepsilon_t, \tag{2.11}
\]

where \( B \) denotes \( A^{-1}\Phi \) and \( C \) denotes \( A^{-1} \).

To identify structural shocks \( \varepsilon_t \), we follow Blanchard and Quah (1993) (BQ) and impose long-term neutrality restrictions. The long-run effects of the shocks are the sum of the impulse responses given in (2.11). The long-run level effects are

\[
D = (I + B + B^2 + ...)C. \tag{2.12}
\]
If the eigenvalues of $B$ are inside the unit circle, then $D = (I - B)^{-1}C$. The long-run neutrality restrictions are imposed by restricting $D$ to be lower triangular. The restrictions impose that the long-run impacts follow a causal chain. This requires that shocks to $\Delta CPI_t$, $\Delta SR_t$ and $ILLQCI_t$ do not affect the level of $IPI_t$ in the long run. Moving down the chain, shocks to $\Delta SR_t$ and $ILLQCI_t$ do not affect the level of $CPI_t$ in the long run. Finally, shocks to $ILLQCI_t$ do not affect the level of $SR_t$ in the long run.

2.3 Descriptions of Variables and Data

To examine the effect of monetary policy on illiquidity connectedness in financial markets, we use data from the Federal Reserve Economic Data (FRED) and Bloomberg. The monthly data for monetary policy, economic activity, and price level are from Board of Governors Federal Reserve System (U.S.). The daily data for constructing illiquidity measures for the stock, currency, gold, oil, and bond markets are from Bloomberg. Because available currency market data begins in 1999, our sample period ranges from 1999 to 2021.

**Illiquidity** We construct financial markets illiquidity from daily futures prices using Amihud (2002) illiquidity measures specified in (2.1) and (2.2). For the stock market, we used the daily SP500 futures prices that are available from 1983 to 2021. We use the daily US Dollar/Euro exchange rate futures prices that are available from 1999 to 2021. The gold market illiquidity is based on the gold daily futures prices that are available from 1975 to 2021. For the oil market, we use daily crude oil futures of the West Texas Intermediate (WTI) that are available from 1983 to 2021. For bond markets, illiquidity, we use Amihud (2002) illiquidity measures specified in (2.2). We group bond markets into short, medium and long terms based on maturity dates. Short-term bonds are treasury bills with maturities upto one year. Medium bonds are treasury notes that are issued with maturities of two and
ten years. Long-term bonds are treasury bonds that mature in 20 years or 30 years. The
daily prices of the bond prices are available for the period from 1977 to 2021.

**Illiquidity connectedness index (ILLQCI)** We measure illiquidity connectedness using the Diebold and Yilmaz (2012, 2014) index specified in section 2.2.1 in (2.7). To examine the effect of monetary policy on illiquidity connectedness, the daily illiquidity connectedness measures are aggregated to monthly frequency taking the monthly average. We plot financial markets illiquidity in Figure 2.1 and discuss them in section 2.4.1.

**Monetary policy instrument** We use the shadow rate (SR) developed by Wu and Xia (2016) as our measure of monetary policy stance. We cannot use the Federal Funds rate in our sample period because after the great financial crisis, the Federal Funds rate is constrained by the ZLB and does not vary. The shadow rate is the federal funds rate when the ZLB is not binding and even becomes negative to account for unconventional monetary policy tools. SR is based on yield rates, and negative SR coincides with quantitative easing (Krippner, 2014).

**Economic activity** We use the IPI to control for economic activity fluctuations. The IPI measures the real output of all relevant establishments located in the U.S., regardless of their ownership, but not those located in U.S. territories. We used the seasonally adjusted monthly data for the IPI for the period January 1999 to May 2021 from the Board of Governors of the Federal Reserve System (U.S.). We measure inflation ($\Delta CPI$) as a percentage change in the CPI. CPI is a price index of a basket of goods and services paid by urban consumers in U.S. city average for all items.

### 2.4 Empirical Results

In this section, we present and discuss the empirical findings of the study. In section 2.4.1 we discuss illiquidity in financial markets. We discuss illiquidity connectedness in financial
markets using the full sample in section 2.4.2. In section 2.4.3, we present the dynamic illiquidity connectedness measures. In section 2.4.4, we present the effect of monetary policy on illiquidity connectedness in these markets.

2.4.1 Illiquidity in financial markets

In Figure 2.1 we present plots of daily illiquidities aggregated to a monthly frequency. We use the Amihud (2002) illiquidity index specified in (2.1) and (2.2) to construct daily illiquidity series for the stock, currency, gold, oil, and bond markets. To capture the peculiarities of the series, we controlled the y-limits of the plots differently. In general, from the plots we observe that during financial and economic turmoil illiquidities tend to increase and spikes. In the following, we discuss illiquidity in each market.

The plot of stock market illiquidity shows spikes during the noticeable crises. Between the two spikes in December 2001 and December 2008, stock market illiquidity was low and moderate. However, after a spike in December 2008 following the financial crisis, we observe an upward shift in levels of illiquidity until it spiked again in October 2014. Again, we also observe a jump in illiquidity and a large shift in levels after December 2017. Stock market illiquidity is also more pronounced during the COVID-19 pandemic period.

Illiquidity in the currency market follows a unique pattern. Before the financial crisis, illiquidity in the currency market was not substantial. During this period, the dollar was depreciating against the euro, especially until February 2002. However, after February 2002, the dollar was appreciating, and in December 2006, we observed a jump in currency illiquidity. Illiquidity is further exacerbated in the currency market during the financial crisis. Following the financial crisis, illiquidity remains above its pre-crisis level. From the plot of the currency illiquidity, we observe that currency illiquidity is stronger during the financial crisis than in other periods. Rose and Spiegel (2012) also show that the global financial crisis led to a surprising appreciation in the dollar, suggesting global dollar illiquidity.
Illiquidity in the gold market is very erratic over the sample period. It also seems that illiquidity in the gold market is not necessarily associated with financial crisis as illiquidity in other markets. We observe unusually low illiquidity in the gold market during early 2014 to mid-2019.

The pattern of illiquidity in the oil market shows that the oil market became more liquid over the sample period. However, there are notable spikes in oil market illiquidity during the 2008 financial crisis and the COVID-19 pandemic.

Considering illiquidity in the long-bond market, we observe three distinct patterns: high illiquidity levels during the dot.com bubble and financial crisis, low illiquidity levels from 2002 to mid-2007, and medium illiquidity levels after mid-2011. The long-bond market was more illiquid during the dot.com bubble and the great financial crisis relative to other periods. The illiquidity of the long-bond market is lower and stable during the period between May 2002 and August 2007. Following the financial crisis, after a jump in November 2007, long-bond illiquidity remained higher until April 2011. After June 2011, illiquidity in the long-bond market is lower and relatively moderate until it increases to some extent following the COVID-19 pandemic crisis.

In the medium bond market, we observe that illiquidity is more pronounced during the financial crisis and COVID-19 pandemic relative to other periods. After peaking in June 2003, the medium bond illiquidity declined until August 2007. Following the financial crisis, the illiquidity of medium bonds increases until it peaks in October 2010 and September 2011. After May 2013, it declines and reaches prefinancial crisis levels in mid-2019. However, following the eruption of the corona virus, illiquidity in the medium bond market jumps in 2020 and exceeds the level of illiquidity of the financial crisis.

Short-bond market illiquidity is low and stable before the financial crisis and after 2015. Following the financial crisis, illiquidity in short bond market increases and also experiences
repeated spikes until the end of 2015. After 2019, illiquidity in the short-bond market increases and spikes twice following both waves of the COVID-19 pandemic.

In summary, illiquidities in financial markets tend to increase and spike during noticeable financial and economic crises. We also identify unique patterns of illiquidity in the stock and oil markets. Although illiquidity in the stock market is trending upward, it is trending downward in the oil market over the sample period.

2.4.2 Static illiquidity connectedness in financial markets

In this section, we examine the total and directional illiquidity connectedness in financial markets in a static framework. To generate the static total and directional illiquidity connectedness, we estimate a VAR for seven illiquidity measures using the full sample. Both connectedness measures are computed from the GFEVD and are therefore not sensitive to the ordering of the illiquidity indices in the VAR model. The GFEVD is calculated at a 21-day horizon. Assuming that investors will hold assets in their portfolio for one month, we set a 21 trading day predictive horizon. The total static illiquidity connectedness tells us the overall average illiquidity spillover index for the full sample. We present stationarity tests in Table 2.2. All illiquidity measures in financial markets are stationary in levels. We present information criteria to select the order of the VAR in Table 2.3. Based on the Bayesian Information Criterion (BIC), we choose lag length of 17 to estimate the VAR.

Because the use of the Euro started in January 1999, our sample period starts in January 1999 and ends in May 2021. The period between 1999 and 2021 captures several financial markets and economic crisis episodes. This helps us to understand the dynamics of the illiquidity spillover in financial markets during this period. Some of the notable events include the dot.com bubble in 2000, the great financial crisis of 2007-2009, and the 2019 COVID-19 pandemic. In this period, monetary policy authorities also pursued different strategies to stabilize the financial markets and stimulate the economy. For instance, before
the financial crisis Fed used conventional monetary policy instruments. Following the 2007-
2009 financial crisis, because of zero lower bound, the Fed used quantitative easing and/or expanding the balance sheet. During the COVID-19 pandemic U.S., because the monetary policy was already loose, the Fed had rely of the Congress pass to stimulus packages.

We present the static illiquidity connectedness in the financial markets in Table 2.4 for the period from January 1999 to May 2021. From the table, we point out five important findings. First, the values for the illiquidity spillover from individual markets to the entire market range between 0.57% for the long-term bond and 36.80% for the short-term bond. This implies that short-term bond market illiquidity contributes the most to overall financial market illiquidity, while long-term bond market illiquidity makes the least contribution to overall market illiquidity. The illiquidities of the medium-term bond and currency markets are the second and third largest contributors to the overall illiquidity of the financial markets. The illiquidity of the stock, gold, and oil markets contributes more to the overall illiquidity of the financial markets than to the long-term illiquidity of the bond market.

Second, the sums of the row of pairwise illiquidity connectedness provide the directional illiquidity connectedness from others to each financial market. The FROM column of the table measures illiquidity spillover received from other financial markets. The FROM ranges between 0.68% for the long-term bond market and 34.04% for the oil market. The TO ranges between 0.57% for the long-term bond market and 36.80% for the short-bond market.

Third, from the table, we observe that the stock, oil, and long-term bond markets are net illiquidity shock receivers while the currency, gold, medium-term bond, and short-term bond markets are net illiquidity shock transmitters. The oil market is the most vulnerable to financial markets’ illiquidity shocks, while the short-term bond market is the largest transmitter of illiquidity shocks.

Fourth, considering the pairwise illiquidity connectedness of financial markets, we observe that idiosyncratic shocks explain the illiquidity connectedness of financial markets more
than systematic illiquidity shocks. The oil and short-term bond markets exhibit the highest pairwise illiquidity connectedness, followed by the currency and short-term bond markets.

Fifth, considering the total illiquidity spillover for the financial markets, we observe that 8.80% of the illiquidity forecast error variance of the financial markets comes from spillovers. In what follows, we extend the analysis to examine illiquidity connectedness in financial markets in a dynamic framework.

2.4.3 Dynamic illiquidity connectedness in financial markets

Many important financial and economic changes have taken place around the world during our sample period. Diebold and Yilmaz (2012) argue that there has been a continued evolution due to the integration of global financial markets resulting from globalization, information technology, and other factors. The outbreak of the COVID-19 pandemic has had a unique impact on financial markets. As a consequence, the variation in the effort of countries to maintain financial market stability through liquidity provision is noticeable. Although static illiquidity connectedness describes illiquidity connectedness on average over the sample period, it is not sufficient to describe connectedness in a rapidly evolving economy. To measure the time-varying total and directional illiquidity connectedness, we use the dynamic connectedness index based on rolling samples. Diebold and Yilmaz (2014) use 100-day rolling samples and 12 days for horizon prediction to analyze the dynamics of spillover of total and net directional illiquidity in return volatility. In our case, given our seven measures of illiquidity and 17 day optimal lag length in the VAR, we used rolling samples of 200 days and 21 days for the prediction horizon to analyze the dynamics of total and net directional illiquidity across financial markets. We use a 21-day predictive horizon assuming that investors hold assets in their portfolio for 21 days. The time-varying connectedness measures are presented in Figure 2.2. The total illiquidity connectedness index fluctuates between 45% and 60%. The average illiquidity connectedness is 43% for the sample period.
We also observe that there are episodes of up-and-down spikes of total illiquidity connectedness. In particular, during the second half of 2001, first quarter of 2002, third quarter of 2006, second half of 2008, and second quarter of 2020 the illiquidity connectedness is higher and the total illiquidity connectedness exceeds 65%. These periods of high illiquidity connectedness correspond to the noticeable crisis of the 2000-2002 Dot.com bubble; the 2007-2009 financial crisis; and the COVID-19 pandemic. During May 2010, financial market illiquidity connectedness dropped below 45%. The period after 2010 is the period of economic and financial activity rebounding due to monetary policy stimulus resulting from repeated quantitative easing.

We also observe several salient financial markets’ illiquidity connectedness cycles. For the period from 1999 to mid 2001, the total illiquidity spillover fluctuates between 45% and 65% with two peaks and troughs. The financial market experienced a burst of total connectedness during the period 2001 to the end of 2002, with total illiquidity connectedness exceeding 75% in September 2001. Financial markets experienced moderate illiquidity connectedness for the period June 2002 to June 2006 and the illiquidity spillover exceeded 50% during late 2005 and late 2006. The financial market again experienced a second burst of illiquidity with a total illiquidity spillover exceeding 60% during the latter part of 2008. After the financial crisis, financial market illiquidity spillover experienced its lowest point below 45% for the first time in May 2010. For the period July 2010 to February 2020, financial markets illiquidity connectedness was stable and moderate. We also observe other upward spikes in illiquidity connectedness in financial markets during March and April 2020 following the COVID-19 pandemic.

We show the time-varying directional financial market illiquidity connectedness in Figure 2.2. We present the net directional illiquidity connectedness, which is the difference between the TO spillover and the FROM illiquidity spillover to examine the directional illiquidity connectedness. Table 2.5 also presents a summary of the total and net directional illiquidity
connectedness in the markets. We observe that on average, the stock, oil and long-term bond markets are net illiquidity shock receivers, whereas the currency, gold, medium-term bond, and short-term bond markets are net illiquidity shock transmitters. This finding is consistent with the static illiquidity connectedness.

From the figures we draw three conclusions. The first conclusion is that the stock and gold markets net illiquidity spillover follow similar patterns. The stock and gold markets are a net illiquidity transmitter during the Dot.com bubble. However, the stock and gold markets are a net receiver of shocks of illiquidity during the financial crisis and COVID-19 pandemic. Second, the currency and oil market net illiquidity appears to follow a similar pattern. The currency and oil markets are net illiquidity shock receivers during the dot.com bubbles. The peculiar feature of net illiquidity spillover from the oil market is that the values are mostly negative throughout the sample period. Third, the three bond markets net illiquidity spillover exhibit a similar pattern during the three crises, unlike the other markets net illiquidity spillover. The net spillover of illiquidity in bond markets follows a unique pattern relative to other markets. Bond markets are net illiquidity transmitters during the three noticeable financial and economic crises. Stock and gold market has similar net illiquidity spillover pattern with bond markets during the dot.com bubble period, whereas the stock, currency, gold and oil markets exhibit different net illiquidity pattern with bond markets during the 2007-2009 financial crisis and COVID-19 periods.

This distinct pattern of net illiquidity spillover of financial markets has implications for portfolio diversification. When the stock, currency and gold markets are net illiquidity shock receivers, the oil and bond markets are net illiquidity transmitters, and vice versa. Because the vulnerabilities of financial assets to illiquidity shocks are different, investors may consider diversifying their assets in their portfolio. This will give investors the opportunity to dynamically diversify their portfolios. It may also help investors discern which component of their portfolio drives the risk and value of their portfolio.
2.4.4 Monetary policy and illiquidity connectedness in financial markets

In this section, we examine how monetary policy shocks affect total illiquidity connectedness in financial markets. We use the SR as an indicator of the monetary policy stance. We used a SVAR to examine the dynamic relationship between monetary policy and total illiquidity connectedness in financial market. We present the Augmented Dickey-Fuller (ADF) stationarity tests in Table 2.2. Because IPI and SR are not stationary in levels, we enter them in first differences in the SVAR. $\Delta CPI$ and ILLQCI are stationary in levels. We also present the optimal lag length selection criteria in Table 2.3. Using the BIC, we set the lag length to 1 to estimate the VAR model.

We base our SVAR analysis on impulse response functions (IRFs). To examine the significance of shocks on variables, we present 90% confidence intervals for the point estimates, which we construct from 1000 Monte Carlo replications. Figure 2.3 shows the IRFs of our SVAR results. Panels A-D of the figure show IRFs plots of the responses of $\Delta IPI$, $\Delta CPI$, $\Delta SR$, and ILLQCI to the four structural shocks.

For the purpose of our study, we focus on the effect of a shock to SR on the total illiquidity connectedness index in the financial markets. Figure 2.3 Panel D shows the response of financial market illiquidity connectedness to a one standard deviation shock to $\Delta IPI$, $\Delta CPI$, $\Delta SR$ and ILLQCI. Financial market illiquidity connectedness responds significantly to these shocks. In particular, shocks to a change in SR increase financial market illiquidity connectedness. This implies that expansionary monetary policy reduces illiquidity connectedness in financial markets. When the Fed increases the funds rate, it reduces money circulation in the economy. This action might alter the beliefs and behaviors of the market agents. Market agents may have negative sentiment about monetary policy tightening and may rush to sell their assets. However, market agents may not be able to sell their assets, as money circulation is drying up due to tightening monetary policy. Also, many market agents try
to sell their assets and no other market agents are willing and able to buy assets, it further exacerbates illiquidity in the financial markets. This causes financial markets to be linked via illiquidity. Thus, contractionary monetary policy increases illiquidity connectedness in financial markets. Considering the connectedness of financial markets illiquidity as a system-wide risk and/or uncertainty, we find evidence of an additional transmission mechanism by which contractionary monetary policy increases risk and/or uncertainty in financial markets. We also observe that IPI and affect illiquidity connectedness in financial markets, whereas illiquidity connectedness does not have an effect on other variables.

2.5 Conclusion

Illiquidity is one of the risk factors that explain financial markets outcomes and economic activity. An empirical investigation on illiquidity spillover over time, which we call illiquidity connectedness in financial markets, is rare. There are also no empirical studies on the effect of monetary policy on illiquidity connectedness in multiple financial markets. In this study, we examine the illiquidity connectedness in the stock, currency, gold, oil, and bond markets. We also examine the effect of monetary policy on illiquidity connectedness in financial markets. We use the Diebold and Yilmaz (2012, 2014) connectedness index constructed from the estimated GFEVD to analyze the total and directional illiquidity connectedness in financial markets. We used a SVAR to examine the dynamic relationship between the monetary policy shock and illiquidity connectedness in financial markets.

The study shows that financial markets are connected through illiquidity. Our finding shows that dynamic illiquidity connectedness in financial markets is substantial. Directional illiquidity connectedness shows that, in different periods, some financial markets are net illiquidity shock transmitters, while others are net illiquidity shock receivers. The noticeable financial and economic episodes can capture peculiar features of total and directional illiq-
illiquidity connectedness in financial markets. In particular, bond markets are a net illiquidity shock transmitter during a noticeable crisis, whereas other financial markets are mostly a net illiquidity shock receiver during these noticeable episodes. Our finding also shows that tightening monetary policy increases illiquidity connectedness in financial markets.

Our finding contributes to studies trying to examine systemic risk across financial markets. Specifically, it quantifies the systemic risk by illiquidity connectedness. It also sheds new light on the possible monetary policy transmission mechanism. Additionally, it provides investors with information about dynamic portfolio diversification and monitoring opportunity by identifying the vulnerability of assets to illiquidity shocks over time.
2.6 References


2.7 Appendix

Table 2.1: Illiquidity connectedness table.

<table>
<thead>
<tr>
<th></th>
<th>X1</th>
<th>X2</th>
<th>...</th>
<th>XN</th>
<th>From</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>$d_{11}^o(H)$</td>
<td>$d_{12}^o(H)$</td>
<td>...</td>
<td>$d_{1N}^o(H)$</td>
<td>$\sum_{j=1}^{N} d_{1j}^o(H), j \neq 1$</td>
</tr>
<tr>
<td>X2</td>
<td>$d_{21}^o(H)$</td>
<td>$d_{22}^o(H)$</td>
<td>...</td>
<td>$d_{2N}^o(H)$</td>
<td>$\sum_{j=1}^{N} d_{1j}^o(H), j \neq 2$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>XN</td>
<td>$d_{N1}^o(H)$</td>
<td>$d_{N2}^o(H)$</td>
<td>...</td>
<td>$d_{NN}^o(H)$</td>
<td>$\sum_{j=1}^{N} d_{1j}^o(H), j \neq N$</td>
</tr>
</tbody>
</table>

To $\sum_{i=1}^{N} d_{i1}^o(H), i \neq 1$ $\sum_{i=1}^{N} d_{i2}^o(H), i \neq 2$ $\ldots$ $\sum_{i=1}^{N} d_{iN}^o(H), i \neq N$ $\frac{1}{N} \sum_{i,j=1}^{N} d_{ij}^o(H), i \neq j$

Table 2.2: Stationarity test.

<table>
<thead>
<tr>
<th>Variables</th>
<th>ADF statistic</th>
<th>Critical values at</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>1%</td>
</tr>
<tr>
<td>Stock</td>
<td>-33.408</td>
<td>-3.96</td>
</tr>
<tr>
<td>Currency</td>
<td>-49.105</td>
<td>-3.96</td>
</tr>
<tr>
<td>Gold</td>
<td>-45.274</td>
<td>-3.96</td>
</tr>
<tr>
<td>Oil</td>
<td>-52.041</td>
<td>-3.96</td>
</tr>
<tr>
<td>Lbond</td>
<td>-25.589</td>
<td>-3.96</td>
</tr>
<tr>
<td>$\Delta CPI$</td>
<td>-10.296</td>
<td>-3.98</td>
</tr>
</tbody>
</table>

Notes: Daily illiquidity of stock, currency, oil, long bond (Lbond), medium bond (Mbond), short bond (Sbond); and monthly series of $\Delta CPI$, and ILLQCI are stationary in levels. However, IPI and SR are stationary after first difference.
Table 2.3: Optimal lag length selection.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>VAR_lag.selection</th>
<th>SVAR_lag.selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>AIC (n)</td>
<td>22</td>
<td>2</td>
</tr>
<tr>
<td>HQ (n)</td>
<td>22</td>
<td>2</td>
</tr>
<tr>
<td>SC (n)</td>
<td>17</td>
<td>1</td>
</tr>
<tr>
<td>FPE (n)</td>
<td>22</td>
<td>2</td>
</tr>
</tbody>
</table>

Notes: VAR\_lag.selection is for the VAR used in illiquidity connectedness estimation, SVAR\_lag.selection is for the VAR used in the SVAR estimation. The AIC, HQ, SC, FPE are Akakie Information Criterion, Hannan–Quinn criterion, Schwarz Criterion, and Final Prediction Error Criterion.

Table 2.4: Static illiquidity connectedness table.

<table>
<thead>
<tr>
<th>Stock</th>
<th>Currency</th>
<th>Gold</th>
<th>Oil</th>
<th>Lbond</th>
<th>Mbond</th>
<th>Sbond</th>
<th>FROM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stock</td>
<td>95.51</td>
<td>0.55</td>
<td>0.20</td>
<td>0.98</td>
<td>0.04</td>
<td>1.78</td>
<td>0.94</td>
</tr>
<tr>
<td>Currency</td>
<td>0.13</td>
<td>94.02</td>
<td>0.60</td>
<td>0.04</td>
<td>0.09</td>
<td>0.39</td>
<td>4.73</td>
</tr>
<tr>
<td>Gold</td>
<td>0.21</td>
<td>0.50</td>
<td>96.66</td>
<td>0.03</td>
<td>0.23</td>
<td>0.83</td>
<td>1.56</td>
</tr>
<tr>
<td>Oil</td>
<td>0.69</td>
<td>2.22</td>
<td>2.03</td>
<td>65.96</td>
<td>0.04</td>
<td>1.02</td>
<td>28.04</td>
</tr>
<tr>
<td>Lbond</td>
<td>0.07</td>
<td>0.07</td>
<td>0.25</td>
<td>0.02</td>
<td>99.32</td>
<td>0.11</td>
<td>0.18</td>
</tr>
<tr>
<td>Mbond</td>
<td>1.25</td>
<td>0.19</td>
<td>0.26</td>
<td>0.89</td>
<td>0.03</td>
<td>96.04</td>
<td>1.34</td>
</tr>
<tr>
<td>Sbond</td>
<td>0.23</td>
<td>4.03</td>
<td>0.29</td>
<td>0.18</td>
<td>0.14</td>
<td>4.23</td>
<td>90.90</td>
</tr>
</tbody>
</table>

| TO     | 2.57     | 7.55  | 3.62 | 2.14  | 0.57  | 8.36  | 36.80| 8.80 |
| NET    | -1.92    | 1.57  | 0.28 | -31.90| -0.12 | 4.40  | 27.69|

Notes: Numbers in the table represent illiquidities in stock, currency, gold, oil, long term bond, medium term bond and short term bond markets. The static measures are based on a VAR with lag 17 and 21 days ahead predictive horizon.
Table 2.5: Summary statistics of dynamic total and net illiquidity connectedness.

<table>
<thead>
<tr>
<th></th>
<th>IllQCI</th>
<th>Stock</th>
<th>Currency</th>
<th>Gold</th>
<th>Oil</th>
<th>Lbond</th>
<th>Mbond</th>
<th>Sbond</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>43.119</td>
<td>-0.618</td>
<td>0.537</td>
<td>0.798</td>
<td>-1.467</td>
<td>-0.385</td>
<td>0.141</td>
<td>0.994</td>
</tr>
<tr>
<td>Variance</td>
<td>43.006</td>
<td>15.871</td>
<td>40.23</td>
<td>19.541</td>
<td>13.747</td>
<td>22.297</td>
<td>28.035</td>
<td>45.082</td>
</tr>
<tr>
<td>Skewness</td>
<td>1.394</td>
<td>2.714</td>
<td>4.825</td>
<td>1.511</td>
<td>1.831</td>
<td>3.272</td>
<td>1.311</td>
<td>3.782</td>
</tr>
<tr>
<td>JB</td>
<td>188.589</td>
<td>2910.131</td>
<td>15795.06</td>
<td>964.212</td>
<td>1486.139</td>
<td>4703.377</td>
<td>509.712</td>
<td>4737.005</td>
</tr>
</tbody>
</table>

Notes: The table presents the summary statistics of total illiquidity connectedness (ILLQCI); and net illiquidity connectedness for Stock, Currency, Gold, Oil, long bond, medium bond, and Short bond markets.
Figure 2.1: Illiquidities across financial markets.

Notes: Illiquidities in financial markets are constructed based on Amihud (2002) illiquidity index. Due to effect of extreme values of illiquidities, y-limits of the plots for stock, currency, gold and oil are controlled in (0,0.08), (0,0.01), (0,0.6) and (0,0.1) intervals to show the details.
Figure 2.2: Total and net dynamic illiquidity connectedness.

Notes: The first plot represents the total dynamic illiquidity spillover index (connectedness). The rest of the plots represent the net directional illiquidity connectedness in stock, currency, gold, oil, long bond, medium bond, and short bond markets.
<table>
<thead>
<tr>
<th>Panel A: Response of IPI to shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta IPI \rightarrow \Delta IPI$</td>
</tr>
<tr>
<td>$\Delta CPI \rightarrow \Delta IPI$</td>
</tr>
<tr>
<td>$\Delta SR \rightarrow \Delta IPI$</td>
</tr>
<tr>
<td>$\text{ILLQCI} \rightarrow \Delta IPI$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Response of $\Delta CPI$ to shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta IPI \rightarrow \Delta CPI$</td>
</tr>
<tr>
<td>$\Delta CPI \rightarrow \Delta CPI$</td>
</tr>
<tr>
<td>$\Delta SR \rightarrow \Delta CPI$</td>
</tr>
<tr>
<td>$\text{ILLQCI} \rightarrow \Delta CPI$</td>
</tr>
</tbody>
</table>

Figure 2.3: Impulse response functions (IRFs) plots.

Notes: The estimated SVAR IRFs are based on Cholesky ordering and BQ 90% bootstrapped confidence intervals with 1 lag, based on 1000 replications.
Figure 2.3: Impulse response functions (IRFs) plots...Continued. The $\Delta IPI$, $\Delta CPI$, $\Delta SR$ are changes in IPI, inflation rate, and SR. ILLQCI is illiquidity connectedness index.
CHAPTER 3
THE IMPACT OF OIL SHOCKS ON STOCK RETURN: A DATA-DRIVEN IDENTIFICATION APPROACH

3.1 Introduction

Studies show that, in addition to being a strategic global commodity, crude oil plays a key role in the world economy and influences the stock market. Following the seminal work of Kilian (2009) showing that oil market demand and supply shocks determine the variation in the real oil price, there is continuing interest in understanding the impact of real oil prices on real stock returns. Although empirical studies attempt to shed light on the relationship between real oil price shocks and real stock returns, the relationship between real oil price shocks and real stock returns is not well developed (Clements et al., 2019; Kilian and Park, 2009).

Estimating the effects of oil shocks on real stock returns is plagued by endogeneity and omitted variables problems. Most studies focus on one-way impact studies that examine the impact of oil prices on stock markets. However, the stock market also affects the variation in oil prices (Degiannakis et al., 2018). Most of the identified models based on economic theory also assume a lower triangular matrix in contemporaneous relationships among variables included in the model. In particular, this means that the stock market does not affect the oil market at the same time. This further supports the idea that oil prices are exogenous.

To address this challenge, Rigobon (2003) developed a heteroskedastic innovation identification approach. The heteroskedastic innovation identification approach is a data-driven
identification method that uses the information content of the data. The heteroskedastic innovation identification approach solves the problem of endogeneity. Following Rigobon (2003) and Rigobon and Sack (2004), Herwartz and Plödt (2016a) have successfully applied a data-driven approach to study the effect of oil price shocks on macroeconomic aggregates in the U.S., the euro area, and China. Herwartz and Plödt (2016b) and Herwartz et al. (2021) also discuss the importance of a data-driven approach for the identification of structural vector autoregression (SVAR) using simulations and an empirical study from the US and the UK.

Studying the impact of crude oil prices is important for several reasons. The increase in crude oil prices directly affects the entire economy, affecting the performance of companies. The increase in the price of crude oil affects the stock market mainly through the effect on stock prices. The increase in oil price increases the cost of production for companies by increasing production input costs and transportation costs, which reduces the profit margin of companies. The rise in oil prices also affects inflation, weakening consumer purchasing power, and investor confidence.

A further examination of the impact of real oil price shocks is important, as factors that directly and indirectly affect real oil price fluctuations affect real equity returns. Kilian (2009) and Kilian and Park (2009) developed an oil market SVAR, in which they identified three major shocks that drive oil prices. These are the global supply of crude oil, the demand for all industrial commodities, including oil, and the demand shocks specific to oil prices. Shocks to these variables indirectly cause real stock returns to fluctuate. Kilian (2009) and Kilian and Park (2009) show that the real aggregate demand, oil supply, and oil-specific demand shocks determine the real variation in oil price. We believe that these shocks will have an effect on real equity returns, both directly and indirectly through real oil prices. Kilian and Park (2009) also show that the monetary policy response to oil demand and
supply shocks is negligible, but fail to include real stock returns in the model. Excluding the actual stock returns from the model raises the problem of omitted variables.

In this study, we examine the response of real stock returns to oil price shocks using a method that overcomes the problem of oil price endogeneity. Most previous studies examined the effect of the oil shock on stock returns using a conventional VAR. In this study, we use a data-driven identification approach to examine the response of the real stock return to oil shocks. Unlike the traditional identification approach, which uses economic theory to identify structural shocks, the data-driven identification approach uses the information content of the data to identify structural shocks. This method overcomes the issues of endogeneity and omitted variables. Olea et al. (2022) contends that the use of a data-driven approach for the identification of SVAR overcomes the endogeneity problem by imposing a strong statistical assumption that shocks are mutually independent. Data-driven identification, which uses the information content of the data, allows us to test whether the identified model based on economic theory is preferable (Lange et al., 2021).

Our study differs from Kilian and Park (2009) in the following ways. They used a conventional SVAR to examine the impact of oil price shocks on stock return. In this study, we apply data-driven identification to examine the effect of a real oil price shock on the real stock return. Our model simultaneously includes both real stock returns and monetary policy in the model, while they add these variables separately. We construct real oil prices by deflating West Texas Intermediate (WTI) futures by the consumer price index, while they use the refiner’s cost. We derive real stock return by deflating the U.S. Standard and Poor’s 500 (SP500) futures by the consumer price index. We use unconventional monetary policy. They use conventional monetary policy. We also used recent data from 1997 to 2021.

We outline the study as follows. First, we present the benchmark model in section 3.2.1. In this section, we also discuss how we extend a three-variable benchmark SVAR model into five variables by incorporating both real stock return and monetary policy. In section
3.2.2, we present a data-driven identification model. A smooth transition heteroskedastic innovation identification approach is the focus of this section. In section 3.3, we present the data and their sources. Then, in section 3.4, we present and discuss our findings.

The main findings of the study show that smooth transition heteroskedastic innovation can uniquely identify the system. Real stock returns significantly respond to oil-specific demand shocks. The findings of the study provide important information to authorities concerned with the stability of the stock and oil markets. Specifically, since the change in oil market shocks has demonstrated major effects on real economic activities, the monetary policy authorities want to stabilize the price in order to stimulate the real economy. Energy policy authorities may also benefit from the study in their policy decision on oil production, distribution, and pricing. It may also help investors to optimally respond to oil market shocks. It also contributes to the literature devoted to examining the relationship between the oil and the stock markets. Examining the effect of oil shocks on real stock returns will help to understand how oil market shocks affect the stock market. Further, it contributes literature devoted to identifying SVAR’s using the information content of the data.

3.2 Empirical Strategy

Suppose that we have a K-dimensional VAR (p) with structural form

\[ Ay_t = \Gamma_0 + \Gamma_1 y_{t-1} + \ldots + \Gamma_p y_{t-p} + \varepsilon_t, \]

(3.1)

and reduced form

\[ y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \]

(3.2)

where \( y_t \) is K x 1 vector of observable, \( v \) is a constant K x 1 constant vector, \( A_i, i=1,2,\ldots,p \) are K x K coefficient matrix, \( B = A^{-1} \) is the matrix of contemporaneous coefficient K x K, \( \varepsilon_t \)
is a vector of uncorrelated structural shocks, with $E(\varepsilon_t) = 0$, and $cov(\varepsilon_t) = \Sigma_\varepsilon$ is a diagonal matrix. The reduced-form error is $u_t = B\varepsilon_t$ with $E(u_t) = 0$ and $cov(u_t) = \Sigma_u$. To uniquely identify matrix $B$, which is the SVAR identification problem, previous methods relied on economic theory. The identification of a SVAR based on economic theory was pioneered by Sims (1980) and Blanchard and Quah (1993). The new methods to identify matrix $B$ are data driven. The data-driven identification approach uses the information content of the data. In both cases, the SVAR identification problem is characterized by the covariance matrix of the reduced-form error.

$$cov(u_t) = \Sigma_u = B\Sigma_\varepsilon B^T.$$ (3.3)

Because the $B$ matrix is not unique, determined by (3.3) we need an additional restrictions to identify $B$. To overcome this identification problem, we can use an economic and/or data-driven approach to identify the $B$ matrix. In this study, benchmarking our model on Kilian (2009), we focus on SVAR identification based on the information content of the data.

### 3.2.1 Benchmark model: Economic theory-based identification

Our benchmark model for structural VAR in (3.1) specifies $y_t = [os_t, ad_t, wti_t]^T$ where $os_t$, $ad_t$, and $wti_t$ are global oil production, global real activity, and the future price of West Texas Intermediate (WTI) crude oil at time $t$. The benchmark model is based on Kilian (2009). The structural shocks of the model are the shocks to the global supply of crude oil, the shocks to the global demand for all industrial commodities, including crude oil, and the shocks to the oil price. These shocks represent oil supply, aggregate demand, and oil-specific demand shocks. The model assumes Cholesky ordering, which implies that the real oil price responds contemporaneously to oil supply and real aggregate demand shocks. Kilian (2009) specifies the structural shock as

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where $\varepsilon_{os,t}$, $\varepsilon_{ad,t}$, and $\varepsilon_{wti,t}$ are structural shocks of oil supply, aggregate demand, and oil-specific demand. The $b'_{ij}$s are contemporaneous impact coefficients. The $u_{os,t}$, $u_{ad,t}$, and $u_{wti,t}$ are errors in the reduced-form equations for the global oil production, global real economic activity, and real oil price.

To examine the effect of oil shocks on stock returns, we modify (3.4) by including stock returns and a variable measuring the Fed’s stance on monetary policy. Following Kilian and Park (2009), we order the monetary policy last,}

$$
\begin{bmatrix}
\varepsilon_{os,t} \\
\varepsilon_{ad,t} \\
\varepsilon_{wti,t} \\
\varepsilon_{rsp,t} \\
\varepsilon_{sr,t}
\end{bmatrix}
= 
\begin{bmatrix}
b_{11} & 0 & 0 & 0 & 0 \\
b_{21} & b_{22} & 0 & 0 & 0 \\
b_{31} & b_{32} & b_{33} & 0 & 0 \\
b_{41} & b_{42} & b_{43} & b_{44} & 0 \\
b_{51} & b_{52} & b_{53} & b_{54} & b_{55}
\end{bmatrix}
\begin{bmatrix}
u_{os,t} \\
u_{ad,t} \\
u_{wti,t} \\
u_{rsp,t} \\
u_{sr,t}
\end{bmatrix}
$$

(3.5)
uses the restricted model and an unrestricted model. The restricted and unrestricted models are the Cholesky ordering-based model and the data-driven identified model.

3.2.2 Heteroskedastic innovation based identification

Identification is based on heteroskedasticity in structural shocks. The identification procedure assumes that the oil market transitions smoothly between two variance regimes. This approach extends Rigobon (2003) who assumed that changes in covariances occur at specified dates considered as structural breaks \( T_s b \). For the two-variance regime, the reduced-form covariance matrix is

\[
E(u_t u_t') = \begin{cases} 
\Sigma_1 & \text{for } t = 1, \ldots, T_{sb} - 1 \\
\Sigma_2 & \text{for } t = T_{sb}, \ldots, T,
\end{cases}
\tag{3.6}
\]

where \( \Sigma_1 \neq \Sigma_2 \).

Since this approach assumes unconditional and exogenous covariance changes of a series at known discrete time points, we use the more general smooth transition in volatility. For two variance states \( \Sigma_1 \neq \Sigma_2 \), the smooth changing covariance matrix at time \( t \) is

\[
E(u_t u_t') = \Omega_t = (1 - G(s_t))\Sigma_1 + G(s_t)\Sigma_2, \quad t = 1, \ldots, T,
\tag{3.7}
\]

where \( G(s_t) \) is the transition function determined by the transition variable \( s_t \). The transition variable may be deterministic, such as time itself, or may be a stochastic transition variable generated within the model. We use the standard logistic function as a smooth transition function, which is given by

\[
G(\gamma, c, s_t) = \left[1 + \exp(-\exp(\gamma)(s_t - c))\right]^{-1}.
\tag{3.8}
\]

Parameters \( \gamma \) and \( c \) determine the slope and location of the transition function.
The identification of structural shocks is made through a smooth transition function that generalizes the identification through changes in volatility (Lütkepohl and Netšunajev, 2017). Based on Lange et al. (2021) and Lütkepohl and Netšunajev (2017) we discuss a smooth transition in volatility identification as follows. The covariance matrices can be decomposed as

\[ \Sigma_1 = BB^T \text{ and } \Sigma_2 = B\Lambda B^T, \quad (3.9) \]

where \( \Lambda \) is the nonnegative diagonal matrix that allows for the change in variance of structural shocks \( \varepsilon_t \) in the second regime. In the first regime, structural shocks have unit variance \( (I_k) \), and the diagonal elements \( \lambda_{ii} > 0 \) in \( \Lambda \) are variances in the second regime. Structural shocks in the system are uniquely identified if all of the \( \lambda_{ii} \) are distinct. In fact, Lütkepohl and Netšunajev (2017) show that \( \Omega \) in (3.7) is invertible if one of the \( \Sigma_1 \) and \( \Sigma_2 \) matrices is positive definite and the other one is positive semidefinite. The implicit assumption is that \( \Sigma_1 \) is invertible to ensure that \( B \) is nonsingular. If \( \Sigma_2 \) is singular, at least one of the \( \lambda_{ii} \) is zero. If more than one \( \lambda_{ii} \) is zero \( B \) is not identified through heteroskedasticity.

To estimate the heteroskedastic innovation-smooth transition variance identified model, we use maximum likelihood. Based on the covariance structure in (3.7) and (3.8), and the assumption of normally distributed shocks \( u_t \), the log-likelihood function is given by

\[ \log L = T\frac{K}{2} \log 2\pi - \frac{1}{2} \sum_{t=1}^{T} \log |\Omega_t| - \frac{1}{2} \sum_{t=1}^{T} u_t^T \Omega_t^{-1} u_t. \quad (3.10) \]

The first step is to maximize the log-likelihood (3.10) with respect to structural parameters \( B \) and \( \Lambda \). This step uses an initial pair of transition parameters \((\gamma, c)\), an initial matrix \( B \) that is the lower triangular decomposition of \( T^{-1} \sum_{t=1}^{T} \hat{u}_t \hat{u}_t^T \) and \( \Lambda \) that is set to an identity matrix. In the second step, the estimated matrices \( \hat{B} \) and \( \hat{\Lambda} \) are used to re-estimate the
reduced-form VAR parameters by means of generalized least squares (GLS)

\[
\hat{\beta} = \left( (Z_t^T \otimes I_k) W_T (Z_T \otimes I_K) \right)^{-1} (Z_t^T \otimes I_K) W_T y,
\]

where \( Z_t \) is \( T \times (1+K_p) \) data matrix containing a leading one for the constant and lag observations \((1, y_{t-1}^T, ..., y_{t-p}^T), y = (y_1^T, ..., y_T^T) \) is \((KT \times 1) \) data vector and \( W_T \) is a block-diagonal \((KT \times KT) \) weighting matrix

\[
W_T = \begin{bmatrix}
\Omega_1^{-1} & \ldots & 0 \\
\vdots & \ddots & \vdots \\
0 & \ldots & \Omega_T^{-1}
\end{bmatrix}
\]

The GLS step provides \( \hat{\beta} \) to update the covariance estimates by means of \( \hat{u}_t = y_t - (Z_t^T \otimes I_k) \hat{\beta} \). The two steps are repeated until the log-likelihood converges. The iterative procedure is evaluated on each pair of parameters \((\gamma, c)\) within a pre-specified range. The pair of parameters that maximizes the log-likelihood in (3.10) is considered to provide the best estimate of the true transition.

To proceed with the heteroskedastic innovation identified SVAR requires two tests. First, we test whether the shock has a unique change in variance. Using the information content of the data, we test whether the diagonal elements of \( \Sigma_2 \) are identical. To test the assumption that each variance changes differently, Lange et al. (2021) propose a Wald statistic to test the null hypothesis \( H_0 : \lambda_{ii} = \lambda_{jj} \). The Wald statistic is

\[
\lambda_{w,ij} = \frac{(\lambda_{ii} - \lambda_{jj})^2}{Var(\lambda_{ii}) + Var(\lambda_{jj}) - 2Cov(\lambda_{ii}, \lambda_{jj})} \sim \chi^2(2), \tag{3.11}
\]
and can be computed for all possible pairs of i and j. The null hypothesis of proportional shifts in variances is rejected for higher values of $\lambda_{w,ij}$. This test is equivalent to testing whether the diagonal elements of the covariance of the shocks in the second regime are distinct. The test ensures that the system is uniquely identified. In addition to heteroskedastic innovation, we need to test that the diagonal elements of $\Sigma_2$ are significantly different from zero to ensure that $\Sigma_2$ is nonsingular.

The second test tests the validity of economic theory based identified SVAR. Following Lütkepohl (2005), Lange et al. (2021) argue that because the heteroskedasticity-based model is fully identified and can be estimated by maximum likelihood, the restriction required to identify the model by economic theory can be tested by means of likelihood ratio statistic.

$$\lambda_{LR} = 2 \left( \log L(\text{vec}(\hat{B})) - \log L(\text{vec}(\hat{B}_r)) \right) \sim \chi^2_N$$

where $\hat{B}$ is the unrestricted maximum likelihood estimator of B in (3.10), $\hat{B}_r$ is the restricted maximum likelihood estimator that imposes the triangular structure on B, and N is the number of restrictions. The null hypothesis that the restricted model holds, which is equivalent to economic theory-based identification and is sufficient to identify the model, is rejected for large values of $\lambda_{LR}$.

### 3.3 Descriptions of Variables and Data

**Oil production** In this study, we measure monthly oil production by global crude oil production. We obtain global crude oil data from the U.S. Energy Information Agency (EIA). The EIA defines crude production as the volume of crude oil produced from oil reservoirs during a given period of time. The amount of such production for a given period is measured as volumes delivered from lease storage tanks to pipelines, trucks, or other media for transport to refineries or terminals with adjustments for (1) net differences between
opening and closing lease inventories and (2) basic sediment and water (BSW). We use global crude oil production in our model to derive an oil supply shock. For ease of interpretation as an oil supply disruption, we multiply oil production by a negative one.

**Economic activity** Following Kilian (2009), we measure economic activity with a world real economic activity index. We include the world real economic activity index in the system as a proxy for global real demand. It is derived from global bulk dry cargo shipping rates that serve as a proxy for the volume of shipping in global industrial commodity markets. The index is expressed as a percent deviation from the trend. We drive the demand shock from the real economic activity index. The monthly data for the world real economic activity index are available Kilian’s on the Google sites.

**Oil price** We measure oil prices using the prices of West Texas Intermediate (WTI) crude oil futures. We obtain monthly data of WTI crude oil futures from the Bloomberg terminal. We deflate WTI futures by the U.S. consumer price index to measure oil price in real value.

**Stock return** We measure the return of the stock market by the return of U.S. SP500 derived from the futures prices of SP500. To account for inflation impact, we measure stock returns in real terms by deflating SP500 futures price by the U.S. consumer price index. We obtain monthly SP500 futures prices from the Bloomberg Terminal.

**Monetary policy** We proxy the monetary policy stance by the shadow rate (SR) developed by Wu and Xia (2016). We cannot use the Federal Funds rate in our sample period because after the great financial crisis, the Federal Funds rate is constrained by the zero lower bound (ZLB) and does not vary. The shadow rate is the federal funds rate when the ZLB is not binding and even becomes negative to account for unconventional monetary policy tools. SR is based on yield rates, and negative SR coincides with quantitative easing (Krippner, 2014). The SR data is available at Federal Reserve Bank of Atlanta. The sample period for all variables ranges from 1997 to 2021. We present the data plots in Figure 3.1.
3.4 Empirical Results

In this section, we present and discuss the empirical findings of the study. In Sections 3.4.1 and 3.4.2 we present and discuss the results of the benchmark model and the results based on the identification by heteroskedastic innovations. For comparison purposes, we also present the restricted model finding, which assumes both a contemporaneous lower triangular impact matrix and heteroskedastic innovations. However, for the main findings of the study, we focus on the preferable model.

3.4.1 Benchmark model result

The benchmark model assumes that a lower triangular impact matrix is present in the contemporaneous relationships among the variables in the system. This benchmark model is based on previous studies of Kilian (2009) and Kilian and Park (2009). The benchmark model implies that the global oil production shock contemporaneously affects all of the other variables. The real economic activity of the world, which is a proxy of real demand, contemporaneously affects the real price of oil, stock returns, and monetary policy. Stock returns and monetary policy respond contemporaneously to all oil shocks. The real price of oil affects both real stock returns and monetary policy contemporaneously. However, all variables respond to each other through lags. We consider this benchmark model as economic theory-based identification.

With this economic theory in mind, we estimate a SVAR to examine the effect of oil shocks on the real stock return. Based on the model estimate under the Cholesky ordering identification, the estimated contemporaneous impact matrix is
The columns are OS, AD, WTI, RSP, and SR. The OS is the change in the log of global crude oil production, AD is the percentage change (in decimal places) of the real aggregate demand index of the world, WTI is the change in the log of real WTI futures prices, and RSP is the percentage change (in decimal places) in a log of real SP500 futures and SR change in shadow rate which is a proxy for the monetary policy instance. The ten observed zeros are imposed by Cholesky orderings. By assumption, from this impact matrix, it is evident that real stock return and monetary policy do not contemporaneously affect oil markets. However, stock and monetary policy shocks affect oil markets through lags. The impact matrix shows that oil supply disruption and oil-specific demand shocks increase the real oil price, while the aggregate demand shock reduces the real oil price. The real stock return responds negatively contemporaneously to the disruption of oil supply and positively to aggregate demand and oil-specific shocks.

We present the impulse response functions (IRFs) for the benchmark model in Figure 3.2. IRFs show that a one-standard positive shock to the global oil supply reduces the real return on stocks for two months. Positive shocks to aggregate demand of one standard deviation decrease the real return on stocks and increase the real return after lag of two months. A one-standard deviation positive shock to the real oil price decreases the real return on stocks until a two-month lag. A positive shock to monetary policy reduces the real return on stocks. The effects of oil supply, demand, and monetary policy shocks on a real stock return are
insignificant; however, the effect of the real oil price shock is significant. The result of the benchmark model is consistent with the previous study.

3.4.2 Heteroskedastic innovation based identification model result

In this section, we first estimate a general unrestricted smooth transition model without imposing restriction on the B matrix. We follow Lütkepohl and Netšunajev (2017) to choose the transition variable for the model. We consider both time and the monetary policy variable as possible transition variables. We estimate a smooth transition model for each of these transition variables and select the model with the highest likelihood function. Since the number of parameters is the same in each model, this is equivalent to minimizing the Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC). Table 3.1 presents the results of two tests for each model. The likelihood function selects time as the transition variable. Other models in which lags of monetary policy variables are used as transition variables also show that there is evidence that the model can be fully identified by the heteroskedastic innovations approach. However, smooth transition models, which contain lags of monetary policy variables as transition variables, have lower likelihoods. Because the transition function for the model with the transition variable $s_t = t$ in Figure 3.6 indicates a sudden change in the transition function, we also present the test for the discrete transition model, which is based on Rigobon (2003). The Rigobon (2003) discrete transition model is a special case of a smooth transition in variances. For the smooth transition model, if at the transition location $c$, the slope $\gamma \to \infty$ there will be discrete transition in variances. Although the test for the Rigobon (2003) model shows that the shocks are heteroskedastic for the estimated transition location, the variances in the second regime are not distinct. Furthermore, the estimated model using the Rigobon (2003) approach has a smaller likelihood. Because the estimated model using the Rigobon (2003) approach has a smaller likelihood and non-unique variances, we choose the smooth transition model as our preferred model.
Given the statistics in Table 3.1 for the models, our preferred model is the VAR identified by heteroskedastic innovation-smooth transition with time as the transition variable. Using our preferred model, we model the effect of real oil price shocks on the real stock returns by heteroskedastic innovation identification. For the preferred model, we test whether the restrictions imposed by economic theory to identify the model are consistent with the data. The identification based on economic theory is based on the SVAR that assumes that the B matrix is lower triangular. Following Lange et al. (2021) we use the LR test to test the validity of the identification based on economic theory. To use the LR test, we first test if the system can be fully identified by heteroskedastic innovations. We use Wald tests to test the identification by heteroskedastic innovations.

Based on the heteroskedastic innovation-smooth transition in the volatility identification approach, we present the significance tests of the variances in the second regime and the likelihood functions in Table 3.1. All pairwise tests that changes in variances are equal are rejected for p-values less than .05. The Wald test shows that the system can be successfully identified by a change in volatility.

For the LR test, we consider the identified model based on economic theory as a restricted model. The restricted model represents the just identified model. We consider the heteroskedastic innovation-identified model as an unrestricted model. Given the unrestricted model, we can test over-identifying assumptions. Because the LR statistic is 17.13 the null hypothesis which is in favor of the identification based on economic theory is rejected for p-values less than .1. This finding implies that identification based on economic theory that makes the impact matrix lower triangular is not consistent with the data.

The distinction between the benchmark model and the restricted model is that the benchmark model does not assume heteroskedasticity in innovation. However, the restricted model assumes both a lower triangular matrix in the impact matrix and heteroskedasticity in innovations. For comparison purposes, we present the impact matrix and its standard error
based on the restricted model as

\[
\text{res} \hat{B} = \begin{bmatrix}
0.0090 & 0 & 0 & 0 & 0 \\
-0.0212 & 0.6703 & 0 & 0 & 0 \\
0.0190 & -0.0026 & 0.0982 & 0 & 0 \\
-0.0002 & 0.0001 & 0.0022 & 0.0070 & 0 \\
0.0068 & 0.0090 & 0.0210 & -0.0113 & 0.2295
\end{bmatrix}
\]

and

\[
\text{res} \hat{B}_{se} = \begin{bmatrix}
0.0006 & 0 & 0 & 0 & 0 \\
0.0526 & 0.0421 & 0 & 0 & 0 \\
0.0051 & 0.0026 & 0.0063 & 0 & 0 \\
0.0003 & 0.0002 & 0.0004 & 0.0005 & 0 \\
0.0082 & 0.0041 & 0.0104 & 0.0128 & 0.0144
\end{bmatrix}.
\]

The contemporaneous impact matrix of the restricted model shows that a disruption of oil supply and a positive oil-specific demand shock significantly increase real oil prices. However, the aggregated demand shock does not have a significant effect on real oil prices. A positive shock to oil-specific demand contemporaneously increases stock returns significantly.

The heteroskedastic innovation test shows that the variances of the shocks in regimes one and two are different from each other. Furthermore, the finding of the study based on identification via a smooth transition in volatility shows that shocks have variances different from one in the second regime. The variances of the shocks to oil aggregate supply, aggregate demand, and real oil are increased relative to regime one. The variances of the shocks to the real stock return and the shadow rate are reduced in the second regime. As the ratio of the respective diagonal elements of the covariance matrix, \( \hat{\Lambda} \) and its standard errors, \( \hat{\Lambda}_{se} \) are greater than 2 the variances of the shocks are significantly different from zero in regime two.
More importantly, the test of equal Eigenvalues in Table 3.1 shows that diagonal elements of \( \hat{\Lambda} \) are distinct. This implies that we can uniquely identify the system using a heteroskedastic innovation identification approach. The covariance matrix \( \hat{\Lambda} \) and its standard error \( \hat{\Lambda}_{se} \) in the second regime are

\[
\hat{\Lambda} = \begin{bmatrix}
3.1604 & 0 & 0 & 0 & 0 \\
0 & 7.3413 & 0 & 0 & 0 \\
0 & 0 & 1.8502 & 0 & 0 \\
0 & 0 & 0 & 0.4066 & 0 \\
0 & 0 & 0 & 0 & 0.8335
\end{bmatrix}
\]

and

\[
\hat{\Lambda}_{se} = \begin{bmatrix}
0.5565 & 0 & 0 & 0 & 0 \\
0 & 1.0526 & 0 & 0 & 0 \\
0 & 0 & 0.3175 & 0 & 0 \\
0 & 0 & 0 & 0.0672 & 0 \\
0 & 0 & 0 & 0 & 0.1594
\end{bmatrix}
\]

Based on heteroskedastic identification of smooth transition innovation, we present the estimated impact matrix and its standard error in matrices \( \hat{B} \) and \( \hat{B}_{se} \). The finding of the study shows that real stock returns respond significantly contemporaneously to oil-specific demand shocks. However, the real return on the stocks does not respond significantly to the shocks of oil supply, aggregate demand, and monetary policy.
\[
\hat{\beta} = \begin{bmatrix}
0.0071 & 0.0005 & -0.0047 & 0.0016 & -0.0018 \\
0.0272 & 0.7434 & 0.1740 & 0.0903 & -0.0871 \\
0.0516 & -0.0057 & 0.0473 & -0.0463 & 0.0401 \\
0.0013 & -0.0002 & 0.0041 & 0.0051 & -0.0012 \\
0.0095 & 0.0131 & -0.0187 & 0.1034 & 0.1839
\end{bmatrix}
\]

\[
\hat{\beta}_{se} = \begin{bmatrix}
0.0013 & 0.0007 & 0.0025 & 0.0011 & 0.0014 \\
0.1219 & 0.0488 & 0.0897 & 0.0766 & 0.0751 \\
0.0130 & 0.0056 & 0.0189 & 0.0157 & 0.0163 \\
0.0011 & 0.0003 & 0.0006 & 0.0008 & 0.0013 \\
0.0141 & 0.0057 & 0.0234 & 0.0621 & 0.0279
\end{bmatrix}
\]

To examine the dynamic relationships among oil shocks, stock returns, and monetary policy, we consider IRFs and the forecast error variance decomposition (FEVD). We present IRFs based on smooth transition identification in Figure 3.4. IRFs based on the smooth transition identification show that both oil supply disruption and oil-specific demand shocks have a significant effect on real stock returns. The effects of aggregate demand and monetary policy shocks on the real return of stocks are not significant. The response of the real stock returns to oil supply disruption becomes significant after a two-month lag and vanishes quickly. Furthermore, the real price of oil responds significantly contemporaneously to oil supply, stock return, and monetary policy shocks.

We present the FEVD in Figure 3.5 and in Tables 3.3 and 3.2. We particularly focus on the real price of oil and the real return of the stock to understand the dynamic relationships between the real price of oil and the real return of the stock. The FEVD plots and the table show that the variation in the forecast error in the real oil price is mainly determined by oil supply shocks, monetary policy, and stock market shocks. These three shocks account for
about 73% in the variation in the forecast error of real oil prices. Oil supply shocks lead by about 30% while monetary stock and policy shock market shocks follow by about 24% and 18%. The variation of approximately 42% forecast error in real stock returns is explained by oil-specific demand, monetary policy, and oil-supply shocks. However, the share of the real demand shock is consistently less than 1% for both real oil prices and real stock returns.

In general, oil supply, oil-specific demand, and stock return shock and monetary policy shocks are important determinants of real oil price variation. The variation in real return on stocks is also mainly explained by the oil-specific demand shock, the monetary policy shock, and the oil-supply shock. The explanatory power of the aggregate demand shock is negligible.

3.5 Conclusion

In this study, we examine the effect of the shock of real oil prices on the real return of the stocks. We extend the study of Kilian and Park (2009) in two main ways. First, we extend the model by incorporating real stock returns and monetary policy into the model. Second, to identify the system, we use a data-driven identification approach. By extending their model, we shed a light on the sources of variation in real oil price, and real stock return. Using data-driven identification, we account for heteroskedastic innovation to accurately estimate the effect of the oil shock on the real stock return.

We use the SVAR identified by heteroskedastic innovation to estimate the model. The heteroskedastic innovation identification approach allows us to test the validity of the SVAR identification by economic theory. Our finding shows that SVAR can be successfully identified by the heteroskedastic innovation approach. The test of the validity of the model shows that the identified model based on economic theory is not an adequate model for our data.
Based on the model identified by heteroskedastic innovation, the oil-specific demand shock significantly affects the real stock return. There is also a significant dynamic relationship between the oil-specific demand shock and real stock returns.

The findings of the study can serve as an important input for authorities concerned with the stability of the stock and oil markets. In particular, monetary policy authorities can use the finding of the study in their effort to stabilize the price and stimulate the real economy. Energy policy authorities may also benefit from the study in their policy decision on oil production, distribution, and pricing. It may help investors to respond optimally to oil shocks.

The finding of the also contributes to the literature devoted to examining the relationship between oil shock and real stock return. Examining the effect of the oil shock on the real stock return helps us to understand how oil markets affect stock markets. In addition, it contributes to the literature trying to identify a SVAR by using the information content of the data. This helps overcome endogeneity and omitted variables. Identification by data driven that is based on information content also allows for testing over identifying assumptions.
3.6 References


Herwartz, H., Lange, A., and Maxand, S. (2021). Data-driven identification in svars—when and how can statistical characteristics be used to unravel causal relationships? *Economic Inquiry*.


Olea, J. L. M., Plagborg-Møller, M., and Qian, E. (2022). Svar identification from higher moments: Has the simultaneous causality problem been solved?


3.7 Appendix
Table 3.1: Test statistics and likelihood for the models.

<table>
<thead>
<tr>
<th></th>
<th>St = t</th>
<th>St = sr_{t-1}</th>
<th>St = sr_{t-2}</th>
<th>Rigobon</th>
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<tr>
<td></td>
<td>Test.statistic</td>
<td>p.value</td>
<td>Test.statistic</td>
<td>p.value</td>
</tr>
<tr>
<td>H₀: λᵢ = λⱼ</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>λ₁ = λ₂</td>
<td>12.160</td>
<td>0.000</td>
<td>11.960</td>
<td>0.000</td>
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<tr>
<td>λ₁ = λ₃</td>
<td>4.170</td>
<td>0.040</td>
<td>4.530</td>
<td>0.030</td>
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<tr>
<td>λ₁ = λ₄</td>
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<td>0.000</td>
<td>12.520</td>
<td>0.000</td>
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<tr>
<td>λ₁ = λ₅</td>
<td>16.140</td>
<td>0.000</td>
<td>18.810</td>
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<tr>
<td>λ₂ = λ₃</td>
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<tr>
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<tr>
<td>λ₂ = λ₅</td>
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<tr>
<td>λ₃ = λ₄</td>
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<td>0.000</td>
<td>4.000</td>
<td>0.050</td>
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<tr>
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<tr>
<td>λ₄ = λ₅</td>
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<td>0.010</td>
<td>3.170</td>
<td>0.080</td>
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</table>

H₀: λᵢ = 0

<p>| | | | | |</p>
<table>
<thead>
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<td>0.000</td>
<td>5.444</td>
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<tr>
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</table>

Likelihood

|        | 1745.65 | 1687.08 | 1690.191 | 1710.197 |

Note that St = t, St = sr_{t-1}, St = sr_{t-2} and Rigobon denotes smooth transition models for transition variables time, one, and two month lag shadow rate and Rigobon discrete transition model.
Table 3.2: Percent contribution of shocks to real oil price variation.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>OS Shock</th>
<th>AD Shock</th>
<th>WTI Shock</th>
<th>RSP Shocks</th>
<th>SR Shock</th>
</tr>
</thead>
<tbody>
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<td>0.37</td>
<td>25.75</td>
<td>24.69</td>
<td>18.54</td>
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<tr>
<td>3</td>
<td>30.09</td>
<td>0.42</td>
<td>26.28</td>
<td>24.99</td>
<td>18.22</td>
</tr>
<tr>
<td>6</td>
<td>30.09</td>
<td>0.42</td>
<td>26.28</td>
<td>24.99</td>
<td>18.22</td>
</tr>
<tr>
<td>9</td>
<td>30.09</td>
<td>0.42</td>
<td>26.28</td>
<td>24.99</td>
<td>18.22</td>
</tr>
<tr>
<td>12</td>
<td>30.09</td>
<td>0.42</td>
<td>26.28</td>
<td>24.99</td>
<td>18.22</td>
</tr>
<tr>
<td>15</td>
<td>30.09</td>
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<td>26.28</td>
<td>24.99</td>
<td>18.22</td>
</tr>
<tr>
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<td>30.09</td>
<td>0.42</td>
<td>26.28</td>
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<td>24.99</td>
<td>18.22</td>
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<tr>
<td>24</td>
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<td>26.28</td>
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<td>0.42</td>
<td>26.28</td>
<td>24.99</td>
<td>18.22</td>
</tr>
</tbody>
</table>

Note that variance decomposition of SVAR based is on smooth transition identification.

Table 3.3: Percent contribution of shocks to real stock return variation.

<table>
<thead>
<tr>
<th>Horizon</th>
<th>OS Shock</th>
<th>AD Shock</th>
<th>WTI Shock</th>
<th>RSP Shocks</th>
<th>SR Shock</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.13</td>
<td>36.28</td>
<td>56.98</td>
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<td>3</td>
<td>3.96</td>
<td>0.21</td>
<td>35.76</td>
<td>56.87</td>
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<td>6</td>
<td>3.96</td>
<td>0.21</td>
<td>35.76</td>
<td>56.87</td>
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<td>0.21</td>
<td>35.76</td>
<td>56.87</td>
<td>3.2</td>
</tr>
</tbody>
</table>

Note that variance decomposition of SVAR is based on smooth transition identification.
Figure 3.1: Plots of variables.

Notes: The OS is the change in the log of global crude oil production, AD is the percentage change (in decimal) world real aggregate demand, WTI is the change in the log of real West Texas Intermediate (WTI) futures prices, RSP is the percentage change (in decimal) in a log of real SP500 futures and SR change in shadow rate which is proxy for monetary policy instance.
Figure 3.2: Plots of IRFs based Cholesky ordering.

Note: IRFs based on 90% confidence intervals based on 1000 bootstrap replications. Structural shocks are identified by Cholesky ordering. The $row_i, column_j$ where $i, j = 1, ..., 5$ are the supply, demand, oil price, stock return, and monetary policy, represents the effect of shocks of one standard deviation to $i$ on $j$. 


Figure 3.3: Plots of IRFs based restricted model.

Note: IRFs based on 90% confidence intervals based on 1000 bootstrap replications. Structural shocks are based, on a restricted model. The restricted model assumes the lower triangular impact matrix and uses the smooth transition in volatility change. The row_i, column_j where i, j = 1, ..., 5 are the supply, demand, oil price, stock return, and monetary policy, represents the effect of shocks of one standard deviation to i on j.
Figure 3.4: Plots of IRFs based on smooth transition.

Note: IRFs based on 90% confidence intervals based on 1000 bootstrap replications. Structural shocks are identified by a smooth volatility transition. row$_i$, column$_j$ where i, j = 1,..., 5 are the supply, demand, oil price, stock return, and monetary policy, representing the effect of one standard deviation shock to i on j.
Figure 3.5: Plot of FEVDs based on smooth transition.

Note: The FEVDs are based on the structural shocks identified by a smooth transition in volatility. The row\(_i\), column\(_j\) where \(i, j = 1, ..., 5\) are the supply, demand, oil price, stock return, and monetary policy.
Figure 3.6: Transition function for $S_t = t$.

Note for the transition function the estimated $c = 131$ and $\gamma = 1.5$. The transition function plot shows that there is a sudden change in variance at October 2008. The plot show that the first and second part of the data have different volatility pattern.