Have the Causal Effects between Equities, Oil Prices, and Monetary Policy Changed Over Time? *

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This Draft: November 8, 2024

Forthcoming in *Journal of Commodity Markets*

Abstract

We reexamine the contemporaneous causal effects between the U.S. stock prices, crude oil prices, and monetary policy from 2005 to 2022. Our study offers two main contributions. First, we generalize a novel identification approach based on exogenous intraday shifts in the volatility in futures markets from two markets to multiple markets. Second, we examine contemporaneous causal effects between the U.S. stock prices, crude oil prices, and monetary policy. We show that the coefficients measuring contemporaneous causality have substantially changed over time. Specifically, we find that since 2008 stock returns affect crude oil returns. This time variation is also evident in the effect of monetary policy on the crude oil returns. We show that this time variation is consistent with two explanations: the ZLB and increased synchronization of crude oil prices with the business cycle.

Keywords: Monetary policy; Financial markets; Oil prices; Intraday data; Futures; Identification; Heteroskedasticity
JEL classification: E44; E52; E58; G14; G18; Q43

*We thank two anonymous referees, Julien Acalin, Kiwoong Byun, Bingxin Li, Jinjing Liu, participants at the 2023 Shanghai Business School International Conference for Finance, the 6th Annual J.P. Morgan Center International Commodities Symposium, 2023 FMA Annual Meeting, 2023 Southern Finance Association Conference, 2023 Australasian Finance and Banking Conference, and seminar participants at West Virginia University and the University of Toledo for their helpful comments.

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1 Introduction

Given the importance of crude oil prices for macroeconomic growth and financial markets, the relationship between the crude oil market and financial markets has been subject to much interest among not only researchers but also traders and investors seeking to optimize investment strategies as well as policymakers and regulators who need to understand the relationship to design effective policies and regulations. However, assessing how crude oil price changes affect financial markets and the reciprocal effects of financial market disruptions on the crude oil market is difficult due to the endogenous relationship between changes in crude oil prices and macroeconomic growth.[1] In this paper, we re-examine the relationship between stock prices, crude oil prices, and monetary policy from 2005 to 2022, considering the issue of endogeneity between the crude oil prices and financial markets. Our paper makes two contributions to the literature.

The first contribution is methodological. To address the endogeneity issue, Kurov, Olson, and Zaynutdinova (2022) propose an identification approach for analyzing contemporaneous relationships between two markets that utilizes intraday data coupled with exogenous volatility shifts (for example, the stock market opening). We extend the Kurov, Olson, and Zaynutdinova (2022) identification approach from two markets to any number of markets, which provides guidance for future research interested in examining contemporaneous causal linkages between multiple markets. The Kurov, Olson, and Zaynutdinova (2022) approach differs from previous literature that primarily relies on structural vector auto-regressions (SVARs). In contrast to SVARs, the approach does not require identifying assumptions such as sign restrictions or Cholesky decompositions to obtain estimates of the structural parameters. Instead, identification is achieved through exogenous changes in the covariance matrix ensuring reliability in inference thereby reducing identification concerns embedded in SVARs.[2]

[1] See, for example, Barsky and Kilian (2002, 2004), Hamilton (2008, 2011), Kilian (2008, 2014), and Kilian and Zhou (2023) for research on relationship between the energy prices and the macroeconomy.

[2] See, for example, Hamilton (1983), Hamilton (1996), Bernanke, Gertler, and Watson (1997, 2004), Hamilton and Herrera (2004), Kilian (2008), Kilian (2009), Hamilton (2011), and Baumeister and Hamilton (2019), Kilian and Lewis (2011).

As Kurov, Olson, and Zaynutdinova (2022) explain, the heteroskedasticity-based identification approach using intraday volatility shifts is also preferable to the heteroskedasticity-based identification approach using daily data pioneered by Rigobon and Sack (2003, 2004). Identification through heteroskedasticity using daily (or lower) frequency data assumes that the timing of volatility regime changes is known whereas in practice volatility regimes have to be estimated which adversely affects the reliability of inference. In contrast, predictable shifts in intraday volatility are known since they are triggered by regular events such as the stock market opening. In addition, intraday volatility shifts are exogenous as they occur regardless of the economic or market conditions, which makes the identification assumptions more plausible than those in identification through heteroskedasticity based on daily (or lower) frequency data.

Our second contribution brings new findings about the contemporaneous causal linkages between stocks, crude oil, and interest rates. Because our volatility shifts are exogenous and intraday (caused by the stock market opening, the Weekly Petroleum Status Report (WPSR) releases, and Federal Open Market Committee (FOMC) announcements and minutes releases), we are able to estimate all six structural relationships between the three markets at the same time. Much of the previous literature has focused on one or two of the relationships. For example, Rigobon and Sack (2003) analyze only the response of interest rates to stock prices, Rigobon and Sack (2004) analyze the response of stock prices and interest rates to monetary shocks, and Alquist, Ellwanger, and Jin (2020) analyze the responses of different markets to crude oil.

Our paper is the first one to explore the influence of stock returns on crude oil returns. We show that the stock returns cause changes in the crude oil returns. Specifically, a positive shock to stock returns increases crude oil returns. This influence is a relatively new phenomenon: it has been in existence only since September of 2008. Complementing literature that has studied the reverse relationship and showed that stock returns react to crude oil returns (for example, Aït-Sahalia and Xiu (2016), Lombardi and Ravazzolo (2016), Foroni, Guérin, and Marcellino (2017), Alquist, Ellwanger, and Jin (2020), Alquist, Bhattarai, and Coibion (2020), and Datta, Johannsen, Kwon, and Vigfusson (2021)), these findings provide evidence of bidirectional causality between stock returns and crude oil returns. Understanding the relation between stock returns and oil prices is important to investors who allocate capital to commodities to diversify their portfolios.[3]

In addition, we contribute to the literature that has studied the reaction of crude oil returns to monetary policy news (for example, Kilian and Vega (2011); Anzuini, Lombardi, and Pagano (2013); Rosa (2014); Basistha and Kurov (2015); Scrimgeour (2015); Yang, Zhang, and Chen (2023)) but has not focused on time variation in this relationship. We again show substantial time-variation: crude oil returns have reacted to Treasury yield changes only since September of 2008. This reaction now resembles the reaction of stock returns to monetary policy expectations.

These new findings improve our understanding of how the crude oil market reacts to the financial markets. Furthermore, we offer two explanations for these changes in the causal linkages between stock returns, the crude oil returns, and monetary policy. First, the ZLB changed the relationship between the crude oil and stock markets after the 2008 financial crisis (Datta et al. (2021)) and second, the shale revolution changed the price dynamics in the domestic U.S. crude oil market such that crude oil prices are now more synchronized with the business cycle. We provide evidence supporting both hypotheses.

The rest of the paper proceeds as follows. Section 2 describes our methodology and data, including Section 2.1.2 that explains our methodological contribution. Section 3 shows our results. Section 4 discusses potential explanations of our results. Section 5 discusses implications of our findings for researchers, investment practitioners, and monetary policymakers.

[3]As an indicator of the importance of crude oil to commodity investors, crude oil futures have by far the largest weight (approximately 40%) in the S&P GSCI index consisting of 24 futures contracts on physical commodities.

2 Methodology and Data

This section describes our methodology and data. Section 2.1 discusses the methodology of identification through heteroskedasticity of intraday asset returns and Section 2.2 presents our data.

2.1 Identification Through Heteroskedasticity of Intraday Asset Returns

This section describes our approach to identifying contemporaneous linkages between markets. We focus on contemporaneous linkages (rather than leads and lags of relationships) for two reasons. First, in modern markets that utilize automated trading, markets affect each other contemporaneously. Second, our focus is on true economic causality rather than Granger causality and the contemporaneous coefficients capture these causal effects. While our study examines causal relationships among three markets (stocks, crude oil, and interest rates), we start our explanation of the identification method with a simpler two-market example (stocks and crude oil) in Section 2.1.1 for clarity. We then generalize the approach to any number of markets in Section 2.1.2 to explain our methodological contribution.

2.1.1 Identification Approach: Two Market Example

Consider the following model of the stock market and the crude oil market:

$$R_{s,t} = \beta R_{o,t} + \gamma z_t + \varepsilon_t, \tag{1}$$

$$R_{o,t} = \alpha R_{s,t} + z_t + \eta_t, \tag{2}$$

where $R_{s,t}$ is the stock return, $R_{o,t}$ is the crude oil return, and z_t represents economic shocks common to both markets, such as macroeconomic news. It is impossible to measure all relevant economic news. For this reason, following Rigobon and Sack (2003) and Rigobon and Sack (2004) we treat z_t as unobserved. The two markets contemporaneously respond to each other as well as to the common economic shocks z_t. The structural innovations ε_t and η_t are assumed to be uncorrelated with each other and with z_t. The coefficients of primary interest (α and β) cannot be consistently estimated with an ordinary least squares (OLS) regression because of simultaneity and omitted variables as we cannot measure and include in the estimation all relevant economic news represented by z_t. Rigobon and Sack (2003) and Rigobon and Sack (2004) offer a solution to this problem: if one can find times when the variance of the structural innovations shifts, the coefficients α and β can be estimated using changes in the covariance matrix of returns.

The two-market model in equations (1) and (2) can be expressed in reduced form as:

$$R_{s,t} = \frac{1}{1-\alpha\beta}[(\beta+\gamma)z_t + \beta\eta_t + \varepsilon_t] \tag{3}$$

$$R_{o,t} = \frac{1}{1-\alpha\beta}[(1+\alpha\gamma)z_t + \eta_t + \alpha\epsilon_t]. \tag{4}$$

Suppose that we want to estimate the coefficient α that captures the response of the crude oil returns to the stock returns. Based on Kurov, Olson, and Zaynutdinova (2022), the predictable increase in the volatility of stock index futures returns after the stock market opening at 9:30 a.m. Eastern Time (ET) can be used for identification of the coefficient α because it provides a large shift in the variance of stock return innovations.[4] Assuming that the variance of ε_t, σ_ε, increases after the market opening, but σ_η and σ_z remain stable, the covariance matrices of the stock and crude oil returns after the stock market opening ($\boldsymbol{\Omega_1}$) and immediately before the stock market opening ($\boldsymbol{\Omega_2}$) are:

[4] As discussed in Kurov, Olson, and Zaynutdinova (2022), the identification assumptions of this approach are more plausible than the assumptions required under identification through heteroskedasticity based on daily data in Rigobon and Sack (2003).

$$\mathbf{\Omega_1} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \sigma_{\varepsilon 1} + \beta^2\sigma_\eta + (\beta+\gamma)^2\sigma_z & \alpha\sigma_{\varepsilon 1} + \beta\sigma_\eta + (\beta+\gamma)(1+\alpha\gamma)\sigma_z \\ . & \alpha^2\sigma_{\varepsilon 1} + \sigma_\eta + (1+\alpha\gamma)^2\sigma_z \end{bmatrix}, \quad (5)$$

and

$$\mathbf{\Omega_2} = \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \sigma_{\varepsilon 2} + \beta^2\sigma_\eta + (\beta+\gamma)^2\sigma_z & \alpha\sigma_{\varepsilon 2} + \beta\sigma_\eta + (\beta+\gamma)(1+\alpha\gamma)\sigma_z \\ . & \alpha^2\sigma_{\varepsilon 2} + \sigma_\eta + (1+\alpha\gamma)^2\sigma_z \end{bmatrix}. \quad (6)$$

The change in the covariance matrix (derived by subtracting equations (5) and (6)) is a function of the structural parameters:

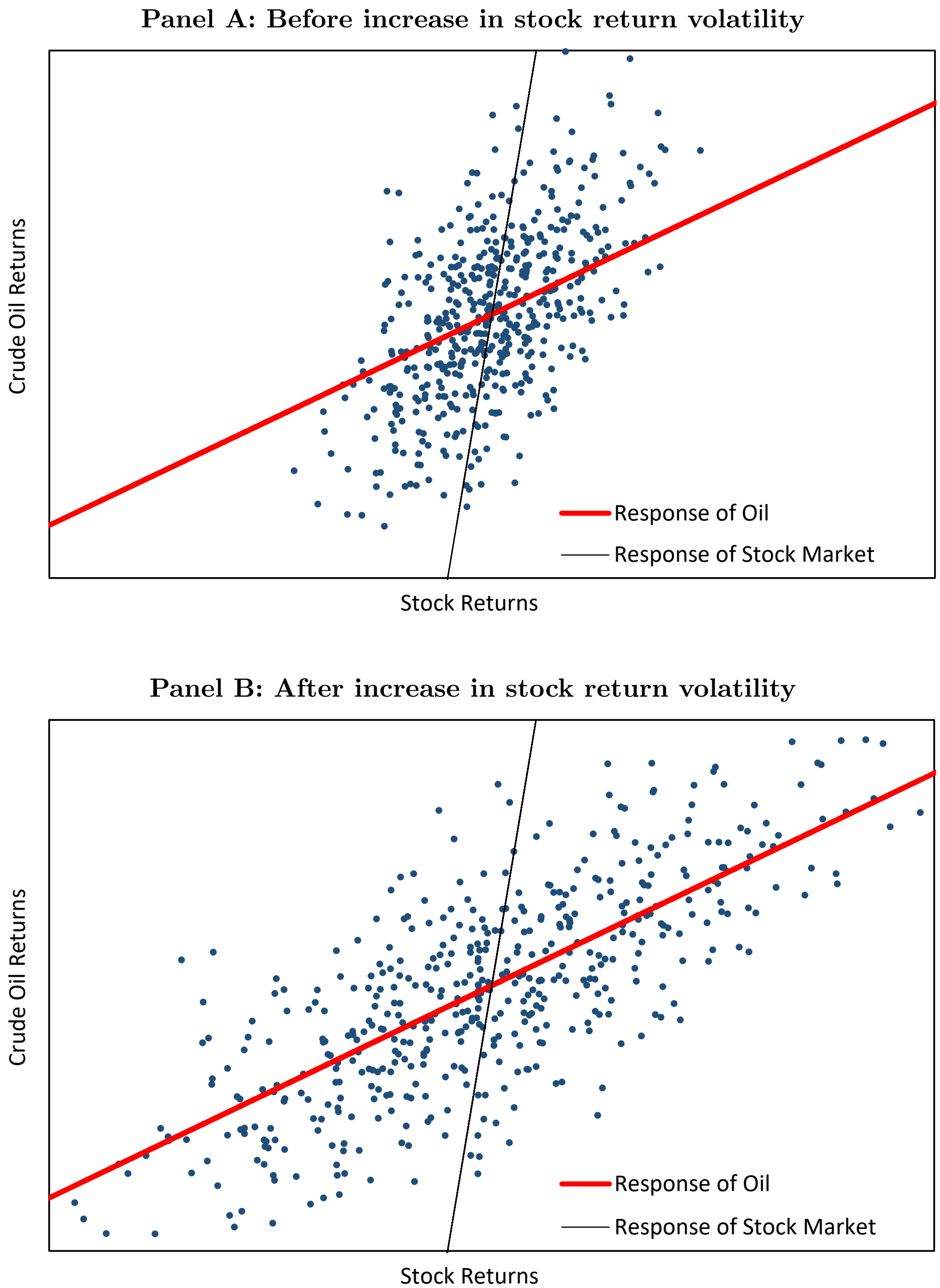
$$\mathbf{\Delta\Omega^s} = \mathbf{\Omega_1} - \mathbf{\Omega_2} = \frac{\sigma_{\varepsilon 1} - \sigma_{\varepsilon 2}}{(1-\alpha\beta)^2} \begin{bmatrix} 1 & \alpha \\ \alpha & \alpha^2 \end{bmatrix} \equiv \delta^s \begin{bmatrix} 1 & \alpha \\ \alpha & \alpha^2 \end{bmatrix}. \quad (7)$$

The two parameters (δ^s and α) can be estimated using the generalized method of moments (GMM). Since we have three moment equations (two equations for the return variances and one equation for their covariance) to estimate the two parameters, the GMM estimator is overidentified. This allows using a standard test of overidentifying restrictions to test the validity of the identification assumption that all of the model parameters except σ_ε are the same before and after the covariance matrix shift (for example, Rigobon and Sack (2004)).

Figure 1 illustrates the identification problem in the relation between stock and crude oil returns. Panel A displays the scatterplot of simulated data for stock and crude oil returns before an increase in stock return volatility. Panel B displays the scatterplot after an increase in the stock return volatility similar in magnitude to the one observed after the stock market opening. This scatterplot clearly traces out the response of crude oil returns to stock returns. Thus, the change in the dispersion of the data from Panel A to Panel B is the mechanism which allows us to estimate the slope coefficients indicated by the lines in the panels.

The above discussion centers on gauging how crude oil returns react to stock returns by using the heightened volatility seen in stock index futures after the stock market begins

Figure 1: Illustration of identification through heteroskedasticity



This figure displays the scatterplot of simulated data for stock and crude oil returns before (Panel A) and after (Panel B) an increase in the stock return volatility.

trading. Similarly, we can estimate a response of the stock returns to the crude oil returns using regular, predictable events that increase volatility of the crude oil return innovations, σ_η. For example, we can use the Weekly Petroleum Status Report (WPSR) released by the U.S. Energy Information Administration (EIA). The WPSR reports contain information about the U.S. crude oil inventory. These announcements are widely followed by traders and other market participants because they often trigger large price changes in petroleum commodities. The WPSR is usually released on Wednesdays at 10:30 a.m. ET with information about crude oil inventory for the week ending on the previous Friday. During some weeks that contain holidays, the WPSR is released at 11:00 a.m. on Thursdays.[5]

Assuming that volatility of the crude oil innovations, σ_η, changes around these events, but σ_ε and σ_z remain stable, the covariance matrices of the stock and crude oil returns after the WPSR releases ($\mathbf{\Omega_1}$) and immediately before the WPSR releases ($\mathbf{\Omega_2}$) are:

$$\mathbf{\Omega_1} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \sigma_\varepsilon + \beta^2\sigma_{\eta 1} + (\beta+\gamma)^2\sigma_z & \alpha\sigma_\varepsilon + \beta\sigma_{\eta 1} + (\beta+\gamma)(1+\alpha\gamma)\sigma_z \\ . & \alpha^2\sigma_\varepsilon + \sigma_{\eta 1} + (1+\alpha\gamma)^2\sigma_z \end{bmatrix}, \tag{8}$$

and

$$\mathbf{\Omega_2} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \sigma_\varepsilon + \beta^2\sigma_{\eta 2} + (\beta+\gamma)^2\sigma_z & \alpha\sigma_\varepsilon + \beta\sigma_{\eta 2} + (\beta+\gamma)(1+\alpha\gamma)\sigma_z \\ . & \alpha^2\sigma_\varepsilon + \sigma_{\eta 2} + (1+\alpha\gamma)^2\sigma_z \end{bmatrix}. \tag{9}$$

The change in the covariance matrix (again derived by subtracting equations (8) and (9)) is then:

$$\mathbf{\Delta\Omega^o = \Omega_1 - \Omega_2} = \frac{\sigma_{\eta 1} - \sigma_{\eta 2}}{(1-\alpha\beta)^2}\begin{bmatrix} \beta^2 & \beta \\ \beta & 1 \end{bmatrix} \equiv \delta^o \begin{bmatrix} \beta^2 & \beta \\ \beta & 1 \end{bmatrix}, \tag{10}$$

and the two parameters (δ^o and β) can again be estimated with GMM using intraday futures data before and after the covariance matrix shift. Alternatively, if we also allow σ_η to change after the stock market opening and allow σ_ε to change after the WPSR releases, the

[5] Another regular, predictable event that increases volatility of the crude oil return innovations is the daily settlement of crude oil futures shortly before 2:30 p.m. ET using the daily settlement times of the Chicago Mercantile Exchange (CME) futures contracts on `www.cmegroup.com/market-data/settlements/settlements-details.html`. However, this is not practical because the 2:30 p.m. ET timing on some days coincides with releases of the Federal Open Market Committee (FOMC) announcements and minutes that also increase the volatility as we explain in Section 2.2.

covariance matrix shifts become:

$$\boldsymbol{\Delta\Omega^s} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \Delta_{\varepsilon 1} + \beta^2\Delta_{\eta 1} & \alpha\Delta_{\varepsilon 1} + \beta\Delta_{\eta 1} \\ . & \alpha^2\Delta_{\varepsilon 1} + \Delta_{\eta 1} \end{bmatrix}, \tag{11}$$

$$\boldsymbol{\Delta\Omega^o} = \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \Delta_{\varepsilon 2} + \beta^2\Delta_{\eta 2} & \alpha\Delta_{\varepsilon 2} + \beta\Delta_{\eta 2} \\ . & \alpha^2\Delta_{\varepsilon 2} + \Delta_{\eta 2} \end{bmatrix}, \tag{12}$$

where $\Delta_{\varepsilon 1}$ and $\Delta_{\varepsilon 2}$ are the changes in variances of stock return innovations around the stock market opening and the WPSR releases, respectively, and $\Delta_{\eta 1}$ and $\Delta_{\eta 2}$ are the changes in variances of crude oil return innovations around the stock market opening and the WPSR releases, respectively. Taken together, these two covariance matrix shifts provide six moment equations that can be used to estimate the six unknown parameters (β, α and the four heteroskedasticity parameters). At least two of the heteroskedasticity parameters ($\Delta_{\varepsilon 1}$ and $\Delta_{\eta 2}$) can be expected to be statistically significant due to a large increase in the variance of stock returns after the stock market opening and a large increase in the variance of crude oil returns after the WPSR releases.

2.1.2 Identification Approach: Generalization to Any Number of Markets

Section 2.1.1 explained the econometric intuition in an example of two markets (stock and crude oil markets). This section demonstrates how to generalize the identification approach to any number of markets by illustrating how to construct the moment equations for any number of markets. This generalization greatly expands the analysis that can be done using this identification approach and broadens the variety of questions it can address.

Using this identification method as a basis, we examine the contemporaneous interaction between the stock and crude oil markets in relation to shifts in monetary policy expectations. We add interest rate changes Δi_t as another observable variable to the model in equations (1) and (2). The contemporaneous linkages between the stock returns, crude oil returns, and interest rate changes can then be described using the following system of equations:

$$R_{s,t} = a_{12}R_{o,t} + a_{13}\Delta i_t + b_1 z_t + \varepsilon_{1t}, \tag{13}$$

$$R_{o,t} = a_{21}R_{s,t} + a_{23}\Delta i_t + b_2 z_t + \varepsilon_{2t}, \tag{14}$$

$$\Delta i_t = a_{31}R_{s,t} + a_{32}R_{o,t} + z_t + \varepsilon_{3t}, \tag{15}$$

where ε_{1t}, ε_{2t}, and ε_{3t} are innovations uncorrelated with each other and with the common economic shocks z_t. In the matrix form, this system of equations can be represented as:

$$\boldsymbol{AR_t} = \boldsymbol{B}z_t + \boldsymbol{\varepsilon_t}, \tag{16}$$

where $\boldsymbol{R_t}$ is a vector of returns and interest rate changes, $\boldsymbol{A}$ is a 3×3 matrix of coefficients measuring contemporaneous linkages among the three markets, $\boldsymbol{B}$ is a vector of coefficients of the common economic shocks, and $\boldsymbol{\varepsilon_t}$ is a vector of innovations. Similarly to the α and β coefficients in equations (1) and (2), the effects of the three markets on one another measured by coefficients a_{ij} $(i \neq j)$ cannot be consistently estimated with OLS due to simultaneity and omitted variables. Our approach of identification through heteroskedasticity using intraday futures data and regular, predictable changes in intraday return volatility again offers a solution to this identification problem. In contrast to the example with two markets discussed above, we allow variances of innovations of all markets to change at the time of the covariance matrix shifts. Assuming that the coefficients measuring cross-market linkages, a_{ij}, and the variance of the common shocks, σ_z, remain stable around the times of these shifts, the change in the return covariance matrix around time S is:

$$\Delta_S \boldsymbol{\Omega} = \frac{1}{|\boldsymbol{A}|^2}\boldsymbol{C}(\boldsymbol{CD_S})^T, \tag{17}$$

where $|\boldsymbol{A}|$ is the determinant of the market response coefficient matrix $\boldsymbol{A}$, $\boldsymbol{D_S}$ is a diagonal matrix with the changes in the variance of return innovations of each market i around time S

(Δ_{iS}) on the main diagonal, and $\boldsymbol{C}$ is the transpose of $\boldsymbol{A}$'s cofactor matrix. The elements of matrix $\boldsymbol{C}$ (c_{km} with $k, m \in \{1, 2, 3\}$) are functions of the market response coefficients a_{ij}. For example, $c_{11} = 1 - a_{23}a_{32}$, $c_{12} = a_{12} + a_{13}a_{32}$, etc. Thus, the elements of the $\Delta_S\boldsymbol{\Omega}$ matrix are made up of the market response coefficients and the changes in the variances of innovations. This approach makes it simple to construct moment equations for any number of markets, as long as one can identify a sufficient number of exogenously determined intraday shifts in the covariance matrix of innovations.

With three markets and one shift in the return covariance matrix, we have nine unknown parameters (six market response coefficients, i.e., a_{12}, a_{13}, a_{21}, a_{23}, a_{31}, and a_{32}, and three innovation variance changes, i.e., Δ_{11}, Δ_{21}, and Δ_{31}) and six moment equations, since $\Delta_S\boldsymbol{\Omega}$ is a 3×3 matrix. Each additional shift in the covariance matrix provides six additional moment equations (three variance changes and three covariance changes) with only three new parameters (changes in the variances of innovations, Δ_{iS}). We use three shifts in the covariance matrix (i.e., $S \in \{1, 2, 3\}$) that provide 18 moment equations with 15 unknown parameters (six market response coefficients and nine heteroskedasticity parameters). Therefore, the model is overidentified, and we can again estimate the model parameters with GMM and use a standard test of overidentifying restrictions to test the validity of our identification assumptions.

2.2 Data and Selection of Covariance Regimes

This section describes the data used in our analysis. We use data for the E-mini S&P 500 futures, West Texas Intermediate (WTI) crude oil futures, and 5-year U.S. Treasury note futures as a proxy for monetary policy expectations.[6] We use the most actively traded

[6]Swanson and Williams (2014) provide evidence that the ZLB became a binding constraint on medium-term rates (defined as Treasury yields with maturity of less than five years) in 2011. Therefore, we use yield changes extracted from 5-year U.S. Treasury note futures as a proxy for monetary policy expectations. We conduct two robustness checks. First, we use yield changes extracted from 10-year U.S. Treasury note futures. Second, we use the first principal component of the 2-, 5-, 10-, and 30-year Treasury yield changes in place of the 5-year Treasury yield changes following Wright (2012) who uses a similar principal component measure to construct a proxy for monetary policy news. The estimates obtained with both of these methods

(usually nearby) contracts for all three futures markets.[7] All three futures contracts are traded on the CME 23 hours a day, with a break from 5:00 p.m. to 6:00 p.m. Eastern Time (ET).

We use intraday returns following well-established literature that utilizes intraday data to study linkages between financial markets such as Andersen, Bollerslev, Diebold, and Vega (2007) who study linkages between stock, bond, and exchange rate markets and D'Amico and Farka (2011) who estimate the response of the stock market to monetary news with intraday data and impose that estimate in the monthly VAR, utilizing the information in the intraday market movements. The benefit of using intraday returns around monetary policy announcements and inventory announcements is that it plausibly mitigates the reverse causality problem.[8] To convert intraday returns of the 5-year Treasury note futures into yield changes, we multiply the returns by the slope coefficient estimate from the regression of daily changes in the 5-year Treasury constant maturity rates on daily returns of the 5-year Treasury note futures.[9]

Our sample period begins on January 1, 2005 because the WTI crude oil futures overnight trading data becomes available on that day. The sample period ends on December 30, 2022. To remove autocorrelation in returns and yield changes, we use residuals from a vector autoregression (VAR) that includes the 15-minute returns for the E-mini S&P 500 futures, WTI crude oil futures, and 5-year Treasury yield changes during their trading hours. The optimal lag length is determined using the Schwarz information criterion as two lags for all three markets.[10]

For the first covariance matrix shift ($S = 1$), we use the 15-minute intervals immediately before and after the U.S. stock market opening at 9:30 a.m. ET described in Section 2.1.1.

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are similar to the results reported in the tables below.

[7]The futures data is from Genesis Financial Technologies.

[8]High frequency data around FOMC announcements has been used extensively in the monetary policy literature. See Cochrane and Piazzesi (2002), Gürkaynak, Sack, and Wright (2007), Stock and Watson (2018), and Bauer and Swanson (2023b) for examples.

[9]The daily Treasury yields are from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis.

[10]The results are almost identical when we use raw returns instead of the VAR residuals.

For the second covariance matrix shift ($S = 2$), we use the 15-minute intervals immediately before and after the release of the WPSR also described in Section 2.1.1.[11] For the third covariance matrix shift ($S = 3$), we use 30-minute intervals immediately before and after the release of scheduled FOMC statements and minutes.[12] We use longer intervals around releases of FOMC statements and minutes because markets take more time to absorb this kind of information (Wright (2012)), which makes the post-announcement volatility spike last longer and provides additional information for identification. During our sample period, FOMC minutes were released at 2 p.m. ET three weeks after the FOMC meeting. Between January 2005 and January 2013, most scheduled FOMC statements were released at 2:15 p.m. The standard release time after January 2013 has been 2:00 p.m.

All three covariance matrix shifts are driven by exogenous events. The U.S. stock market opening (used for the first covariance shift, $S = 1$) takes place at the same time every trading day regardless of the economic or market conditions. The schedules of the WPSR announcements and FOMC announcement and minutes releases (used for the second and third covariance shifts, $S = 2$ and $S = 3$, respectively) are known well in advance and also take place regardless of economic or market conditions. No other major regularly scheduled macroeconomic announcements occur in the intraday intervals that we used for the estimation and therefore the markets are not systematically affected by other events during our intraday intervals. This makes our identification assumptions (i.e., the variances of economic shocks σ_z and coefficients a_{ij} not changing from immediately before to immediately after a given event) reasonable. As explained in Section 2.1, we use the test of overidentifying restrictions to test the validity of the identification assumptions.

Some of the Treasury yield changes around the FOMC releases may be due to the Federal Reserve revealing its private information about the economy through its decisions and communications. Studies adopting this line of reasoning (for example, Nakamura and Steinsson (2018)) call this the "Fed information effect." If the amount of macroeconomic information

[11]The dates and times of the WPSR releases are from Bloomberg.

[12]The dates and times of the FOMC statements and minutes releases are from Bloomberg.

revealed by the FOMC releases is substantial, it may invalidate our identification assumption that the variance of the common shocks z_t remains stable around the times of the covariance matrix shifts. In a recent study, Bauer and Swanson (2023a) cast doubt on the existence of the "Fed information effect." They show that, instead of revealing its private information, the Federal Reserve simply responds to incoming economic news. This economic news flow is represented by z_t in our model.

It is important to note that although equations (13)−(15) present a time series model, we do not use a complete time series in the main estimation. Instead, the GMM estimation uses only intraday intervals immediately before and after the three types of events discussed above. This allows assuming that the variances of the structural innovations shift at the time of the event but the variance of the common shocks, z_t, remains stable. This approach obviates the need to model seasonality in intraday volatility (for example, Andersen, Bollerslev, Diebold, and Vega (2003)) and is consistent with other identification-through-heteroskedasticity studies that also rely on subsets of time series data (for example, Andersen et al. (2007) and Ehrmann, Fratzscher, and Rigobon (2011)).

We obtain our sample as follows. In our sample period, there are 287 days with FOMC announcement or minutes releases. In addition to these FOMC announcement or minutes releases, each of these days has a stock market opening. Each of these days also occurs during a week when a WPSR was released. Therefore in each week we analyze three covariance matrix shifts: a covariance matrix shift around the FOMC announcement and minutes releases, a covariance matrix shift around the stock market opening on that same day, and a covariance matrix shift around the WPSR releases in that same week. Each covariance matrix shift has a period before the shift and a period after the shift. This means that we have six sets of returns and yield changes for each of our 287 weeks. We therefore have 287 $\times$ 3 $\times$ 2 = 1,722 observations in our sample period.

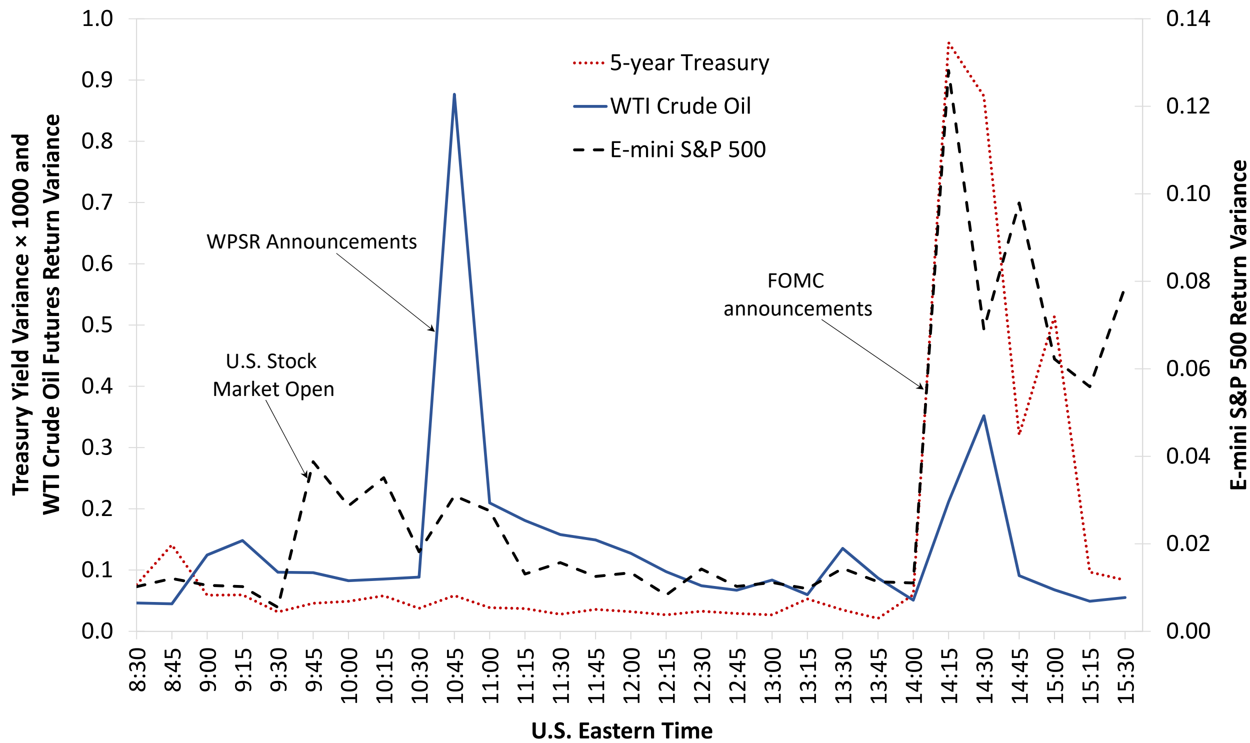
Figure 2 shows variances of the VAR residuals for the three futures markets from 8:30 a.m. to 3:30 p.m. ET computed across 187 trading days that contain both the FOMC announcements and the WPSR announcements. Unsurprisingly, the variance of the E-mini S&P 500 futures returns (dashed black line) increases by a factor of approximately seven after the U.S. stock market opens at 9:30 a.m. ET. This confirms that the variances of stock returns are higher during periods of elevated trading activity around the market opening, as more information is impounded into stock and index futures prices through trading (for example, French and Roll (1986)).[13] The WPSR announcements trigger a large volatility spike in the WTI crude oil futures market (solid blue line) after 10:30 a.m. Both the 5-year Treasury yields (dotted red line) and the E-mini S&P 500 futures returns become very volatile after the release of FOMC statements and minutes around 2 p.m. ET.[14] This clear evidence of heteroskedasticity of returns and Treasury yield changes supports our selection of covariance matrix shifts around these three events for identification.

The use of intraday financial market data for identification through heteroskedasticity is also supported by Lewis (2022), who shows that monetary shocks identified using daily data suffer from weak identification, which negatively influences reliability of inference. Intraday data, on the other hand, provides strong identification because variance changes across regimes are much larger in intraday data. For example, the variance of daily changes in the 5-year Treasury constant maturity yield increases by only a factor of 1.6 (i.e., 60% increase) on days with the FOMC events in our sample. In comparison, the variance of the 15-minute yield changes shown in Figure 2 increases by a factor of 16 (i.e., 1,500% increase, so 25 times higher than the 60% increase) immediately after the announcement.

[13] Equity trading that begins after the stock market opening impounds private information about individual stocks. One can easily trade in futures markets on information of macroeconomic nature before the stock market opens. Therefore, our identification assumption that the intensity of the flow of macroeconomic information influencing multiple markets (σ_z) remains stable around the stock market opening is plausible. As mentioned above, we test the validity of our identification assumptions using a test of overidentifying restrictions.

[14] The increase in volatility of crude oil futures return innovations around 2:30 p.m. is likely driven, at least in part, by the daily settlement price of these futures contracts taking place shortly before 2:30 p.m. as explained in Section 2.1.1.

Figure 2: Intraday variation in volatility of stocks, crude oil, and Treasury yields



The sample period is from January 1, 2005 to December 30, 2022. The variance for each 15-minute interval is computed using residuals from a vector autoregression of 15-minute returns for the E-mini S&P 500 futures (black dashed line), WTI crude oil futures (blue solid line), and 5-year U.S. Treasury yields (red dotted line). Only days that contain both the Federal Open Market Committee and the Weekly Petroleum Status Report announcements (187 days) are used to construct this figure.

3 Results

This section presents our results. Section 3.1 shows results for our full sample period from January 1, 2005 to December 30, 2022. Section 3.2 then shows results of our subsample analysis.

3.1 Full Sample Results

We begin by constructing the moment equations using equation (17), where $\Delta_S\boldsymbol{\Omega}$, $\boldsymbol{A}$, $\boldsymbol{C}$, and $\boldsymbol{D_S}$ are 3×3 matrices and then estimate the model parameters with GMM. The p-value of the test of overidentifying restrictions is approximately 0.21, indicating that our identification assumptions are not rejected by the data. Table 1 reports the GMM parameter estimates.

We first discuss results of the heteroskedasticity parameter estimates in Panel b) and follow with the coefficient estimates in Panel a).

Consistent with Figure 2, five of the nine heteroskedasticity parameter estimates Δ_{iS} in Panel b) are statistically significant. These parameters measure the change in the variance of stock return innovations around the opening of the U.S. stock market (Δ_{11}), the change in the variance of crude oil return innovations around the WPSR announcements (Δ_{22}), and the change in the variance of innovations in interest rates (Δ_{33}) around the FOMC announcements and minutes releases. The statistical significance of these estimates shows that using the stock market opening, the WPSR announcements, and the FOMC announcements and minutes releases for identification through heteroskedasticity with intraday data is valid.

While the stock market opening affects only the variance of stock returns and the WPSR announcements affect only the variance of crude oil returns, the FOMC announcements and minutes releases increase the variance of structural innovations in all three markets: stock returns (Δ_{13}), crude oil returns (Δ_{23}), and Treasury yield changes (Δ_{33}). This highlights our methodological contribution: because our methodology does not assume that variances of the structural innovations in some markets are constant, it can more accurately model the relationship between the stock, crude oil, and interest rate markets. This extends previous literature such as Rigobon and Sack (2004) that assumes the variance of innovations in the stock market to be constant around the FOMC announcements. This assumption in the Rigobon and Sack (2004) methodology is driven by using only one variance shift around the FOMC announcements, which precludes the methodology from identifying additional parameters. In contrast, as explained in Section 2, our methodology uses multiple variance shifts (around the stock market opening, the WPSR announcements, and the FOMC announcements and minutes), which allows estimating additional parameters and accounting for the variance shifts that occur in these markets as shown in Table 1 Panel b).

The six coefficient estimates in Panel a) measure contemporaneous causal linkages between the three markets. In our analysis, the interesting coefficients are a_{21}, which represents

Table 1: Contemporaneous linkages between stock index, 5-year U.S. Treasury yield, and WTI crude oil futures returns: Full sample 01/01/2005–12/30/2022

	Coefficient	Standard error
Panel a) Response coefficient estimates		
Response of stock returns to crude oil returns (a_{12})	0.0634***	(0.0223)
Response of stock returns to Treasury yield changes (a_{13})	-4.2277***	(1.4044)
Response of crude oil returns to stock market returns (a_{21})	0.6608***	(0.1185)
Response of crude oil returns to Treasury yield changes (a_{23})	1.8419	(2.6615)
Response of Treasury yield changes to stock returns (a_{31})	0.0095***	(0.0029)
Response of Treasury yield changes to crude oil returns (a_{32})	-0.0004	(0.0009)
Panel b) Heteroskedasticity parameter estimates		
Stocks around 9:30 a.m. (Δ_{11})	0.0366***	(0.0083)
Oil around 9:30 a.m. (Δ_{21})	0.0163	(0.0248)
Treasury yields around 9:30 a.m. (Δ_{31})	0.0009	(0.0007)
Stocks around WPSR (Δ_{12})	0.0102	(0.0069)
Oil around WPSR (Δ_{22})	0.7159***	(0.1188)
Treasury yields (Δ_{32})	0.0019	(0.0017)
Stocks around FOMC (Δ_{13})	0.1431***	(0.0469)
Oil around FOMC (Δ_{23})	0.3757***	(0.1193)
Treasury yields around FOMC (Δ_{33})	0.1954***	(0.0395)

The sample period is from January 1, 2005 to December 30, 2022 and contains data from days with scheduled Federal Open Market Committee (FOMC) announcements, FOMC minutes, and the Energy Information Administration‘s Weekly Petroleum Status Report (WPSR) released in the same weeks ($287 \times 3 \times 2 = 1722$ observations). Δ_{iS} is the change in the variance of innovations of returns or yield changes of market i around time S. i is 1, 2, and 3 for the E-mini S&P 500 futures returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield changes, respectively. $S = 1$ for the covariance matrix shift around the stock market opening at 9:30 a.m. ET, $S = 2$ for the covariance matrix shift after the WPSR releases (typically at 10:30 a.m.), and $S = 3$ for the covariance matrix shift after FOMC announcements and releases of FOMC minutes. To measure the change in the covariance matrix around FOMC announcements and releases of FOMC minutes, we use 30-minute intervals before and after the announcement time. 15-minute intervals are used to compute returns and yield changes for the other two covariance matrix shifts. The parameters are estimated with GMM. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The p-value of the test of overidentifying restrictions is 0.2107. Δ_{31}, Δ_{32}, and Δ_{33} and the corresponding standard errors are multiplied by 100 for readability.

the influence of stock market returns on crude oil returns, a relationship not previously explored in literature, and a_{23}, which measures the effect of Treasury yield changes on crude oil returns, a subject not comprehensively analyzed in previous literature as discussed in Section 3.2.2. The crude oil market returns react positively to increases in stock prices (a_{21}): a one percent increase in the S&P 500 index increases crude oil prices by approximately 0.66%. We do not find a significant response of crude oil returns to Treasury yield changes (a_{23}). However, the more detailed subsample analysis in Section 3.2 shows that using the entire sample period obscures time variation in these coefficients.

As far as the remaining four coefficients are concerned, encouragingly our results are broadly consistent with previous literature. Stock returns respond positively to increases in crude oil prices (a_{12}). This finding is qualitatively similar to the results reported by Alquist, Ellwanger, and Jin (2020) for the period from September 2008 to October 2017 based on estimating the response of financial markets to crude oil price changes using instrumental variables obtained from the surprise components of the WPSR announcements.[15] Consistent with previous studies, we find a negative response of stock returns to changes in Treasury yields (a_{13}): the coefficient is approximately -4.2 and is similar to estimates in Bernanke and Kuttner (2005) and Rigobon and Sack (2004). Consistent with Kurov, Olson, and Zaynutdinova (2022), we find a small but statistically significant response of monetary policy expectations to stock returns (a_{31}). The estimate of the reaction of the Treasury yields to crude oil returns (a_{32}) is not statistically significant, which agrees with Kilian and Lewis (2011) and Kilian (2014). However, it could also be the case that the Federal Reserve changed its response to crude oil price shocks over the 2005-2021 period due to the declining crude oil price pass-through into overall inflation as explained by Chen (2009). This is plausible given the increased domestic production resulting from the U.S. shale revolution. We discuss literature about these four coefficients in more detail in Section 4.4.

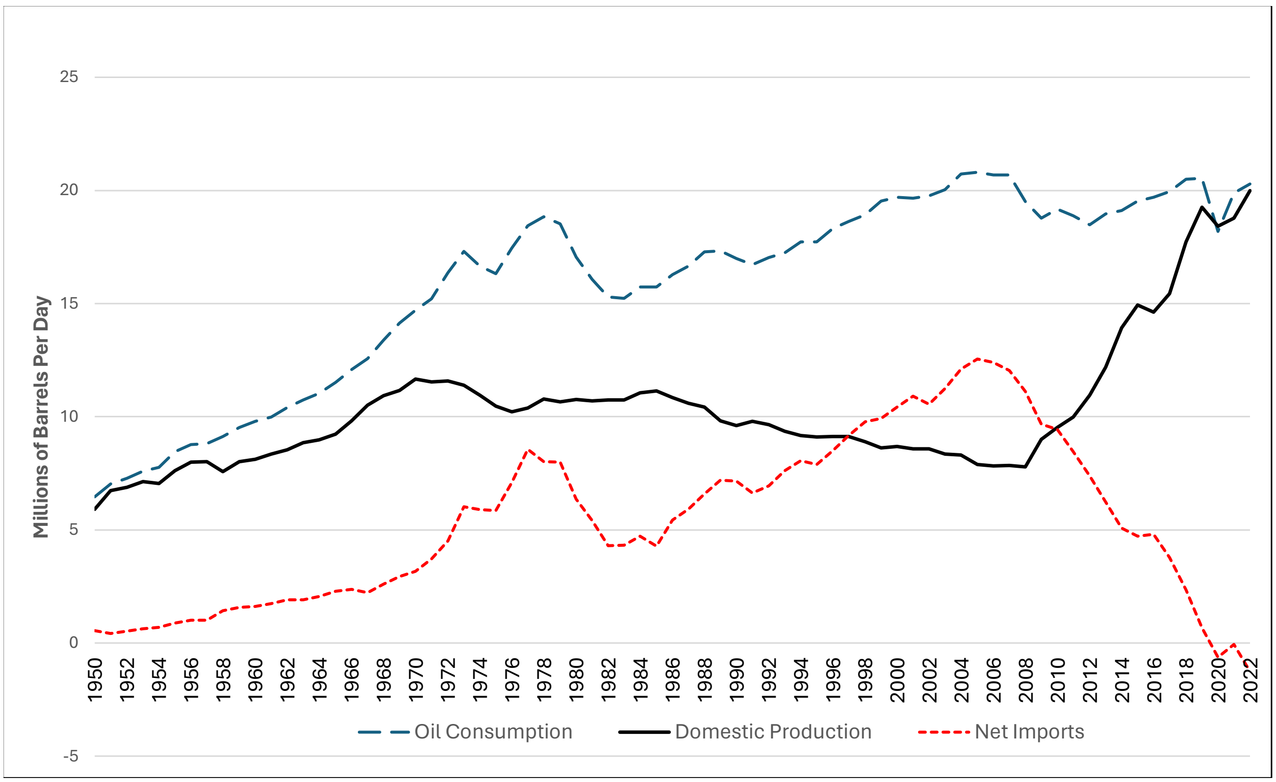
3.2 Subsample Results

The difficulty of assessing the contemporaneous causal linkages between the crude oil and financial markets due to the endogenous relationship between changes in energy prices and macroeconomic growth is even more pronounced when structural changes occur within energy markets following technological innovations and market events shift the framework of monetary policy. A prime example of such a structural break is the U.S. shale oil boom over

[15] Kilian and Park (2009) also study the reaction of stock returns to crude oil prices and find that the reaction differs depending on whether the crude oil price changes are driven by the crude oil market demand or supply shocks.

the 2005 - 2022 time period. As noted by the International Energy Agency (IEA), U.S. oil production surged from around 8 million barrels per day in 2005 to nearly 19 million barrels in 2021; concurrently, the domestic production of natural gas experienced significant growth rising 87% over the same time period (IEA, 2019). Shale oil production now accounts for almost two thirds of all U.S. oil production, according to the Energy Information Administration (EIA). The increase in domestic energy production has significantly reduced the United States' reliance on energy imports, as evidenced by Figure 3, which displays Primary Energy Net Imports from 1950 to 2022.[16]

Figure 3: U.S. crude oil production, consumption, and net imports (1950-2022)



This figure shows the U.S. crude oil production (black solid line), consumption (blue dashed line), and net imports (red dotted line) from January 1, 1950 to December 30, 2022. The data is from the U.S. Energy Information Administration.

Financial markets have also undergone notable transformations. The onset of the COVID-19 pandemic saw a drastic downturn in stock markets in which the S&P 500 index dropped by 34% over 23 trading days and crude oil futures settled at a negative price of $-37 in

[16]Kilian (2016) discusses the impact of the shale oil revolution on the U.S. oil market.

April of 2020. In response to both the 2008 financial crisis and the recession induced by COVID-19, the U.S. interest rates touched the unprecedented zero lower bound (ZLB), as the Federal Reserve adjusted the federal funds rate target to a range of 0-0.25%. Subsequent to the unprecedented easing in 2020 during the COVID-19 pandemic, the Federal Reserve tightened the monetary policy at the fastest rate since the Volker disinflation in the early 1980s.

To account for time variation in the causal linkages between the stock market, crude oil market, and monetary policy, this section repeats the analysis of Section 3.1 for several subsamples. Section 3.2.1 describes how our subsamples are determined and Section 3.2.2 reports our results.

3.2.1 Breakpoint Test

Because our 2005-2022 sample period includes the shale revolution, the 2008 financial crisis, the ZLB, and the COVID-19 pandemic, it is plausible that the structural relationships between our three markets have changed. We take a data-driven approach and examine the changes in the reduced-form correlations to find the different regimes.[17] Because we examine three markets (stocks, crude oil, and interest rates), we calculate three reduced-form correlations. We compute realized correlations based on Andersen, Bollerslev, Diebold, and Labys (2001) as follows:

$$RC_t = \frac{\Sigma_{i=1}^{n} R_{k,i} R_{m,i}}{\sqrt{\Sigma_{i=1}^{n} R_{k,i}^2 \Sigma_{i=1}^{n} R_{m,i}^2}}, \tag{18}$$

where $R_{k,i}$ and $R_{m,i}$ are continuously compounded returns of markets k and m, respectively, in a 5-minute intraday interval i, and n is the number of such intervals in week t.[18] The weekly realized correlations for the three futures markets during our sample period are presented in Figure 4. The figure shows that the three realized correlations tend to move

[17] Alquist, Ellwanger, and Jin (2020) use a similar approach to identify a structural break in their study of the effect of crude oil prices on financial markets from 2003 to 2017.

[18] We use estimated yield changes in place of returns for the 5-year Treasury note futures.

together. Because we need to utilize the information in all three correlations to select our subsamples, we use principal component analysis to capture changes in the comovement of the correlations over time. The use of principal component analysis in this context offers several benefits. First, it allows us to reduce the dimensionality of our data, summarizing the information from three different correlations into a single measure which makes it easier to identify the structural breaks in the relationships between all three markets simultaneously, rather than examining each pairwise correlation separately. Second, by focusing on the first principal component, we capture the most important driver of changes in the correlations. This overall measure of comovement is particularly useful in our context, as we are interested identifying the structural breaks in the correlations between stocks, crude oil and interest rates. The first principal component can be interpreted as a composite index of market integration, representing the degree to which all three markets (stocks, crude oil, and interest rates) move together. A higher value of this component indicates stronger overall correlation among the markets, while a lower value suggests weaker linkages. The standardized first principal component of the three realized correlations is shown in the bottom right panel of Figure 4. It has positive loadings, ranging from 0.51 to 0.64, on all three realized correlations and captures approximately 73% of their common variation. The first order autocorrelation of the first principal component is approximately 0.85.

To determine if the comovement among the markets significantly changed during our sample period, we use the Bai and Perron (2003) multiple breakpoint test to test for structural breaks in the mean of the standardized first principal component of the three realized correlations.[19] The test identifies two structural breaks.[20] The first structural break is dur-

[19]To conduct the structural break test, we estimate a least squares regression with breaks in the intercept and no other regressors using heteroskedasticity and autocorrelation consistent covariance matrix with Newey and West (1994) automatic lag length selection. We allow the error distributions to differ across breaks and use the Bai-Perron sequential F-test for L versus $L+1$ breaks.

[20]The 95% confidence interval dates are June 6, 2008−October 3, 2008 for the first break date and April 13, 2012−April 4, 2014 for the second break date. The estimates of the breaking intercept of the standardized first principal component are -0.98 (t-stat$=-9.36$) in the first subsample, 0.86 (t-stat$=5.89$) in the second subsample, and -0.04 (t-stat$=-0.36$) in the third subsample. The adjusted R^2 of the regression with breakpoints is approximately 39%.

ing the trading week ending on September 12, 2008, which is three days before the Lehman Brothers investment bank collapsed. This date is consistent with the timing of structural breaks around the financial crisis identified in previous literature analyzing the relationship between crude oil and stock markets: Lombardi and Ravazzolo (2016), Foroni et al. (2017), Alquist, Ellwanger, and Jin (2020), and Datta et al. (2021) identify structural breaks on September 5, 2008, in early 2007, in September of 2008, and in 2008, respectively.[21] In addition to this structural break identified in the previous literature, our analysis – including the Treasury market in addition to the crude oil and stock markets – finds a second structural break during the trading week ending on May 10, 2013. This is just before Ben Bernanke, the Federal Reserve Chair, delivered the May 22, 2013 "taper tantrum" speech, in which he signaled that the Federal Reserve would soon start reducing bond purchases under its quantitative easing program. This announcement led to one of the largest monetary policy shocks since the 1980s with long-term U.S. Treasury yields increasing by approximately 100 basis points over the subsequent six months (for example, Sinha and Smolyansky (2022)).[22]

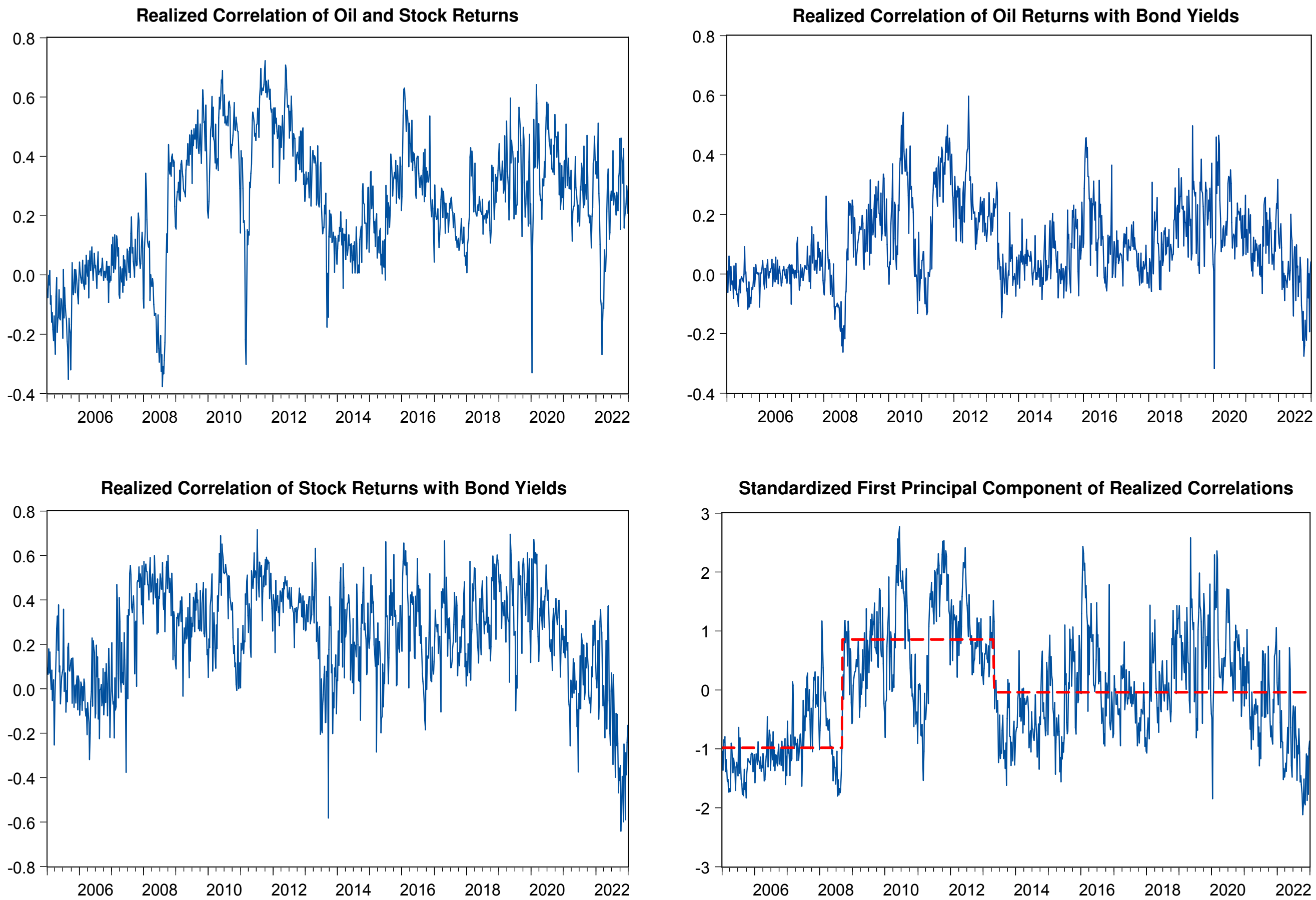
Given these two structural break dates, we divide the sample period into three subsamples: 01/01/2005-09/05/2008, 09/06/2008-05/03/2013, and 05/04/2013-12/30/2022. The bottom right panel of Figure 4 shows sizable shifts in the value of the first principal component from one subsample to the next predicted by the regression with breaks in the intercept.[23] We subsequently repeat the analysis in Section 3.1 to examine if the structural relationships between the three markets have changed across these three subsamples.

[21] The sample periods in Lombardi and Ravazzolo (2016), Foroni et al. (2017), Alquist, Ellwanger, and Jin (2020), and Datta et al. (2021) are 1980-2015, 1973-2015, 2003-2017, and 1983-2017, respectively. Alquist, Ellwanger, and Jin (2020) also analyze the relationship between crude oil and U.S. Treasury bonds and find a structural break in September of 2008.

[22] Kurov and Stan (2018) show that the increase in monetary policy uncertainty during the taper tantrum influenced the response of stock, Treasury security, and crude oil markets to U.S. macroeconomic news.

[23] As a robustness check, we also used the Qu and Perron (2007) methodology based on our three realized correlations. Qu and Perron (2007)) develop a method for identifying structural breaks within a system of equations in multivariate regression models. The method allows for changes in both regression coefficients and the covariance matrix. Qu and Perron (2007) use a quasi-maximum likelihood estimation procedure and a likelihood ratio-based testing method to identify the structural breaks. The results from the Qu and Perron (2007) test were nearly identical to our reported results; the break dates were 09/05/2008 and 6/14/2013.

Figure 4: Realized Correlations and Their First Principal Component



The weekly realized correlations are computed using 5-minute returns for the WTI crude oil futures and the E-mini S&P 500 futures, and yield changes computed from prices of the 5-year Treasury note futures. The dashed red line represents the predicted values of the standardized first principal component of the three realized correlations in the three subsamples identified using the Bai and Perron (2003) multiple breakpoint test. The sample period is from January 1, 2005 to December 30, 2022.

3.2.2 Subsample Analysis

Table 2 displays the results from our subsamples. For ease of comparison, Column 1 displays the results from the full sample (01/01/2005-12/30/2022) shown in Table 1. Columns 2, 3, and 4 show the results for the first (01/01/2005-09/05/2008), second (09/06/2008-05/03/2013), and third (05/04/2013-12/30/2022) subsamples, respectively. The standard errors for the response coefficients as well as heteroskedasticity parameters in each subsample are reported in Tables A1, A2, and A3 in the Appendix. Again, as explained in Section 3.1, the statistical significance of the heteroskedasticity parameter estimates in Panel b) shows that using the stock market opening, the WPSR announcements, and the FOMC announcements and minutes releases for identification through heteroskedasticity with intraday data is valid in all three subsamples.

Table 2: Contemporaneous linkages between stock index returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield: Comparison of sample periods

	Full Sample	Subsample 1	Subsample 2	Subsample 3
	01/01/2005 -12/30/2022	01/01/2005 -09/05/2008	09/06/2008 -05/03/2013	05/04/2013 -12/30/2022
	Panel a) Response coefficient estimates			
Stocks to oil (a_{12})	0.0634***	−0.0969**	0.1179***	0.0977***
Stocks to Treasury yields (a_{13})	−4.2277***	−2.4271	−3.0067	−5.9035***
Oil to stocks (a_{21})	0.6608***	0.1469	0.7832***	0.4865***
Oil to Treasury yields (a_{23})	1.8419	2.2841	6.7871*	−4.8413***
Treasury yields to stocks (a_{31})	0.0095***	0.0075	0.0108***	0.0081**
Treasury yields to oil (a_{32})	−0.0004	−0.0055***	0.0003	0.0014**
	Panel b) Heteroskedasticity parameter estimates			
Stocks around 9:30 a.m. (Δ_{11})	0.0366***	0.0148***	0.0607***	0.0317***
Oil around 9:30 a.m. (Δ_{21})	0.0163	−0.0158	0.0910**	0.0037
Treasury yields around 9:30 a.m. (Δ_{31})	0.0009	0.0012	0.0003	0.0007
Stocks around WPSR (Δ_{12})	0.0102	0.0167***	0.0014	0.0046
Oil around WPSR (Δ_{22})	0.7159***	0.7074***	0.6067**	0.7186***
Treasury yields around WPSR (Δ_{32})	0.0019	−0.0010	−0.0020	0.0036*
Stocks around FOMC (Δ_{13})	0.1431***	0.2330**	0.2483**	0.0649***
Oil around FOMC (Δ_{23})	0.3757***	0.1298*	0.3076**	0.4242***
Treasury yields around FOMC (Δ_{33})	0.1954***	0.2100***	0.2986**	0.1798***

This table displays the response coefficient estimates and heteroskedasticity parameter estimates for the full sample from Table 1 in the first column and for the three subsamples in the second, third, and fourth columns. Δ_{iS} is the change in the variance of innovations of returns or yield changes of market i around time S. i is 1, 2, and 3 for the E-mini S&P 500 futures returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield changes, respectively. $S = 1$ for the covariance matrix shift around the stock market opening at 9:30 a.m. ET, $S = 2$ for the covariance matrix shift after the WPSR releases (typically at 10:30 a.m.), and $S = 3$ for the covariance matrix shift after FOMC announcements and releases of FOMC minutes. To measure the change in the covariance matrix around FOMC announcements and releases of FOMC minutes, we use 30-minute intervals before and after the announcement time. 15-minute intervals are used to compute returns and yield changes for the other two covariance matrix shifts. The parameters are estimated with GMM. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

The observed changes in the coefficients between the three subsamples in our study highlight the dynamic nature of the underlying market relationships. The emergence of statistically significant coefficients in our later two subsamples, contrasted with their initial non-significance, suggests that the structural relationships evolved. As discussed in Section 3.1, the reaction of crude oil returns to stock returns (measured by a_{21}) has not been studied in previous literature. Our results therefore bring a new finding showing how crude oil returns react to stock returns. This reaction substantially varies over time. While crude oil returns do not react to stock returns in the first subsample, they do react in the second and third subsamples when a positive shock to stock returns increases crude oil returns. What explains the change in the causality? Cieslak and Vissing-Jorgensen (2021) analyze the stock market mentions in the FOMC minutes and find that the FOMC participants view the stock market as a leading indicator of the economy (mainly through the stock market's impact on consumption). Demand for crude oil is driven by the economy. Therefore, if stock returns drive the economy (beyond the common shock z in our model), the stock returns will influence crude oil returns. In other words, the stock returns provide information about the economy important for the crude oil returns even after controlling for the effect of Treasury yield changes, which underscores the importance of analyzing contemporaneous causal linkages in all three markets simultaneously.

The reaction of crude oil returns to the Treasury yields (a_{23}) has been studied by previous literature (Kilian & Vega, 2011; Rosa, 2014; Basistha & Kurov, 2015; Scrimgeour, 2015) but the literature did not focus on time variation.[24] Our results therefore expand this literature by showing substantial time variation. Again, in the first subsample crude oil returns do not react to Treasury yield changes but they react in the second and third subsamples: In terms of this response to monetary policy expectations, crude oil prices have come to behave more similarly to stock prices. In the third subsample the coefficients measuring the response to Treasury yield changes are now similar for stock returns (a_{13} equal to -5.90 in the third subsample) and crude oil returns (a_{23} equal to -4.84 in the third subsample).

As a robustness check, we estimated the model parameters for stock return and crude oil

[24]Kilian and Vega (2011) do not find evidence of crude oil returns reacting to monetary policy news from 1983 to 2008 whereas Rosa (2014), Basistha and Kurov (2015), and Scrimgeour (2015) conclude that crude oil returns do react to monetary policy news in 1999-2011, 1994-2008, and 1994-2008 sample periods, respectively.

return after dropping the Treasury yield changes from the model. Data from all days with WPSR releases is included in this estimation, which more than triples the number of observations. Instead of using the releases of FOMC statements and minutes, we used the time of the stock market close at 4:00 p.m. to get another volatility shift to obtain overidentification. The resulting estimates are qualitatively similar to the estimates in Table 2.

As an additional robustness check, we also estimated the model with all three markets by using subsamples based on the subprime mortgage crisis and the COVID-19 pandemic. Lehman Brothers declared bankruptcy on September 15, 2008. We adopt this date for the beginning of the second subsample. Baker et al. (2020) date the beginning of the COVID-19 crisis to February 24, 2020, and we adopt this date for the beginning of the third subsample. Overall, the resulting estimates are qualitatively similar to the estimates in Table 2. We still observe a sign change in the response of stock returns to crude oil returns after the first subsample, the stock returns become more sensitive to changes in Treasury yields over time, and crude oil returns become more sensitive to stock returns. The results of these two robustness checks are not tabulated to save space but are available upon request.

4 Potential Explanations

This section discusses three possible explanations that have been proposed in previous literature regarding the increased correlation between the crude oil market and financial markets in Sections 4.1, 4.2, and 4.3. Section 4.4 then provides additional discussion of related literature.

4.1 Changes in Monetary Policy and the Zero Lower Bound

Our sample period from 2005 to 2022 includes unprecedented monetary policy adopted by the Federal Reserve as a reaction to the financial crisis of 2008. The federal funds rate target range was reduced to 0-0.25% in December 2008 and it remained at the ZLB until December

2015. The ZLB was again in effect from March 2020 to March 2022 as the Federal Reserve reacted to the COVID-19 recession. The ZLB has been proposed in previous literature (Datta et al., 2021) as the explanation for increased correlation between the stock and crude oil returns.

We test for the ZLB explanation in the following way. Datta et al. (2021) build a theoretical model (a New Keynesian dynamic stochastic general equilibrium model that includes crude oil) showing that at the ZLB, the sign of the response of stock returns to structural shocks changes, the effects of some shocks increase, and the correlation between the stock and crude oil returns increases. One prediction from this model is the stock and crude oil returns becoming more responsive to macroeconomic news. Datta et al. (2021) use data from 1980 to 2017 to analyze the correlations of stock returns and crude oil returns and provide empirical evidence for this increased responsiveness during the 2008-2014 period. We therefore test whether the responsiveness of the stock and crude oil returns to macroeconomic news changes in our second subsample, almost all of which coincided with the federal funds target rate being at the ZLB. We proceed in two steps. First, we determine which macroeconomic announcements should be included in the analysis. Second, we estimate a regression to test whether the responsiveness of the stock and crude oil returns to macroeconomic news changes in our second subsample.

We begin by extracting the U.S. macroeconomic announcement data from Bloomberg. Following Kurov, Sancetta, and Wolfe (2022), we use the Bloomberg relevance score ranging from 0 to 100 corresponding to the least and the most impactful announcements, respectively, and we analyze only announcements with a score of 75 or higher. There are 30 such announcements. We regress the E-mini S&P 500 futures returns, crude oil futures returns, and 5-year Treasury yield changes in the 10-min window centered on the announcement time on the standardized announcement surprises, S_{mt}, computed as:

$$S_{mt} = \frac{A_{mt} - E_{t-\tau}[A_{mt}]}{\sigma_m}, \tag{19}$$

where m stands for a macroeconomic announcement m, t stands for the announcement release time t, A_{mt} is the actual announcement, $E_{t-\tau}[A_{mt}]$ is the market's expectation of the announcement before its release proxied by the median forecast of professional forecasters obtained from Bloomberg. Following Balduzzi, Elton, and Green (2001), $\tau > 0$. $\sigma_m = \sqrt{\frac{1}{N_m - 1}\Sigma_{i=1}^{N_m}(S_{im} - \overline{S}_m)^2}$ (with $\overline{S}_m$ standing for the average surprise) is the standard deviation of the announcement which standardizes the various announcements to a common scale. The sample period is from January 1, 2005 (beginning of our first subsample) to May 3, 2013 (the end of our second subsample). We omit our third subsample to avoid a potential bias due to some time periods of the third subsample being at the ZLB. Following previous literature such as Balduzzi et al. (2001), we estimate the following event study regression that uses only the 10-minute intervals during which there was at least one announcement:

$$R_t = \alpha + \sum_{m=1}^{30} \beta_m S_{mt} + \epsilon_t. \tag{20}$$

In intervals when there is no surprise for a given announcement, the surprise for this announcement is set to zero. This model specification accounts for simultaneous releases of multiple announcements.[25] We estimate the regression in equation (20) for the E-mini S&P 500 futures returns, crude oil futures returns, and 5-year Treasury yields. We then test which announcements are jointly significant at the 5% level to find announcements that move at least one of these three markets. Five announcements have p-values exceeding 5%, indicating that they do not move any of the three markets. In the following analysis we therefore include only the 25 announcements that showed statistical significance at least at the 5% significance level, indicating that they move at least one of our three markets.[26]

[25] For example, Change in Nonfarm Payrolls and Unemployment Rate are always released at the same time as part of the U.S. Department of Labor's Employment Situation report.

[26] These announcements are: ADP Employment Change, Change in Nonfarm Payrolls, Conference Board Consumer Confidence, the Consumer Price Index (CPI), Durable Goods Orders, Chicago Purchasing Manager Index, Existing Home Sales, Empire Manufacturing Index, Factory Orders, Gross Domestic Product (GDP), Housing Starts, Industrial Production, Initial Jobless Claims, ISM Manufacturing Index, ISM Nonmanufacturing Index, Leading Index, Monthly Budget Statement, New Home Sales, Personal Income, Pending Home Sales, Philadelphia Fed Business Outlook, Advance Retail Sales, Trade Balance, the University of Michigan Consumer Confidence (preliminary), and Unemployment Rate. All these announcements except

Using these 25 announcements we estimate a regression for the same period (January 1, 2005 - May 3, 2013) with the same dependent variables as in equation (20):

$$R_t = \alpha_0 + \alpha_1 ZLB_t + b\sum_{m=1}^{25} \hat{\beta}_m S_{mt} + c\sum_{m=1}^{25} \hat{\beta}_m S_{mt} ZLB_t + u_t. \tag{21}$$

ZLB_t is an indicator variable equal to one after September 5, 2008 and zero otherwise. $\hat{\beta}_m$ estimates are obtained from estimating the regression in equation (20) using the period from January 1, 2005 to May 3, 2013. Therefore, $b + c = 1$ by construction. The coefficient c measures the change in the average response to the news after September 5, 2008. This estimation approach assumes that the relative magnitudes of the response coefficients in equation (20) are constant in the two subsamples. Only the overall magnitude of these coefficients is allowed to shift in the period after September 5, 2008. Swanson and Williams (2014) use a similar estimation to examine time variation in the response of the U.S. interest rates to macroeconomic news. Table 3 displays the results.

Consistent with Datta et al. (2021), we find clear evidence that the reaction of the stock returns and the crude oil returns to macroeconomic news announcements is stronger in our second subsample. Datta et al. (2021) interpret this increased responsiveness as the ZLB causing the increased correlation between the stock and crude oil returns. On the other hand, the average response of the 5-year Treasury yields to macroeconomic news is weaker in our second subsample. Consistent with Swanson and Williams (2014), this indicates that medium-term interest rates were somewhat constrained by the ZLB.

4.2 Synchronization of Crude Oil Prices with the Business Cycle

Another possible explanation is that the shale revolution helped synchronize changes in crude oil prices to the business cycle. Alquist, Bhattarai, and Coibion (2020) provide a useful framework for thinking about our results by separating commodity shocks into direct

Initial Jobless Claims are released monthly. The Initial Jobless Claims announcements are released weekly.

Table 3: Average Effect of ZLB on the Market Response to Macroeconomic News

	b	c	R^2
E-mini S&P500	0.36 (0.054)***	0.64 (0.071)***	31.43%
Crude oil	0.00 (0.041)	1.00 (0.073)***	22.58%
5-year Treasury note	1.35 (0.112)***	-0.35 (0.165)**	36.71%

The table reports estimates for the event study regression in equation (21). The returns and yield changes used as the dependent variables are computed from five minutes before to five minutes after a macroeconomic news release. Only the 25 announcements that affect at least one of the three markets according to the joint Wald test are included in the estimation. The sample period is from January 1, 2005 to May 3, 2013 and contains 2,263 observations. The regressions are estimated using ordinary least squares with White (1980) heteroskedasticity consistent covariance matrix. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

and indirect shocks. Direct shocks are those that directly impact the price of the commodity through changes in the supply and demand curves of the commodity. These direct shocks would occur regardless of whether there was a change in the general-equilibrium level of aggregate income. In our sample period, the crude oil shale revolution is the most prominent direct shock that substantially affected the supply of crude oil produced in the U.S.[27] In contrast, indirect shocks impact commodity prices only indirectly through changes in aggregate income. Alquist, Bhattarai, and Coibion (2020) separate these indirect shocks into demand and supply channels. In the demand channel, when economic activity is high, the demand for commodities is high, thereby increasing their prices. In our sample period, there are two main indirect shocks: the 2008 financial crisis and the COVID-19 pandemic.

The 2008 financial crisis was an indirect demand shock that synchronized the crude oil market with the business cycle and therefore with the stock market. This is supported by the a_{21} coefficient changing from statistically insignificant in the first subsample to the statistically significant positive in the second subsample. This is consistent with Alquist, Bhattarai, and Coibion (2020) in that the indirect shocks (i.e., changes in the general equilibrium conditions) have a large impact on commodity prices.

[27]One could also argue that changes in the Organization of Petroleum Exporting Countries production are direct shocks.

After the 2008 financial crisis, the shale revolution substantially increased U.S. crude oil production. Figure 3 shows the U.S. crude oil consumption, production, and net imports. To provide a historical perspective, the figure begins in 1950 and extends to 2022. Domestic production increased from approximately 8 million barrels per day in 2005 to almost 19 million barrels per day in 2021. The striking feature of this figure is that the decline in net imports from the peak of 12.55 million barrels per day in 2005 – leading to the U.S. becoming a net exporter for the first time after the export ban was lifted in 2015 – is clearly a result of this increased domestic production (U.S. Energy Information Administration, 2022). This is a pertinent point because unexpected increases in the price of *imported* crude oil are the primary channel through which crude oil price shocks adversly affect the U.S. economy. Unexpected increases in *imported* crude oil prices reduce domestic consumption due to the increased share of domestic income that is sent abroad. In contrast, changes in the price of *domestic* crude oil simply redistribute domestic income.[28] As a result, we would expect crude oil returns to become more synchronized with the U.S. business cycle.

Previous literature shows that corporate cash flows and the equity risk premium vary over the business cycle: corporate cash flows increase (decrease) and the equity risk premium decreases (increases) in economic expansions (contractions). Therefore, if the crude oil prices have become more synchronized with the business cycle, we would expect the crude oil prices to become more correlated with corporate cash flows and the equity risk premium. We therefore analyze this correlation. We proceed in three steps.

First, we estimate monthly cash flow news and discount rate news for the S&P 500 index using the return decomposition approach of Campbell and Shiller (1988). Second, we compute correlations of these monthly cash flow news and discount rate news with the returns of the most liquid WTI crude oil futures contract. Third, since the discount rate consists of two components (the risk-free interest rate and the equity risk premium), we

[28]Melek, Plante, and Yücel (2017) show in a dynamic stochastic general equilibrium model that the shale revolution and the lifting of the crude oil export ban increase the U.S. consumption of fuel due to lower prices of crude oil.

analyze which of these two components drives the discount rate news correlation. We now explain each of these three steps in detail.

First, we begin by estimating monthly cash flow news and discount rate news for the S&P500 index using the Campbell and Shiller (1988) accounting identity for decomposing the unexpected stock returns into news about future dividends and future discount rates:

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j \Delta r_{t+1+j} = N_{CF,t+1} - N_{DR,t+1}. \quad (22)$$

The r_{t+1} is the log stock return, E_t and E_{t+1} denote expectations at times t and $t+1$, Δd_{t+1} stands for a one-period change in the log dividends, and ρ is the constant discount factor. $N_{CF,t+1}$ and $N_{DR,t+1}$ are news about the future cash flows and news about future discount rates, respectively. We estimate the first-order VAR to construct time series of these aggregate cash flow news and discount rate news based on Campbell and Vuolteenaho (2004):

$$\mathbf{z_{t+1}} = \mathbf{a} + \mathbf{B z_t} + \mathbf{u_{t+1}}. \quad (23)$$

The $\mathbf{z_{t+1}}$ represents the vector of state variables, $\mathbf{a}$ and $\mathbf{B}$ denote coefficient matrices, and $\mathbf{u_{t+1}}$ stands for the vector of shocks. Following previous literature, the variables in the VAR are: the log of excess stock market return, the log of the Shiller's cyclically-adjusted P/E ratio, the credit spread computed as the difference between BAA and AAA corporate yields obtained from the FRED database, and the implied volatility spread computed as the difference between implied volatilities of the S&P 500 puts and calls obtained from OptionMetrics.[29] We use data from January 2000 to December 2022 for this VAR estimation. We use a sample period that is longer than the sample period used in Sections 3.1 and 3.2.2 following Bernanke and Kuttner (2005) because it provides more observations for estimating the VAR coefficients. The VAR coefficient estimates are reported in Table A4 in the Ap-

[29]These variables are used, for example, by Campbell and Vuolteenaho (2004), Bernanke and Kuttner (2005), and Atilgan, Bali, and Demirtas (2015).

pendix. All three return predictors are statistically significant in the market excess return equation. The R^2 of this equation is about 6.7%.

We then compute the discount rate news as:

$$N_{DR,t+1} = \mathbf{e1}'\lambda\mathbf{u_{t+1}}. \tag{24}$$

The **e1** denotes the vector with the first element equal to one and other elements equal to zero. The $\lambda \equiv \rho\mathbf{B}(\mathbf{I} - \rho\mathbf{B})^{-1}$ denotes the matrix capturing the long-term effects of VAR innovations on the four state variables. We use 0.95 annualized discount factor based on Campbell and Vuolteenaho (2004). The cash flow news is then computed with the market return shock and the discount rate news as:

$$N_{CF,t+1} = (\mathbf{e1}' + \mathbf{e1}'\lambda)\mathbf{u_{t+1}}. \tag{25}$$

Second, we compute correlations of the above monthly cash flow news and discount rate news with the crude oil returns. Table 4 shows these correlations. We find that in the first subsample the crude oil returns are not correlated with either the cash flow news or the discount rate news. In contrast, in the second and third subsamples the correlation of the crude oil returns with the cash flows news is positive and statistically significant, indicating that the crude oil prices have become more synchronized with the business cycle. The correlations in the third subsample are noticeably lower in absolute value than the corresponding estimates in the second subsample.[30]

Third, we analyze the relationship between the crude oil return and the equity risk premium. From Table 4 we know that the correlation of the crude oil returns with the discount rate news is negative in the second and third subsamples. Since the discount rate news includes both the risk-free interest rate and the equity risk premium components, in this final step we need to find out which component drives the discount rate news result. Therefore, we compute correlation of the crude oil return with risk-free interest rate proxies.

[30] The correlations remain similar if we add the term spread as an additional predictor in the VAR or estimate the VAR in the 2005-2022 period.

Table 4: Correlations of Cash Flow News, Discount Rate News, and Crude Oil Returns

	N_{CF}	N_{DR}
Panel a) Subsample 1 (01/01/2005-08/31/2008)		
N_{DR}	0.372**	
Oil return	−0.184	−0.063
Panel b) Subsample 2 (09/01/2008-04/30/2013)		
N_{DR}	0.090	
Oil return	0.596***	−0.318**
Panel c) Subsample 3 (05/01/2013-12/30/2022)		
N_{DR}	−0.080	
Oil return	0.348***	−0.235**

The table shows Pearson correlations between the estimated monthly cash flow news (N_{CF}), discount rate news (N_{DR}), and the returns of most liquid WTI crude oil futures contract. The crude oil futures returns are appropriately adjusted for contract rollovers. Panels a), b), and c) report results for subsamples 1, 2, and 3, respectively. *, **, *** indicate that the correlation is statistically significant at 10%, 5%, and 1% levels, respectively.

We use the 3-month Treasury bill and the 10-year Treasury note as the risk-free interest rate proxies. These correlations are positive for both the changes in the 3-month Treasury bill yields and the changes in the the 10-year Treasury note yields in both the second and third subsamples.[31] This means that the negative correlation of the crude oil return with the discount rate news is driven by the equity risk premium rather than the risk-free interest rate, again indicating that the crude oil prices have become more synchronized with the business cycle.

4.3 Financialization of Commodity Markets

Tang and Xiong (2012), Basak and Pavlova (2016), and Henderson, Pearson, and Wang (2015) present evidence that the financialization of commodity markets increased the correlation of equities with commodity markets.[32] Tang and Xiong (2012) and Büyükşahin and

[31] The correlation of crude oil return and the 3-month Treasury bill yield changes is 0.486 and 0.480 in the second and third subsamples, respectively. The correlation of crude oil return and the 10-year Treasury note yield changes is 0.336 and 0.350 in the second and third subsamples, respectively. All four correlations are significant at the 1% level.

[32] Fattouh, Kilian, and Mahadeva (2013) provide a survey of literature on financialization of the oil market.

Robe (2014) argue that the changes are likely due to the entry of institutional investors into commodity futures markets. While evidence from Section 4.2 indicates that crude oil returns correlate more with cash flow news and the risk premium in the more recent times, suggesting potential market financialization, it is improbable that financialization alone influenced our observed increase in the impact of the stock market and monetary policy expectations on the crude oil market. This stems from the fact that the relationships, as shown in Table 2, shifted markedly during the 2008 financial crisis, whereas the process of financialization has been more incremental over time.

4.4 Related Literature

Sections 4.1, 4.2, and 4.3 discussed potential explanations for the reaction of the crude oil returns to stock returns and Treasury yields. This section examines the other four response coefficients highlighted in Table 2, cross-referencing them with prior studies. Encouragingly, they align well with existing literature.

The response of stock returns to crude oil returns (a_{12}) is negative in the first subsample (01/01/2005 - 09/05/2008) but changes to a positive response in the following two subsamples, which is consistent with Aït-Sahalia and Xiu (2016), Alquist, Bhattarai, and Coibion (2020), Datta et al. (2021), Foroni et al. (2017), and Lombardi and Ravazzolo (2016). Datta et al. (2021) and Foroni et al. (2017) attribute this change to the ZLB while Alquist, Ellwanger, and Jin (2020) argue that the positive reaction of the crude oil prices to stock returns after the financial crisis might be driven by the crude oil prices being increasingly related to the equity risk premium.

The response of stock returns to interest rate changes (a_{13}) has been documented by, for example, Bernanke and Kuttner (2005) who report a coefficient of approximately -4, similar to our coefficient of -4.23 for the full sample. This is consistent with standard economic theory predicting that an unexpected monetary policy tightening will depress stock prices.[33]

[33]The estimate of the a_{13} coefficient increases to -5.90 in the last subsample. The U.S. equity valuations

The response of the Treasury yields to stock returns (a_{31}) also agrees with the previous literature. The coefficient is positive across our three subsamples with the largest, statistically significant impact during the second subsample that contains the financial crisis. This is consistent with Kurov, Olson, and Zaynutdinova (2022) who show that the response of monetary policy expectations to changes in stock prices is asymmetric, depending on the economic environment. The response of monetary policy expectations to stock prices is stronger during recessions and bear markets than during bull markets. This pattern of the Federal Reserve loosening monetary policy in response to declines in asset prices is known as the "Fed put."

The response of the Treasury yield changes to crude oil returns (a_{32}) is statistically significant and negative in the 01/01/2005-09/05/2008 subsample, insignificant in the 09/01/2008-05/13/2013 subsample, and significant and positive in the 05/04/2013 - 12/13/2022 subsample. However, for the subsamples in which there is a statistically significant effect, the coefficient estimates are rather small. For example, in the last subsample when the coefficient is positive and statistically significant, a 10% increase in the price of crude oil induces only an approximately 1.4 basis point increase in the Treasury yields. Our results therefore indicate that the Federal Reserve does not substantially react to crude oil price changes. This is consistent with Kilian and Lewis (2011) who find no evidence that the Federal Reserve has responded to crude oil price shocks. This is the case even in the third subsample where inflation reached historical highs in 2021-2022. This is perhaps due to the Federal Reserve focusing on core inflation that excludes energy prices (Bullard, 2013) and the inflation being driven by factors other than crude oil prices such as supply factors related to labor shortages, production constraints, and shipping delays and demand factors related to the fiscal stimulus

have been high in recent years, with the average cyclically adjusted P/E ratio for the S&P 500 index hovering above 30. When stock prices are high relative to fundamentals, expected returns are low and a given change in the discount rate has a much larger impact on stock prices than when the expected returns are higher. For example, the value of a perpetuity will decline by 9% if the discount rate increases from 10% to 11%, but that same value will fall by 18% if the discount rate increases from 4.5% to 5.5%. It is therefore not surprising that stocks are more sensitive to the Treasury yields when expected returns were low. The cyclically adjusted P/E ratio data is from Robert Shiller's website (`http://www.econ.yale.edu/~shiller/data.htm`).

(Shapiro, 2022).

5 Conclusion

We take a fresh look at a frequently studied question of the relationships between stock prices, crude oil prices, and monetary policy. Estimating the contemporaneous causal effects of oil shocks on financial markets is a challenge due to the endogenous relationship between changes in energy prices and economic activity. We make two contributions to the literature. First, we use the Kurov, Olson, and Zaynutdinova (2022) two-market identification approach based on exogenous changes in the intraday volatility of index futures to estimate the contemporaneous response coefficients and we generalize this approach to any number of markets. This novel generalization greatly expands the questions that can be answered using this identification approach. Second, we use this identification approach to examine contemporaneous causal linkages between three markets: crude oil, stocks, and interest rates. We find significant changes in these causal linkages over time. In particular, we find that since 2008 stock returns affect crude oil returns. This time variation is also evident in the effect of monetary policy on the crude oil returns and it has made crude oil behave more like a financial asset.

Our findings have implications for researchers, monetary policy makers, and investment practitioners. Researchers and monetary policy makers can conclude from these findings that the structural parameters utilized in dynamic stochastic general equilibrium (DSGE) models should not be assumed to be time-invariant. Investment practitioners will appreciate the findings for their practical application to portfolio diversification.

A Appendix

Table A1: Contemporaneous linkages between stock index returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield: Subsample 01/01/2005–09/05/2008

	Coefficient	Standard error
Panel a) Response coefficient estimates		
Response of stock returns to crude oil returns (a_{12})	−0.0969**	(0.0412)
Response of stock returns to Treasury yield changes (a_{13})	−2.4271	(3.8349)
Response of crude oil returns to stock market returns (a_{21})	0.1469	(0.1290)
Response of crude oil returns to Treasury yield changes (a_{23})	2.2841	(1.7803)
Response of Treasury yield changes to stock returns (a_{31})	0.0075	(0.0094)
Response of Treasury yield changes to crude oil returns (a_{32})	−0.0055***	(0.0018)
Panel b) Heteroskedasticity parameter estimates		
Stocks around 9:30 a.m. (Δ_{11})	0.0148***	(0.0033)
Oil around 9:30 a.m. (Δ_{21})	−0.0158	(0.0152)
Treasury yields around 9:30 a.m. (Δ_{31})	0.0012	(0.0012)
Stocks around WPSR (Δ_{12})	0.0167***	(0.0061)
Oil around WPSR (Δ_{22})	0.7074***	(0.1988)
Treasury yields (Δ_{32})	−0.0010	(0.0022)
Stocks around FOMC (Δ_{13})	0.2330**	(0.1105)
Oil around FOMC (Δ_{23})	0.1298*	(0.0774)
Treasury yields around FOMC (Δ_{33})	0.2100***	(0.0601)

The sample period is from January 1, 2005 to September 5, 2008 and contains data from days with scheduled Federal Open Market Committee (FOMC) announcements, FOMC minutes, and the Energy Information Administration‘s Weekly Petroleum Status Report (WPSR) released in the same weeks ($59 \times 6 = 354$ observations). Δ_{iS} is the change in the variance of innovations of returns or yield changes of market i around time S. i is 1, 2, and 3 for the E-mini S&P 500 futures returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield changes, respectively. $S = 1$ for the covariance matrix shift around the stock market opening at 9:30 a.m. ET, $S = 2$ for the covariance matrix shift after the WPSR releases (typically at 10:30 a.m.), and $S = 3$ for the covariance matrix shift after FOMC announcements and releases of FOMC minutes. To measure the change in the covariance matrix around FOMC announcements and releases of FOMC minutes, we use 30-minute intervals before and after the announcement time. 15-minute intervals are used to compute returns and yield changes for the other two covariance matrix shifts. The parameters are estimated with GMM. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The p-value of the test of overidentifying restrictions is 0.8962. Δ_{31}, Δ_{32}, and Δ_{33} and the corresponding standard errors are multiplied by 100 for readability.

Table A2: Contemporaneous linkages between stock index returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield: Subsample 09/06/2008–05/03/2013

	Coefficient	Standard error
Panel a) Response coefficient estimates		
Response of stock returns to crude oil returns (a_{12})	0.1179***	(0.0309)
Response of stock returns to Treasury yield changes (a_{13})	−3.0067	(2.6159)
Response of crude oil returns to stock market returns (a_{21})	0.7832***	(0.1611)
Response of crude oil returns to Treasury yield changes (a_{23})	6.7871*	(3.4741)
Response of Treasury yield changes to stock returns (a_{31})	0.0108***	(0.0041)
Response of Treasury yield changes to crude oil returns (a_{32})	0.0003	(0.0015)
Panel b) Heteroskedasticity parameter estimates		
Stocks around 9:30 a.m. (Δ_{11})	0.0607***	(0.0226)
Oil around 9:30 a.m. (Δ_{21})	0.0910**	(0.0404)
Treasury yields around 9:30 a.m. (Δ_{31})	0.0003	(0.0021)
Stocks around WPSR (Δ_{12})	0.0014	(0.0152)
Oil around WPSR (Δ_{22})	0.6067**	(0.2299)
Treasury yields (Δ_{32})	−0.0020	(0.0028)
Stocks around FOMC (Δ_{13})	0.2483**	(0.1057)
Oil around FOMC (Δ_{23})	0.3076**	(0.1344)
Treasury yields around FOMC (Δ_{33})	0.2986**	(0.1220)

The sample period is from September 6, 2008 to May 3, 2013 and contains data from days with scheduled Federal Open Market Committee (FOMC) announcements, FOMC minutes, and the Energy Information Administration‘s Weekly Petroleum Status Report (WPSR) released in the same weeks ($75 \times 6 = 450$ observations). Δ_{iS} is the change in the variance of innovations of returns or yield changes of market i around time S. i is 1, 2, and 3 for the E-mini S&P 500 futures returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield changes, respectively. $S = 1$ for the covariance matrix shift around the stock market opening at 9:30 a.m. ET, $S = 2$ for the covariance matrix shift after the WPSR releases (typically at 10:30 a.m.), and $S = 3$ for the covariance matrix shift after FOMC announcements and releases of FOMC minutes. To measure the change in the covariance matrix around FOMC announcements and releases of FOMC minutes, we use 30-minute intervals before and after the announcement time. 15-minute intervals are used to compute returns and yield changes for the other two covariance matrix shifts. The parameters are estimated with GMM. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The p-value of the test of overidentifying restrictions is 0.7534. Δ_{31}, Δ_{32}, and Δ_{33} and the corresponding standard errors are multiplied by 100 for readability.

Table A3: Contemporaneous linkages between stock index returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield: Subsample 05/04/2013–12/30/2022

	Coefficient	Standard error
Panel a) Response coefficient estimates		
Response of stock returns to crude oil returns (a_{12})	0.0977***	(0.0179)
Response of stock returns to Treasury yield changes (a_{13})	−5.9035***	(0.6628)
Response of crude oil returns to stock market returns (a_{21})	0.4865***	(0.1546)
Response of crude oil returns to Treasury yield changes (a_{23})	−4.8413**	(2.1404)
Response of Treasury yield changes to stock returns (a_{31})	0.0081**	(0.0041)
Response of Treasury yield changes to crude oil returns (a_{32})	0.0014**	(0.0006)
Panel b) Heteroskedasticity parameter estimates		
Stocks around 9:30 a.m. (Δ_{11})	0.0317***	(0.0075)
Oil around 9:30 a.m. (Δ_{21})	0.0037	(0.0322)
Treasury yields around 9:30 a.m. (Δ_{31})	0.0007	(0.0007)
Stocks around WPSR (Δ_{12})	0.0046	(0.0045)
Oil around WPSR (Δ_{22})	0.7186***	(0.1553)
Treasury yields (Δ_{32})	0.0036*	(0.0020)
Stocks around FOMC (Δ_{13})	0.0649***	(0.0107)
Oil around FOMC (Δ_{23})	0.4242***	(0.1636)
Treasury yields around FOMC (Δ_{33})	0.1798***	(0.0326)

The sample period is from May 4, 2013 to December 30, 2022 and contains data from days with scheduled Federal Open Market Committee (FOMC) announcements, FOMC minutes, and the Energy Information Administration's Weekly Petroleum Status Report (WPSR) released in the same weeks ($153 \times 6 = 918$ observations). Δ_{iS} is the change in the variance of innovations of returns or yield changes of market i around time S. i is 1, 2, and 3 for the E-mini S&P 500 futures returns, WTI crude oil futures returns, and 5-year U.S. Treasury yield changes, respectively. $S = 1$ for the covariance matrix shift around the stock market opening at 9:30 a.m. ET, $S = 2$ for the covariance matrix shift after the WPSR releases (typically at 10:30 a.m.), and $S = 3$ for the covariance matrix shift after FOMC announcements and releases of FOMC minutes. To measure the change in the covariance matrix around FOMC announcements and releases of FOMC minutes, we use 30-minute intervals before and after the announcement time. 15-minute intervals are used to compute returns and yield changes for the other two covariance matrix shifts. The parameters are estimated with GMM. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The p-value of the test of overidentifying restrictions is 0.2548. Δ_{31}, Δ_{32}, and Δ_{33} and the corresponding standard errors are multiplied by 100 for readability.

Table A4: Vector Autoregression (VAR) Parameter Estimates

	Constant	$r^e_{m,t}$	PE_t	CS_t	VS_t	R^2
$r^e_{m,t+1}$	0.167	0.047	−1.442***	−1.098**	0.881**	0.067
	(0.282)	(0.077)	(0.424)	(0.471)	(0.361)	
PE_{t+1}	−0.024***	0.020***	0.958***	−0.020	0.028**	0.976
	(0.009)	(0.003)	(0.012)	(0.013)	(0.012)	
CS_{t+1}	0.022	−0.031***	−0.022	0.924***	0.019	0.932
	(0.016)	(0.006)	(0.018)	(0.038)	(0.018)	
VS_{t+1}	0.041	−0.011	0.063	0.023	0.826***	0.712
	(0.033)	(0.009)	(0.043)	(0.048)	(0.040)	

This table shows the ordinary least squares parameter estimates for the first-order vector autoregression including a constant, the log excess return of the S&P 500 index ($r^e_{m,t}$), the log of the Shiller's cyclically-adjusted P/E ratio (PE_t), the credit spread computed as the difference between BAA and AAA corporate yields (CS_t), and the implied volatility spread computed as the difference between volume-weighted implied volatilities of the S&P 500 puts and calls (VS_t). All variables are measured at monthly intervals. All variables except the market excess return are standardized to a mean of zero and standard deviation of one. The sample period is from January 2000 through December 2022 and contains 276 observations. Heteroskedasticity consistent standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

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