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

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Abstract

We reexamine the contemporaneous causal effects between the U.S. stock prices, crude oil prices, and monetary policy from 2005 to 2023. 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
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2 Methodology and 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:

$$R_{s;t} = R_{o;t} + z_t + \varepsilon_t; \tag{1}$$

$$R_{o;t} = R_{s;t} + z_t + {}_t; \tag{2}$$

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. The two markets contemporaneously respond to each other as well as to the common economic shocks z_t. The structural innovations ε_t and ${}_t$ are assumed to be uncorrelated with each other and with z_t. The coefficients of primary interest (and) cannot be consistently estimated with an ordinary

Rigobon and Sack (2004) o er a solution to this problem: if one can nd times when the variance of the structural innovations shifts, the coe cients and 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:

$$R_{s;t} = \frac{1}{1}[(\;+\;)z_t + \;_t + "_t] \tag{3}$$

$$R_{o;t} = \frac{1}{1}[(1 + \;)z_t + \;_t + \;_t]: \tag{4}$$

Suppose that we want to estimate the coe cient 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 identi cation of the coe cient because it provides a large shift in the variance of stock return innovations.[2] Assuming that the variance of $"_t$, $_"$, increases after the market opening, but and $_z$ remain stable, the covariance matrices of the stock and crude oil returns after the stock market opening ($_1$) and immediately before the stock market opening ($_2$) are:

$$_1 = \frac{1}{(1 \quad)^2}\begin{bmatrix} _{"1} + \;^2 \; + (\;+\;)^2 \;_z & _{"1} + \; + (\;+\;)(1 + \;) \;_z \\ : & ^2 \;_{"1} + \; + (1 + \;)^2 \;_z \end{bmatrix}; \tag{5}$$

and

$$_2 =$$

$$^{s} = \quad {}_{1} \qquad {}_{2} = \frac{"1 \qquad "2}{(1 \qquad)^{2}} \begin{bmatrix} 1 \\ \\ {}_{2} \end{bmatrix} {}^{s} \begin{bmatrix} 1 \\ \\ {}_{2} \end{bmatrix} : \qquad (7)$$

The two parameters (^{s} and) 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 overidenti ed. This allows using a standard test of overidentifying restrictions to test the validity of the identi cation assumption that all of the model parameters except " are the same before and after the covariance matrix shift (for example, Rigobon and Sack (2004)).

Figure 1 illustrates the identi cation 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 similar7(c)27-3

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Assuming that volatility of the crude oil innovations, , changes around these events, but $_{\epsilon}$ and $_{z}$ remain stable, the covariance matrices of the stock and crude oil returns after the WPSR releases ($_{1}$) and immediately before the WPSR releases ($_{2}$) are:

$$_{1} = \frac{1}{(1 \quad)^2} \begin{bmatrix} _{\epsilon} + {}^2 \, _{1} + (\; + \;)^2 \, _{z} & _{\epsilon} + \; _{1} + (\; + \;)(1 + \;) \, _{z} \\ : & {}^2 \, _{\epsilon} + \; _{1} + (1 + \;)^2 \, _{z} \end{bmatrix}; \tag{8}$$

and

$$_{2} = \frac{1}{(1 \quad)^2} \begin{bmatrix} _{\epsilon} + {}^2 \, _{2} + (\; + \;)^2 \, _{z} & _{\epsilon} + \; _{2} + (\; + \;)(1 + \;) \, _{z} \\ : & {}^2 \, _{\epsilon} + \; _{2} + (1 + \;)^2 \, _{z} \end{bmatrix}: \tag{9}$$

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

$$^{o} = \; _{1} \quad _{2} = \frac{1}{(1 \quad)^2} \begin{bmatrix} {}^2 & \\ & 1 \end{bmatrix} \; ^{o} \begin{bmatrix} {}^2 & \\ & 1 \end{bmatrix}; \tag{10}$$

and the two parameters (^{o} and) can again be estimated with GMM using intraday futures data before and after the covariance matrix shift. Alternatively, if we also allow 963t1.076 Td [(;002 change after the stock market opening and allow $_{\epsilon}$ to change after the WPSR releases, the covariance matrix shifts become:

$$_{s} = \frac{1}{(1 \quad)^2} \begin{bmatrix} _{\epsilon 1} + {}^2 \, _{1} & _{\epsilon 1} + \; _{1} \end{bmatrix}$$

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., $_{11}$, $_{21}$, and $_{31}$) and six moment equations, since $_{S}$ 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, $_{iS}$). 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 intraday 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.[4] We use the most actively traded (usually nearby) contracts for all three futures markets.[5] 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). To convert intraday returns of 5-year Treasury note futures into yield changes, we multiply the returns by the slope coefficient estimate from the regression of daily changes in 5-year Treasury constant maturity rates on daily returns of 5-year Treasury note futures.[6]

Our sample period begins on January 1, 2005 because the WTI crude oil futures overnight

[4] 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 are similar to the results reported in the tables below.

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

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

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.[7]

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. 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.[8] 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.[9] We use longer intervals around releases of FOMC statements and minutes because markets take more time to absorb this kind of information (see, 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 estima-

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

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

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

tion and therefore the markets are not systematically a ected by other events during our

The use of intraday financial market data for identification through heteroskedasticity is 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.

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 model of 15-minute returns for the E-mini S&P 500 futures, WTI crude oil futures, and 5-year U.S. Treasury yields. Only days that contain both the Federal Open Market Committee and the Weekly Petroleum Status Report announcements 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 $_{S}$, A , C , and D_{S} are 3Ö3 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 identi cation assumptions are not rejected by the data. Table 1 reports the GMM parameter estimates. We rst discuss results of the heteroskedasticity parameter estimates in Panel b) and follow with the coe cient estimates in Panel a).

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

While the stock market opening a ects only the variance of stock returns and the WPSR announcements a ect 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 ($_{13}$), crude oil returns ($_{23}$), and Treasury yield changes ($_{33}$). This highlights our methodological contribution: because our methodology does not assume that variances

We discuss literature about these four coefficients in more detail in Section 4.4.

3.2 Subsample Results

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.[12] 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:

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

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.[13] The weekly realized correlations for the three futures markets during our sample period are presented in Figure 3. The figure shows that the three realized correlations tend to move 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

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over time. The standardized first principal component of the three realized correlations is shown in the bottom right panel of Figure 3. 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.[14] The test identifies two structural breaks.[15] The first structural break is during 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, Guerin, and Marcellino (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.[16] 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 Federal Reserve Chairman's May 22 "taper tantrum" speech in which he signaled that the Federal Reserve would soon start reducing bond purchases under its quantitative

[14] 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

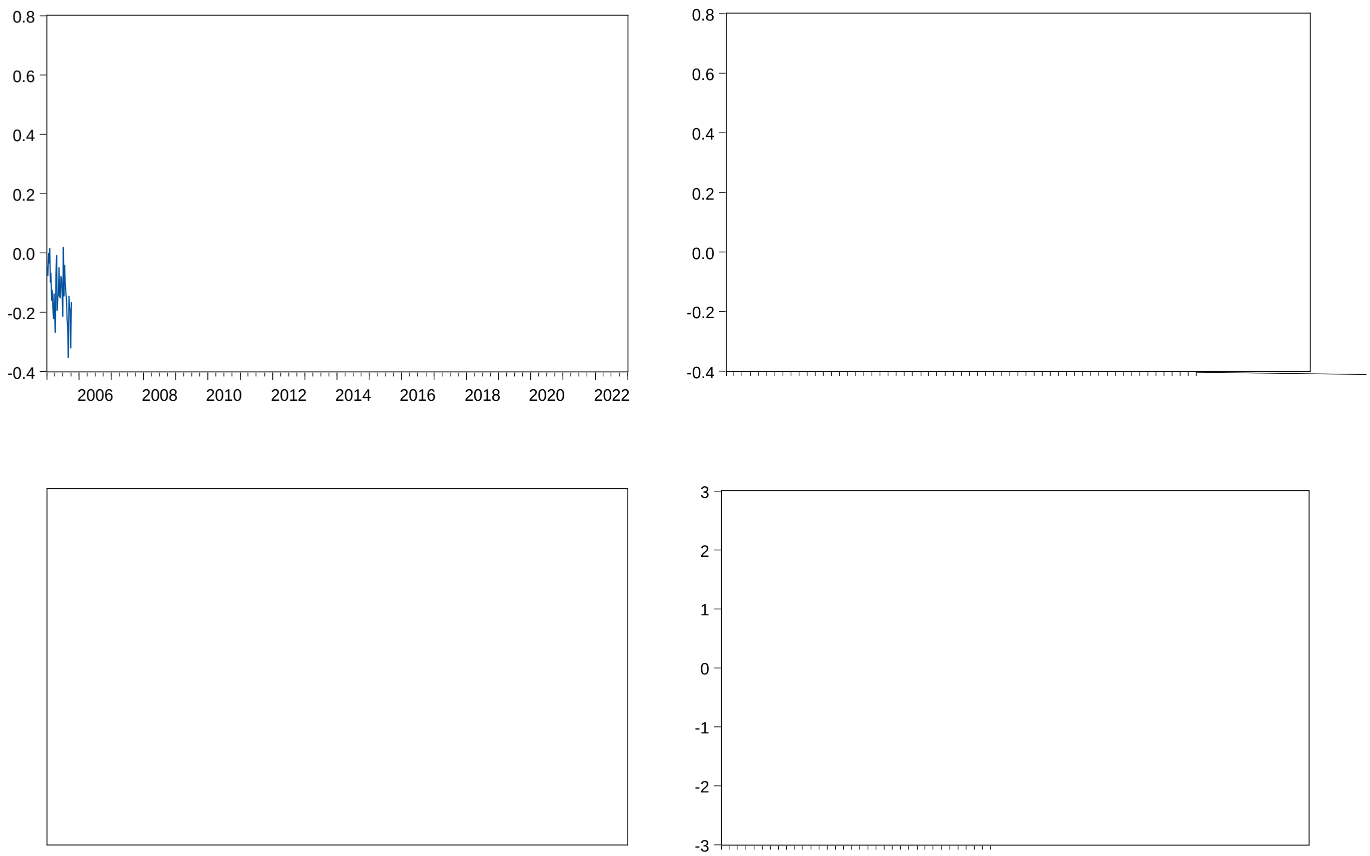
easing program. This announcement led to one of the largest monetary policy shocks since the 1980s with long-term U.S. Treasury yields increasing by approximately 100 basis points over the subsequent six months (for example, Sinha and Smolyansky (2022)).[17]

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 3 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. 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.

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-

Figure 3: 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 rst principal component of the three realized correlations in the three subsamples identi ed using the Bai and Perron (2003) multiple breakpoint test. The sample period is from January 1, 2005 to December 30, 2022.

studied in previous literature. Our results therefore bring a new nding 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 rst 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 nd 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

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 coe cient 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. ($_{11}$)	0:0366***	0:0148***	0:0607***	0:0317***
Oil around 9:30 a.m. ($_{21}$)	0:0163	0:0158	0:0910**	0:0037
Treasury yields around 9:30 a.m. ($_{31}$)	0:0009	0:0012	0:0003	0:0007
Stocks around WPSR ($_{12}$)	0:0102	0:0167***	0:0014	0:0046
Oil around WPSR ($_{22}$)	0:7159***	0:7074***	0:6067**	0:7186***
Treasury yields around WPSR ($_{32}$)	0:0019	0:0010	0:0020	0:0036*
Stocks around FOMC ($_{13}$)	0:1431***	0:2330**	0:2483**	0:0649***
Oil around FOMC ($_{23}$)	0:3757***	0:1298*	0:3076**	0:4242***
Treasury yields around FOMC ($_{33}$)	0:1954***	0:2100***	0:2986**	0:1798***

This table displays the response coe cient estimates and heteroskedasticity parameter estimates for the full sample from Table 1 in the rst column and for the three subsamples in the second, third, and fourth columns. *, **, and *** indicate statistical signi cance at 10%, 5%, and 1% levels, respectively.

returns drive the economy (beyond the common shock z in our model), the stock returns will in uence 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 e ect 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.[18] Our results therefore expand this literature by showing substantial time variation. Again, in the rst subsample crude oil returns do not

[18] Kilian and Vega (2011) do not nd 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 1999-2001, 1994-2008, and 1994-2008 sample periods, respectively.

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).

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.

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 next describe this test.

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:

$$S_{mt} = \frac{A_{mt} \quad E_t \quad [A_{mt}]}{m}; \tag{19}$$

where m stands for a macroeconomic announcement m, t stands for the announcement release time t, A_{mt} is the actual announcement, $E_t \quad [A_{mt}]$ 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), > 0. $_m =$

$q \quad \frac{1}{N_m}$

announcement is set to zero. This model speci cation accounts for simultaneous releases of multiple announcements.[19] 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 signi cant at the 5% level to nd announcements that move at least one of these three markets. Five announcements have p

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.

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.

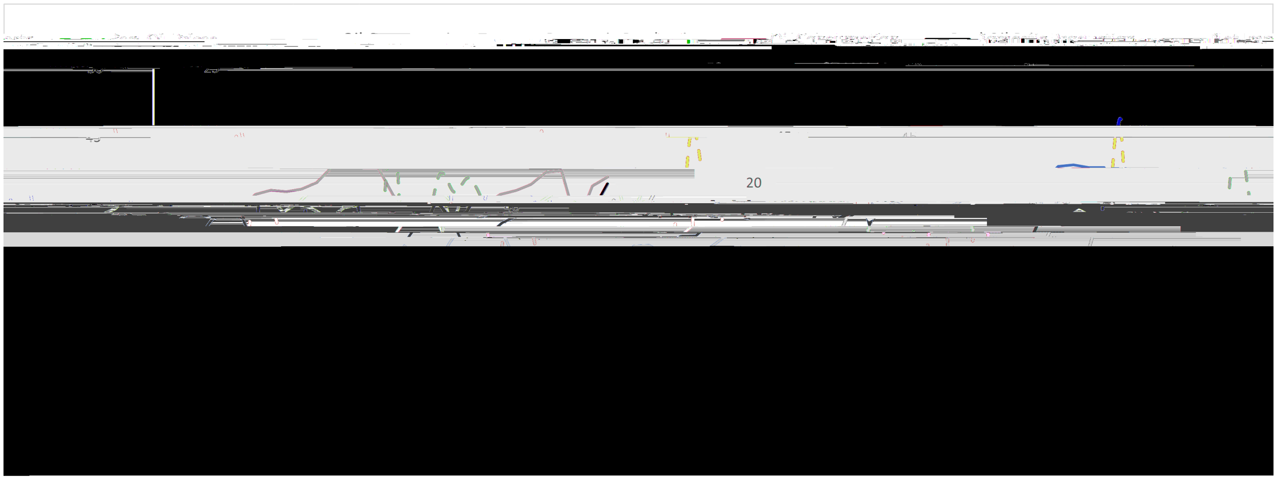
4.2 Synchronization of Crude Oil Prices with the Business Cycle

Another possible explanation is that the shale revolution helped synchronize changes in direct shock that substantially affected the supply of crude oil produced in the U.S.[21] 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.

After the 2008 financial crisis, the shale revolution substantially increased U.S. crude oil production. Figure 4 shows the U.S. crude oil consumption, production, net imports, and real oil prices. 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 we would expect crude oil returns to become more synchronized with the U.S. business cycle.

Figure 4: 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.

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 consists of two components (the risk-free interest rate and the equity risk premium), we 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:

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

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):

$$z_{t+1} = a + Bz_t + u_{t+1}$$

the VAR coefficients. The VAR coefficient estimates are reported in Table A4 in the Appendix. All three return predictors are statistically significant in the market excess return equation. The R^2 of this equation is about 6.7%.

We than compute the discount rate news as:

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

The e1 denotes the vector with the first element equal to one and other elements equal to zero. The $\lambda \equiv \rho B(I - \rho B)^{-1}$ 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:

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

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.[24]

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.

[24] 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 ow 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, relation of equities with commodity markets. Tang and Xiong (2012) and Büyüksahin and 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, prices.[26]

The response of the Treasury yields to stock returns (a_{31}

production constraints, and shipping delays and demand factors related to the fiscal stimulus (Shapiro, 2022).

5 Conclusion

We take a fresh look at a frequently studied question of the relationships between the monetary policy, crude oil prices, and stock returns. 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

	Coe cient	Standard error
Panel a) Response coe cient 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. ($_{11}$)	0:0148***	(0:0033)
Oil around 9:30 a.m. ($_{21}$)	0:0158	(0:0152)
Treasury yields around 9:30 a.m. ($_{31}$)	0:0012	(0:0012)
Stocks around WPSR ($_{12}$)	0:0167***	(0:0061)
Oil around WPSR ($_{22}$)	0:7074***	(0:1988)
Treasury yields ($_{32}$)	0:0010	(0:0022)
Stocks around FOMC ($_{13}$)	0:	

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

	Coe cient	Standard error
Panel a) Response coe cient estimates		
Response of stock returns to crude oil returns (a_{12})	0:1179***	(0

0

0:0

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

	Coe cient	Standard error
Panel a) Response coe cient 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. ($_{11}$)	0:0317***	(0:0075)
Oil around 9:30 a.m. ($_{21}$)	0:0037	(0:0322)
Treasury yields around 9:30 a.m. ($_{31}$)	0:0007	(0:0007)
Stocks around WPSR ($_{12}$)	0:0046	(0:0045)
Oil around WPSR ($_{22}$)	0:7186***	(0:1553)
Treasury yields ($_{32}$)	0:0036*	(0:0020)
Stocks around FOMC ($_{13}$)	0:0649***	(0:0107)
Oil around FOMC ($_{23}$)	0:4242***	(0:1636)
Treasury yields around FOMC ($_{33}$)	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 6 = 918 observations). $_{iS}$ 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 signi cance at 10%, 5%, and 1% levels, respectively. The p-value of the test of overidentifying restrictions is 0.2548. $_{31}$, $_{32}$, and $_{33}$ 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 rst-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 di erence between BAA and AAA corporate yields (CS_t), and the implied volatility spread computed as the di erence 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 signi cance at 10%, 5%, and 1% levels, respectively.

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