Journal of Financial Risk Management, 2026, 15(3), 275-298
https://www.scirp.org/journal/jfrm
ISSN Online: 2167-9541
ISSN Print: 2167-9533

How Does the Trade Policy Uncertainty of the United States Affect the Prices of Crude Oil in Futures Markets?

Qi Wang[1], Dongdan Jiao[2*], Xiangyun Xu[1]

[1]School of International Trade and Economics, Anhui University of Finance and Economics, Bengbu, China
[2]Institute of Scientific and Technical Information of China, Beijing, China
Email: 3202400188@aufe.edu.cn, *dongdansherry@163.com, xuxiangyun_ecnu@sina.com

How to cite this paper: Wang, Q., Jiao, D. D., & Xu, X. Y. (2026). How Does the Trade Policy Uncertainty of the United States Affect the Prices of Crude Oil in Futures Markets? *Journal of Financial Risk Management, 15,* 275-298.
https://doi.org/10.4236/jfrm.2026.153016

Received: August 29, 2026
Accepted: September 18, 2026
Published: September 21, 2026

Abstract

Although the rise of trade policy uncertainty has become a hot topic in recent years, few studies explore whether and how the U.S. trade policy uncertainty affects the prices of commodities in futures markets. This paper aims to fill the gap theoretically and empirically. By extending the crude oil's pricing model of Knittel and Pindyck (2016) and employing the Structural Vector Autoregression (SVAR) model, we demonstrate that the impacts of trade policy uncertainty shocks are insignificant before Donald Trump was elected as president of United States for first time but negatively significant since then and for the full sample, echoing the facts that the trade policy uncertainty began to increase and attracted the attention of market participants after 2016M11. In addition, our arguments are also applicable to other "pro-cyclical" commodities such as copper, gasoline oil and soybean. Our findings hold important implications for participants in commodity markets.

Keywords

Trade Policy Uncertainty, Crude Oil, Structural VAR Model

1. Introduction

The Sino-U.S. trade war initiated by the Trump administration in 2017 has led to a sharp rise in trade policy uncertainty (abbreviated as TPU) of U.S. and then triggered the rise of TPU in other countries such as China and Japan. Although such uncertainty remained relatively stable during the Biden administration, it escalated again after Trump was re-elected president of the United States (see Figure 1) and he imposed the so-called "reciprocal tariff" on the imports from almost all countries. The surge of TPU not only loomed the perspective of global economy, distorted the international trade and global supply chain, but also had tremendous impact on financial markets including commodity markets. The return of U.S. protectionism reignited the research on the impacts of TPU as well as Sino-U.S. trade war on trade flows (Feng et al., 2017; Benguria et al., 2022), global supply chain (Freund et al., 2024), import prices and welfare (Amiti et al., 2019; Fajgelbaum et al., 2020), investment and innovation (Caldara et al., 2020; Benguria et al., 2022; Zhang et al., 2025) and global financial markets (Egger & Zhu, 2020; Carlomagno & Albagli, 2022). However, relatively few studies explore the impact of the TPU shock on the movement of commodity's prices, except for Sun et al. (2021), who show both positive and negative effects of TPU of U.S. to agricultural commodity prices. Therefore, this paper attempts to fill the gap and investigates whether and how such kind of policy uncertainty affects the prices of commodities, by taking the crude oil as an example.

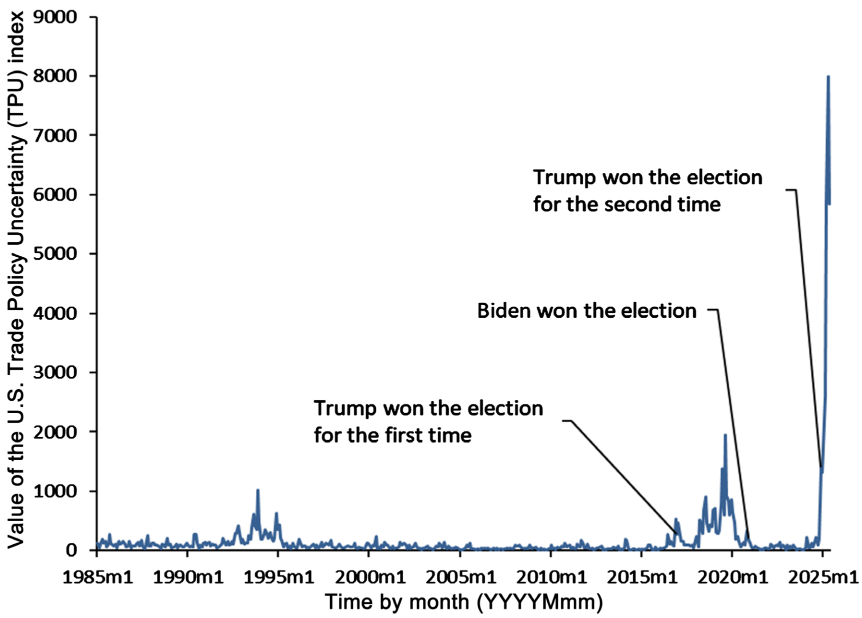

Figure 1. The evolution of the TPU index of USA. Note: The TPU index of US is constructed by Baker, Bloom and Davis, please see the website (http://www.policyuncertainty.com/) for more information.

Specifically, we build a theoretical model to demonstrate the specific channels through which TPU can have an impact on oil's prices at first. By augmenting the model of Knittel and Pindyck (2016), we decompose the return of crude oil in futures market and verify that TPU shocks can drive the prices of oil through six channels, including global demand, supply, speculation, risk-free interest rate, risk premium, and other channels, thus providing solid foundation for the empirical analysis.

Then, we employ the classical Structural Vector Autoregression (SVAR) model to estimate the impacts of TPU shocks. The short-run identification strategy of restrictions in SVAR model is based on Kilian (2009) and Kilian and Zhou (2022). Our empirical results show that: 1) A rise in the TPU index indeed decreases the prices of crude oil overall, but such impact is not contemporaneous and persists over several months; 2) The role of TPU shocks is muted before 2016M11, when Donald Trump won the presidency election for the first time, and became significantly negative since then; 3) the effects of TPU shocks on crude oil prices mainly through global demand channel, though the supply channel and speculation channel also take effect during the post-2016M11 period; 4) The impacts of TPU shocks on prices of other commodities such as copper, gasoline oil and soybean are similar to crude oil, therefore our points are also suitable for other "pro-cyclical" commodities.

Our contribution is twofold. First, we offer new insights into the role of TPU on the prices of commodities in futures market. While it is straightforward that the rise of TPU would hamper the global demand for pro-cyclical commodities including crude oil in long or middle-term, but such idea is incomplete, as in an era of financialization of commodities, the price of crude oil is also affected by other factors such as the risk aversion of investors, change of speculation or inventory demand, the adjustment of crude oil's supply, all of which are also intertwined with the shock of TPU. Though the effects of TPU or trade tensions (including U.S.-China trade war) on global financial markets (including FX, stock, bond markets) have been investigated recently (Burggraf et al., 2020; Egger & Zhu, 2020; Carlomagno & Albagli, 2022), more effort is still necessary to investigate such effect on commodity markets theoretically and empirically. To the best of our knowledge, the paper is the first to do so. In addition, we highlight the different responses of crude oil's price to a positive TPU shock before and after 2016M11, therefore can provide more implications for participants in commodity markets.

Second, we construct a theoretical framework to demonstrate the exact channels through which a TPU shock can impact crude oil's prices. Our framework synthesizes the key factors into the decomposition of commodity returns in futures markets, not only providing a solid theoretical foundation for empirical analysis in this paper, which is also suitable for analyzing the impacts of other types of shocks to the movements of commodity's prices. We believe our theoretical model also echoes the voluminous empirical studies in related literature (Kilian, 2009; Kilian & Zhou, 2022; Baumeister & Hamilton, 2019). Especially, we incorporate the risk premium into our theoretical model, thus can help to bridge the two parallel strands of literature: one focuses on the role of risk premium or risk appetite (Bessembinder, 1992; Bessembinder & Lemmon, 2002; Bianchi, 2021) and another focuses on the traditional demand-supply-inventory (or speculation) framework.

The remainder of this paper is organized as follows: Section 2 introduces the theoretical model. In Section 3, we describe the variables, data, and specifications for empirical model. Section 4 presents the empirical results and comparison analysis, and Section 5 shows the robustness tests. Finally, Section 6 draws conclusions and provides the limitations of this study.

2. Theoretical Framework

2.1. The *K-P* Model

Suppose in the market of crude oil, given the spot price (P_t) at time t and the futures price ($F_{t,T}$) for delivery at $t+T$, Let $\psi_{t,T}$ denote the (capitalized) flow of marginal convenience yield from holding a unit of inventory. Assume that an investor shorts at time t, and at time $t+T$ will obtain $\psi_{t,T}+F_{t,T}-P_t-\kappa_{t,T}$, which means that the return from holding one unit of inventory during this period equals convenience yield plus the capital gain and minus physical storage cost ($\kappa_{t,T}$). If the investor sells the inventory, the return would be $r_{t,T}P_t$, $r_{t,T}$ is the compounded risk-free rate from t to $t+T$. Therefore, to avoid arbitrage opportunities, there must be:

$$\psi_{t,T}-\kappa_{t,T}=\left(1+r_{t,T}\right)P_t-F_{t,T} \tag{1}$$

According to present value model of rational commodity pricing by Pindyck (1993), P_t equals the discount value of present payoff (marginal convenience yield net of storage costs, $\psi_{t,T}-\kappa_{t,T}$) and the expected value of future's price (E_tP_{t+T}), which means that:

$$P_t=\frac{1}{1+\mu_{t,T}}\left(\psi_{t,T}-\kappa_{t,T}+E_tP_{t+T}\right) \tag{2}$$

where $\mu_{t,T}=r_{t,T}+\rho_{t,T}$ is the commodity-specific discount rate, $\rho_{t,T}$ is a risk premium which accounts for the systematic risk in its price. Substituting Equation (2) into Equation (1), then we get:

$$F_{t,T}=E_tP_{t+T}+\left(r_{t,T}-\rho_{t,T}\right)P_t \tag{3}$$

E_tP_{t+T} can deviate from this equilibrium $E_t\overline{P}_{t+T}$ as speculators bet on higher (or lower) future spot prices, $s_{t,T}$ is a shifter that accounts for deviations due to speculation.

$$E_tP_{t+T}=E_t\overline{P}_{t+T}+s_{t,T} \tag{4}$$

According to the explanations of Knittel and Pindyck (2016), expected future spot price under rational expectation reflects the value of expected fundamentals. Therefore, we assume that the future equilibrium spot price is only related to supply and demand factors,

$$E_t\overline{P}_{t+T}=E_tg\left(z_{1,t+T},z_{2,t+T}\right) \tag{5}$$

$z_{1,t+T}$ and $z_{2,t+T}$ are the fundamental factors which can affect the demand and supply during $\left[t,t+T\right]$, $z_{1,t}$ includes the demand for downstream products of commodities, technological changes, and other random shocks, $z_{2,t}$ includes a set of variables such as production cost, total supply capacity (the development of new oil field or mine, and new alternative resources) and random shocks.

According to Jensen's Inequality, $f\left(E\left(X\right)\right) \neq E\left(f\left(X\right)\right)$, the difference between two functions is Jensen Gap. However, according to Gao et al. (2019), the Jensen gap would be small enough for the application and is often written off as approximation error. Therefore,

$$E_t \overline{P}_{t+T} \approx g\left(E_t z_{1,t+T}, E_t z_{2,t+T}\right) \tag{6}$$

Substituting Equations (4) and (6) into Equation (3), then:

$$F_{t,T} = g\left(E_t z_{1,t+T}, E_t z_{2,t+T}\right) + s_{t,T} + \left(r_{t,T} - \rho_{t,T}\right) P_t \tag{7}$$

Equation (7) means that commodity futures prices depend on expectations of future equilibrium spot prices, the degree of speculation, risk-adjusted rate of return from holding the commodity.

2.2. The Decomposition of Commodity Returns in Futures Markets

Based on Equation (7), we can derive:

$$\begin{aligned} \Delta F_{t+1,T} &= \left(E_{t+1} - E_t\right)\overline{P}_{t+T} + \Delta s_{t+1,T} + \left(r_{t+1,T} - \rho_{t+1,T}\right)P_{t+1} - \left(r_{t,T} - \rho_{t,T}\right)P_t \\ &= \left(E_{t+1} - E_t\right)\overline{P}_{t+T} + \Delta s_{t+1,T} + \left(\Delta r_{t+1,T} - \Delta\rho_{t+1,T}\right)P_t \\ &\quad + \left(r_{t,T} - \rho_{t,T}\right)\Delta P_{t+1} + \left(\Delta r_{t+1,T} - \Delta\rho_{t+1,T}\right)\Delta P_{t+1} \end{aligned} \tag{8}$$

As $\left(\Delta r_{t+1,T} - \Delta\rho_{t+1,T}\right)\Delta P_{t+1} \approx 0$, according to Campbell and Shiller (1988), the change in the log of P_t is approximately equal to the proportional change in the level, therefore:

$$\begin{aligned} \Delta Ln\left(F_{t+1,T}\right) &\approx \frac{\Delta F_{t+1,T}}{F_{t,T}} = \frac{\Delta F_{t+1,T}}{P_t}\frac{P_t}{F_{t,T}} \\ &\approx \frac{1}{1-basis_t}\left[\left(E_{t+1} - E_t\right)\frac{\overline{P}_{t+T}}{P_t} + \frac{\Delta s_{t+1,T}}{P_t} \right. \\ &\quad \left. + \left(r_{t,T} - \rho_{t,T}\right)\frac{\Delta P_{t+1}}{P_t} + \left(\Delta r_{t+1,T} - \Delta\rho_{t+1,T}\right)\right] \end{aligned} \tag{9}$$

where the futures basis is $basis_t = \frac{P_t - F_{t,T}}{P_t}$, it is generally determined by convenience yield, the risk-free rate, and so on (Acharya et al., 2013). We assume $g\left(z_{1,t+T}, z_{2,t+T}\right)$ is a linear function $E_t g\left(z_{1,t+T}, z_{2,t+T}\right) = g\left(E_t z_{1,t+T}, E_t z_{2,t+T}\right)$, and referring the approach of Engel and West (2005) and Coibion and Gorodnichenko (2015), we assume that both the changes of demand factor and supply factor ($\Delta z_{1,t}$ and $\Delta z_{2,t}$) follow AR(1) process, that is:

$$\Delta z_{1,t+1} = \varphi\Delta z_{1,t} + \xi_{t+1,T}, \Delta z_{2,t+1} = \omega\Delta z_{2,t} + \nu_{t+1,T} \tag{10}$$

$\xi_{t+1,T}$ and $\nu_{t+1,T}$ follows a normal distribution with a mean of zero. According to Equation (6), we have:

$$\begin{aligned} \left(E_{t+1} - E_t\right)\overline{P}_{t+T} &= g\left\{\left(E_{t+1} - E_t\right)\left(z_{1,t} + \sum_{j=1}^{T}\Delta z_{1,t+j}\right), \left(E_{t+1} - E_t\right)\left(z_{2,t} + \sum_{j=1}^{T}\Delta z_{2,t+j}\right)\right\} \\ &= g\left\{\frac{\varphi - \varphi^T}{1-\varphi}\xi_{t+1,T}, \frac{\omega - \omega^T}{1-\omega}\nu_{t+1,T}\right\} \end{aligned} \tag{11}$$

Equation (11) implies that changes in the expectation of future equilibrium prices depend on the contemporaneous demand and supply shocks.

Knittel and Pindyck (2016) prove that under two assumptions: 1) the supply of commodity includes imports and domestic production is indistinguishable; 2) the supply and demand functions are isoelastic, if writing supply as $X = k_S P_t^{\eta_S}$ and demand as $Q = k_D P_t^{\eta_D}$, the change rate or return of spot price can be written as:

$$\Delta \ln P_{t+1} = \frac{1}{\eta_S - \eta_D}\left(\Delta \ln k_D - \Delta \ln k_S\right) + \frac{1}{\eta_S - \eta_D}\Delta \ln \frac{X_{t+1}}{Q_{t+1}} \tag{12}$$

Any change in market fundamentals is reflected in a change in k_D and k_S, implying that the first term of Equation (12) is determined by fundamentals shocks such as $\xi_{t+1,T}$ and $\nu_{t+1,T}$. The second term is the speculative component of price changes ($\Delta \ln P_{t+1}^S$) and is related to the change of inventories ($\Delta N_{t+1} = X_{t+1} - Q_{t+1}$). As speculative activity that increases spot prices requires a build-up of inventories, and there is a positive link between speculation and inventories changes[1], which means that $s_{t+1,T} = \lambda \ln\left(1 + \frac{\Delta N_{t+1}}{Q_{t+1}}\right)$. So, the second term ($\Delta \ln P_{t+1}^S$) is also positively correlated with the change of speculation ($\Delta s_{t+1,T}$). For simplicity, we assume there is a linear relationship between $\Delta \ln P_{t+1}^S$ and $\Delta s_{t+1,T}$, then:

$$\frac{\Delta P_{t+1}}{P_t} \approx \Delta \ln P_{t+1} = h\left(\xi_{t+1,T}, \nu_{t+1,T}\right) + \alpha + \beta \Delta s_{t+1,T} + \upsilon_{t+1,T} \tag{13}$$

β has a positive value[2], $\upsilon_{t+1,T}$ represents other random shocks. Substituting Equations (11) and (13) into Equation (9) gives:

$$\Delta Ln(F_{t+1,T}) \approx \frac{1}{1-basis_t}\left\{ \underbrace{\frac{1}{P_t} g\left\{\frac{\varphi - \varphi^T}{1-\varphi}\xi_{t+1,T}, \frac{\omega - \omega^T}{1-\omega}\nu_{t+1,T}\right\} + \frac{r_{t,T} - \rho_{t,T}}{P_t} h\left\{\xi_{t+1,T}, \nu_{t+1,T}\right\}}_{\text{Demand and Supply Shock}} \right.$$
$$\left. + \underbrace{\frac{1+\beta\left(r_{t,T} - \rho_{t,T}\right)}{P_t}\Delta s_{t+1,T}}_{\text{Speculation Shock}} + \left(\underbrace{\Delta r_{t+1,T}}_{\substack{\text{Risk-free Rate} \\ \text{Shock}}} - \underbrace{\Delta \rho_{t+1,T}}_{\substack{\text{Risk Premium} \\ \text{Shock}}} \right) + \underbrace{\upsilon_{t+1,T}}_{\text{Other Shock}} \right\} \tag{14}$$

2.3. Introducing the Shocks of TPU

Suppose there is a positive TPU shock ($Tpus_{t+1}$) at time $t+1$, since financial markets (including futures markets) respond quickly to the news (including TPU

[1]Some theoretical models about the speculation in commodity futures markets (Acharya et al., 2013; Li, 2018) also point out that the net long position of speculators (or net short position of hedgers) is positively correlated with inventory levels.

[2]Although different scholars have estimated different supply and demand elasticities (Kilian & Murphy, 2012; Knittel & Pindyck, 2016; Baumeister & Hamilton, 2019), there is a consensus that the supply elasticity is positive while the demand elasticity is negative, as suggested by Knittel and Pindyck (2016) who believe that the supply and demand elasticities of crude oil are 0.1 and −0.1, respectively.

shocks), and although there are changes in contract maturities in the futures market, market participants can maintain continuity of contracts through the switch of the main contracts. Therefore, participants, under new information conditions, still form expectations for the equilibrium spot price on day $t+T$. Differentiating Equation (14) with respect to $Tpus_{t+1}$, we obtain:

$$\frac{\partial \Delta Ln\left(F_{t+1,T}\right)}{\partial Tpus_{t+1}} \approx \frac{1}{1-basis_t}\left\{\underbrace{A\frac{\partial \xi_{t+1,T}}{\partial Tpus_{t+1}}}_{\substack{\text{Global Demand}\\ \text{Shock Channel}}}+\underbrace{B\frac{\partial \nu_{t+1,T}}{\partial Tpus_{t+1}}}_{\substack{\text{Supply Shock}\\ \text{Channel}}}+\underbrace{C\frac{\partial \Delta s_{t+1,T}}{\partial Tpus_{t+1}}}_{\substack{\text{Speculation or Inventory}\\ \text{Demand Shock Channel}}} + \left(\underbrace{\frac{\partial \Delta r_{t+1,T}}{\partial Tpus_{t+1}}}_{\substack{\text{Risk-free Rate}\\ \text{Shock Channel}}}-\underbrace{\frac{\partial \Delta \rho_{t+1,T}}{\partial Tpus_{t+1}}}_{\substack{\text{Risk Premium}\\ \text{Shock Channel}}}\right)+\underbrace{\frac{\partial \upsilon_{t+1,T}}{\partial Tpus_{t+1}}}_{\substack{\text{Other Shock}\\ \text{Channel}}}\right\} \tag{15}$$

where A, B and C are determined by the various variables of period t including P_t, $r_{t,T}$, $\rho_{t,T}$ and the parameters φ, ω, which are known in period $t+1$. Equation (15) shows that the impact of a TPU shock on the return of crude oil in futures markets can be transmitted through the following channels of shock: global demand, supply, speculation or inventory demand, risk-free interest rate, risk premium, and the other.

3. Structural VAR Model: Specification and Identification

3.1. Model Specification

Following Kilian (2009) and Kilian and Zhou (2022), we employ the SVAR model to assess the impacts of TPU shocks of U.S. on crude oil prices in futures markets, and our baseline model is specified as follows:

$$A_0 y_t = \alpha + \sum_{j=1}^{P} A_j y_{t-j} + \varepsilon_t \tag{16}$$

where ε_t represents a vector of serially uncorrelated errors. The reduced form error e_t can be decomposed as $e_t = A_0^{-1}\varepsilon_t$. Based on the theoretical model in Section 2, we select appropriate proxy variables to proxy different types of shocks. Exactly, we set:

$$y_t = \left[LnTPU_t, LnVIX_t, \Delta LnPRD_t, grea_t, Lncrdoil_t, \Delta N_t, rr_t\right]^{\mathrm{T}} \tag{17}$$[3]

$LnTPU_t$ is the logarithm of TPU index of U.S., we use the index constructed by Baker, Bloom and Davis as the proxy indicator for empirical analysis. Such

[3]It should be noted that the variables in the SVAR model are in levels instead of difference, as estimating a VAR model in levels is robust to co-integration of unknown form and could alleviate the model misspecification problem (Hamilton, 1994; Ma & Zhang, 2022). In addition, we can obtain long-term information based on the level variables rather than the first-difference variables (Chen et al., 2016). In recent years, it has become the standard practice in macroeconomic and financial research to estimate the VAR or SVAR model.

index reflects the frequency of articles in mainstream U.S. newspapers that discuss policy-related economic uncertainty and also contain one or more references to trade policy such as import tariffs, import duty, import barrier, government subsidies and so on (Baker et al., 2016). The data of TPU index of U.S. comes from the website (http://www.policyuncertainty.com/).

We utilize $LnVIX_t$ which equals the logarithm of CBOE Implied Volatility Index to proxy the risk premium, as such index is widely used to reflect market sentiment in U.S. and world financial markets. Many scholars, such as Robe and Wallen (2016) show that the option implied volatilities of crude oil are driven in part by the VIX, meanwhile Adrian and Shin (2010) document that VIX index is a good proxy for broker-dealers' risk-bearing capacity in futures markets. Li (2018) also finds that the implied risk premiums with constant market risk aversion in crude oil markets are highly correlated to VIX index. $\Delta LnPRD_t$ equals the growth of global crude oil production and we use it to proxy supply factor of crude oil, and the data is sourced from the U.S. Energy Information Administration. $grea_t$ is the index of global real economic activity which is constructed by Lutz Kilian, and is widely used to capture the shifts in the global demand of industrial commodities or energy[4]. ΔN_t is the change of inventories of crude oil and used to reflect the speculation or inventory demand for oil (Kilian & Murphy, 2012; Kilian & Zhou, 2022), the data of inventory (N_t) is constructed following the method of Kilian and Murphy (2012) and the original data comes from U.S. Energy Information Administration[5]. $Lncrdoil_t$ represents the logarithm of crude oil's real prices. The real prices are obtained by deflating the NYMEX WTI futures prices with the CPI index of U.S., and the data of CPI index and crude oil futures prices come from the FRED database and WIND Info, respectively. rr_t is the real risk-free rate, we use the U.S. 1-Year Real Interest Rate to proxy it, and the data is sourced from the FRED database. Similar to Kilian and Zhou (2022), we seasonally adjust the proxy variables for supply, global demand, real prices and inventory demand. The choice of lag p is based on the AIC criterion.

Though the data of TPU index of U.S. can originate from 1985M1, the data for VIX index only can be obtained since 1990M1, and data on global crude oil production are available only through 2025M2. Therefore, our sample covers from 1990M1-2025M2.

3.2. Identifying Restrictions

Following the method of Chen et al. (2016) and Benk and Gilman (2023), the identifying restrictions on A_0^{-1} include the short-run identification assumptions

[4]The data comes from the website (https://www.dallasfed.org/research/igrea).

[5]Although in theoretical model, we prove that it should be $\ln X_t - \ln Q_t = \ln\left(1 + \frac{\Delta N_t}{Q_t}\right)$ while not ΔN_t which is directly linked with the speculation demand of crude oil, however as $\ln X_t - \ln Q_t$ is a monotonically increasing function of ΔN_t, and ΔN_t is widely utilized in literature, therefore we still use ΔN_t in order to align with previous studies.

set forth by Kilian (2009) and Kilian and Murphy (2012). Exactly, our short-run identification restrictions are based on the following assumptions.

1) TPU shocks are assumed to be exogenous and do not respond to any other innovations within the same month.

2) Risk premium shocks are influenced by the TPU shocks contemporaneously. A rise in TPU index, particularly the intensification of Sino-U.S. trade war, can trigger investors' concerns about the deterioration of global economic outlook (Fajgelbaum & Khandelwal, 2022) and cause the increment in risk aversion of investors (Carlomagno & Albagli, 2022).

3) Supply shocks are assumed to react to global demand and inventory demand shocks, or unpredicted changes (other shocks) in oil prices only with a lag, which is a plausible assumption given the time and cost needed to adjust the production capacities (Kilian, 2009; Benk & Gilman, 2023), but supply shocks can have contemporaneous impact on real prices and global demand of crude oil (Kilian & Zhou, 2022).

4) Speculation or inventory demand shocks respond to all shocks except for other shocks of oil's prices within same month. Such identification is not only consistent with the classical setting on the relationship among the variables in crude oil's market (Kilian & Murphy, 2012; Baumeister & Hamilton, 2019), but also with the existing literature which highlights that speculation on futures market is determined by some specific factors, such as hedging pressure or hedging demand related to inventory levels (Bessembinder, 1992; De Roon et al., 2000) which is further related to demand and supply factors, risk preference of speculators and producers in futures markets (Acharya et al., 2013; Etula, 2013; Li, 2018), but changes in futures prices in previous period (Sanders & Irwin, 2011; Cheng & Xiong, 2014).

5) Risk-free rate shocks are influenced by shocks of TPU, risk premium, as well as the shocks in crude oil market within same month. An increment in market panic can lead to a decrease in global risk-free interest rates (Fernandez-Perez et al., 2020). Additionally, Kilian and Zhou (2022) find that changes in crude oil prices caused by shocks in the crude oil market can lead to a decline in real interest rates of U.S. in short term.

Based on previous analysis, the identifying restrictions on the elements of A_0^{-1} are summarized in expression (18):

$$e_t = \begin{bmatrix} e_t^{tpu} \\ e_t^{vix} \\ e_t^{prd} \\ e_t^{wip} \\ e_t^{p} \\ e_t^{inv} \\ e_t^{realrate} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 & 0 & 0 \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & 0 & 0 \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} & 0 \\ a_{71} & a_{72} & a_{73} & a_{74} & a_{75} & a_{76} & a_{77} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{tpushock} \\ \varepsilon_t^{riskpremium} \\ \varepsilon_t^{aggsupply} \\ \varepsilon_t^{aggdemand} \\ \varepsilon_t^{othershock} \\ \varepsilon_t^{speculationdemand} \\ \varepsilon_t^{riskfreerate} \end{bmatrix} \tag{18}$$

where element 0 in the matrix denotes that there are no expected contemporaneous responses from specific shocks; the nonzero elements a_{ij} are the coefficients of the i 's responses to the shocks j.

Accordingly, causal interpretations are conditional on the recursive ordering.

4. Empirical Results and Comparison Analysis

4.1. Baseline Results

According to the AIC criterion, we set the lag p to be 3, and the orthogonal impulse response functions (abbreviated as IRFs) of crude oil's prices to one standard deviation of TPU shocks for the full sample are presented in the first subplot of Figure 2. It can be found that the prices of crude oil decrease about 8 months later after a positive TPU shock, and such effect can last for long time, with the peak at 14 months later, indicating that the rise of TPU index of U.S. indeed has a negative impact on crude oil markets, but such impact is not significant immediately.

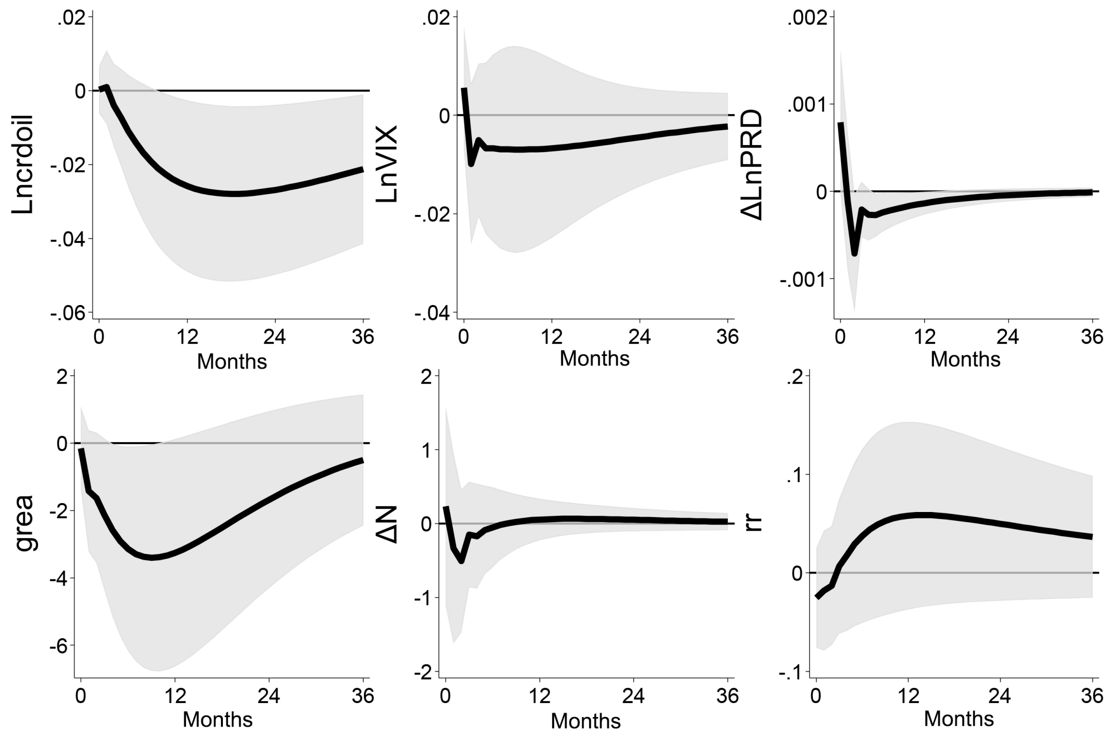

Figure 2. IRFs of crude oil's prices and other variables to a one-standard-deviation TPU shock. Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

The IRFs of other variables to a positive TPU shock are also shown in Figure 2. Obviously, the IRFs are significantly negative for $grea_t$, we argue that such result is consistent with our expectation and existing literature. For example, many scholars and market analysts have proved that the uncertainties in U.S.' trade policy cannot only slow down the aggregate or corporate investment of U.S. or related countries (such as China) gradually (Caldara et al., 2020; Benguria et al., 2022), but also depress the global international trade (Feng et al., 2017; Fajgelbaum &

Khandelwal, 2022) and may bring the world into economic recession (Mao & Gorg, 2020). However, the responses of other variables except for $grea_t$ to a TPU shock are insignificant, indicating that the TPU shocks mainly exert impact on crude oil prices through the channel of global demand shock, and the impact of other channels is subtle. Especially, we don't find a positive TPU shock can induce the rise of VIX index, the result is somewhat different with some studies on the impact of China-US trade frictions. For example, Burggraf et al. (2020) find that negative tweets by Trump about trade frictions have a significant negative impact on both the S & P 500 index and VIX index, and similarly, Carlomagno and Albagli (2022) demonstrate that typical negative news on trade frictions significantly raise investor's risk aversion by concerns about the deteriorating global economic outlook. We argue that as TPU index is constructed by the frequency of related articles in leading U.S. newspapers, though a typical trade friction event will trigger the increment of TPU index, the related reports or news may disappear quickly after the event if the subsequent tariff or trade constraints was implemented. In contrast, an ongoing trade negotiation between U.S. and China or other countries and even a tweet of Donald Trump with vague expression on trade policy may trigger some reports or news in newspaper. Therefore, the rise of TPU is not necessarily related to the deterioration of market sentiments.

The IRFs of crude oil's price to one-standard deviation shocks of other variables are presented in **Figure 3**. The rise of VIX index leads to the decline in oil's prices, indicating crude oil is viewed as a risky asset. A positive supply shock will bring down the oil price, while a rise in global demand will drive up the prices, such results are consistent with classical studies on the role of different factors in movement of crude oil's prices (Kilian & Murphy, 2012; Baumeister & Hamilton, 2019; Kilian & Zhou, 2022). But the change of inventories fails to move the prices of crude oil, we argue that: 1) though Kilian and Lee (2014) find evidence of speculation driving up the real prices in the physical market for crude oil, but also find evidence that speculation may lower the real prices during different episodes; 2) the measure of world inventories contains a lot of error (Baumeister & Hamilton, 2019). In addition, the response to a risk-free rate shock is insignificant, which is also consistent with Kilian and Vega (2011), who find that energy prices are predetermined with respect to monetary policy as macroeconomic news tends not to affect energy prices immediately.

4.2. Comparison between Two Periods

Since Donald Trump was elected as the president of U.S. in 2016M11, the world entered a period with high level of TPU, especially after he was re-elected as president at the end of 2024. Though the TPU of U.S. remained stable during Biden administration, the "U.S.-Sino trade war" continued after Joe Biden was inaugurated. Therefore, we split the whole sample into two subsamples: the period before 2016M11 (period 1) and period after 2016M11 (period 2), and investigate the distinction on the role of U.S.' TPU.

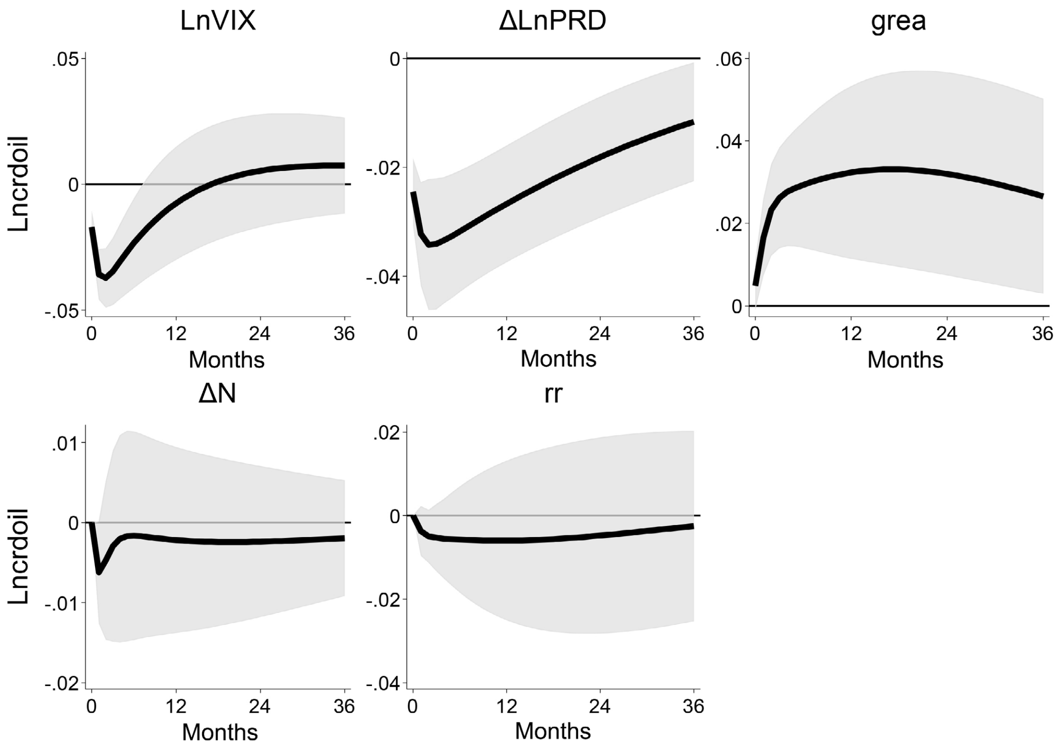

Figure 3. IRFs of crude oil's prices to one-standard-deviation shocks in the SVAR model. Note: the solid-dotted lines represent the estimated impulse responses to the corresponding shock. The gray area shows pointwise 10th - 90th percentile bands.

The split at 2016M11 is event-based rather than a formal structural-break test, and estimates for the shorter post-2016 subsample should therefore be interpreted cautiously.

The empirical results for two periods are shown in Figure 4. Obviously, the responses of all variables (including crude oil's prices) to a TPU shock are insignificant before 2016M11, indicating the role of TPU shocks in period 1 had little effect on crude oil's market. While the responses of real prices, supply, global demand and speculation proxies to a TPU shock are significant after 2016M11, especially, a rise in TPU index can depress the prices, supply growth and global demand of crude oil, and increase the change of inventories after a few months, though the responses of market sentiment and interest rate are still insignificant. The results are quite different with period 1, but live up to our expectation. Indeed, the protectionism and inconstancy of U.S.' trade policy since the first win of presidency election for Donald Trump, global trade tensions and possible economic recession had become a hot topic of news report and attracted the attention of world, therefore empowering the role of TPU shocks for commodity markets. As the global demand decreased gradually after the positive TPU shocks, the supply and inventories of crude oil also adjusted correspondingly. Another explanation for the initial insignificant response of crude oil prices may lie in that: exporters attempt to avoid possible tariff increases in future by exporting to U.S. in advance, as the import tariff rates of U.S. have indeed increased after the hike of TPU index.

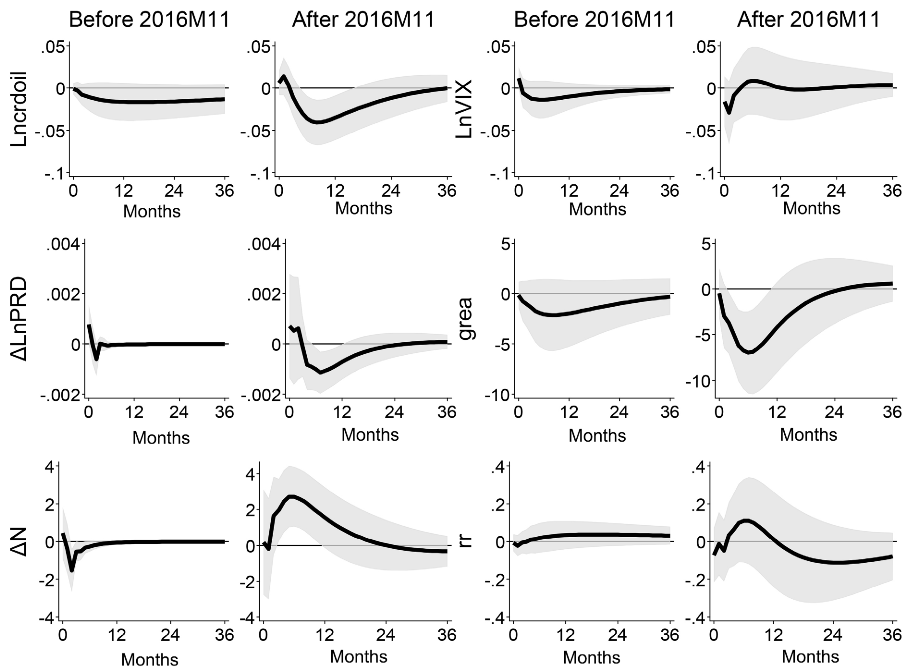

Figure 4. IRFs of crude oil's prices and other variables to a one-standard-deviation TPU shock for two periods. Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

To compare the contributions of TPU shocks to the prices fluctuations in two periods, we decompose price variances of crude oil into seven components using a variance decomposition approach, and the results for TPU shocks are shown in Table 1[6]. Noticeably, the contributions of TPU shocks are tiny in period 1, but such contributions soared in period 2, indicating that TPU shocks have an important role on oil prices' fluctuations since the first election of Donald Trump as president, and the results are consistent with the fact that the uncertainty in trade policy became an important factor for the world economy and the turbulence of global financial markets.

Table 1. Contributions of U.S. TPU shocks to the oil price fluctuations.

Month	6	12	18	24	30	36
Before 2016M11	0.02%	0.06%	0.09%	0.10%	0.11%	0.11%
After 2016M11	3.55%	14.10%	20.20%	21.20%	20.80%	20.50%

Note: The contributions to the oil price fluctuations are at the horizon of 36 months and the variance decomposition results already reach a stable state in month 36.

4.3. Comparison with the Results Using the TPU Index of Caldara et al. (2020)

Caldara et al. (2020) also construct an aggregate TPU index of U.S. based on text searches of the electronic archives of seven newspapers since 1960M1, exactly, the

[6]In order to save space, we only show the contributions of TPU shocks in paper, and we can provide the complete results upon request.

aggregate measure represents the monthly share of articles discussing trade policy uncertainty[7]. Compared to the index of Baker et al. (2016), the search terms used by Caldara et al. (2020) differ slightly, as they do not explicitly search for mentions of legislation or institutions, therefore, the volatility of their TPU index is less during the negotiation of NAFTA but is larger in period 2. We utilize the logarithm of aggregate TPU index of Caldara et al. (2020) as proxy for the TPU of U.S., and re-estimate the SVAR model with same identifications, and present the empirical results in **Figure 5**.

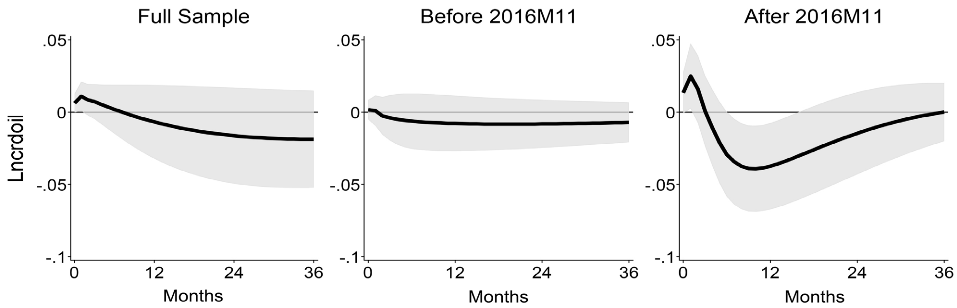

Figure 5. IRFs of crude oil's prices to a one-standard-deviation TPU shock using the index of Caldara et al. (2020). Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

The results confirm that the effects of TPU shocks are significant in period 2 but insignificant in period 1, further proving that the uncertainties associated with U.S.' trade policy can be reflected in the movement of crude oil prices only after 2016M11. Interestingly, the response of crude oil prices is insignificant for the whole sample, we argue that as two indicators are constructed by searching slightly different terms from somewhat different newspapers sources, and the volatility of TPU index of Caldara et al. (2020) appears to be lower before 2016M11, resulting in different IRFs of crude oil prices for the full sample. For example, the correlation coefficient between the TPU index of Caldara et al. (2020) and Baker et al. (2016) is .627, .960 and .942 in period 1, period 2 and full sample, respectively.

4.4. Comparison with Other Commodities

We also investigate the responses of other commodities' prices to TPU shocks. Exactly, we replace the production growth, changes in inventories and real prices (in logarithm) of other commodities for crude oil in Equation (17), and keep other variables and identification restrictions unchanged. We select gold (COMEX), copper (COMEX), gasoline (NYMEX) and soybean (CBOT) for comparison, as these commodities are regarded as important commodities commonly and span from industrial metal, energy and agricultural products. We collect the data for global refined copper production (primary + recycled) from ICSG and the data for the production of soybean from WIND Info. As there is no data for the production of gasoline, we utilize the data of crude oil's production to replace it. The

[7]The data comes from the website (https://www.matteoiacoviello.com/tpu.htm).

data for global refined copper inventories is obtained from the International Copper Study Group (ICSG). We construct an estimate of gasoline inventories for OECD countries as the same method for global crude oil stocks in Kilian and Murphy (2012) and Baumeister and Hamilton (2019). The data for global soybean inventories is obtained from the U.S. Department of Agriculture (USDA). As the production of gold is limited comparing with the stocks, we ignore the production growth of gold in SVAR model, and keep the identifications restrictions unchanged for other variables. Similar to crude oil, we also seasonally adjust the proxy variables for supply, real prices and inventory demand of the selected commodities.

Figure 6 summarizes the empirical results for the selected commodities in three periods. The responses of gold's prices are negligible, indicating that as a safe-haven asset, the prices of gold are not affected significantly by the TPU shocks, one important reason is that the movement of TPU index exerts little impact on the risk appetite of investors. But the IRFs of prices of other three commodities are negatively significant in period 2, with a peak about 10 months later, while are insignificant in period 1 or full sample, such results are similar to **Figure 3**. As copper, gasoline oil and soybean are also regarded as pro-cyclical commodities[8] and a positive TPU shock can depress the global demand for these commodities in period 2, it is rational that the prices of these commodities tend to decrease after the rise of TPU index.

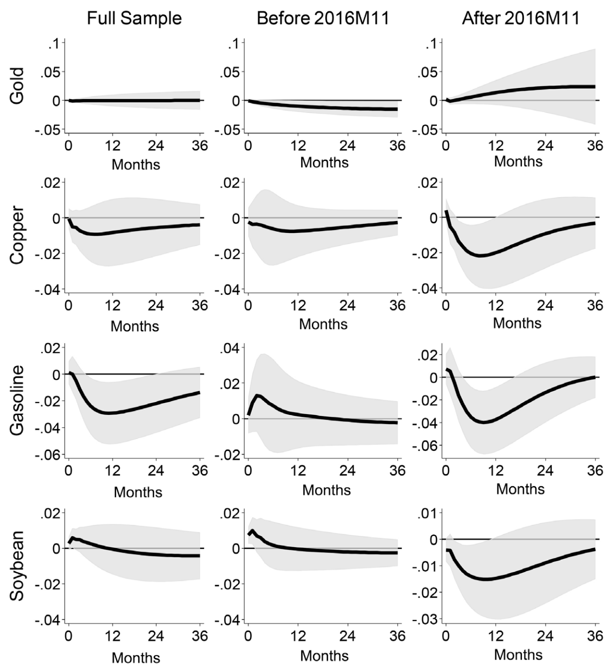

Figure 6. IRFs of selected commodities' prices to a one-standard-deviation TPU shock. Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

[8]We do find that the responses of the three commodities' prices to a global demand shock is significantly negative, we don't show the results for space limitation but it can be required upon request.

Similarly, we decompose the prices variances of the selected commodities into seven components, and Table 2 shows the results for the contributions of TPU shocks in two periods. Similar to Table 1, the contributions of TPU shocks increased considerably after 2016M11, especially for copper and gasoline. Our results further confirm that the uncertainty of trade policy originated by U.S. government indeed became more important for commodity markets since Donald Trump was elected as president of U.S. in November 2016.

Table 2. Contributions of TPU shocks to price fluctuations of four commodities.

Commodity and subsample		6	12	18	24	30	36
Gold	Before 2016M11	.26%	.40%	.49%	.56%	.61%	.66%
	After 2016M11	.51%	3.98%	8.53%	11.30%	12.10%	11.70%
Copper	Before 2016M11	.11%	.18%	.29%	.37%	.41%	.43%
	After 2016M11	6.19%	19.30%	25.30%	27.60%	28.50%	28.80%
Gasoline	Before 2016M11	1.38%	1.16%	1.00%	.90%	.85%	.84%
	After 2016M11	5.02%	21.50%	29.20%	31.00%	30.90%	30.70%
Soybean	Before 2016M11	1.47%	.94%	.86%	0.92%	1.00%	1.08%
	After 2016M11	8.49%	14.70%	13.70%	12.00%	10.90%	10.60%

Note: The contributions to the commodity price fluctuations are at the horizon of 36 months and the variance decomposition results already reach a stable state in month 36.

5. Robustness

5.1. Replacing the VIX Index with OVX Index

Though the VIX index is utilized in related literature as a reasonable proxy for market sentiment of investors or risk premium in global financial markets, it is originally constructed to reflect the implied volatility of U.S. stock markets. Therefore, we use the CBOE Crude Oil ETF Volatility Index (which is an estimate of the expected 30-day volatility of crude oil as priced by the United States Oil Fund) to proxy the risk premium in crude oil markets. The data comes from the FRED database (https://fred.stlouisfed.org/series/OVXCLS) and has only been available since 2007M5[9], so there will be some data loss to use the OVX index.

Replacing the VIX index with OVX index in Equation (17) and re-estimating the SVAR model, we get the results which are shown in Figure 7. It can be seen that the IRFs of crude oil's prices to a TPU shock for three periods are same as in Figure 2 and Figure 3, and the responses of OVX index to a TPU shock and the responses of crude oil prices to an OVX shock are also similar to the corresponding responses about VIX index. Therefore, our baseline results are robust after using the OVX index to proxy the risk premium in crude oil markets.

[9]The correlation between VIX index with OVX index is 0.75 in our sample.

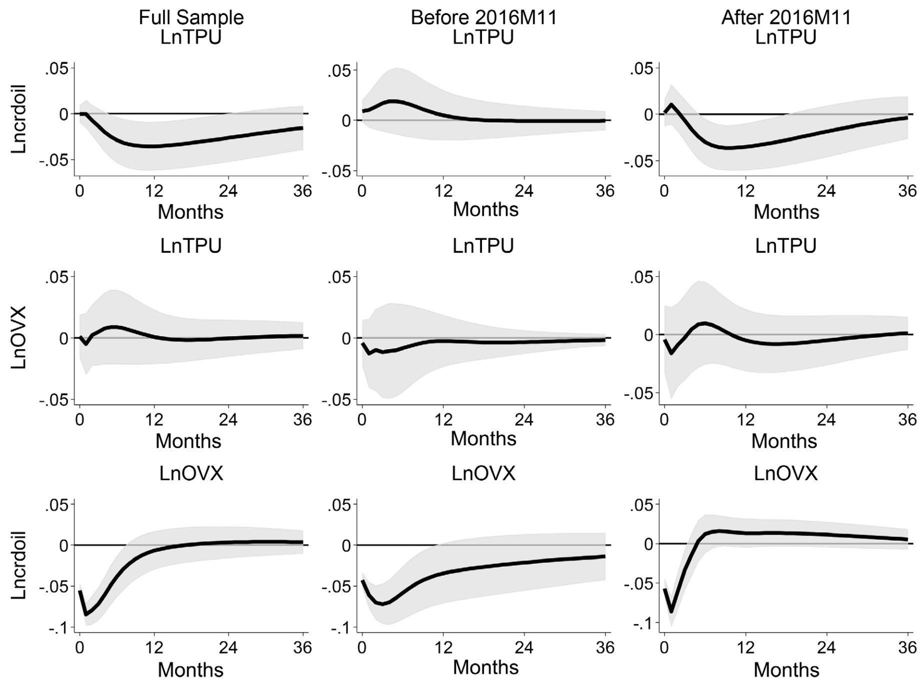

Figure 7. Selected impulse responses using the OVX index. Note: the solid-dotted lines represent the estimated impulse responses to the corresponding shock. The gray area shows pointwise 10th - 90th percentile bands.

5.2. Using Different Variables to Proxy Aggregate Demand and Inventories Demand

Global industrial output growth ($\Delta LnWIP_t$) is another commonly used indicator to reflect the global demand for crude oil (Baumeister & Hamilton, 2019; Benk & Gilman, 2023), so we re-estimate the baseline empirical model by replacing $grea_t$ with $\Delta LnWIP_t$ in Equation (17), and the data of global industrial output comes from the personal website of Professor Christiane Baumeister[10]. **Figure 8** indicates that the rise of TPU index has negative impact on the growth of global industrial output, with smaller impact in period 1, and the rise of global industrial output growth will push up the prices of crude oil, consistent with the conclusion of Baumeister and Hamilton (2019). The IRFs of crude oil prices to a TPU shock in three periods are also similar with **Figure 2** and **Figure 3**, so our results keep unchanged after using different indicators to proxy global demand factor.

Unlike Kilian and Murphy (2012), Baumeister and Hamilton (2019) utilize the change of inventories relative to production of previous month ($\Delta N_t / PRD_{t-1}$) to reflect the inventory demand in their empirical work. Therefore, we use $\Delta N_t / PRD_{t-1}$ to replace ΔN_t in Equation (17) as a robustness test[11]. We can find that the selected IRFs in **Figure 9** are highly similar to the corresponding IRFs in **Figure 2** and **Figure 3**, further indicating that our baseline results are robust.

[10] https://sites.google.com/site/cjsbaumeister/research

[11] We also construct a variable $\ln X_t - \ln Q_t$ to be the proxy for inventory demand, and the empirical results keep unchanged. We don't show the results for space limitation but it can be required upon request.

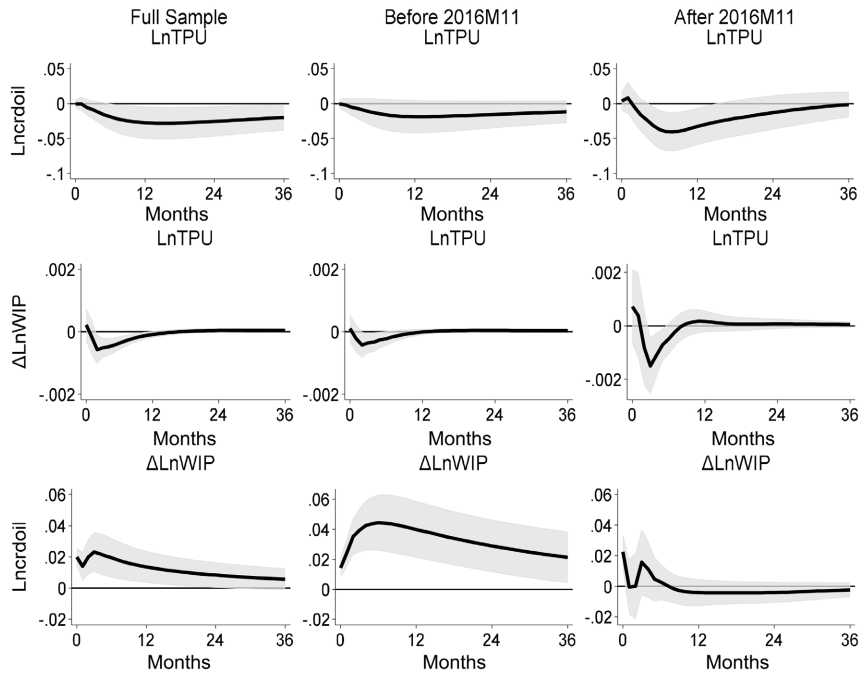

Figure 8. Selected IRFs after using $\Delta LnWIP_t$ to proxy global aggregate demand. Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

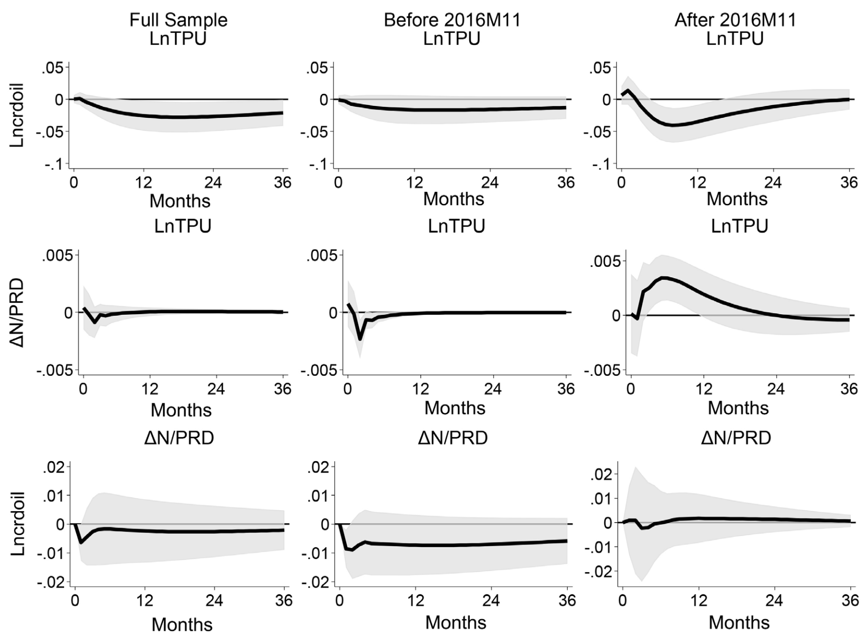

Figure 9. Selected IRFs after using $\Delta N_t / PRD_{t-1}$ to proxy inventories demand. Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

5.3. Taking the Exchange Rate of U.S. Dollar into the SVAR Model

The role of exchange rate of U.S. dollar in the commodity price movements is widely recognized in literature (Scrimgeour, 2015), according to Kilian and Zhou

(2022), because a depreciation of U.S. dollar makes it less expensive for other countries to import oil and can raise global activity and oil price, the denomination effect of currency in global commodity markets can be regarded as a type of demand factor for oil. As the increment of TPU index may affect the trade balance of U.S. and then the movement of exchange rate of U.S. dollar based on the classical theory of exchange rate determination, it is beneficial to analyzing what channels can TPU impact crude oil prices through further, by adding the exchange rate of U.S. dollar into our baseline SVAR model. Following the method of Kilian and Zhou (2022), we add the logarithm of the Real Broad Effective Exchange Rate of U.S.[12] ($LnREER_t$) into Equation (17), and order $LnREER_t$ in SVAR model after rr_t for two reasons: 1) Exchange rate shocks respond to interest rate (or monetary policy) shocks and risk premium shocks contemporaneously. The Obstfeld-Rogoff sticky-price model (Obstfeld & Rogoff, 1995) suggests that when there is exchange rate or price stickiness in the short term, an increase in interest rates will cause the currency to appreciate. Some studies prove that during the periods of global financial market turbulence, the U.S. dollar is preferred by investors as a safe-haven asset, leading to an appreciation of the U.S. dollar to most other currencies (Fratzscher, 2009; Cerutti et al., 2021); 2) Kilian and Zhou (2022) conjecture that innovations in the real price of oil may affect the U.S. real exchange rate contemporaneously, whereas exogenous shocks to the U.S. real exchange rate will not affect the real price of oil within the same month, but only with a delay.

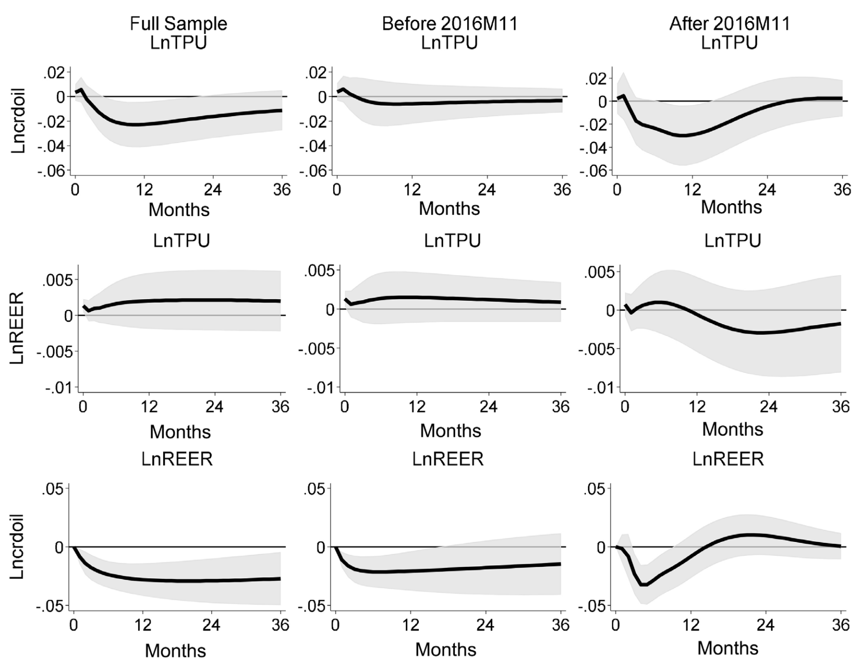

Figure 10. Selected IRFs after adding $LnREER_t$ into the SVAR model. Note: the solid-dotted lines represent the estimated impulse responses to the TPU shock. The gray area shows pointwise 10th - 90th percentile bands.

[12]The data comes from FRED database and the website is https://fred.stlouisfed.org/series/RBUSBIS.

It is clear that the responses of crude oil's prices to a TPU shock in three periods in **Figure 10** are similar with the corresponding results in **Figure 2** and **Figure 3**. In addition, consistent with Scrimgeour (2015) and Kilian and Zhou (2022), the appreciation of U.S. Dollar leads to the decrement of oil's prices, but the response of $LnREER_t$ to a TPU shock is always insignificant, one plausible explanation is that the uncertainty of trade policy has a limited effect on the trade balance of U.S. and investor's sentiment in financial markets.

6. Conclusions

The return of protectionism has become an important feature of the current global economy, and the uncertainty of trade policy is likely to remain high for some time, yet few studies focus on the impacts of TPU shocks on commodity markets, this paper aims to fill the gap. By extending the crude oil's pricing model of Knittel and Pindyck (2016) and employing the SVAR model, we show that the impacts of TPU shocks are insignificant before Donald Trump was elected as president of U.S. for first time but negatively significant since then and for the full sample, such results echo the fact that the TPU began to increase and attracted the attention of market participants after 2016M11. In addition, the impacts of TPU shocks on real prices of other commodities such as copper, gasoline oil and soybean are similar, therefore our points are not specific to the crude oil and suitable for the "procyclical" commodities. The findings of this paper carry some implications for investors, for example, as the effects of TPU shocks are long-lasting and insignificant contemporaneously as TPU shocks exert impacts mainly through global demand shock, investors should pay more attention to the middle or long-term movement of crude oil prices rather than just short-term fluctuations in an era with high level of TPU index.

Like any study, this paper has several limitations. First, our theoretical model is based on the rational present value model of commodity prices, and is a static model essentially, ignoring the subjective expectation formation on the TPU index in the future and the early response of suppliers, refiners and consumers in crude oil or petroleum markets. Therefore, our theoretical effect is a simplification of reality; Second, we identify the non-linear characteristics of the impact of TPU shocks on crude oil prices by splitting the dataset, which is straightforward but has inherent limitations, more advanced econometric methods could be employed to explore the contingency of such impacts. These aspects need further investigation in future research.

Data Availability

The data of TPU index of U.S. is available from the website (http://www.policyuncertainty.com/trade_uncertainty.html), the data of global real economic activity index ($grea_t$) comes from the website (https://www.dallasfed.org/research/igrea), the data of the growth of global crude oil production (PRD_t) and inventory of crude oil (N_t) is sourced from the U.S.

Energy Information Administration, and the data of CPI index which is used to construct the real price of crude oil and VIX index, OVX index, real risk-free rate (rr_t), Real Broad Effective Exchange Rate of U.S. ($REER_t$) comes from the FRED database, while the data of crude oil futures prices and global industrial output (WIP_t) comes from WIND Info and the personal website of Professor Christiane Baumeister (https://sites.google.com/site/cjsbaumeister/research), respectively.

For other commodities, the data for global refined copper production (primary + recycled) comes from ICSG and the data for the production of soybean from WIND Info, the data for global inventories of refined copper and soybean is obtained from the International Copper Study Group (ICSG) and U.S. Department of Agriculture (USDA), respectively.

It should be noted that the data of some variables (e.g., the futures prices of commodities) comes from paid database (WIND Info), it is illegal to share the data publicly, but the data of other variables can be available from the public websites and the exact websites have been listed above or in the text.

Author Contributions

Conceptualization: Dongdan Jiao, Xiangyun Xu;

Methodology: Qi Wang, Dongdan Jiao;

Software: Qi Wang, Dongdan Jiao;

Data curation: Qi Wang;

Writing-original draft: Dongdan Jiao, Xiangyun Xu.

Funding Statement

There is no funding support for this study.

Conflicts of Interest

The authors declare no competing interests.

References

Acharya, V. V., Lochstoer, L. A., & Ramadorai, T. (2013). Limits to Arbitrage and Hedging: Evidence from Commodity Markets. *Journal of Financial Economics, 109,* 441-465. https://doi.org/10.1016/j.jfineco.2013.03.003

Adrian, T., & Shin, H. S. (2010). Liquidity and Leverage. *Journal of Financial Intermediation, 19,* 418-437. https://doi.org/10.1016/j.jfi.2008.12.002

Amiti, M., Redding, S. J., & Weinstein, D. E. (2019). The Impact of the 2018 Tariffs on Prices and Welfare. *Journal of Economic Perspectives, 33,* 187-210. https://doi.org/10.1257/jep.33.4.187

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131,* 1593-1636. https://doi.org/10.1093/qje/qjw024

Baumeister, C., & Hamilton, J. D. (2019). Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. *American Economic Review, 109,* 1873-1910. https://doi.org/10.1257/aer.20151569

Benguria, F., Choi, J. R., Swenson, D. L., & Xu, M. Z. (2022). Anxiety or Pain? The Impact of Tariffs and Uncertainty on Chinese Firms in the Trade War. *Journal of International Economics, 137,* Article 103608. https://doi.org/10.1016/j.jinteco.2022.103608

Benk, S., & Gillman, M. (2023). Identifying Money and Inflation Expectation Shocks to Real Oil Prices. *Energy Economics, 126,* Article 106878. https://doi.org/10.1016/j.eneco.2023.106878

Bessembinder, H. (1992). Systematic Risk, Hedging Pressure, and Risk Premiums in Futures Markets. *Review of Financial Studies, 5,* 637-667. https://doi.org/10.1093/rfs/5.4.637

Bessembinder, H., & Lemmon, M. L. (2002). Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. *The Journal of Finance, 57,* 1347-1382. https://doi.org/10.1111/1540-6261.00463

Bianchi, D. (2021). Adaptive Expectations and Commodity Risk Premiums. *Journal of Economic Dynamics and Control, 124,* Article 104078. https://doi.org/10.1016/j.jedc.2021.104078

Caldara, D., Iacoviello, M., Molligo, P., Prestipino, A., & Raffo, A. (2020). The Economic Effects of Trade Policy Uncertainty. *Journal of Monetary Economics, 109,* 38-59. https://doi.org/10.1016/j.jmoneco.2019.11.002

Campbell, J. Y., & Shiller, R. J. (1988). Stock Prices, Earnings, and Expected Dividends. *The Journal of Finance, 43,* 661-676. https://doi.org/10.1111/j.1540-6261.1988.tb04598.x

Carlomagno, G., & Albagli, E. (2022). Trade Wars and Asset Prices. *Journal of International Money and Finance, 124,* Article 102631. https://doi.org/10.1016/j.jimonfin.2022.102631

Cerutti, E. M., Obstfeld, M., & Zhou, H. N. (2021). Covered Interest Parity Deviations: Macro-Financial Determinants. *Journal of International Economics, 130,* Article 103447. https://doi.org/10.1016/j.jinteco.2021.103447

Chen, H., Liao, H., Tang, B. J., & Wei, Y. M. (2016). Impacts of OPEC's Political Risk on the International Crude Oil Prices: An Empirical Analysis Based on the SVAR Models. *Energy Economics, 57,* 42-49. https://doi.org/10.1016/j.eneco.2016.04.018

Cheng, I. H., & Xiong, W. (2014). Financialization of Commodity Markets. *Annual Review of Financial Economics, 6,* 419-441. https://doi.org/10.1146/annurev-financial-110613-034432

Coibion, O., & Gorodnichenko, Y. (2015). Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts. *American Economic Review, 105,* 2644-2678. https://doi.org/10.1257/aer.20110306

De Roon, F. A., Nijman, T. E., & Veld, C. (2000). Hedging Pressure Effects in Futures Markets. *The Journal of Finance, 55,* 1437-1456. https://doi.org/10.1111/0022-1082.00253

Egger, P. H., & Zhu, J. (2020). The US-Chinese Trade War: An Event Study of Stock-Market Responses. *Economic Policy, 35,* 519-559. https://doi.org/10.1093/epolic/eiaa016

Engel, C., & West, K. D. (2005). Exchange Rates and Fundamentals. *Journal of Political Economy, 113,* 485-517. https://doi.org/10.1086/429137

Etula, E. (2013). Broker-Dealer Risk Appetite and Commodity Returns. *Journal of Financial Econometrics, 11,* 486-521. https://doi.org/10.1093/jjfinec/nbs024

Fajgelbaum, P. D., & Khandelwal, A. K. (2022). The Economic Impacts of the US-China Trade War. *Annual Review of Economics, 14,* 205-228. https://doi.org/10.1146/annurev-economics-051420-110410

Fajgelbaum, P. D., Goldberg, P. K., Kennedy, P. J., & Khandelwal, A. K. (2020). The Return to Protectionism. *The Quarterly Journal of Economics, 135,* 1-55. https://doi.org/10.1093/qje/qjz036

Feng, L., Li, Z. Y., & Swenson, D. L. (2017). Trade Policy Uncertainty and Exports: Evidence from China's WTO Accession. *Journal of International Economics, 106,* 20-36. https://doi.org/10.1016/j.jinteco.2016.12.009

Fernandez-Perez, A., Fuertes, A. M., Gonzalez-Fernandez, M., & Miffre, J. (2020). Fear of Hazards in Commodity Futures Markets. *Journal of Banking & Finance, 119,* Article 105902. https://doi.org/10.1016/j.jbankfin.2020.105902

Fratzscher, M. (2009). What Explains Global Exchange Rate Movements during the Financial Crisis? *Journal of International Money and Finance, 28,* 1390-1407. https://doi.org/10.1016/j.jimonfin.2009.08.008

Freund, C., Mattoo, A., Mulabdic, A., & Ruta, M. (2024). Is US Trade Policy Reshaping Global Supply Chains? *Journal of International Economics, 152,* Article 104011. https://doi.org/10.1016/j.jinteco.2024.104011

Gao, X., Meera, S., & Adrian, R. (2019). Bounds on the Jensen Gap, and Implications for Mean-Concentrated Distributions. *Australian Journal of Mathematical Analysis and Applications, 16,* 1-16.

Hamilton, J. (1994). *Time Series Analysis*. Princeton University Press.

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review, 99,* 1053-1069. https://doi.org/10.1257/aer.99.3.1053

Kilian, L., & Lee, T. K. (2014). Quantifying the Speculative Component in the Real Price of Oil: The Role of Global Oil Inventories. *Journal of International Money and Finance, 42,* 71-87. https://doi.org/10.1016/j.jimonfin.2013.08.005

Kilian, L., & Murphy, D. P. (2012). Why Agnostic Sign Restrictions Are Not Enough: Understanding the Dynamics of Oil Market Var Models. *Journal of the European Economic Association, 10,* 1166-1188. https://doi.org/10.1111/j.1542-4774.2012.01080.x

Kilian, L., & Vega, C. (2011). Do Energy Prices Respond to U.S. Macroeconomic News? A Test of the Hypothesis of Predetermined Energy Prices. *Review of Economics and Statistics, 93,* 660-671. https://doi.org/10.1162/rest_a_00086

Kilian, L., & Zhou, X. Q. (2022). Oil Prices, Exchange Rates and Interest Rates. *Journal of International Money and Finance, 126,* Article 102679. https://doi.org/10.1016/j.jimonfin.2022.102679

Knittel, C. R., & Pindyck, R. S. (2016). The Simple Economics of Commodity Price Speculation. *American Economic Journal: Macroeconomics, 8,* 85-110. https://doi.org/10.1257/mac.20140033

Li, B. (2018). Speculation, Risk Aversion, and Risk Premiums in the Crude Oil Market. *Journal of Banking & Finance, 95,* 64-81. https://doi.org/10.1016/j.jbankfin.2018.06.002

Ma, X. T., & Zhang, Z. (2022). Expectations, Credit Conditions, and Housing Boom-Bust: Evidence from SVAR with Sign and Zero Restrictions. *Journal of Banking & Finance, 134,* Article 106330. https://doi.org/10.1016/j.jbankfin.2021.106330

Mao, H., & Gorg, H. (2020). Friends Like This: The Impact of the US-China Trade War on Global Value Chains. *The World Economy, 43,* 1776-1791. https://doi.org/10.1111/twec.12967

Obstfeld, M., & Rogoff, K. (1995). Exchange Rate Dynamics Redux. *Journal of Political Economy, 103,* 624-660. https://doi.org/10.1086/261997

Pindyck, R. S. (1993). The Present Value Model of Rational Commodity Pricing. *The Economic Journal, 103,* 511-530. https://doi.org/10.2307/2234529

Robe, M. A., & Wallen, J. (2016). Fundamentals, Derivatives Market Information and Oil

Price Volatility. *Journal of Futures Markets, 36,* 317-344. https://doi.org/10.1002/fut.21732

Sanders, D. R., & Irwin, S. H. (2011). The Impact of Index Funds in Commodity Futures Markets: *a Systems Approach*. *The Journal of Alternative Investments, 14,* 40-49. https://doi.org/10.3905/jai.2011.14.1.040

Scrimgeour, D. (2015). Commodity Price Responses to Monetary Policy Surprises. *American Journal of Agricultural Economics, 97,* 88-102. https://doi.org/10.1093/ajae/aau054

Sun, T. T., Su, C. W., Mirza, N., & Umar, M. (2021). How Does Trade Policy Uncertainty Affect Agriculture Commodity Prices? *Pacific-Basin Finance Journal, 66,* Article 101514. https://doi.org/10.1016/j.pacfin.2021.101514

Zhang, J., Wu, W. R., Yang, J. Y., & Xiao, Y. (2025). Trade Policy Uncertainty and Corporate Innovation—Evidence from the US-China Trade War. *Pacific-Basin Finance Journal, 89,* Article 102590. https://doi.org/10.1016/j.pacfin.2024.102590

Burggraf, T., Fendel, R., & Huynh, T. L. D. (2020). Political News and Stock Prices: Evidence from Trump's Trade War. *Applied Economics Letters, 27,* 1485-1488. https://doi.org/10.1080/13504851.2019.1690626