Documents de travail

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Document de Travail n° 2022 – 36

Décembre 2022

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Asymmetries in the oil market: Accounting for the growing role of China through quantile regressions*

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Abstract

This paper investigates the role of political tensions between the US and China and global market forces in explaining oil price fluctuations. To this end, we rely on quantile regressions—quantile autoregressive distributed lag (QARDL) error-correction model—to account for possible asymmetric effects of those determinants, depending on both the level of oil prices and the period. Our results show evidence of a quantile-dependent long-term relationship between oil prices and their determinants over the 1958-2022 period, with an exacerbated effect of US-China political tensions in times of high oil prices. Furthermore, this quantile-dependent cointegrating relationship is time-varying across quantiles, highlighting the increased role played by China in the oil market since the mid-2000s.

Keywords: Oil prices, political tensions, quantile regressions.
JEL: Q41, F51, C22

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1. Introduction

Accounting for respectively 19.9% and 16.4% of world oil consumption in 2021,[1] the United States and China are two key players in the oil market. While the major role of the United States has been established for many years, that of China dates to the mid-2000s when the boom in oil prices was mainly driven by growth in emerging markets and, primarily, China. This increasing role of the Chinese economy has been accompanied by tensions between the two countries, with significant impacts on the oil market. The US-China trade war provides an emblematic example with a succession of threats and tariffs that have affected oil market fundamentals, such as oil supply and demand. The present paper tackles this issue and aims to investigate the dynamics of the oil market by accounting for the potential asymmetric effects of US-China political tensions on oil prices depending on their level.

Identifying the factors contributing to the explanation of oil prices has been a long-standing topic of study.[2] Several contributions argue that exogenous political events, like terrorist attacks or wars, are the primary cause of oil price fluctuations (see, e.g., Hamilton, 2003, 2009*a*). These explanations are particularly interesting for analyzing oil price changes in the wake of the two oil price shocks of the 1970s. However, the literature evolved towards a more nuanced view where exogenous political events are only a part of the explanation. Various empirical studies have shown that market forces (global demand, global supply, inventories, precaution demand, speculative demand) also play an essential role in driving oil price fluctuations (Bodenstein et al., 2012; Lippi and Nobili, 2012; Baumeister and Peersman, 2013; Kilian and Hicks, 2013; Kilian and Lee, 2014; Kilian and Murphy, 2014; Cross, Nguyen and Tran, 2022).

Our paper falls into this strand of the literature by considering the role of both political tensions between the US and China and global market forces in explaining oil price fluctuations. The literature linking political tensions between the two countries and the oil market dynamics is inexistent, apart from Cai et al. (2022) which is the study closest to ours. Relying on the structural vector autoregressive (SVAR) methodology over the 1971-2019 period, the authors show that US-China political tensions pull down oil demand and raise supply at medium- and long-run horizons.

We go further than Cai et al. (2022) by considering possible asymmetric impacts of political tensions and market forces on the oil price dynamics, depending on both the level of real oil prices and the period. The effect of the explanatory variables may indeed change over time—especially if the period under study is long—but also according to the level reached by the oil price. As it is well known, the role of China as an international key player mainly starts in the mid-2000s, making it relevant to rely on time-varying schemes. Regarding asymmetric effects, it is worth mentioning that oil demand may increase if prices are low but does not necessarily decrease in high oil price

[1]Source: BP Statistical Review of World Energy 2021.

[2]See Baumeister and Kilian (2016) for an overview of the evolution of the literature regarding the causes of fluctuations in the real price of oil.

regimes as there is no immediate substitution possibility. Similarly, the impact of political tensions on the oil market may differ depending on the oil price level.

To account for such asymmetric effects, we rely on the quantile autoregressive distributed lag model (QARDL) developed by Cho et al. (2015). This framework enables us to consider the existence of long-term, cointegrating relationships between oil prices and their determinants that can vary across quantiles, i.e., according to the level of oil prices. Furthermore, such a specification allows for locational asymmetry because the estimated parameters can vary depending on the location of oil prices within their conditional distribution. In other words, compared to the usual ARDL method, the QARDL approach has the advantage of introducing potential asymmetries in the various levels reached by oil prices. To go a step further, given that our period under study covers more than 65 years, we extend the QARDL model to a time-varying quantile ARDL specification to account for the time-varying nature of the cointegrating relationship.

Our results show the existence of a quantile-dependent cointegrating relationship between oil prices and their determinants, namely US-China political tensions, world oil demand, and global oil supply over the period ranging from January 1958 to March 2022. In particular, the effect of tensions between the two countries is exacerbated in times of high oil prices. Moreover, we find that this quantile-dependent cointegrating relationship is time-varying across quantiles. This finding is particularly interesting as it highlights the increased role played by China in the oil market since the mid-2000s.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the QARDL methodology and data, and provides some preliminary analysis. The estimation results are displayed and discussed in Section 4. Section 5 concludes the paper.

2. Literature review

In this literature review, we focus on studies that explore: (i) the relative importance of market and political forces in driving the real oil price dynamics, (ii) the existence of time-varying patterns in the oil market, and (iii) the consideration of asymmetric dynamics. The first set of studies is directly linked to our work since it relies on a quantitative measure of political tensions to estimate the influence of political events on the dynamics of the real price of oil. The second set of investigations, which explores the existence of time-varying patterns in the oil market, is also worth mentioning since the Chinese role on the international scene—and thus on the oil market—has been primarily at play since the mid-2000s (Cross, Nguyen and Zhang, 2022). Turning to the third set of studies dealing with asymmetries in the oil market, the underlying idea is that the impact of political tensions could differ depending on the oil price quantiles. Overall, this section provides an overview of studies that consider time-varying patterns and asymmetries in the relationship between the real price of oil and political tensions.

Cai et al. (2022) is the first attempt to disentangle the causal effects of market forces (oil supply and demand) and exogenous political events relying on a quantitative measure for political tensions between the US and China.[3] Using an SVAR model with monthly data over the period spanning from January 1971 to December 2019, they show that bilateral political tensions have a causal impact on oil demand, supply, and prices . During the whole period, a deterioration of the political relationship between the US and China induces a decrease in oil demand, an increase in oil supply, and a rise in the real price of oil. The authors also show that these effects may change according to the current state of the political relations, suggesting a time-varying pattern for these causal mechanisms.

Before Cai et al. (2022), various contributions have explored the quantitative impact of political tensions and geopolitical risks on the oil price dynamics.[4] Chen et al. (2016) use the political risk associated with OPEC countries as a measure of political tensions thanks to a transformation of the well-known International Country Risk Guide (hereafter ICRG) index. Their SVAR analysis shows that the two main contributors to oil price fluctuations are political risk shocks and demand shocks over the January 1998-September 2014 period. Interestingly, they find that political risk shocks in the Middle East positively influence oil prices, whereas political risk shocks in North Africa and South America have no impact. Lee et al. (2017) extend Chen et al. (2016)'s paper to the G7 countries and find that political risk shocks in the US have a different impact on the world economy given the size of the US economy and the status of the dollar in the international monetary system.

Beyond the use of the ICRG index, Miao et al. (2017) and Perifanis and Dagoumas (2019) proxy the geopolitical risk factors with the number of terrorist attacks coming from the Global Terrorism Database.[5] Specifically, Miao et al. (2017) examine the predictability of crude oil prices using daily data from January 04, 2002, to September 25, 2015. Relying on LASSO (Least Absolute Shrinkage and Selection Operator) methods, they find that market (demand, supply, speculation) and geopolitical (captured by the number of terrorist attacks in the MENA region) factors are the most important determinants of oil prices. Perifanis and Dagoumas (2019) investigate the long-run relations between various determinants of oil prices—demand, supply, speculation variables, US shale oil production, and the number of terrorist attacks in the MENA region—over the 2008-2017 period with monthly data. They show that oil prices are mainly driven by fundamentals such as consumption, OPEC production, or US shale oil production, but do not find a significant impact of indicators measuring political instability such as the number of terrorist attacks in oil-producing countries.

[3] This measure is the political relation index discussed in Yan and Qi (2009) and Yan et al. (2010). It fluctuates between -9 and 9 according to the occurrence of "bad" or "good" political events, using a scale similar to the Goldstein scale (Goldstein, 1992). It shows improved relationships between the US and China at the end of the 1970s and the 1990s, when positive diplomatic developments occurred. Besides, it indicates that the relationship deteriorated considerably during the Tiananmen Square event in 1989, after the bombing of the Chinese embassy in Belgrade in 1999, and during Trump's administration. See Cai et al. (2022) for more details, as well as Yan (2010) who discusses the instability of China-US political relations over the 1950-2009 period.

[4] See Chen et al., 2016; Lee et al., 2017; Miao et al., 2017; Perifanis and Dagoumas, 2019; Abdel-Latif and El-Gamal, 2020; Qin et al., 2020; Caldara and Iacoviello, 2022.

[5] This open-source database can be accessed here: https://www.start.umd.edu/gtd/.

Along with studies using quantitative measures of political tensions, Caldara and Iacoviello (2022) introduce the geopolitical risk (hereafter GPR) in the empirical literature. GPR is a monthly index generated by running automated text searches on the electronic archives of 11 North American and British newspapers, available since 1985.[6] Assuming that the GPR index only contemporaneously reacts to its own shocks, the authors offer an interesting distinction between geopolitical acts and geopolitical threats. Indeed, they find that geopolitical acts reduce uncertainty and produce minor economic effects. Besides, geopolitical threats increase uncertainty (especially for firms) and may have larger economic consequences than the occurrence of conflicts, as underlined by Bloom et al. (2007). In their empirical investigation, the authors show that an increase in the GPR index leads to a short-lived decrease in oil prices of around 7% after 3 months over the 1985-2016 period.

Abdel-Latif and El-Gamal (2020) use the GPR index to investigate the interactions between oil prices, financial liquidity, and geopolitical risks. They estimate a quarterly Global VAR (hereafter GVAR) over the 1979-2017 period for 53 countries, arguing that financial liquidity and geopolitical risks are endogenous to the US. They show that one-standard-deviation shocks to the GPR index (i) induce a persistent and significant increase in oil prices of around 4%, and (ii) harm investment, especially in the MENA region for commodity exporters (like Saudi Arabia, Bahrain, or Qatar). Besides, the impact on investment is more mixed for other countries which are not commodity exporters.

Baumeister and Peersman (2013) explore the role of time-varying elasticities for oil demand and supply in explaining the coexistence between reduced oil production volatility and larger oil price volatility. They recall that several reasons may explain some gradual time variation in the parameters. Firstly, spot markets have gradually become increasingly important relative to long-term oil contracts (Hubbard, 1986). Secondly, investments in the oil sector require a long-time span, and the response to price incentives may be gradual (Hamilton, 2009*b*; Smith, 2009). Capacity constraints in oil production may thus exhibit some time-varying patterns depending on the historical episode under scrutiny (Kilian, 2008). Thirdly, the quest for a substitute for oil production took place over an extended time period (Dargay and Gately, 2010). Efforts towards energy conservation are reflected in the slow variation in the energy share over time, and the effect of oil prices on consumption varies smoothly (Edelstein and Kilian, 2009).

Along with studies that acknowledge time-varying schemes in the oil market (see, for example, Herrera et al. (2019) for a brief survey), some authors find that the relationship between oil prices and geopolitical events could also exhibit time-varying patterns (Noguera-Santaella, 2016; Monge et al., 2017; Song et al., 2022). Using monthly data from September 1859 to March 2013, Noguera-Santaella (2016) examines 32 major geopolitical events (from the 1861-1865 American Civil War to the Arab Spring started in December 2010) to estimate their impact on oil prices and their volatility. Relying on both AR(1) and GARCH(1,1) models along with dummy variables

[6] The Recent GPR index—which relies on 11 newspapers—and the Historical GPR index—which uses 3 newspapers and starts in 1900—are available at: https://www.matteoiacoviello.com/gpr.htm.

accounting for the geopolitical events, he found that 6 out of 32 geopolitical events have had an impact on real oil prices, all of them occurring before 2000. Moreover, 20 out of 32 geopolitical events have affected volatility, with 17 events occurring before 2000. During the 2000s, market forces appear to be the main driver of oil price fluctuations.

Monge et al. (2017) investigate the statistical properties of real oil prices before and after important geopolitical events. Using monthly data between January 1946 and November 2014, they examine the unit root properties of six geopolitical events previously identified in the literature (the 1973 Yom Kippur War followed by the Arab oil embargo in 1973/74, the 1978/79 Iranian Revolution, the 1980-1988 Iran-Iraq War, the 1990/91 Persian Gulf War, the 2002 Venezuelan crisis and the 2003 Iraq War, and the 2011 Libyan uprising). Using fractional unit root tests, they show that the real price of oil is stationary, but follows a long-memory process (the order of integration being equal to $d = 0.78$ in the "best" model). After establishing the presence of two structural breaks in the oil price series (in October 1973 and October 1990), they estimate the order of integration for the three sub-periods and find that the null of mean reversion is rejected, even when nonlinear time trends are accounted for. Considering a window size of 120 months centered around each of the six major geopolitical events, they find some evidence of time-varying patterns as the persistence in the series is stronger when the window size increases, as witnessed by the monotonic increase in the integration order, d.

Following the contributions of Coleman (2012) and Miao et al. (2017), Song et al. (2022) explore the time-varying interactions between oil prices and terrorist attacks. They distinguish between the number of terrorist incidents per month and their brutality, proxied by the number of fatalities per attack each month. Using time-varying causality tests based on a bi-variate VAR over the January 1995-December 2018 period, they show that terrorist incidents Granger-caused oil prices between (i) January 2001 and March 2003, (ii) October 2008 and September 2008, and (iii) February 2015 and January 2016. During the first episode, the influence of terrorist incidents on oil prices was negative, while being positive for the two following periods.

Finally, two contributions are worth mentioning as they rely on quantile regressions to explore asymmetries and the heavy tail behavior of oil prices, together with the impact of geopolitical risks and political uncertainty (Qin et al., 2020; Apergis et al., 2021).[7] Using quantile regressions with daily data over the period spanning from June 28, 1990 to October 31, 2018, Qin et al. (2020) investigate the asymmetric effects of geopolitical risks on energy (including oil) returns and volatility. They reject the stability of the impact of geopolitical risks on energy across quantiles, with geopolitical risks harming crude oil returns in the case of a bearish market. They also show that geopolitical threats positively impact crude oil volatility from the quantile 0.3, but have no significant effect for lower quantiles. Unfortunately, they do not control for market forces (energy demand and production) in their regressions.

Using monthly data between 2001 and 2019, Apergis et al. (2021) examine the existence of asymmetries in the impact of US partisan political uncertainty on oil prices, thanks to a QARDL

[7] See Koenker (2017) for a survey on the use and development of quantile regressions in various economic domains.

model and a partisan conflict index built by Azzimonti (2018). In their main regressions, they put emphasis on the growth channel to explain such a potential asymmetric effect. Higher uncertainty puts a strain on economic growth and reduces oil demand, which in turn provokes a decrease in oil prices. The authors find (i) a cointegrating relationship only for quantiles greater than 0.5, and (ii) a positive impact of US partisan political uncertainty on oil prices from the quantile 0.5 as well. This result shows that political uncertainty matters only in a bullish oil market.

3. Methodology and data

3.1. Methodology

To assess whether asymmetric effects between oil prices and their determinants are at play, we rely on the QARDL framework developed by Cho et al. (2015). Such a specification allows us to estimate the coefficients at various quantile levels and, in turn, capture the asymmetric relationship between integrated series at different quantiles.

The QARDL model is specified as follows:

$$wti_t = \alpha_*(\tau) + \sum_{j=1}^{p} \phi_{j*}(\tau) wti_{t-j} + \sum_{j=0}^{q} \boldsymbol{\theta}_{j*}(\tau)' \mathbf{X}_{t-j} + U_t(\tau) \tag{1}$$

where wti_t denotes the real price of oil at time t, $\mathbf{X}_t$ is the matrix of explanatory variables, $U_t(\tau)$ is the error term, and $\tau \in (0, 1)$ stands for the quantile level.

Following Cho et al. (2015), Equation (1) can be rewritten in the error-correction form (that is, the QARDL-ECM representation) as follows:

$$\Delta wti_t = \alpha_*(\tau) + \zeta_*(\tau)(wti_{t-1} - \boldsymbol{\beta}_*(\tau)' \mathbf{X}_{t-1}) + \sum_{j=1}^{p-1} \phi_j^*(\tau) \Delta wti_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\theta}_j^*(\tau)' \Delta \mathbf{X}_{t-j} + U_t(\tau) \tag{2}$$

where, for $j = 1, ..., p-1$:

$$\phi_j^*(\tau) = -\sum_{h=j+1}^{p} \phi_{h*}(\tau) \tag{3}$$

and:

$$\boldsymbol{\theta}_j^*(\tau) = -\sum_{h=j+1}^{p} \boldsymbol{\theta}_{h*}(\tau) \tag{4}$$

with $\boldsymbol{\theta}_0^*(\tau) = \boldsymbol{\theta}_{0*}(\tau)$.

$\zeta_*(\tau)$ is the quantile error-correction term given by:

$$\zeta_*(\tau) = \sum_{j=1}^{p} \phi_{j*}(\tau) - 1 \tag{5}$$

and $\boldsymbol{\beta}_*(\tau)$ denotes the vector of quantile long-run parameters.

As shown by Equation (2), the short- and long-run parameters are quantile dependent, meaning that the QARDL coefficients can be affected by the shock $U_t(\tau)$ at each point of time and, thus, can vary across quantiles. Cho et al. (2015) derive the full asymptotic theory for this QARDL-ECM specification, and show that the estimators of the short- and long-run coefficients asymptotically follow a (mixture) normal distribution.

3.2. Data and preliminary analysis

We consider monthly data ranging from January 1958 to March 2022. For the oil-market-related variables, we rely on the real price of oil (*wti*), world oil demand (*wip*), and global oil supply (*gop*). Our dependent variable, *wti*, is the WTI spot price deflated by the US consumer price index. Turning to world oil demand, *wip*, we use the industrial production index measured by Baumeister and Hamilton (2019) by considering 23 OECD countries and six major emerging economies (Brazil, China, India, Indonesia, the Russian Federation, and South Africa). All those variables are expressed in logarithmic terms and retrieved from Christiane Baumeister's website.[8] We update the data until March 2022, following the methodology presented in Baumeister and Hamilton (2019).

Our main variable of interest is the US-China political relation index (*pri*), which allows us to assess the effects of US-China political tensions on the oil market.[9] This index is divided into six sections, ranging from -9 to 9, which classify political relations as confrontation (-9), rival, disharmonious, common, harmonious, and friendly (9).

Table A.1 in Appendix reports some basic descriptive statistics for the four first-differenced series. All variables exhibit high kurtosis levels and depart from Gaussianity, as shown by the Jarque-Bera test. This property adds support for using quantile methods to provide robust inference.

Indeed, as recalled by Koenker and Xiao (2004), usual unit root tests may be characterized by poor power performance under departures from the Gaussian case, especially for distributions with heavy tails like ours. To overcome this limit, we apply Koenker and Xiao (2004)'s quantile unit root tests, which consist in examining the unit root property in each quantile separately. By providing a detailed look at the dynamics of the series, these tests allow us to detect possible

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

[9] The index is extracted from the Institute of International Relations' website at Tsinghua University. For more details on this index, see Cai et al. (2022).

asymmetries, i.e., to consider different adjustment mechanisms toward the long-run equilibrium value—mean-reverting behavior—at different quantiles.

Briefly speaking, Koenker and Xiao (2004)'s quantile unit root test consists in extending the usual ADF-type regression:

$$y_t = \alpha + \rho y_{t-1} + \sum_{j=1}^{p-1} \phi_j \Delta y_{t-j} + u_t \tag{6}$$

as follows:

$$Q_y(\tau|I_{t-1}) = \alpha(\tau) + \rho(\tau) y_{t-1} + \sum_{j=1}^{p-1} \phi_j(\tau) \Delta y_{t-j} + Q_u(\tau) \tag{7}$$

where $Q_y(\tau|I_{t-1})$ denotes the τ-th quantile of y_t conditional on the past information, and $Q_u(\tau)$ is the τ-th quantile of u_t. $\rho(\tau)$ measures the speed of mean reversion of y_t within each quantile τ, and the test consists of testing the unit root null hypothesis, i.e., $\rho(\tau) = 1$.

The results displayed in Tables B.1 to B.4 in Appendix indicate that all series are not constant unit root processes, i.e., there is an asymmetry in persistence. Specifically, the autoregressive coefficient, $\rho(\tau)$, augments when we move from lower to higher quantiles for the real oil price and the US-China political relation index. This result is particularly interesting as it shows that these two series are more stationary during low oil price episodes and friendly relationships between the two countries than during regimes of high prices and huge tensions. In other words, during high oil price periods and conflicting relationship episodes, political tensions and the price of oil itself tend to be more persistent. This finding is consistent with the fact that political tensions are likely to be exacerbated in times of a bullish oil market. At the 5% significance level, the unit root hypothesis is not rejected for quantiles higher than 0.4 for *wti* and 0.1 for *pri* contrary to lower quantiles, illustrating asymmetric adjustment dynamics of both series.

Turning to oil demand and supply, the results in Tables B.2 and B.3 in Appendix indicate that the unit root hypothesis is not rejected at lower quantiles, while it is the case at higher quantiles. This result is logical as it suggests that when oil demand and supply are high, they tend to exhibit a mean-reverting behavior.

Overall, this preliminary analysis illustrates the relevance of the quantile framework by highlighting asymmetry phenomena. Furthermore, the existence of different behaviors of the series in terms of persistence depending on the quantiles justifies investigating the dynamics of their relationship at various quantiles through the use of QARDL models.

4. Empirical results

4.1. Quantile ARDL error-correction model

Our preliminary analysis suggests that the impact of the explanatory variables on oil prices may be heterogeneous across quantiles, i.e., may depend on the location of oil prices within their conditional distribution. To address this hypothesis and assess the stability of the long-term relationship across the quantiles, we estimate the QARDL error-correction model given by Equation (2) with $\mathbf{X}_t = (wip_t, gop_t, pri_t)$.[10]

Table 1 and Figure 1 report the estimation results of the long-term part of the QARDL error-correction model—i.e., the dynamic trends of the estimated coefficients associated with the error-correction term and the variables in levels (long-run cointegrating coefficients). In addition to the quantile estimates of the four parameters of interest, Figure 1 provides the 90% confidence intervals against quantile indices ranging from 0.05 to 0.95.[11]

As shown, the error-correction term is significantly negative for quantiles greater than 0.4 and increases in absolute terms when moving to higher quantiles. In other words, the higher the oil price, the stronger the adjustment speed toward the long-term equilibrium. This result highlights the existence of asymmetries as mean reversion is at play when oil prices are high, whereas there is no cointegration at lower quantiles in line with Apergis et al. (2021)'s conclusions. Such asymmetric behavior is consistent with the fact that the negative impact of an oil price increase on the economy is stronger than the positive effect of a fall[12]—some authors (e.g., Mork, 1989) have even shown that an oil price decrease has no impact on economic activity.

One usual explanation of this asymmetry relies on the time required to set up additional production capacities: investment is not immediate, while the decline in the profitability of oil-consuming firms is rapid. Furthermore, according to Hamilton (1988), adjustment costs—due to sectoral imbalances, coordination failures between firms, etc.—may lead to an asymmetric response to the oil price change. Indeed, a rise in the price of oil slows down economic activity (directly and indirectly). In contrast, a fall can have both positive (direct) and negative (indirect) effects, which tend to compensate for each other. It should be noted that the price of petroleum products may also contribute to the asymmetric relationship between the price of oil and economic activity, as gasoline prices increase more quickly when the price of oil rises than they fall when the price decreases. Finally, Bernanke et al. (1997) put forward a possible role for monetary policy in explaining the asymmetry phenomenon: while in the case of a rise in the oil price, monetary authorities pursue a restrictive policy to fight inflation, they do not react when the price falls. This difference in the reaction of monetary authorities to a rise and a fall in the oil price provides a way to explain the asymmetry phenomenon.

Turning to oil demand, the associated coefficient decreases as the oil price rises but remains significant all the time. When prices are high, the impact of demand on prices is smaller than for the low quantiles, but the effect remains significant. This result is logical because the elasticity of demand to oil prices is very low in the short run. Thus, even if prices are high, the economy's needs for oil are still present, and there is no possibility of—short-term—substitution.

[10] We retain $p = 3$ and $q = 1$ for the QARDL-ECM estimation. Similar results (available upon request to the authors) are obtained for $p = 12$ and $q = 1$.

[11] The confidence intervals have been calculated using Feng et al. (2011)'s wild bootstrap method.

[12] See, e.g., Mork (1989), Mory (1993), Mork et al. (1994), Peter Ferderer (1996), Brown and Yücel (2002), and Lardic and Mignon (2006, 2008).

Regarding the coefficient related to global oil supply, it is always significant and increases when moving to higher quantiles. It is negative for the low quantiles and becomes positive from the 0.6 quantile onwards. When prices are low, an increase in production tends to lower prices, leading producers to generally decrease their production to raise prices. When prices are high, increased production positively impacts prices, but the effect tends to decrease in the case of a strong bullish market. Producers do not reduce their production when prices are high (but may do so when prices reach very high levels), which is consistent with the low elasticity of demand and the fact that they benefit from rising prices.

Finally, the impact of political tensions is always positive and augments with the price of oil: the higher the quantiles, the greater the influence of political tensions. This finding is particularly interesting as it indicates that the effect of political tensions between China and the US is exacerbated in times of high oil prices—confirming the quantile unit root test conclusions. This result is also in line with Qin et al. (2020) who have shown that the impact of geopolitical risks varies across quantiles.

Overall, our findings show the existence of location asymmetries between lower and medium-to-higher quantiles for the four key coefficients, with a quantile-dependent cointegrating relationship between oil prices and their determinants. Following Xiao (2009) and Cho et al. (2015), such quantile-dependent cointegration may come from the fact that the underlying relationship between non-stationary series (for some quantiles) can vary over time because of heterogeneous shocks arriving at different dates. As argued by Cho et al. (2015), the quantile cointegrating framework is particularly suitable in such conditions as the quantile coefficients can be considered as random parameters—randomness coming from a common shock arising at each point of time.

4.2. Time-varying quantile ARDL-ECM model

Given that our period under study covers more than 65 years and to account for the time-varying nature of the cointegrating relationship, we extend our previous analysis by estimating a time-varying quantile ARDL error-correction model. To this end, we re-estimate our specification (Equation (2)) using the robust rolling estimation procedure proposed by Cho et al. (2015). The corresponding results are displayed in Figure 2.

Since our previous findings show evidence of cointegration for quantiles greater than 0.4, we focus on the results for τ equal to 0.5 and 0.75. Figure 2 clearly shows that the rolling quantile estimates of the four coefficients were not highly time-varying before the mid-2000s. This is consistent with the fact that China was not a key player on the international scene before that date, explaining its negligible impact on the oil market. Important time-varying patterns in the parameters are observed after the mid-2000s due to the increasing role of China worldwide, highlighting the relevance of the time-varying approach.

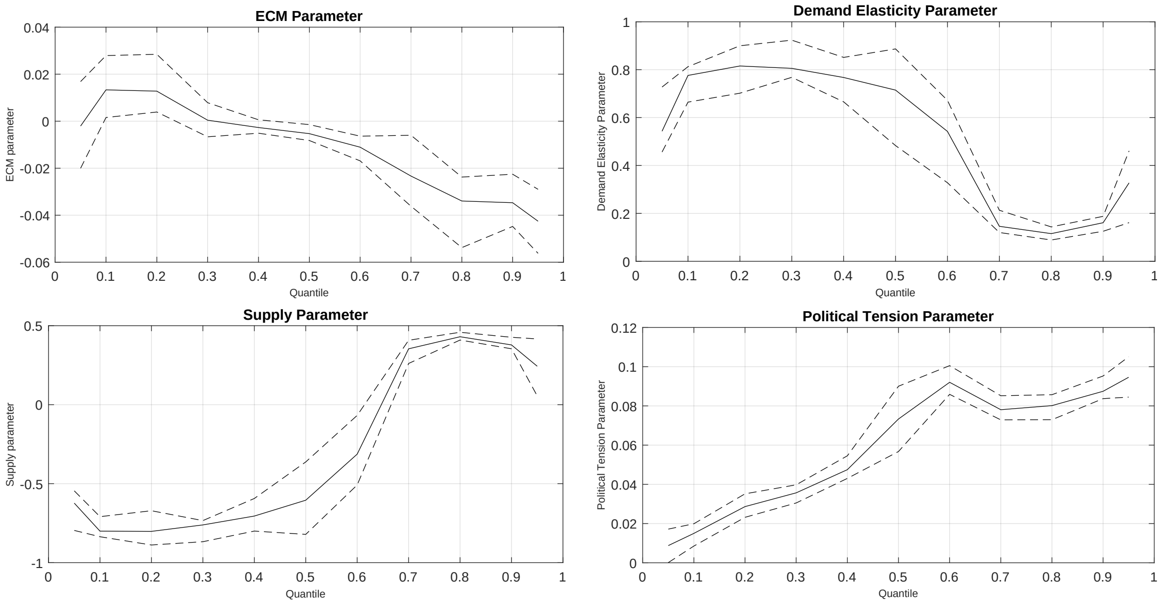
This is confirmed by the strong time-varying evolution of the error-correction term after the mid-2000s. As shown, the speed of adjustment tends to increase after 2005, before stabilizing and decreasing since the mid-2010s. The cointegrating relationship has been effective since the 2010s for $\tau = 0.5$ and around 2005 for $\tau = 0.75$. This is consistent with the fact that no long-term

Table 1: Quantile regressions for variables in levels

	Quantile	Coefficient	Std. Error	t-Statistic	Prob.
wip	0.100	0.776064	0.094813	8.185224	0.0000
	0.200	0.815416	0.084120	9.693486	0.0000
	0.300	0.808494	0.091616	8.824809	0.0000
	0.400	0.767398	0.107158	7.161381	0.0000
	0.500	0.714708	0.160457	4.454218	0.0000
	0.600	0.550065	0.113406	4.850411	0.0000
	0.700	0.148907	0.047491	3.135480	0.0018
	0.800	0.117502	0.036946	3.180347	0.0015
	0.900	0.165771	0.032858	5.045026	0.0000
gop	0.100	−0.800276	0.088849	−9.007153	0.0000
	0.200	−0.801699	0.086438	−9.274839	0.0000
	0.300	−0.762415	0.098199	−7.764007	0.0000
	0.400	−0.704797	0.116421	−6.053847	0.0000
	0.500	−0.604502	0.179825	−3.361613	0.0008
	0.600	−0.321607	0.151417	−2.123987	0.0340
	0.700	0.353739	0.066024	5.357736	0.0000
	0.800	0.429804	0.049226	8.731160	0.0000
	0.900	0.377204	0.042341	8.908701	0.0000
pri	0.100	0.014987	0.005671	2.642531	0.0084
	0.200	0.028649	0.005210	5.498696	0.0000
	0.300	0.035453	0.005621	6.307362	0.0000
	0.400	0.047474	0.006698	7.088210	0.0000
	0.500	0.073317	0.010797	6.790593	0.0000
	0.600	0.091656	0.005234	17.51134	0.0000
	0.700	0.077452	0.005374	14.41162	0.0000
	0.800	0.079716	0.004940	16.13752	0.0000
	0.900	0.086424	0.004407	19.61079	0.0000
constant	0.100	2.482283	0.104608	23.72937	0.0000
	0.200	2.459719	0.112834	21.79939	0.0000
	0.300	2.406176	0.128315	18.75210	0.0000
	0.400	2.439783	0.145586	16.75840	0.0000
	0.500	2.469138	0.162724	15.17377	0.0000
	0.600	2.203284	0.184212	11.96058	0.0000
	0.700	1.262839	0.129958	9.717267	0.0000
	0.800	1.153926	0.109468	10.54124	0.0000
	0.900	1.245208	0.090217	13.80243	0.0000

Note: Wald tests for symmetric quantiles and slope equality strongly reject the null hypotheses of symmetry between quantile and slope equality, respectively. Source: authors' calculations.

Figure 1: QARDL error-correction model



Note: This figure reports the estimated parameters (solid middle line) using all available observations for different quantile levels (0.05, 0.10, . . . , 0.95) with 90% confidence intervals (outer dotted lines). Source: authors' calculations.

equilibrium relationship was at play before China became a key player on the international scene and, in turn, on the oil market.

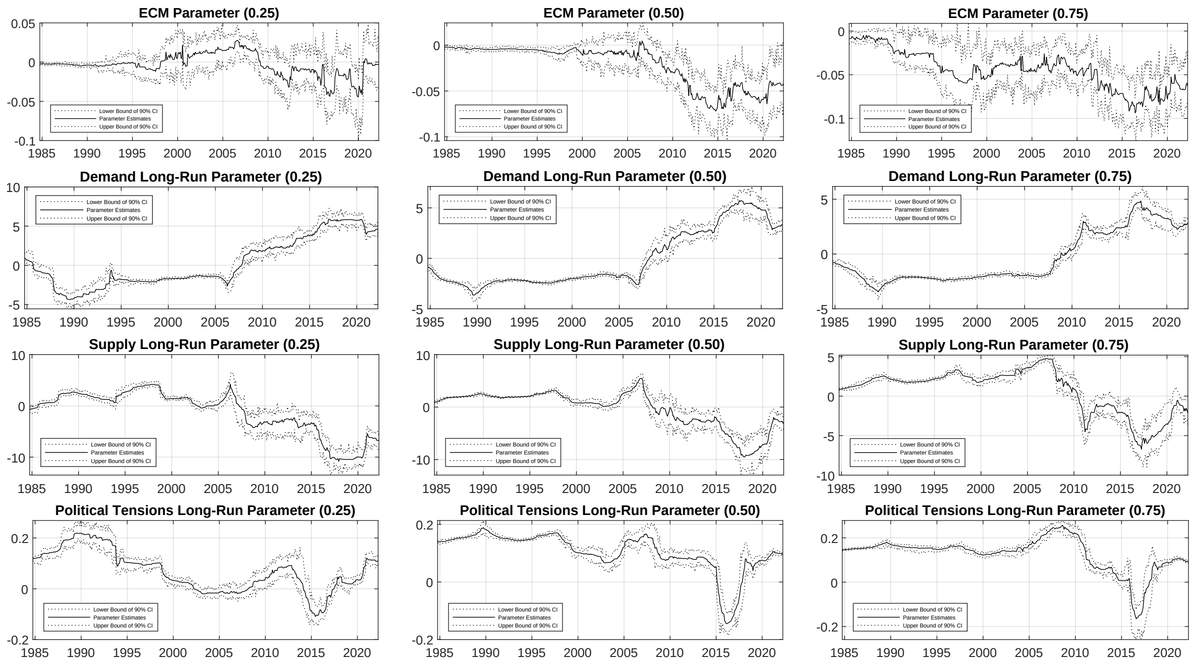
From this period, the oil-demand effect on prices becomes positive, with the corresponding coefficient following an upward trend. This clearly illustrates the major impact of Chinese demand on the price of oil: the rise in oil prices was driven by Chinese growth—and, therefore, Chinese demand. The demand effect on the oil price has increased over time, in line with China's growing weight. As expected, a decreasing trend is observed in 2020-2021 due to the Covid-19 pandemic and the subsequent reduction in economic activity.

Turning to oil supply, its coefficient has followed a downward trend since the 2007-2008 global financial crisis. This evolution can be explained by various factors, such as the spectacular shale oil and gas boom since 2009 that profoundly disrupted the oil market and OPEC's supremacy. During the 2015-2020 period, prices sharply fell due to the battle for market share and global price-fixing between key players such as Russia and Saudi Arabia. The negative estimated coefficients associated with oil supply during that period are thus consistent with those important changes affecting global oil production.

As shown in Figure 2, the impact of political tensions between China and the US was relatively stable and positive before 2005, especially for $\tau = 0.75$. The effect increased in the mid-2000s, i.e., when China started to play a major role at the global level. The most interesting result is that this impact strongly changed and became negative in 2015 during the trade war with the US. The deterioration of political relations between the two countries created uncertainty that has strongly affected the oil market, pulling prices down. At the end of the period, once the effect of the shock has passed, the impact of political tensions recovers a "normal" pattern, illustrating a "new normal" regime.

Overall, our findings show that the cointegrating relationship between the price of oil and its determinants is both quantile-dependent and time-varying across quantiles. This result is particularly interesting as it clearly highlights the increased role played by China in the oil market since the mid-2000s.

Figure 2: Time-varying QARDL error-correction model



Note: The parameters are estimated using the rolling window method, and each window has a size of 320 observations. The first date on the horizontal axis is August 1984. The number of out-of-sample observations is 452. Source: authors' calculations.

5. Conclusion

This paper assesses the role of political tensions between the US and China and global market forces (oil demand and supply) in explaining oil price fluctuations. We pay particular attention to the potential existence of asymmetries between oil prices and their determinants depending on the level reached by oil prices, as well as possible time-varying effects across the January 1958-March 2022 period.

We show that oil prices and their determinants are not constant unit root processes, meaning there is an asymmetry in persistence. In particular, during periods of high oil prices and conflicting relationships between China and the US, political tensions and the price of oil itself tend to be more persistent.

We estimate a quantile autoregressive distributed lag (QARDL) error-correction model to account for such asymmetric behavior. Our main findings show that (i) the higher the oil price, the stronger the adjustment speed toward the long-term equilibrium, (ii) the effect of US-China political tensions is exacerbated during high oil price periods, and (iii) significant time-varying patterns in the parameters associated with oil prices' determinants are observed.

Overall, our results highlight the increasing role of China in the oil market since the mid-2000s. Given that US-China political tensions are accentuated during a bullish oil market, and due to their significant impact on the oil market, special attention must be paid to the diplomatic relationships between the two countries. Limiting conflictual relationships helps to mitigate high price pressures, which is crucial in the current context of increased global inflation.

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Appendix A. Descriptive statistics

Table A.1: Descriptive statistics on first-differenced series

	wti	*wip*	*gop*	*pri*
Mean	0.0016	0.0028	0.0019	−0.0026
Median	−0.0023	0.0033	0.0030	0.0000
Maximum	0.8418	0.0477	0.0650	2.1000
Minimum	−0.5601	−0.0915	−0.1457	−2.2000
Std. Dev.	0.0818	0.0077	0.0162	0.2286
Skewness	0.8099	−2.7499	−1.9796	−0.9828
Kurtosis	26.3085	36.8219	17.7130	37.7551
Jarque-Bera	17514.54	37671.24	7448.104	38877.88
Probability	0.000	0.000	0.000	0.000
Observations	770	770	770	770

Source: authors' calculations.

Appendix B. Quantile unit root tests

Table B.1: Quantile unit root tests for the oil price

				Critical values		
τ	$\hat{\rho}(\tau)$	$\hat{\rho}(OLS)$	ADF(τ)	1%	5%	10%
0.1	0.955	0.988	-3.732	-3.312	-2.668	-2.319
0.2	0.961	0.988	-5.320	-3.377	-2.733	-2.386
0.3	0.981	0.988	-4.291	-3.374	-2.730	-2.383
0.4	0.994	0.988	-2.645	-3.361	-2.717	-2.369
0.5	0.999	0.988	-0.732	-3.364	-2.720	-2.372
0.6	1.009	0.988	2.765	-3.386	-2.743	-2.397
0.7	1.025	0.988	4.940	-3.404	-2.766	-2.421
0.8	1.035	0.988	3.896	-3.416	-2.780	-2.437
0.9	1.027	0.988	2.450	-3.379	-2.736	-2.388

Note: We use 12 lags in the quantile unit root tests. The null is the presence of a unit root for the specified quantile τ. $\hat{\rho}(\tau)$ is the estimate of the largest autoregressive root at each quantile, $\hat{\rho}(OLS)$ is the usual OLS estimate of the autoregressive root, and $ADF(\tau)$ is the quantile unit root test statistic. Source: authors' calculations.

Table B.2: Quantile unit root tests for the oil demand

				Critical values		
τ	$\hat{\rho}(\tau)$	$\hat{\rho}(OLS)$	ADF(τ)	1%	5%	10%
0.1	0.999	0.999	1.087	-3.334	-2.689	-2.341
0.2	1.000	0.999	-0.569	-3.390	-2.749	-2.403
0.3	1.000	0.999	-0.138	-3.426	-2.791	-2.449
0.4	1.000	0.999	-0.883	-3.442	-2.809	-2.469
0.5	0.999	0.999	-2.058	-3.441	-2.808	-2.468
0.6	0.998	0.999	-4.395	-3.420	-2.784	-2.441
0.7	0.998	0.999	-4.314	-3.396	-2.756	-2.411
0.8	0.998	0.999	-3.060	-3.355	-2.362	-2.043
0.9	0.998	0.999	-2.305	-3.249	-2.605	-2.256

Note: We use 12 lags in the quantile unit root tests. The null is the presence of a unit root for the specified quantile τ. $\hat{\rho}(\tau)$ is the estimate of the largest autoregressive root at each quantile, $\hat{\rho}(OLS)$ is the usual OLS estimate of the autoregressive root, and $ADF(\tau)$ is the quantile unit root test statistic. Source: authors' calculations.

Table B.3: Quantile unit root tests for the oil supply

				Critical values		
τ	$\hat{\rho}(\tau)$	$\hat{\rho}(OLS)$	ADF(τ)	1%	5%	10%
0.1	1.002	0.992	0.739	-3.412	-2.775	-2.431
0.2	0.999	0.992	-0.543	-3.467	-2.839	-2.502
0.3	0.996	0.992	-2.064	-3.486	-2.861	-2.525
0.4	0.994	0.992	-4.348	-3.480	-2.854	-2.518
0.5	0.993	0.992	-4.483	-3.468	-2.840	-2.502
0.6	0.993	0.992	-4.865	-3.439	-2.807	-2.466
0.7	0.993	0.992	-5.835	-3.403	-2.764	-2.420
0.8	0.988	0.992	-4.807	-3.362	-2.718	-2.370
0.9	0.982	0.992	-6.179	-3.217	-2.573	-2.224

Note: We use 12 lags in the quantile unit root tests. The null is the presence of a unit root for the specified quantile τ. $\hat{\rho}(\tau)$ is the estimate of the largest autoregressive root at each quantile, $\hat{\rho}(OLS)$ is the usual OLS estimate of the autoregressive root, and $ADF(\tau)$ is the quantile unit root test statistic. Source: authors' calculations.

Table B.4: Quantile unit root tests for the political tensions

				Critical values		
τ	$\hat{\rho}(\tau)$	$\hat{\rho}(OLS)$	ADF(τ)	1%	5%	10%
0.1	0.989	0.998	-2.155	-3.064	-2.401	-2.059
0.2	0.996	0.998	-1.512	-3.027	-2.371	-2.024
0.3	1.000	0.998	0.000	-2.967	-2.322	-1.967
0.4	1.000	0.998	0.503	-2.922	-2.286	-1.925
0.5	1.000	0.998	2.751	-2.905	-2.267	-1.905
0.6	1.000	0.998	2.665	-2.911	-2.276	-1.914
0.7	1.000	0.998	0.000	-2.951	-2.309	-1.952
0.8	1.011	0.998	3.699	-2.994	-2.344	-1.992
0.9	1.012	0.998	1.896	-3.037	-2.379	-2.033

Note: We use 12 lags in the quantile unit root tests. The null is the presence of a unit root for the specified quantile τ. $\hat{\rho}(\tau)$ is the estimate of the largest autoregressive root at each quantile, $\hat{\rho}(OLS)$ is the usual OLS estimate of the autoregressive root, and $ADF(\tau)$ is the quantile unit root test statistic. Source: authors' calculations.