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The asymmetric impact of oil prices, interest rates and oil price uncertainty on unemployment in US

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Manuscript

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Abstract

In this study, we investigate the presence of asymmetric interactions between oil prices, oil price uncertainty, interest rates and unemployment in a cointegration framework. Utilizing the nonlinear auto-regressive distributed lag (NARDL) approach, we show the asymmetric responses of unemployment to changes in oil prices, oil price uncertainty and interest rates in the long-run. More specifically, the results of our analyses suggest that an increase in oil price results in increased unemployment while there is no significant impact of reduced oil prices. On the other hand, reduced oil price uncertainty leads to a decrease in unemployment whereas an increase in oil price uncertainty does not have an impact. We also observe increased unemployment in response to a decrease in interest rates as the impact of increased interest rates is not significant. Last but not least, we find that option-implied oil price volatility, as a measure of oil price uncertainty, outperforms the conditional volatility of crude oil prices in predicting unemployment. This study provides valuable implications for policymakers to design sound economic policies.

Keywords: Asymmetric effects; Unemployment; Nonlinear ARDL (NARDL); Oil prices; Oil price uncertainty; Interest rates

JEL classification: C32; E24; G31; Q43

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1. Introduction

Due to the negative economic and social effects of increased unemployment rates, the reasons behind this increase needs to be carefully assessed. Among macroeconomic risk factors that affect the level of unemployment, previous research emphasizes that oil prices and interest rate risks are important due to their far-reaching impacts on economic activity (Carruth et al., 1998; Lardic and Mignon, 2008; Dogrul and Soytas, 2010). Also, some recent studies reveal the central role of oil price uncertainty in influencing investment, aggregate output and unemployment (Elder and Serletis, 2009, 2010; Kocaaslan, 2019). The other key issue on the link between oil markets and economic activities is the asymmetric impact of oil prices on macroeconomic variables (Mork, 1989). In the related literature, little attention has been devoted to understanding the asymmetric relationships between oil prices and unemployment. Up to our knowledge, there is no empirical study that jointly investigates the asymmetric impacts of oil prices, oil price uncertainty and interest rates on unemployment in a cointegration framework. To fill this information gap, using a nonlinear auto-regressive distributed lag (NARDL) method developed by Shin et al. (2014), this study estimates the impact of positive and negative changes in oil prices, oil price uncertainty and interest rates on unemployment in US. We also compare the information content of implied oil price volatility (as a measure of oil price uncertainty) on unemployment with that of the conditional volatility of oil price changes.

In the related literature, some recent studies use the NARDL model to investigate the asymmetric interactions between oil prices and unemployment for the US (Kisswani and Kisswani, 2019) and the countries in Central and Eastern Europe (Cuestas and Gil-Alana, 2018) while some others model oil price uncertainty for a better understanding of the impact of oil price shocks on unemployment rates (Lee et al., 1995; Jo, 2014; Elder and Serletis, 2009, 2010; Kocaaslan, 2019). Our study departs from these studies in the following aspects.

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First, even though previous research documents the asymmetric impact of oil price changes on unemployment, there is no study investigating the asymmetric impact of oil price uncertainty and interest rates on unemployment rates. To fill this gap, we model and estimate the nonlinear relationships between oil prices, oil price uncertainty, interest rates, and unemployment. Kisswani and Kisswani, (2019) and Cuestas and Gil-Alana (2018) use the NARDL model to test the asymmetric impact of oil prices on unemployment rates in the US and the countries in Central and Eastern Europe, respectively, but they do not consider the role of oil price uncertainty and interest rates. This paper, jointly accounts for the asymmetric impact of oil prices, oil price uncertainty and interest rates on unemployment rates, to produce a more complete picture of the response of unemployment to positive and negative changes in oil prices, oil price uncertainty and interest rates, using a cointegration framework (NARDL model).

Second, the crude oil volatility index (OVX) is used as a measure of oil price uncertainty while also controlling for the impact of the conditional volatility of oil price changes used by various studies (e.g. Lee et al., 1995; Hamilton, 2003; Sadorsky, 2006; Yoon and Ratti, 2011). We use the OVX obtained from options markets to capture the forward-looking elements of oil price uncertainty. Rather than using historical price volatilities (than either realized volatilities or ARCH/GARCH models), some pioneering studies emphasize the importance of implied volatilities from options markets to measure the latent volatility series (Christensen and Prabhala, 1998; Jorion, 1995; Fleming, 1998; Poon and Granger, 2003; Szakmary et al., 2003; Kellogg, 2014). This allows us to take forward looking information into account. Market players use options markets mostly to hedge unexpected price changes. Therefore, the implied volatility indices are forward-looking and hence indicate the consensus among market players on the expected uncertainty. Besides, when there is a high fear of financial crises, higher volatilities are frequently observed in options markets. In this respect, the implied

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volatility is also a good indicator of investors' sentiment (Maghyereh et al., 2016). Accounting for global financial crisis and employing different oil price and interest rate variables do not alter our results.

The study proceeds as follows. Section 2 identifies the main economic mechanisms through which oil prices, oil price uncertainty and interest rates influence unemployment. Section 3 briefly summarizes the empirical evidence from existing works. Section 4 and 5 introduce the data characteristics and econometric framework, respectively. Section 6 provides empirical results. Section 7 and 8 discuss the main implications of our findings and concludes the study with main remarks and future research directions, respectively.

2. Theoretical Background

Oil price fluctuations can affect the economy (e.g. unemployment rates) through different mechanisms (Lardic and Mignon, 2008). The first one is the supply-side effect caused by increasing oil prices leading to the reduced availability of a basic input and consequently to the increased production costs, the slowing growth of output and less productivity (Brown and Yucel, 1999, 2002). The second mechanism is the wealth transfer effect implying the reduced (increased) purchasing power in oil-importing (oil-exporting) countries due to a rise in oil prices (Dohner, 1981). This mechanism gives rise to reduced consumer demand and, hence reduced GDP growth in oil-importing countries. Third, there is a real-balance effect through which rising oil prices cause an increase in money demand (Pierce and Enzler, 1974; Mork, 1994). The failure of meeting this demand by monetary authorities leads to increased interest rates, which may have negative impacts on economic activity. The fourth mechanism (inflation effect) is that the increased inflation associated with the increased oil prices may force monetary authorities to apply a tight monetary policy leading to a deteriorating investment climate (Tang et al., 2010). The fifth mechanism works through the impact of oil price shocks on the labor market. The rising oil prices force firms to adapt to the changing

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production structures and eventually generate the reallocation of labor and capital across sectors, which have a large impact on unemployment in the long-run (Loungani, 1986).

In this study, we first consider the efficiency-wage model of Carruth et al. (1998) to theoretically relate the changes in interest rates and oil prices to unemployment rate fluctuations[1]. This model is based on the simple idea that a change in equilibrium unemployment depends on the labor demand changes arising from the fluctuations in real input prices (e.g. oil prices and the price of credit "interest rates"). Via this mechanism, an increase in oil prices leads to increased production costs and reduced profit margins. For the adjustment of equilibrium in economy, the price of labor (wages) decline. As a result of the decline in wages, unemployment rates increase because of the inverse relationship between wages and unemployment. A similar mechanism works for the rising interest rates. Overall, following the Carruth et al. (1998) model, we take into consideration the impacts of oil prices and interest rates on unemployment for our analyses.

The second motivation comes from the theories of investment under uncertainty and real options (Henry, 1974; Bernanke, 1983; Brennan and Schwartz, 1985; Majd and Pindyck, 1987), as in the studies of Elder and Serletis (2009, 2010). According to these theories, managers do not tend to make irreversible investment decisions for their firms under uncertain economic conditions. This tendency brings about the postponement of investment projects until uncertainty disappears. Also, micro-level investment decisions crucially influence macroeconomic fluctuations through negative impacts on large industries (e.g. the automobile industry) (Bernanke, 1983). Besides, agents may not distinguish whether the initial shock is permanent or transitory in the presence of high uncertainty (Bernanke, 1983; Elder and Serletis, 2010). Therefore, a transitory shock may be perceived as a permanent shock by individuals. Given these assertions, one could argue that uncertainty about oil prices is

[1] For a detailed exposition of the model, see Carruth et al. (1998).

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important in affecting aggregate investment, consumption and hence unemployment. Based on this argument, we also test the impact of oil price uncertainty on unemployment to make a correct economic analysis on the link between oil price dynamics and unemployment.

Third, we are interested in the nonlinear characteristics of the relationships between the variables of interest since the linearity assumption potentially restricts our economic analyses, which may lead to misrepresentation of the relationships. Some research emphasizes that fluctuations in oil prices have an asymmetric impact on the overall economy (e.g. Mork, 1989). The adverse effect of increasing energy prices on economic activity is considerably stronger than the stimulating impact of falling oil prices on economic growth. This asymmetric impact could be due to the reallocation of labor and capital across sectors in response to changing energy prices (Davis, 1987; Hamilton, 1988; Davis and Haltiwanger, 2001). Business cycle fluctuations (e.g. changes in interest rates and uncertainty) have a big influence on the asymmetric behavior of macroeconomic indicators (Neftci, 1984; Acemoglu and Scott, 1997). In light of such information, to overcome the potential bias stemming from the linearity assumption, we concentrate our effort on the non-linear relationships between the variables under consideration.

3. Empirical Evidence

The link between oil price dynamics and unemployment has attracted great interest in the economics literature. The focus of many studies is the transmission channel through which oil price fluctuations change the level of unemployment in the developed countries. For the US labor markets, Loungani (1986) implies that the primary reason behind increased unemployment rates is the unexpected amount of reallocation of labor across sectors due to rising oil prices. Hamilton (1983) provides evidence of a strong link between oil prices and unemployment for the US. Gisser and Goodwin (1986) show the predictive power of oil prices on various macroeconomic indicators (e.g. unemployment), supporting the findings of

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Hamilton (1983). Mory (1993) suggests an asymmetric link by emphasizing that the negative impact of increasing oil prices on economic activity and unemployment appears to be stronger compared to the positive impact of declining oil prices. Hooker (1996) demonstrates the reduced predictive ability of oil price shocks on economic indicators for the updated sample. Keane and Prasad (1996) conclude that oil price fluctuations result in changes in relative wages and employment shares across sectors. Uri (1996) documents the presence of the empirical link between crude oil prices and agricultural employment in the USA. Using a theoretical framework, Carruth et al. (1998) empirically explore the strong effect of real oil prices on unemployment for the US. Davis and Haltiwanger (2001) show the greater sensitivity of job destruction to oil shocks in the short-run than the sensitivity of job creation. The findings of Gil-Alana and Henry (2003), Caporale and Gil-Alana (2002), and Gil-Alana (2003) suggest that oil prices and unemployment are fractionally cointegrated for the United Kingdom, Canada, and Australia.

More recently, Ewing and Thompson (2007) point out the negative correlation between crude oil prices and unemployment cycles in the US. Similarly, Lescaroux and Mignon (2008) report the big impact of oil prices on unemployment for the US. The analysis of Andreopoulos (2009) suggests the forecasting ability of real oil prices for unemployment only in recessions. Herrera and Karaki (2015) imply that the impact of oil price shocks on employment in U.S. manufacturing industries occurs primarily through aggregate channels (such as reduced potential output and income transfers). For twenty-six OECD countries including developed and developing ones, Katircioglu et al. (2015) document the negative impact of oil price shocks on employment. Karlsson et al. (2018) demonstrate the negative response of the unemployment rate in Norway to oil price shocks, most probably because Norway is an oil-exporting country. Employing the nonlinear autoregressive distributed lag (NARDL) model, conversely to previous research, Kisswani and Kisswani (2019) find the

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significant effect of negative oil price innovations on total unemployment rather than positive oil price innovations in the US.

The literature is very scarce on the relationships between oil prices and unemployment in developing countries. Papapetrou (2001) finds the negative impacts of oil price shocks on employment for Greece. Similar to this finding, the estimates of Dogrul and Soytas (2010) confirm the significant causality from real oil prices to unemployment for Turkey. Using a fractional integration technique, a study on the countries in Central and Eastern Europe, Cuestas and Gil-Alana (2018) point out that rising (declining) oil prices increase (reduce) the unemployment rates [2].

As for the impact of oil price uncertainty on unemployment rates, Lee et al. (1995) take into account the conditional variance of oil price changes to model oil price uncertainty and examine the impact of normalized oil price shocks on economic activity[3]. They find the significant impact of positive oil price shocks on economic growth rather than negative oil price shocks. Jo (2014) uses the stochastic volatility process to test the impact of oil price uncertainty on global economic activity. The results of this study support the negative impacts of oil price uncertainty on world industrial production. Elder and Serletis (2009, 2010) utilize a GARCH-in-mean VAR model and show the depressing effects of oil price uncertainty on investment growth for the US and Canada. Motivated by these findings, Kocaaslan (2019), using a GARCH-in-mean VAR model, investigate the effect of oil price uncertainty on unemployment in the US and find that rising oil price uncertainty leads to increased unemployment rates.

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[2] They also employ the NARDL model to test the effect of oil prices on unemployment rates for the countries in Central and Eastern Europe , but do not find significant results in the long-run.

[3] In this study, they utilize the generalized autoregressive conditional heteroskedasticity (GARCH) model to obtain the conditional variance of oil price changes, which is used to normalize unexpected part of the rate of change in real oil price. The oil price shocks are deflated by its contemporaneous conditional standard deviation.

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As shown in the previous studies summarized above, there is no study that empirically and jointly models long- and short-run asymmetries between oil prices, oil price uncertainty, interest rates, and unemployment. Utilizing the NARDL model, this paper attempts to fill this gap.

4. Data Characteristics

We use two measures for oil prices. The first one is the composite refiner acquisition cost (RAC) of crude oil and the second one is the crude oil price of the West Texas Intermediate (WTI). The RAC is a weighted average of domestic and imported crude oil costs. To this respect, the RAC is a broader measure than the crude oil spot price of WTI paid to domestic producers in the US (Elder and Serletis, 2010). We use both oil price series (RAC and WTI) for robustness check. Oil price series are collected from the U.S. Energy Information Administration (EIA). We employ the crude oil volatility index (OVX) obtained from options markets as a proxy for oil price uncertainty. The OVX measures 30-day volatility expectations in the United States Oil Fund option prices. We also use two measures of interest rates. The first is the yield on a 3-month US Treasury bill (TBILL), which is widely used in the empirical literature. Second, for robustness, the federal funds rate (FF) is used to comparatively evaluate the impact of monetary policy on unemployment. Interest rate series, U.S. unemployment rate, and OVX are sourced from the Federal Reserve Bank of St. Louis. For our empirical investigation, we use monthly data from 2007:M5 to 2019:M4. The sample period is based on the availability of OVX data since the OVX has no data prior to May, 2007[4].

Several studies use the conditional volatility of crude oil prices obtained from generalized autoregressive conditional heteroskedasticity (GARCH (1,1)) model (Bollerslev, 1986), which

[4] We also use the oil price and interest rate series deflated by consumer price index (CPI) for the analyses throughout the study and obtain very similar results, which are provided upon request.

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is commonly used in the economics and finance literature[5], to measure oil price uncertainty (e.g.Lee et al., 1995; Hamilton, 2003; Sadorsky, 2006; Yoon and Ratti, 2011; Wang et al., 2017). To compare the information content of implied oil price volatility on unemployment with that of the conditional volatility of oil price changes, we also obtain the conditional volatility of oil price changes using the GARCH (1,1) model. The conditional standard deviation of the changes in crude oil prices (the conditional standard deviation of RAC (CSDRAC) and WTI (CSDWTI)) is used for empirical analyses as in similar studies (Lee et al., 1995; Elder and Serletis, 2010; Kocaaslan, 2019). The conditional variance equation for the GARCH (1,1) is specified as below[6]:

$$h_t = \Upsilon_0 + \Upsilon_1 \varepsilon_{t-1}^2 + \Upsilon_2 h_{t-1} \tag{1}$$

h_t, ε_{t-1}^2, and h_{t-1} represent the conditional variance, lagged squared errors and lagged conditional variance, respectively. The estimates of the variance equations for the RAC and WTI are reported in Table 1. We find statistically significant ARCH (Υ_1) and GARCH (Υ_2) parameters for both series, meaning that the conditional variances of oil prices significantly depend on their lagged conditional variances and lagged squared errors.

[Table 1 about here]

Table 2 provides the summary statistics of the variables under consideration. The statistics indicate the non-normal distribution of our time series. To reduce non-normality in the data for the analyses and for consistent findings, we use the logarithmic transformations of the series.

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[5] Bollerslev et al. (1992) argue that GARCH (1,1) model suits well for many applied situations.

[6] We specify the conditional mean equation with a constant only, which is commonly used in the literature. As in most studies, the first difference of the logarithm of crude oil prices is considered as the return of oil prices (dependent variable) in the mean equation. We do not observe a significant problem applying several diagnostic tests (the tests on the squared residuals and ARCH-LM tests). For robustness, we also use some widely-used specifications for the equations (e.g. incuding AR(1) term in the mean equation) to obtain the conditional variances. Our main results are not sensitive to different specifications. The results are provided upon request.

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The NARDL model requires that the time series should be integrated of order 1 or 0, but not 2 (Shin et al., 2014). To test the stationarity characteristics of the series, Dickey-Fuller GLS detrended test (DF-GLS) (Elliot et al., 1996) is used[7]. The tests are applied by considering intercept and both intercept and trend. Table 3 reports the output of the unit root tests. The findings suggest that the variables are integrated of order 1 or 0. Based on these findings, we can utilize the NARDL model without any hesitation.

[Tables 2 and 3 about here]

5. Econometric Framework

For empirical analyses, we employ the nonlinear autoregressive distributed lag (NARDL) model developed by Shin et al. (2014) to investigate the cointegrating relationships and asymmetric interactions between the variables. This model is an extension of the linear ARDL model (Pesaran et al., 2001; Pesaran and Shin, 1998). The performance of the ARDL models is very strong for small sample size works (Pesaran and Shin, 1998; Pesaran et al., 2001; Shin et al., 2014). The NARDL model does not require that the variables have the same integration order. Unlike other counterpart models (e.g. vector error correction model (VECM)), the integration orders of the variables could be a mixture of I (0) and I (1). The use of this novel method enables us to distinguish between short- and long-term effects of the oil price, oil price uncertainty and interest rates on the unemployment rate. In addition, we can easily capture asymmetric relationships between the variables. Another important property of the NARDL model is that it does not suffer from convergence problem (due to a large number of estimated parameters) that some other non-linear models (e.g. nonlinear threshold vector error correction model) face. Utilizing the NARDL model also allows us to avoid endogeneity bias. Due to these advantages, we prefer to use the NARDL model to apply rigorous

[7] Also, to account for a structural breakpoint, we conduct the modified augmented Dickey-Fuller (MADF) test (Kim and Perron, 2009). The results are very similar and are available from the authors upon request.

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macroeconomic analysis in this study. Following the study of Shin et al. (2014), we first consider the below nonlinear long-run cointegrating regression[8];

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \tag{2}$$

With y_t refers to LUNEMP and x_t refer to explanatory variables, such as $LRAC_t$ (or $LWTI_t$), $LOVX_t$, $LCSDRAC_t$ (or $LCSDWTI_t$), and LFF_t (or $LTBILL_t$). β^+ and β^- are the associated long-run parameters. x_t is a k*1 vector of regressors, which enters the model asymmetrically and is defined as $x_t = x_0 + x_t^+ + x_t^-$ where x_0 represents the initial value. The NARDL model utilizes the decomposition of the predetermined explanatory variables into their positive and negative partial sums for increases and decreases, respectively.

$$x_t^+ = \sum_{i=1}^{t} \Delta x_i^+ = \sum_{i=1}^{t} \max(\Delta x_i, 0) \tag{3}$$

$$x_t^- = \sum_{i=1}^{t} \Delta x_i^- = \sum_{i=1}^{t} \min(\Delta x_i, 0) \tag{4}$$

Equation 2 can be extended to jointly model the long- and short-run asymmetries within the NARDL framework. The error correction representation of the NARDL model is the following (Eqs. (5)–(8))[9];

$$\begin{aligned}
\Delta LUNEMP_t &= \mu + \chi LUNEMP_{t-1} + \omega_1^+ LRAC_{t-1}^+ + \omega_1^- LRAC_{t-1}^- + \omega_2^+ LOVX_{t-1}^+ + \omega_2^- LOVX_{t-1}^- + \\
&\omega_3^+ LCSDRAC_{t-1}^+ + \omega_3^- LCSDRAC_{t-1}^- + \omega_4^+ LFF_{t-1}^+ + \omega_4^- LFF_{t-1}^- + \sum_{i=1}^{p-1} \tau \Delta LUNEMP_{t-i} + \sum_{i=0}^{q-1} \varphi_1^+ \Delta LRAC_{t-i}^+ + \\
&\sum_{i=0}^{q-1} \varphi_1^- \Delta LRAC_{t-i}^- + \sum_{i=0}^{q-1} \varphi_2^+ \Delta LOVX_{t-i}^+ + \sum_{i=0}^{q-1} \varphi_2^- \Delta LOVX_{t-i}^- + \sum_{i=0}^{q-1} \varphi_3^+ \Delta LCSDRAC_{t-i}^+ + \sum_{i=0}^{q-1} \varphi_3^- \Delta LCSDRAC_{t-i}^- + \\
&\sum_{i=0}^{q-1} \varphi_4^+ \Delta LFF_{t-i}^+ + \sum_{i=0}^{q-1} \varphi_4^- \Delta LFF_{t-i}^- + \varepsilon_t
\end{aligned} \tag{5}$$

[8] For the detailed information about the NARDL model, see Shin et al. (2014).

[9] We also consider the importance of pre- and post-crisis differences and use a dummy variable for the collapse of Lehman Brothers in September 2008, the value of which is one if it is in the post-crisis period (after the collapse of Lehman Brothers (September 2008)) and zero otherwise. We do not find significant dummies. The results are available from authors.

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$$\Delta LUNEMP_t = \mu + \chi LUNEMP_{t-1} + \omega_1^{+} LWTI_{t-1}^{+} + \omega_1^{-} LWTI_{t-1}^{-} + \omega_2^{+} LOVX_{t-1}^{+} + \omega_2^{-} LOVX_{t-1}^{-} + \omega_3^{+} LCSDWTI_{t-1}^{+} + \omega_3^{-} LCSDWTI_{t-1}^{-} + \omega_4^{+} LFF_{t-1}^{+} + \omega_4^{-} LFF_{t-1}^{-} + \sum_{i=1}^{p-1} \tau \Delta LUNEMP_{t-i} + \sum_{i=0}^{q-1} \varphi_1^{+} \Delta LWTI_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_1^{-} \Delta LWTI_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_2^{+} \Delta LOVX_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_2^{-} \Delta LOVX_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_3^{+} \Delta LCSDWTI_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_3^{-} \Delta LCSDWTI_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_4^{+} \Delta LFF_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_4^{-} \Delta LFF_{t-i}^{-} + \varepsilon_t \quad (6)$$

$$\Delta LUNEMP_t = \mu + \chi LUNEMP_{t-1} + \omega_1^{+} LRAC_{t-1}^{+} + \omega_1^{-} LRAC_{t-1}^{-} + \omega_2^{+} LOVX_{t-1}^{+} + \omega_2^{-} LOVX_{t-1}^{-} + \omega_3^{+} LCSDRAC_{t-1}^{+} + \omega_3^{-} LCSDRAC_{t-1}^{-} + \omega_4^{+} LTBILL_{t-1}^{+} + \omega_4^{-} LTBILL_{t-1}^{-} + \sum_{i=1}^{p-1} \tau \Delta LUNEMP_{t-i} + \sum_{i=0}^{q-1} \varphi_1^{+} \Delta LRAC_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_1^{-} \Delta LRAC_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_2^{+} \Delta LOVX_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_2^{-} \Delta LOVX_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_3^{+} \Delta LCSDRAC_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_3^{-} \Delta LCSDRAC_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_4^{+} \Delta LTBILL_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_4^{-} \Delta LTBILL_{t-i}^{-} + \varepsilon_t \quad (7)$$

$$\Delta LUNEMP_t = \mu + \chi LUNEMP_{t-1} + \omega_1^{+} LWTI_{t-1}^{+} + \omega_1^{-} LWTI_{t-1}^{-} + \omega_2^{+} LOVX_{t-1}^{+} + \omega_2^{-} LOVX_{t-1}^{-} + \omega_3^{+} LCSDWTI_{t-1}^{+} + \omega_3^{-} LCSDWTI_{t-1}^{-} + \omega_4^{+} LTBILL_{t-1}^{+} + \omega_4^{-} LTBILL_{t-1}^{-} + \sum_{i=1}^{p-1} \tau \Delta LUNEMP_{t-i} + \sum_{i=0}^{q-1} \varphi_1^{+} \Delta LWTI_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_1^{-} \Delta LWTI_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_2^{+} \Delta LOVX_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_2^{-} \Delta LOVX_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_3^{+} \Delta LCSDWTI_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_3^{-} \Delta LCSDWTI_{t-i}^{-} + \sum_{i=0}^{q-1} \varphi_4^{+} \Delta LTBILL_{t-i}^{+} + \sum_{i=0}^{q-1} \varphi_4^{-} \Delta LTBILL_{t-i}^{-} + \varepsilon_t \quad (8)$$

We estimate the above-shown equations to investigate the asymmetric interactions and cointegration relationship between the variables of interest. LUNEMP, LRAC (LWTI), LOVX, LCSDRAC (LCSDWTI), and LFF (LTBILL) are the unemployment rate, the composite refiner acquisition cost (RAC) of crude oil (the crude oil price of the West Texas Intermediate (WTI)), the crude oil volatility index (OVX), the conditional standard deviation

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of RAC (CSDRAC) (the conditional standard deviation of WTI (CSDWTI)) and the federal funds rate (FF) (3-month US Treasury bill (TBILL)) in logarithms, respectively. The Δ denotes the first difference of the variables. The coefficients χ and ω_j represent the long-run coefficients of the model as the τ and φ_j refer to the short-run coefficients for the variables with j=1, 2, 3, 4.

Initially, following the bounds-testing procedure (Pesaran and Shin, 1998; Shin et al., 2014), we use the F-statistic to test the null hypothesis of no nonlinear cointegration that $\chi=\omega_1^+ = \omega_1^- = \omega_2^+ = \omega_2^- = \omega_3^+ = \omega_3^- = \omega_4^+ = \omega_4^- = 0$. Then, the standard Wald test is used to test the short- and long-run symmetries (Shin et al. 2014). To investigate the presence of long-run nonlinearities, we test the null hypothesis of long-run symmetry that is $\beta^+ = \beta^-$ where $\beta^+ = -\omega_j^+/\chi$ and $\beta^- = -\omega_j^-/\chi$ with j=1, 2, 3, and 4. The existence of short-run symmetry can be evaluated by testing the null hypothesis that $\sum_{i=0}^{q-1}\phi_k^+ = \sum_{i=0}^{q-1}\phi_k^-$ with k= 1, 2, 3, and 4. The results from our analyses are presented in the following section.

6. Empirical findings

In this section, we provide the empirical findings from the above-developed nonlinear models. The optimal lag length in the unrestricted error correction models is selected by using the Schwarz information criterion (SIC)[10]. We conduct a series of stability and diagnostic tests to check the robustness of our analyses[11]. We do not determine a significant violation of standard regression assumptions.

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[10] Following the study of Pesaran and Shin (1998), we use the Schwarz Information Criterion (SIC) considering the well-performance of the ARDL-SIC estimators for small sample size cases. For robustness, the Akaike information Criterion (AIC) and general-to-specific approach (starting with p=12 and q=12 to drop insignificant stationary regressors) are employed to choose the optimal lag length for the analyses. We find very similar results about the asymmetric relationships. The findings are available from author upon request.

[11] We apply the CUSUM (cumulative sum), CUSUM of Square and Ramsey RESET tests to control for the stability of our results. To test for serial correlation and heteroskedasticity, we use the Breusch-Godfrey serial

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As mentioned in the preceding section, we first test the presence of the asymmetric cointegration relationships between the variables utilizing the F-test statistics (Shin et al., 2014). In Table 4, we report the F-statistics testing whether there is a nonlinear cointegration relationship between the chosen variables in the long-run or not. Larger F-statistics than upper critical values suggest the rejection of the null hypothesis of no cointegration. Our results indicate the presence of the asymmetric cointegration relationships between the variables. The results enable us to assess whether oil prices, oil price uncertainty, and interest rates asymmetrically influence unemployment rates in the long- and short-run.

[Table 4 about here]

Before discussing the findings from our analysis, it would be instructive to explain the meaning of the coefficients for the asymmetric parameters. A significantly negative coefficient for the negative (positive) fluctuations of an independent variable demonstrates that when the independent variable decreases (increases), the dependent variable tends to increase (decrease). As regards to the meaning of the positive coefficients, a significantly positive coefficient for the negative (positive) fluctuations of an independent variable demonstrates that when the independent variable decreases (increases), the dependent variable tends to decrease (increase).

Our baseline findings suggest that the unemployment rate is significantly and asymmetrically affected by the fluctuations in oil prices, oil price uncertainty and interest rates in the long-run, but not in the short-run. We find that rising oil prices lead to increasing unemployment rates while there is no significant impact of declining oil prices. Conversely, the opposite of this relationship holds true for the oil price uncertainty. Namely, it is observed that declining oil price uncertainty significantly reduces unemployment rates whereas rising oil price

correlation LM test, correlograms of residuals, squared residuals, the Ljung–Box Q statistics, the Breusch-Pagan-Godfrey heteroskedasticity and ARCH LM tests. The results are provided upon request.

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uncertainty does not have a significant effect on unemployment. As for the impact of interest rates, unemployment rates appear to increase in response to declining interest rates, but do not respond to rising interest rates. The Wald test results confirm these asymmetric interactions[12]. Last, our results show that implied oil price volatility (as a measure of oil price uncertainty) perform much better in predicting unemployment rates compared to the conditional volatility of crude oil prices (the other well-known measure of oil price uncertainty)[13]. Our results are robust to different measures of interest rates and oil prices. In the following sections, the economic and policy implications of our research are discussed in detail.

[Tables 5, 6, 7, and 8 about here]

7. Discussion

The responses of economic actors and market participants to oil price dynamics and macroeconomic developments differ depending on the stage of economic activity. In this sense, nonlinear analyses, which consider the asymmetric interactions between variables, potentially enable a better understanding of the key role of oil prices, oil price uncertainty and interest rates in affecting unemployment compared to linear analyses. Therefore, to correctly analyze the behavior of labor markets, we used the NARDL model to investigate the asymmetric effect of oil prices, oil price uncertainty and interest rates on unemployment rates in this study. Our main results suggest a nonlinear relationship between the variables of interest. The results are noteworthy for several key reasons as discussed below.

[12] We do not provide the Wald test results for the short-run coefficients since there is no statistically significant short-run coefficient. Also, our focus is on the long-run relationships.

[13] As mentioned in the previous sections, the implied oil price volatility and the conditional volatility of oil prices appear in the same model according to our framework. We also separately enter the implied volatility and the conditional volatility into two different NARDL models and, as expected, observe that the model including the implied volatility have greater explanatory power than the model including the conditional volatility. For these separate specifications, we observe that a decrease in both volatilities results in reduced unemployment, which is similar to the impact of implied volatility in the original model including both the implied volatility and the conditional volatility. Our findings are consistent with the studies of Poon and Granger (2003), Szakmary et al. (2003) and Kellogg (2014). The findings are provided upon request.

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Firstly, in all the discussions about oil price and labor market implications, one should not lose sight of the state of the current economic conditions and expectations: that oil price does not affect the unemployment directly but it depends on how this effect translates into other macroeconomic indicators - on the expectations about the oil price movements and the interest rates. With these considerations, oil price increase will inform the economy about possible increases in the production costs and companies have to operate not only against the shrinking profits but also against extremes of expectations. We find that oil price increase causes an increase in unemployment. That is reflection of the worsening economic conditions for the production sector and possibly for its economic ramifications. On the other hand, a decrease in oil price does not have any significant effect on the unemployment. This finding can be interpreted in conjunction with our model's structure (asymmetric) and independent variables (oil price, oil price uncertainty and interest rates). A reduction in any input price can in principle increase the production and lead to an increase in the employment in the economy in the long run. However, we are accounting for the uncertainty of the oil prices in our equations, that transforms the interpretation accordingly as such that the episodes of oil price decreases likely to coincide with a decrease in the uncertainty regarding the oil price (global better economic conditions, less worry about energy security etc.). In that respect, decrease in price is not conveyed to a decrease in unemployment because companies can be reluctant to invest in uncertain times even if the price level is low. Therefore, employment effects of oil price decreases are not permanent if the new price level is not anticipated to sustain permanently. Firms rather prefer stable prices to better form their expectations and this gives more stimulus to the economy as unemployment responds to a decrease in uncertainty in price movements, but not the decrease in price itself. Moreover, failure to account for the determining role of oil price uncertainty and interest rates in the relationship can likely to produce biased estimates (Kisswani and Kisswani, (2019)). By reversing expectations, the oil

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price decrease could lead to more employment opportunities through the traditional economic channel - increase in labor demand. Our estimations reveal that the joint modelling brings critical new insights into these relationships.

Secondly, oil price uncertainty offers a counterbalance to the oil price changes in our model and brings possible new explanations to the unemployment dynamics in an oil importing country. Economic actors respond to expectations and capturing this effect drew upon the joint modelling of oil price and price uncertainty. We found an asymmetric effect regarding the uncertainty as such that an increase in uncertainty does not translate into a significant effect on the unemployment. However, less uncertain economic conditions with a decrease in oil price volatility reduce unemployment as firms shape their expectations accordingly and respond positively to the stable conditions; i.e. via with more investment. This explanation rests within the boundaries of the theoretical transmission mechanisms of Carruth et al (1998), however asymmetric structure of our model identifies the separate role of the different moments of oil price on the transmission. This new finding requires some explanations as it brings new insights into our understanding of the factors affecting the long run unemployment – oil price dynamics. Firstly, earlier studies using data before 1980s mostly find (Hamilton, (1983)) that oil price strongly cause economic growth and unemployment. However, more recent studies using data from 1980s and 1990s for the U.S. economy have found a different result, namely that there exists no significant causality between oil prices and unemployment. Yet the subsequent research explored different functional form assumptions and included oil price volatility as a measure in the estimation equations. (Mork (1989), Lee et al. (1995), Ferderer (1996), Hamilton (1996) and Hooker (1996, 1997)). Volatility measures proved to be important and oil price increases are found to matter more compared to oil price decreases. Carruth et al (1998) reestablished the causality between oil price and unemployment in a smaller system estimation that has rooted in a structural relationship between unemployment,

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oil prices and interest rates. However, although they found a positive causal relationship between oil prices and unemployment, their evidence is weak for the role of interest rates. Also when all the shocks to the unemployment comes from the demand side - which is one of the main assumptions of the Carruth et al (1998) model - the equilibrium unemployment is neutral with respect to the labor supply[14]. Even though, this can be theoretically appealing, there are certain reasons to believe that the labor supply responds to the real price changes in the economy and furthermore this response is likely to be asymmetric. Forini et al. (2018) find that labor supply shocks affect the participation rate and contribute to its decline in the aftermath of the Great Recession. This among other things can partially explain the no response when oil prices decrease, i.e. participation in the labor market can decrease as labor demand increases. This also supports the use of oil price uncertainty to account for the economic uncertainty in shaping the workers' expectations through the asymmetric effect of the transition to the firms and the labor force.

For the period under consideration, US has experienced a big economic downturn that devastated world financial markets as well as the banking and real estate industries. In this period, FED employed a series of measures to mitigate the effects of the crises on the economy[15]. Interest rate cuts was one of these measures. Even though policy rate gradually decreased throughout 2008 – at the peaks of the recession - U.S. economy still witnessed a period of a large increase in unemployment. Carruth et al (1998) and subsequent studies using the same theoretical underpinnings assume that interest rate is the rental price of capital. Therefore, an increase in the rental price of capital has exactly the same effect of an increase

[14] Changes in the labor supply will not affect the equilibrium unemployment rate.

[15] For robustness, we take into consideration the impact of global crisis on unemployment using a dummy variable. The crisis period corresponds to an increasing trend in unemployment rates (from 5 % to 10 % between April 2008 to October 2009). The dummy is coded as one for the April 2008–October 2009 period. As expected, we observe the positive and significant impact of the crisis dummy on unemployment rates. We also find that the significance and magnitude of significant coefficients decrease a little but the significant variables in the original model still significantly (and similarly) influence unemployment rates. Overall assessment suggests that our results are robust to the impact of global crisis on unemployment. The results are provided upon request.

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in the price of oil since both are inputs to the production function, as such an increase in either decreases the profitability for firms. However, in the empirical applications, interest rates and oil prices (or the proxies for them to be exact) might not be the same sort of input to the production function due to several reasons. Firstly, interest rates are generally a policy decision and they are embedded with expectations of the future state of the economy. In that respect, a decrease in interest rates might be an indicator of a possible precautionary or even preventive policy for the worsening economic conditions. If that is the case, the theoretical counterpart of the interest rate – the rental price of capital – should adjust to include the uncertainty surrounding the economic activity. In that case empirical results can easily indicate a negative relationship between decreasing interest rates and unemployment. For the increase in interest rates, as in Carruth et al (1998), we find a positive but insignificant effect. This result together with the previous one can be interpreted as such it is through other mechanisms in the economy that interest rates affect the unemployment in the long run, yet a period of consequent decreases in interest rate is generally a monetary policy shift (Caplin and Leahy, 1996) and can be inefficient to convey the long run relationship. Interest rates movement to the extent that they narrow the gap between rental price and borrowing rate are likely to behave as a long run determinant of employment, though in practice including the uncertainty of real prices (oil price uncertainty in our case) can capture some of these concerns and become a much more explicit part of unemployment dynamics.

Option-implied oil price volatility, as a proxy for oil price uncertainty, performs better in predicting unemployment rates compared to the conditional volatility of crude oil prices. The main reason behind this result could be that option-implied volatility is a market-based measure of volatility and hence better reflects investors' expectation about future volatility than a GARCH-based volatility measure (Poon and Granger, 2003). Based on this superiority, the option-implied oil price volatility includes more relevant and useful information regarding

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oil price uncertainty changes, which cannot be conveyed by the GARCH-based oil price volatility. In sum, our findings imply that the higher implied volatility from the oil options market provides valuable information on the uncertainty in oil markets to market participants and is a better representative of market sentiment with respect to future market conditions.

8. Conclusions

Previous research emphasizes the crucial role of oil prices, oil price uncertainty, and interest rates in influencing investment behavior and hence unemployment rates. However, existing studies do not jointly model the long- and short-run asymmetries between these variables in a cointegration framework. Also, there is a lack of knowledge on what is the performance of option-implied oil price volatility and the conditional volatility of crude oil prices, as a measure of oil price uncertainty, in predicting unemployment rates. In this study, using a cointegration approach (NARDL model), we investigate the asymmetric interactions between oil prices, oil price uncertainty, interest rates, and unemployment rates in US and evaluate the comparative performance of the implied oil price volatility and the conditional volatility of crude oil prices in the prediction of unemployment rates.

There are 2 important findings in this study. First finding is the asymmetric nature of the effects of oil prices, oil price uncertainty and interest rates on unemployment rates. Increases and decreases in oil prices are perceived differently by market participants. Increased oil prices lead to increased unemployment, but decreased oil prices have no effect. A similar argument holds for oil price uncertainty. Decreased uncertainty in the oil market promotes employment, but increased uncertainty does not have a meaningful impact. The asymmetry is also observed in the case of interest rate changes. As interest rates decline unemployment rises, but unemployment does not respond to increased interest rates. As pointed out by Caplin and Leahy (1996), in the face of an interest rate cut by monetary authorities during

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recessions, economic agents may take positions in expectations of further cuts. Hence, one may observe increases in unemployment rates even in the face of decreasing interest rates.

Second important finding is that price is not the only link between oil and labor markets. Oil price uncertainty plays an important role which should be accounted for in forecasting unemployment rates. To that respect, we also show that implied oil volatility is a better predictor of unemployment rates than conditional oil volatility.

These findings have important implications for policy makers and scholars. In order to curb unemployment, policy makers can reduce oil price uncertainty to lessen the negative impact of rising oil prices. This seems to be a more effective policy than interest rate cuts. Increased energy security and diversifying away from oil may reduce the responsiveness of labor market to oil volatility shocks in the long-run. A more direct tool that may be employed to reduce oil market uncertainty is the Strategic Petroleum Reserves (SPR). Release and purchase decisions targeting volatility rather than price can reduce uncertainty and prevent companies from postponing their irreversible investment decisions which in turn reduces unemployment. In this respect a useful extension to this study would be to estimate the responsiveness of oil volatility to SPR strategies. A more direct extension would be to question if these links are time-varying and whether they depend on the level of oil price, interest rate, and/or oil price uncertainty. There are several other paths in which the literature may proceed regarding the choice of countries as well, since oil and labor market links may differ across countries due to different development levels, macroeconomic characteristics, labor policies, and energy import levels.

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Tables

Table 1. Variance equation results

Variables	Model	Υ_0	Υ_1	Υ_2
RAC	GARCH(1,1)	0.001489***	0.467049***	0.322460**
WTI	GARCH(1,1)	0.001914***	0.298059***	0.468914**

Notes: Table 1 reports the estimated coefficients in the variance equations for the GARCH (1,1) model. ** Significant at the 5% level; *** Significant at the 1% level. $\Upsilon1$ and $\Upsilon2$ refer to ARCH and GARCH parameters, respectively.

Table 2. Descriptive statistics

	UNEMP	RAC	WTI	OVX	CSDRAC	CSDWTI	FF	TBILL
Mean	6.5140	75.0047	75.0741	36.1008	0.0773	0.0871	0.8135	0.6901
Median	6.1000	73.5400	75.7200	32.5200	0.0623	0.0764	0.1800	0.1500
Maximum	10.0000	129.0300	133.8800	88.9300	0.2892	0.2425	5.2600	4.8200
Minimum	3.6000	28.5300	30.3200	15.6100	0.0476	0.0612	0.0700	0.0100
Std. Dev.	2.0247	24.2836	23.2698	13.5314	0.0396	0.0301	1.2108	1.0458
Skewness	0.2780	0.0399	0.1067	1.4329	2.7808	2.4478	2.1194	1.9316
Kurtosis	1.6298	1.8321	2.1073	5.6214	12.4260	10.2939	7.0956	6.3707
Jarque-Bera	13.0287	8.1648	5.0201	89.8778	713.6998	459.7903	207.0043	156.6194
Probability	0.0015	0.0169	0.0813	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Table 2 provides the descriptive statistics of the time series for the sample period. , UNEMP, RAC, WTI, OVX, CSDRAC, CSDWTI, FF, and TBILL refer to the unemployment rate, the composite refiner acquisition cost (RAC) of crude oil, the crude oil price of the West Texas Intermediate (WTI), the crude oil volatility index (OVX), the conditional standard deviation of RAC (CSDRAC), the conditional standard deviation of WTI (CSDWTI), the federal funds rate (FF) and 3-month US Treasury bill (TBILL), respectively.

Table 3. Unit root test results

		DF-GLS Statistics		DF-GLS Statistics
LUNEMP	Intercept	-1.316824	Intercept	-1.43599
LRAC		-2.796274***	and Trend	-2.900835*
LWTI		-2.530970**		-2.67334
LOVX		-2.542461**		-2.688523
LCSDRAC		-4.051506***		-4.077090***
LCSDWTI		-3.678512***		-3.833477***
LFF		-0.718023		-0.576536
LTBILL		-0.769861		-0.664296
DLUNEMP	Intercept	-1.198361**	Intercept	-11.05426***
DLRAC		-4.850986***	and Trend	-5.857946***
DLWTI		-4.165919***		-7.235167***
DLOVX		-9.077273***		-10.57046***
DLCSDRAC		-11.32793***		-10.10303***
DLCSDWTI		-12.52375***		-12.53598***
DLFF		-7.665901***		-7.972245***
DLTBILL		-10.12316***		-10.29021***

Notes: Table 3 provides the results of the Dickey-Fuller GLS detrended test (DF-GLS) tests. D and L are the first differences and log operators, respectively. Superscripts *, **, *** represent the significance at 10%, 5%, and 1% levels, respectively.

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Table 4. Bounds-testing procedure results

Cointegration Hypotheses	F Stat.
$F(LUNEMP_t/LRAC_t^+, LRAC_t^-, LOVX_t^+, LOVX_t^-, LCSDRAC_t^+, LCSDRAC_t^-, LFF_t^+, LFF_t^-)$	6.271637***
$F(LUNEMP_t/LWTI_t^+, LWTI_t^-, LOVX_t^+, LOVX_t^-, LCSDWTI_t^+, LCSDWTI_t^-, LFF_t^+, LFF_t^-)$	6.067829***
$F(LUNEMP_t/LRAC_t^+, LRAC_t^-, LOVX_t^+, LOVX_t^-, LCSDRAC_t^+, LCSDRAC_t^-, LTBILL_t^+, LTBILL_t^-)$	5.949965***
$F(LUNEMP_t/LWTI_t^+, LWTI_t^-, LOVX_t^+, LOVX_t^-, LCSDWTI_t^+, LCSDWTI_t^-, LTBILL_t^+, LTBILL_t^-)$	6.033700***

Notes: Table 5 presents Bounds-testing procedure results. For the NARDL models; the critical values are 2.22-3.39 and 2.79-4.10 for 5%, and 1 % significance levels, respectively. Superscript *** represents significance at 1% level. LUNEMP, LRAC, LWTI, LOVX, LCSDRAC, LCSDWTI, LFF, and LTBILL refer to the unemployment rate, the composite refiner acquisition cost (RAC) of crude oil, the crude oil price of the West Texas Intermediate (WTI), the crude oil volatility index (OVX), the conditional standard deviation of RAC (CSDRAC), the conditional standard deviation of WTI (CSDWTI), the federal funds rate (FF) and 3-month US Treasury bill (TBILL) in logarithms, respectively.

Table 5. NARDL estimation results (Dependent variable: $\triangle LUNEMP_t$)

Panel A. Estimated coefficients				
EV	Coefficient	Std. Error	t-statistic	Prob.
C	0.314489	0.067454	4.662281	0.000
$LUNEMP_{t-1}$	-0.195658	0.043866	-4.460358	0.000
$LRAC_{t-1}^+$	0.07339	0.031807	2.307394	0.023
$LRAC_{t-1}^-$	-0.032129	0.024984	-1.28595	0.201
$LOVX_{t-1}^+$	-0.023219	0.020025	-1.159527	0.249
$LOVX_{t-1}^-$	0.068626	0.017771	3.861729	0.000
$LCSDRAC_{t-1}^+$	0.006112	0.021132	0.289252	0.773
$LCSDRAC_{t-1}^-$	0.007125	0.012973	0.549212	0.584
LFF_{t-1}^+	0.002479	0.012541	0.19765	0.844
LFF_{t-1}^-	-0.027676	0.007201	-3.843272	0.000
$\triangle LRAC_t^+$	0.116949	0.063278	1.848171	0.067
$\triangle LRAC_t^-$	-0.096659	0.057831	-1.671398	0.097
$\triangle LOVX_t^+$	-0.034098	0.025431	-1.340819	0.183
$\triangle LOVX_t^-$	0.011117	0.027119	0.409931	0.683
$\triangle LCSDRAC_t^+$	-0.003648	0.019756	-0.18464	0.854
$\triangle LCSDRAC_t^-$	0.005165	0.020873	0.247462	0.805
$\triangle LFF_t^+$	-0.017228	0.024619	-0.699782	0.485
$\triangle LFF_t^-$	-0.005273	0.021995	-0.239755	0.811
Panel B. Long-run coefficents and symmetry test results				
$LRAC^+$	0.3751***	$LRAC^-$	-0.1642	
$LOVX^+$	-0.1187	$LOVX^-$	0.3508***	
$LCSDRAC^+$	0.0312	$LCSDRAC^-$	0.0364	
LFF^+	0.0127	LFF^-	-0.1415***	
$W_{LR,\ LRAC}$	5.217108**	$W_{LR,\ LOVX}$	22.92449***	
$W_{LR,\ LCSDRAC}$	0.9696	$W_{LR,\ LFF}$	4.138023**	
R^2	0.412619	Adj. R^2	0.331436	

Notes: EV denotes the explanatory variables. LUNEMP, LRAC, LOVX, LCSDRAC, and LFF refer to the unemployment rate, the composite refiner acquisition cost (RAC) of crude oil, the crude oil volatility index (OVX), the conditional standard deviation of RAC (CSDRAC), and the federal funds rate (FF) in logarithms, respectively. The superscripts "+" and "−" refer to positive and negative partial sums, respectively. $LRAC^+$, $LRAC^-$, $LOVX^+$, $LOVX^-$, $LCSDRAC^+$, $LCSDRAC^-$, LFF^+ and LFF^- are the estimated long-run coefficients for the positive and negative changes of corresponding variables. $W_{LR,\ LRAC}$, $W_{LR,\ LOVX}$, $W_{LR,\ LCSDRAC}$, and $W_{LR,\ LFF}$ refer to the standard Wald test for the null of long-run symmetry for the corresponding variable. Superscripts *, **, *** represent the significance at 10%, 5%, and 1% levels, respectively.

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Table 6. NARDL estimation results (Dependent variable: $\Delta LUNEMP_t$)

Panel A. Estimated coefficients

EV	Coefficient	Std. Error	t-statistic	Prob.
C	0.279459	0.065267	4.281811	0.000
$LUNEMP_{t-1}$	-0.175383	0.042761	-4.101441	0.000
$LWTI_{t-1}^{+}$	0.073492	0.028457	2.582597	0.011
$LWTI_{t-1}^{-}$	-0.022473	0.018378	-1.222796	0.224
$LOVX_{t-1}^{+}$	-0.020989	0.019063	-1.101058	0.273
$LOVX_{t-1}^{-}$	0.072504	0.01855	3.908591	0.000
$LCSDWTI_{t-1}^{+}$	0.02192	0.021728	1.008817	0.315
$LCSDWTI_{t-1}^{-}$	0.013719	0.019451	0.705346	0.482
LFF_{t-1}^{+}	-0.000809	0.013839	-0.058473	0.954
LFF_{t-1}^{-}	-0.021673	0.00693	-3.127521	0.002
$\Delta LWTI_t^{+}$	0.094973	0.057227	1.659575	0.100
$\Delta LWTI_t^{-}$	-0.060146	0.056271	-1.06887	0.287
$\Delta LOVX_t^{+}$	-0.024501	0.0264	-0.92805	0.355
$\Delta LOVX_t^{-}$	0.008195	0.02714	0.301966	0.763
$\Delta LCSDWTI_t^{+}$	0.010044	0.023604	0.425509	0.671
$\Delta LCSDWTI_t^{-}$	0.031551	0.034156	0.923739	0.357
ΔLFF_t^{+}	-0.014353	0.025019	-0.573661	0.567
ΔLFF_t^{-}	-0.008699	0.022083	-0.393923	0.694

Panel B. Long-run coefficents and symmetry test results

$LWTI^{+}$	0.4190***	$LWTI^{-}$	-0.1281
$LOVX^{+}$	-0.1197	$LOVX^{-}$	0.4134***
$LCSDWTI^{+}$	0.125	$LCSDWTI^{-}$	0.0782
LFF^{+}	-0.00461	LFF^{-}	-0.1236***
$W_{LR,\ LWTI}$	11.91830***	$W_{LR,\ LOVX}$	45.07724***
$W_{LR,\ LCSDWTI}$	0.097902	$W_{LR,\ LFF}$	1.51561
R^2	0.400594	Adj. R^2	0.317749

Notes: EV denotes the explanatory variables. LUNEMP, LWTI, LOVX, LCSDWTI, and LFF refer to the unemployment rate, the crude oil price of the West Texas Intermediate (WTI), the crude oil volatility index (OVX), the conditional standard deviation of WTI (CSDWTI), and the federal funds rate (FF) in logarithms, respectively. The superscripts "+" and "−" refer to positive and negative partial sums, respectively. $LWTI^{+}$, $LWTI^{-}$, $LOVX^{+}$, $LOVX^{-}$, $LCSDWTI^{+}$, $LCSDWTI^{-}$, LFF^{+} and LFF^{-} are the estimated long-run coefficients for the positive and negative changes of corresponding variables. $W_{LR,\ LWTI}$, $W_{LR,\ LOVX}$, $W_{LR,\ LCSDWTI}$, and $W_{LR,\ LFF}$ refer to the standard Wald test for the null of long-run symmetry for the corresponding variable. Superscripts *, **, *** represent the significance at 10%, 5%, and 1% levels, respectively.

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Table 7. NARDL estimation results (Dependent variable: $\Delta LUNEMP_t$)

Panel A. Estimated coefficents				
EV	Coefficient	Std. Error	t-statistic	Prob.
C	0.213636	0.057805	3.695823	0.000
$LUNEMP_{t-1}$	-0.13279	0.03735	-3.55529	0.001
$LRAC_{t-1}^{+}$	0.096102	0.036544	2.629748	0.010
$LRAC_{t-1}^{-}$	-0.025775	0.025492	-1.011088	0.314
$LOVX_{t-1}^{+}$	-0.020167	0.02116	-0.953037	0.342
$LOVX_{t-1}^{-}$	0.052061	0.016608	3.134748	0.002
$LCSDRAC_{t-1}^{+}$	0.007198	0.020706	0.347631	0.729
$LCSDRAC_{t-1}^{-}$	0.025548	0.013864	1.842785	0.068
$LTBILL_{t-1}^{+}$	0.00383	0.005429	0.70554	0.482
$LTBILL_{t-1}^{-}$	-0.010024	0.004281	-2.341591	0.021
$\Delta LRAC_t^{+}$	0.121347	0.0664	1.827515	0.070
$\Delta LRAC_t^{-}$	-0.091726	0.051699	-1.774224	0.079
$\Delta LOVX_t^{+}$	-0.028742	0.025503	-1.127013	0.262
$\Delta LOVX_t^{-}$	-0.000455	0.027321	-0.016657	0.987
$\Delta LCSDRAC_t^{+}$	-0.003489	0.020265	-0.17216	0.864
$\Delta LCSDRAC_t^{-}$	0.012381	0.021352	0.579859	0.563
$\Delta LTBILL_t^{+}$	0.002519	0.009508	0.264964	0.792
$\Delta LTBILL_t^{-}$	-0.002702	0.009446	-0.286091	0.775
Panel B. Long-run coefficents and symmetry test results				
$LRAC^{+}$	0.7237***	$LRAC^{-}$	-0.1941	
$LOVX^{+}$	-0.1519	$LOVX^{-}$	0.3921***	
$LCSDRAC^{+}$	0.0542	$LCSDRAC^{-}$	0.1924	
$LTBILL^{+}$	0.0288	$LTBILL^{-}$	-0.0755***	
$W_{LR, LRAC}$	6.971298***	$W_{LR, LOVX}$	13.52900***	
$W_{LR, LCSDRAC}$	0.464488	$W_{LR, LTBILL}$	6.948093***	
R^2	0.386212	Adj. R^2	0.301379	

Notes: EV denotes the explanatory variables. LUNEMP, LRAC, LOVX, LCSDRAC, and LTBILL refer to the unemployment rate, the composite refiner acquisition cost (RAC) of crude oil, the crude oil volatility index (OVX), the conditional standard deviation of RAC (CSDRAC), and 3-month US Treasury bill (TBILL) in logarithms, respectively. The superscripts "+" and "–" refer to positive and negative partial sums, respectively. $LRAC^{+}$, $LRAC^{-}$, $LOVX^{+}$, $LOVX^{-}$, $LCSDRAC^{+}$, $LCSDRAC^{-}$, $LTBILL^{+}$ and $LTBILL^{-}$ are the estimated long-run coefficients for the positive and negative changes of corresponding variables. $W_{LR, LRAC}$, $W_{LR, LOVX}$, $W_{LR, LCSDRAC}$, and $W_{LR, LTBILL}$ refer to the standard Wald test for the null of long-run symmetry for the corresponding variable. Superscripts *, **, *** represent the significance at 10%, 5%, and 1% levels, respectively.

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Table 8. NARDL estimation results (Dependent variable: $\triangle LUNEMP_t$)

Panel A. Estimated coefficents				
EV	Coefficient	Std. Error	t-statistic	Prob.
C	0.185365	0.055991	3.31059	0.001
$LUNEMP_{t-1}$	-0.115616	0.035959	-3.215258	0.002
$LWTI_{t-1}^{+}$	0.076491	0.03175	2.409139	0.018
$LWTI_{t-1}^{-}$	-0.00373	0.019747	-0.188901	0.851
$LOVX_{t-1}^{+}$	-0.022242	0.019517	-1.139639	0.257
$LOVX_{t-1}^{-}$	0.05795	0.017608	3.291182	0.001
$LCSDWTI_{t-1}^{+}$	0.038363	0.019885	1.929225	0.056
$LCSDWTI_{t-1}^{-}$	0.032264	0.021169	1.524104	0.130
$LTBILL_{t-1}^{+}$	0.001849	0.005556	0.33285	0.740
$LTBILL_{t-1}^{-}$	-0.007475	0.003807	-1.96361	0.052
$\triangle LWTI_t^{+}$	0.102641	0.059693	1.719491	0.088
$\triangle LWTI_t^{-}$	-0.061479	0.051171	-1.201453	0.232
$\triangle LOVX_t^{+}$	-0.021172	0.026542	-0.797692	0.427
$\triangle LOVX_t^{-}$	0.000731	0.027395	0.026667	0.979
$\triangle LCSDWTI_t^{+}$	0.019776	0.023045	0.858182	0.393
$\triangle LCSDWTI_t^{-}$	0.047513	0.034688	1.369747	0.173
$\triangle LTBILL_t^{+}$	0.002806	0.009814	0.285928	0.775
$\triangle LTBILL_t^{-}$	0.000293	0.009685	0.030213	0.976
Panel B. Long-run coefficents and symmetry test results				
$LWTI^{+}$	0.6616***	$LWTI^{-}$	-0.0323	
$LOVX^{+}$	-0.1924	$LOVX^{-}$	0.5012***	
$LCSDWTI^{+}$	0.3318	$LCSDWTI^{-}$	0.2791	
$LTBILL^{+}$	0.016	$LTBILL^{-}$	-0.0647***	
$W_{LR,\ LWTI}$	7.782957***	$W_{LR,\ LOVX}$	33.12822***	
$W_{LR,\ LCSDWTI}$	0.057125	$W_{LR,\ LTBILL}$	2.796759*	
R^2	0.378777	Adj. R^2	0.292917	

Notes: EV denotes the explanatory variables. LUNEMP, LWTI, LOVX, LCSDWTI, and LTBILL refer to the unemployment rate, the crude oil price of the West Texas Intermediate (WTI), the crude oil volatility index (OVX), the conditional standard deviation of WTI (CSDWTI), and 3-month US Treasury bill (TBILL) in logarithms, respectively. The superscripts "+" and "–" refer to positive and negative partial sums, respectively. $LWTI^{+}$, $LWTI^{-}$, $LOVX^{+}$, $LOVX^{-}$, $LCSDWTI^{+}$, $LCSDWTI^{-}$, $LTBILL^{+}$ and $LTBILL^{-}$ are the estimated long-run coefficients for the positive and negative changes of corresponding variables. $W_{LR,\ LWTI}$, $W_{LR,\ LOVX}$, $W_{LR,\ LCSDWTI}$, and $W_{LR,\ LTBILL}$ refer to the standard Wald test for the null of long-run symmetry for the corresponding variable. Superscripts *, **, *** represent the significance at 10%, 5%, and 1% levels, respectively.

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