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Has the Asymmetric Effect of Oil Price Change in Inflation Expectations Been Impacted by the COVID-19 Outbreak? A Comparison Between the United States and China

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Abstract

Economists and policymakers believe that households' and firms' expectations of future inflation are key determinants of actual inflation. This paper applies the ARDL model and nonlinear ARDL model to long-term inflation-targeting policy mechanisms in the United States and China to assess the impact of oil price dynamics and asymmetries on inflation expectations, as well as the difference of this impact before and after the COVID-19 pandemic. In order to show the significant role of the COVID-19 outbreak, this paper includes the data from 2010 to 2021 and takes the pandemic period as a structural break. Taking oil price changes as a variable of interest, and introducing some other significant variables, we find that during the pandemic, the positive impact of oil price shock on U.S. inflation expectations has enhanced, whereas the positive impact on Chinese inflation expectations has weakened. There is also sufficient evidence of the existence of the asymmetric effects of oil price changes on inflation expectations in both countries, but the positive oil price change in the United States has always played a larger role than the negative oil price shock. In China, the impact of positive oil price shock was greater than that of negative oil prices before the epidemic and the effect of negative oil price shocks has increased significantly in the COVID-19 regime.

Keywords: oil price changes, asymmetric effect, inflation expectation, COVID-19 outbreak

1. Introduction

Oil is one of the important non-renewable energy sources, and it also plays an irreplaceable role in world production activities, resulting in oil prices being closely related to the development of the world economy. With the continuous spread of the COVID-19 epidemic and the sustained higher oil prices since the end of 2020, the impact of oil prices on inflation is particularly prominent. Given the interaction of inflation and inflation expectations (Lagoa, 2017; Marfatia, 2018), oil price shocks can also significantly affect inflation expectations. Therefore, this paper aims to study the changes in inflation expectations in the United States and China affected by oil price shocks before and after the COVID-19 outbreak, and the changes in the asymmetry of oil price shocks in the short and long term.

Because of the importance of oil, oil prices have always been the focus of scholars. With the advent of more research on the relationship between oil prices and other macroeconomic variables, we find that oil price changes have effects on production cost (Bresnahan & Ramey, 1993), economic growth (Nie, 2023), income (Bohi, 1991), consumption expenditure (Kilian, 2008; Nie, 2023), and unemployment (Davis & Haltiwanger, 2001). In the United States and China, as the largest importers of crude oil, scholars' research on topics related to oil shock has never stopped since the 1970s. Blanchard and Gal í(2010) studied the difference in the impact of oil price shocks on inflation and economic activity in the United States in the 1970s and after 2000, arguing that market structure, monetary policy, oil's share in the market, and uncertainty policies contribute to this difference. Coibion and Gorodnichenko (2015) used the rise in oil prices to explain the absence of deflation in the United States during the Great Recession, and the rise in inflation expectations was also one of the transmission mechanisms of the effect of oil prices on inflation. Chen et al. (2020) also discovered the transmission mechanism of decomposed oil shocks to Chinese inflation. Li and Guo (2022) used the Nonlinear ARDL model with multiple thresholds to find that oil price shock has a significant asymmetric effect on Chinese inflation in the short term, which indicates that the inflation effect is more significant when oil price falls. Inflation and its important driver, inflation expectations (Armantier et al., 2020; Istiak & Alam, 2019a), are both affected by oil price changes (Armantier et al., 2016). At present, economists and scholars generally recognize the existence of oil price shocks, which are affecting inflation mainly by five mechanisms: discretionary income effect, uncertainty effect, precautionary savings effect, operating cost effect and reallocation effects (Edelstein & Kilian, 2009; Pal & Mitra, 2019). The most direct impact of oil price shocks on Chinese and American households' inflation expectations is the change of disposable income.

In recent decades, there has been extensive literature exploring the importance and determinants of inflation expectations. The Reserve Bank's Second Quarter Review of Monetary Policy 2012-13 noted that a central premise of monetary policy is that low and stable inflation and well-anchored inflation expectations contribute to a conducive investment climate and consumer confidence, which is key to sustained growth on a higher trajectory in the medium-term. The survey-based approach to measuring inflation expectation presents both short-term and long-term forecasts on inflation and covers different target groups, including households or professional forecasters. Pfajfarabc and Žakeljd (2014) think that Central banks increasingly attribute more importance to the developments of households' inflation expectations as they signal future inflationary risks. Mohanty (2012) proposed that there are two ways of forming inflation expectations. The first is a variant of adaptive behavior wherein expectations are formed by extrapolating past and current experiences into the future. The second way of forming inflation expectations in a forward-looking manner is rational expectations. D'Acunto et al. (2021) propose that the changes in prices affect inflation expectations, with positive changes in prices having a greater effect than negative changes. Liu (2019) agrees that economic policy uncertainty works on China's inflation expectations as well. Ueda (2010) also includes that exogenous prices and monetary policy shocks have significant effects on the formation of household inflation expectations by exploring household inflation expectations in the United States and Japan. Zhang (2011) explores the impact of monetary policy on Chinese household inflation expectations. Ghosh et al. (2021) point out that India's Inflation expectations are determined by factors such as output, inflation rate, monetary policy, exchange rate, economic policy uncertainty, oil prices, and financial volatility. Kortelainen et al. (2011) apply the conventional New Keynesian macro model to the estimation of inflation expectations in Europe and the United States, and conclude that the use of measurement expectations greatly reduces the impact of lagged output and inflation terms on economic forecasts' importance. Aristidou (2018) analyzes the US data from 1950-2016 through the Phillips curve, arguing that although the importance of future inflation expectations will change over time, depending on the monetary policy regime and economic environment, future expectations contribution to current inflation is greater than past inflation.

By affecting the real interest rate, inflation expectations have an impact on the intertemporal decisions of private households and firms on savings, consumption, and investment. There are two central functions that inflation expectations can perform in central banking. First, as important inputs into price and wage setting, they provide a summary statistic of where inflation is likely to be headed. Second, they may be used to assess the credibility of the central bank's inflation objective. More scholars are realizing the importance of inflation expectations to economic development. By analyzing inflation expectations in the United States and Europe, Ciccarelli, and Garcia (2015) find that inflation expectations have spillover effects across countries, which suggests a need for coordinated policy actions, mainly in times of crisis; Lagarde (2020) suggests the ability to manage households' inflation expectations is key for the effectiveness of monetary and fiscal policies. The impact of oil price shocks on inflation expectations has also attracted more attention from scholars. Cao and Shapiro (2016) point out that oil prices have pervasive effects on inflation expectations with breakeven inflation or inflation swap rates. Hammoudeh and Reboredo (2018) propose that U.S. oil prices have non-linear effects on market-based 5- and 10-year inflation expectations components, which are more prevalent in the medium term than in the long run. Kilian and Zhou (2021) predict that rising oil prices in 2021 will have an impact on US household inflation expectations, with a peak response of 1.2 percentage points for 1-year household inflation expectations and a peak response of 0.2 percentage points for 5-year expectations.

Affected by the epidemic, the uncertainty of economic development in the United States and China has increased. Two of the most notable results are the rising of households' inflation expectations and oil price shocks (Apergis, 2021; Tan et al., 2022). All the study, related to the impact of oil price shocks in the United States and China on inflation expectations and the effect of the epidemic on the relationship between oil price changes and inflation expectations, is conducive to helping inflation expectations play a better anchoring role and explaining the differences in economic development before and after the epidemic. To reflect reasonable short- and long-term asymmetries in oil price dynamics at the same time, we apply ARDL and Nonlinear ARDL frameworks to two long-term inflation-targeting policy mechanisms (Nasir, 2020), using the Phillips curve to assess the relationship between oil price changes and inflation expectations (Eser et al., 2020) and the asymmetric differences before and after the epidemic.

This paper mainly has the following four contributions. We use a reasonable method to convert quarterly qualitative data on China's residents' inflation expectations into quantitative data and substitute monthly inflation expectations with reasonable indexes based on previous research and finally study them as dependent variables, which provides the basis and conditions for future research on Chinese residents' inflation expectations. Based on existing research, we use the Carson-Parkin Method to convert China's only data reflecting residents' inflation expectations from qualitative data into quantitative data. For further robustness checks, we refer to and use the arithmetic average of real interest rates and lagged inflation rates to show residents' monthly inflation expectations. Please refer to the data description section for specific instructions. Second, this is a complement to the ARDL and NARDL models under different regimes. Most previous studies only considered the impact of shocks within a specific time period, and rarely explored the comparison under different regimes. Some previous scholars have used the NARDL model to compare the different effects of oil shock under pre-ZLB and ZLB regimes on the inflation rate in New Zealand. However, our paper is the first to focus on the different effects of oil price changes on inflation expectations under different regimes, pre-COVID and COVID periods. Third, to the best of our knowledge, this article is the first to compare the differences in the asymmetry of oil price shocks between China and the United States before and after the epidemic. As the U.S. and China are the world's largest importers of crude oil and the countries most affected by the COVID-19 outbreak, it is of great significance to research this topic but there is limited research that explores the role of the COVID-19 pandemic event in the impact of oil prices on inflation expectations. We solved the problem of fewer samples during the epidemic by introducing a dummy variable and interactive variable, so as to see the change in the effect, and conducted a robustness test through high-frequency data to achieve a comparison of the asymmetric impacts in the U.S. and China before and after the epidemic.

The structure of this article is as follows. In Section 2, we explain the data and methodology of the study. In Section 3, we provide preliminary test results for model suitability. A comparison of empirical results between the United States and China is presented in Section 4. In Section 5, we examine the causality of the variables and the robustness of the results. Section 6 further discusses and concludes the results.

2. Methodology

2.1 Data

As mentioned in the introduction, to explore the impact of oil prices on inflation expectations, this paper uses data from the United States and China. The reasons for choosing these two countries are as follows: First, China and the United States are currently the importers with the largest volume of crude oil in the world. The impact of crude oil price shocks on their inflation expectations is more significant, exploring which is of great significance for the formulation of policies in the two countries and the future consumption structure of consumers; second, as countries with the largest GDP in the world, both the United States and China economies have suffered from the COVID19 epidemic. By comparing the impact of oil price shocks under the two regimes of pre-COVID19 and COVID19, we can greatly reflect the world trend of changes in the impact of oil price shocks before and after the epidemic. Third, the United States is in a free market economic system, while China adopts an economic system in which open competition and government regulation coexist. Research on the impact of oil price shocks before and after the epidemic also reflects the impacts of different economic systems under special circumstances, which has significance in studying the effectiveness of different economic systems and policies.

To analyze the impact of potential determinants, including oil prices, on inflation expectations, we draw on the approach of Nasir et al. (2020) to designate lagged inflation expectations, deflated crude oil prices, actual inflation rate, seasonally adjusted GDP, and economic policy uncertainty. Given that these factors are under standard theories and are often empirically identified as the main determinants of inflation, we emphasize that these factors are influential factors in inflation expectations and their dynamics. It is worth noting that according to the analysis from Jose and Frederick (2006), they support the presence of a cointegrating relationship between the crude oil and natural gas price time series, providing significant statistical evidence that WTI crude oil and Henry Hub natural gas prices have a long-run cointegrating relationship. Natural gas is also an important source of energy for residential heating. Crude oil is one of the most important components of gasoline, and the price of gasoline is influenced by crude oil, which is closely related to people's lives, and is one of the criteria by which people measure price levels and change inflation expectations. Given the importance of crude oil, natural gas, and gasoline in households' daily lives, we will use the same Nonlinear ARDL model but replace the endogenous variables crude oil price and gasoline price as follows natural gas price and gasoline price, respectively, in order to investigate the existence of asymmetry in the impact of price changes in gasoline and natural gas on inflation expectations.

Considering the continuity and availability of data, we use quarterly and monthly observations from January 2010 to December 2021 for data analysis. First, we will use quarterly observations to draw overall conclusions, but considering the limited post-pandemic data, we will take monthly data for robustness check. The details of the variables are as follows:

Inflation expectations:

There are two main sources of data on inflation expectations, market-based inflation expectations, and survey-based inflation expectations. This article focuses on the latter, and more specifically, the survey data on inflation expectations with households as respondents.

The U.S. inflation expectations data is based on households' inflation expectations provided by the Michigan survey. The inflation expectations of consumers from the University of Michigan's Survey of Consumer Attitudes and Behavior. In this survey, the data on consumer sentiment are collected by interviewing a random sample of approximately 500 U.S. households each month. The consumer sentiment represents the forecast of the respondents About some key macroeconomic variables, such as inflation, interest rates, and unemployment. We get the monthly and quarterly data of inflation expectations from the Federal Reserve Economic Database maintained by the Federal Reserve Bank of St Louis. All the data is quantitative.

China's quarterly inflation expectations data are based on the quarterly survey given by the People's Bank of China for more than 20,000 savings users in 50 different cities across the country since 1999 (the Urban Depositor Questionnaire Report of the Statistics and Analysis Department of People's Bank of China[1]). With three options, i,e, up, unchanged, and down, the survey gives us residents' qualitative views on the change in CPI over the next three months, as well as the percentage of each option. The method in this paper to convert these qualitative data into quantitative indicators is C-P Method (Carlson & Parkin, 1975). The basic principle of this method is: Assuming that respondents' expectations for future price level changes are subject to a specific probability distribution, and that there is a "sensibility interval" centered at 0. If the respondent's judgment on the price increase in the next period exceeds the range, "up" is selected, if it falls below the range, "down" is selected, "unchanged" otherwise. Respondents' answers were symmetrical and normally distributed, and the average realized in the past was equal to the expected average. In order to test the convincingness of the inflation expectation calculated by this method, we refer to the correlation test of historical data by many scholars and find that the correlation between the inflation expectation calculated by the C-P method and the price expectation index since 2000 is even as high as 0.78. Chinese monthly inflation expectation is the arithmetic average of the real interest rate and lagged inflation rate, which adopts the method of Yu et al. (2018). Given that there is no direct monthly household inflation expectation in China, many scholars try to reflect residents' inflation expectations through substitutable variables, so as to reflect the impact of residents' inflation expectations on economic development. The Chinese government even proposed for the first time in 2009 to control inflation expectations as one of the focuses of macroeconomic regulation[2]. Yu et al. (2018) used a VAR expectation model with additional forward-looking policy variables and a Kalman filter recursive algorithm to confirm that the inflation expectation since 2002 calculated by this method is unbiased, and the mean value of the expected error is zero and there is no autocorrelation. Therefore, this paper also uses this method to calculate monthly residents' inflation expectations, thereby making the possibility for robustness testing. More details in methods references are in Appendix C[3].

Crude oil price:

Crude oil prices in the US and China are the oil prices in real terms deflated RAC by U.S. and China CPI (Elder and Serletis, 2010), in which RAC is the composite refiners' acquisition cost (RAC) of crude oil from the website of the Federal Reserve Bank of St. Louis. The crude oil (petroleum) price is utilized as the proxy indicator of global crude oil price, and the unit is US dollars per barrel. The specific calculation formula is as follows,

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[1] Link: http://www.pbc.gov.cn/diaochatongjisi/116219/116227/index.html.

[2] See https://www.adb.org/publications/anchoring-inflationary-expectations-prc.

[3] The methods we refer to have all been verified to give inflation expectations that are highly fitted to actual inflation. Considering the space of this paper, we do not show specific data and results, but the authors can provide them on request.

$$WTI_t = \ln\left(\frac{Oil\ price_t}{CPI_t}\right),$$

$$\Delta WTI_t = \ln\left(\frac{Oil\ price_t}{CPI_t}\right) - \ln\left(\frac{Oil\ price_{t-1}}{CPI_{t-1}}\right).$$

Inflation rate:

China's monthly inflation rate is calculated from the growth rate of month-on-year CPI data released by the National Bureau of Statistics, and the quarterly inflation rate is obtained after the monthly average, and seasonally adjusted. Inflation in the United States is seasonally adjusted quarterly and monthly year-over-year growth in the CPI index. We get the monthly and quarterly CPI data of CPI from the Federal Reserve Economic Database maintained by the Federal Reserve Bank of St Louis.

GDP:

GDP in this paper is the logarithm of GDP per capita (unit is US billion dollar). U.S. quarterly and monthly GDP data the real GDP from the Federal Reserve Bank of St. Louis from 2010 to 2021, which has been seasonally adjusted. China's quarterly GDP is seasonally adjusted 2010-2021 data from the National Bureau of Statistics of China. Since China does not have direct monthly GDP data, in order to reflect the development trend of monthly GDP as much as possible, this paper substitutes it with the monthly industrial-added value data from the National Bureau of Statistics of China. The growth of China's GDP is mainly due to the growth of the added value of the three industries. The added value of the secondary industry accounts for an average of 41.93% of the added value of the GDP from 2010 to 2021, and the added value of the industry is an important part of the secondary industry. Moreover, according to China's historical data, after 2000, the correlation coefficient between the growth rate of China's quarterly industrial added value and the quarterly GDP growth rate was as high as 0.9264. Therefore, the industrial-added value is an important surrogate indicator for measuring Chinese GDP.

EPU:

Uncertainty of economic policy is an important variable that reflects the economic risk caused by the uncertainty of government policy in the future. Baker et al. (2016) define the EPU index into three main components: the first component quantifies newspaper coverage of policy-related economic uncertainty in major national newspapers by constructing a normalized index of the number of news articles discussing EPU; the second component reflects the number of federal tax code provisions that will expire in the next 10 years to measure the degree of uncertainty about the path the federal tax code will take in the future; the last component uses divergence among economic forecasters as a proxy for uncertainty, Specifically, the differences between individual forecasters' forecasts of the consumer price index, federal spending, and future levels of state and local spending are used to construct uncertainty indices about important macroeconomic variables.

U.S. economic policy uncertainty (EPU) index is the monthly and average quarterly data from the Federal Reserve Bank of St. Louis. China's monthly EPU index is from https://www.policyuncertainty.com/china_monthly.html, developed from Steven J. Davis, Dingqian Liu, and Xuguang S. Sheng’s working paper "Economic Policy Uncertainty in China since 1949: Perspectives from Mainland Newspapers". They began quantifying concepts related to uncertainty using two mainland Chinese newspapers, People's Daily and Guangming Daily, starting in October 1949[4]. China's quarterly data is an average of the monthly EPU index.

2.2 Econometric Specification

The main purpose of this study is to investigate the impact of the COVID-19 outbreak on oil price shocks and the impact of oil price shocks on inflation expectations in the United States and China. In the basic model, this paper uses the quarterly data of inflation expectations, oil price shock, inflation rate, GDP, and EPU index from 2010 to 2021 for linear and nonlinear regression analysis. However, considering the limited number of quarterly data, we introduce a dummy variable to show the effect of structural break, and an interactive variable to reflect the difference in oil price shocks before and after the break, so as to ensure the integrity of the sample and the differences on oil dynamics. In a further robustness check, we will conduct the same analysis using monthly data from the United States and China, but the difference is that we divide the sample into the full sample, pre-COVID19 and COVID19 regimes (i.e. full sample with two sub-samples), while excluding the effects of dummy variable and interactive variable on the model, in each sample to analyze the linear and nonlinear effects

[4] Link: www.policyuncertainty.com.

of lagged inflation expectations, oil price shock, inflation rate, GDP and EPU index on inflation expectations.

First, in order to reflect the relationship between the target endogenous and exogenous variables and households' inflation expectations in the United States and China and, we propose a model as follows:

$$E\pi_{t+if} = \delta_{0f} + \delta_{1f}E\pi_{tf} + \delta_{2f}WTI_{tf} + \delta_{3f}INF_{tf} + \delta_{4f}GDP_{tf} + \delta_{5f}EPU_{tf} + \delta_{6f}Du_{tf} + \delta_{7f}(WTI * Du)_{tf} + u_{tf}\ , \tag{1}$$

where $E\pi_t$ stands for inflation expectation(unit is %), WTI_t shows oil prices, which is the deflated global crude oil price(unit is U.S. Dollars per Barrel), INF_t indicates real inflation rate(unit is %), GDP_t is the logarithm of GDP per capita (unit is US dollar), and EPU_t shows economic policy uncertainty. Du_t is the dummy variable used to separate the full sample from 2010Q1 -2021Q4 into two regimes of pre-COVID19 and COVID19, where $Du_t = 0$ if data was collected in pre-COVID19 regime and $Du_t = 1$ if data was collected in COVID19 regime. $(WTI * Du)_t$ is the interactive variable, which indicates the volatility of oil prices after the epidemic. δ_{0f} is a constant term, representing the lowest inflation expectations in the United States and China. $\delta_{1f}, \delta_{2f}, \delta_{3f}, \delta_{4f,} \delta_{5f}, \delta_{6f}, \delta_{7f}$ are the coefficients of variables, reflecting the impact of each variable on inflation expectations. f is the symbol of countries, i,e, when $f = 1$, the country is U.S,; when $f = 2$, the country is China.

If the coefficient of the dummy variable $\widehat{\delta_{6f}}$ is not equal to 0 and is meaningful, it indicates that the outbreak of the COVID19 epidemic is an important breakpoint, and the impact of oil price changes on inflation expectations is significantly different before and after this structural break. If the coefficient of the interactive variable $\widehat{\delta_{7f}}$ is greater than 0 and meaningful, it means the impact of oil price changes on inflation expectation in the COVID19 regime is bigger than the effect in the pre-COVID19 regime, while if $\widehat{\delta_{7f}} < 0$ and have significant, it shows that the impact of oil price changes on inflation expectation in COVID19 regime is smaller than the effect in the pre-COVID19 regime.

Notably, Eq.1 can only deduce the long-term effects of exogenous variables. In order to explore both the short-term and long-term effects of oil price shocks before and after the epidemic, this paper adopts both the autoregressive distributed lag (ARDL) model developed by Pesaran, Shin, and Smith (2001), and the nonlinear autoregressive distributed lag (Nonlinear ARDL) model developed by Shin, Yu, and Greenwood-nimmo (2014).

2.2.1 ARDL-ECM

An autoregressive distributed lag (ARDL) model is an ordinary least square (OLS) based model applicable for both non-stationary time series and times series with mixed order of integration. There are many advantages of the ARDL Model: 1. The model shows the effects from both explanatory variables and lagged dependent variables; 2. by confirming the co-integration relationship between variables, the model can be used to analyze short-term and long-term dynamics; 3. the error estimation of the model is suitable for both small and large samples; 4. the model has relatively less requirements on independent variables, that is, variables can be stationary at I(0) or I(1), or the mixed of both; 5. ARDL model is the only approach that provides us with some explicit tests through which we can explore that exclusive cointegration exists or not instead of assuming vector existence (Nkoro and Uko, 2016). Because of the limited number of samples during the pandemic so far, ARDL Error Correction Model is more robust and suitable for this research.

According to the cointegration theory of Engle (1982); Engle and Granger (1987), if all the variables are I(1) and cointegrated, we can use an error correction model (ECM) to represent the dynamic relationship between variables. In the ARDL model, Pesaran and Shin (1999) proposed that if variables are stationary at either I(0) or I(1) and are cointegrated with each other, we can use ARDL-ECM model to express the dynamic relationship. Especially, ARDL model determines the cointegration relationship more efficiently when the sample size is small. Therefore, if inflation expectations, deflated oil price, inflation rate, GDP, EPU, dummy variable and interactive variable are stationary at I(0) or I(1) and are cointegrated in the long run, we can estimate ECM based on ARDL (ARDL-ECM) as follows:

$$\Delta E\pi_{t+if} = \sum_{i=1}^{n1}\theta_{1if}\Delta E\pi_{t-if} + \sum_{i=1}^{n2}\theta_{2if}\Delta WTI_{t-if} + \sum_{i=1}^{n3}\theta_{3if}\Delta INF_{t-if} + \sum_{i=1}^{n4}\theta_{4if}\Delta GDP_{t-if} + \sum_{i=1}^{n5}\theta_{5if}\Delta EPU_{t-if} + \sum_{i=1}^{n6}\theta_{6if}\Delta Du_{t-if} + \sum_{i=1}^{n7}\theta_{7if}\Delta(WTI * Du)_{t-if} + ect_{t-1f} + \varepsilon_{tf}\ , \tag{2}$$

where

$$ect_{t-1f} = \Phi_{1f}E\pi_{t-1f} - \mu_f - \Phi_{2f}WTI_{t-1f} - \Phi_{3f}INF_{t-1f} - \Phi_{4f}GDP_{t-1f} - \Phi_{5f}EPU_{t-1f} - \Phi_{6f}Du_{t-1f} - \Phi_{7f}(WTI * Du)_{t-1f} . \quad (3)$$

Δ is the first difference operator; ε_t captures the error term. $n1$, $n2$,…, $n7$ are the optimal lag orders of different variables selected by Akaike information criterion (AIC) and Schwarz information criterion (SIC). For the coefficients, θ_1, θ_2,…, θ_7 represent the short run while δ_1, δ_2,…, δ_7 represent the long run. After obtaining the ARDL model, we need to use the unit root test to determine whether the included dependent variables are stationary at the level sequence I(0) or the first-order difference I(1). When all variables are stationary, we can confirm cointegration between variables using boundary tests based on F and t correlation statistics (McNown et al. 2018). Pesaran, Shin, and Smith (2001) generated key table values or F and t- statistics obtained from the analysis, and in this paper, we use only F statistics[5]. The F-statistic asymptotic table critical values can be used with two different bounds, where the variable is assumed to be stationary at either I(0) or I(1). If the calculated F-statistic exceeds the critical values, a clear conclusion can be drawn. However, if the calculated value is between the two bounds, it is impossible to draw firm conclusions about the cointegration relationship without knowing the stability of the variables.

Long run coefficients are Φ_{1f}, Φ_{2f}, Φ_{3f}, Φ_{4f} , Φ_{5f} , Φ_{6f},Φ_{7f}; μ_f is the constant term. The long-run coefficient of oil price changes pass-through to inflation expectation can be defined as $T_{WTI} = -\frac{\theta_{2if}}{\theta_{1if}}$.

To check our model's reliability, we employed several diagnostic tests, such as autocorrelation, normality distributed, and heteroskedasticity tests. Besides, we also used the Cumulative Sum of Recursive Residuals test (CUSUM test) and Cumulative Sum of Square Recursive Residuals test (CUSUMSQ test) to test the stability of the short-run and the long-run coefficients.

According to the ARDL Error Correction Model, we can explore the short-term and long-term effects of determinants on inflation expectations, analyze whether there is a structural break in the impact of oil price change on inflation expectations before and after the COVID19 outbreak, and if so, what the change on the impact of oil price change is after the break.

2.2.2 Nonlinear ARDL Model

However, fluctuations in global oil prices may have asymmetric and non-linear effects on short- and long-term inflation expectations (Mihajlović & Marjanović, 2020; Long & Liang, 2018), therefore asymmetric and Nonlinear ARDL models are appropriate and necessary for studying the nonlinear and asymmetric relationships.

The nonlinear ARDL model is a single-equation error correction model that can accommodate asymmetry in the long-run equilibrium relationship and/or the short-run dynamic coefficients via the use of partial sum decompositions of the independent variable(s) proposed by Shin, Yu, and Greenwood-nimmo (2014). In the Nonlinear ARDL, since we focus on exploring the asymmetric effect of oil price changes on inflation expectations, we move oil price changes decomposed into its negative and positive partial sums, which makes it possible to test whether oil shock has symmetric or asymmetric effects on inflation expectations in the short- and the long-run. Therefore, the deflated oil price WTI_{tf} is expressed as:

$$WTI_{tf} = WTI_{tf}^0 + WTI_{tf}^+ + WTI_{tf}^- , \quad (4)$$

where f is still the symbol of countries, i,e, when $f = 1$, the country is U.S,; when $f = 2$, the country is China. WTI_f^+ and WTI_f^- are partial sums that capture the increase and decrease of the oil price in U.S and China, expressed as:

$$WTI_{tf}^+ = \sum_{i=1}^{t} \Delta WTI_{tf}^+ = \sum_{i=1}^{t} MAX(\Delta WTI_{if}, 0) \quad (5)$$

$$WTI_{tf}^- = \sum_{i=1}^{t} \Delta WTI_{tf}^- = \sum_{i=1}^{t} MIN(\Delta WTI_{if}, 0) \quad (6)$$

[5]The authors performed boundary tests for both F and t statistics. Since the conclusions of the two data are consistent, the t-test results are not shown in this paper but can be provided by the authors upon request.

where $\Delta WTI_{if} = WTI_{tf} - WTI_{t-1f}$.

After introducing the positive and negative shocks of oil prices into the basic VAR model Eq.1, we rewrite Eq.1 as follows:

$$E\pi_{t+if} = \omega_{0f} + \omega_{1f}E\pi_{tf} + \omega_{2f}^{+}WTI_{tf}^{+} + \omega_{2f}^{-}WTI_{tf}^{-} + \omega_{3f}INF_{tf} + \omega_{4f}GDP_{tf} + \omega_{5f}EPU_{tf} + \omega_{6f}Du_{tf} + \omega_{7f}(WTI * Du)_{tf} + u_{tf}' , \quad (7)$$

where ω_{0f} is the constant term representing the lowest inflation expectations in the US and China. $\omega_{1f}, \omega_{2f}^{+}, \omega_{2f}^{-}, \omega_{3f}, \omega_{4f}, \omega_{5f}, \omega_{6f}, \omega_{7f}$ are the coefficients reflecting the effect of variables on inflation expectation in the Nonlinear ARDL model, where ω_{2f}^{+} represents the long-term impact of positive oil prices shock on inflation expectations, and, ω_{2f}^{-} represents the long-term impact of negative oil prices shock on inflation expectations. By comparing the significant differences between these two coefficients, it can be confirmed that there is an asymmetric impact between positive and negative changes in oil prices in the long term.

Therefore, to introduce both the long- and short-term effects of rising and declining oil price, we apply the Nonlinear ARDL model as follow:

$$\begin{aligned}\Delta E\pi_{t+if} = \Omega_f &+ \sum_{i=1}^{k}\tau_{1if}\Delta E\pi_{t-if} + \sum_{i=1}^{l}(\tau_{2if}^{+}\Delta WTI_{t-if}^{+} + \tau_{2if}^{-}\Delta WTI_{t-if}^{-}) + \sum_{i=1}^{m}\tau_{3if}\Delta INF_{t-if} \\ &+ \sum_{i=1}^{n}\tau_{4if}\Delta GDP_{t-if} + \sum_{i=1}^{p}\tau_{5if}\Delta EPU_{t-if} + \sum_{i=1}^{q}\tau_{6if}\Delta Du_{t-if} + \sum_{i=1}^{r}\tau_{7if}\Delta(WTI * Du)_{t-1f} \\ &+ \omega_{1f}E\pi_{t-1f} + \omega_{2f}^{+}WTI_{t-1f}^{+} + \omega_{2f}^{-}WTI_{t-1f}^{-} + \omega_{3f}INF_{t-1f} + \omega_{4f}GDP_{t-1f} \\ &+ \omega_{5f}EPU_{t-1f} + \omega_{6f}Du_{t-1f} + \omega_{7f}(WTI * Du)_{t-1f} + e_{tf} .\end{aligned} \quad (8)$$

All variables are as previously described. k, l, m, n, p, q, r are the optimal lag orders of variables selected by the Akaike information criterion (AIC) and Schwarz information criterion (SIC). To establish the relationship between the positive and negative oil prices shocks and inflation expectations, according to the boundary test proposed by Pesaran, et al., (2001), we believe that the long-term effects of oil price changes are $a_1 = -\frac{\omega_{2f}^{+}}{\omega_{1f}}$ and $a_2 = -\frac{\omega_{2f}^{-}}{\omega_{1f}}$. The short-term impact of positive oil prices on inflation expectations, $\sum_{i=1}^{l}\tau_{2if}^{+}$ measures the short-term impact of negative oil prices on inflation expectations. In this case, we capture the asymmetry of oil price changes in the short-run and long-run.

Before that, we also need to confirm that all variables are stationary at I(0) or I(1) or the mixture. It is also necessary to confirm that all variables are not stationary at I(2). This is because I(2) invalidates the calculation of the F statistic to test for cointegration (Ibrahim, 2015). We perform the unit root test with and without structural breaks to find the order of integration. Then, long-run and short-run asymmetry in the nonlinear ARDL model can be tested by the standard Wald test. In the long run, the null hypothesis is $a_1 = a_2$. A significant difference in these two values would affirm an asymmetric relationship in the long run. In the same way, $\sum_{i=1}^{l}\tau_{2if}^{+} = \sum_{i=1}^{l}\tau_{2if}^{-}$ indicates that there is no asymmetry in the short run. Moreover, the existence of cointegration could be assessed using the bounds test where the null hypothesis ($\omega_{1f} = \omega_{2f}^{+} = \omega_{2f}^{-} = \omega_{3f} = \omega_{4f} = \omega_{5f} = \omega_{6f} = \omega_{7f}$) means no cointegration.

Similarly, we can also implement the error correction model (ECM) of the Nonlinear ARDL model as follows:

$$\begin{aligned}\Delta E\pi_{t+if} = &\sum_{i=1}^{k}\tau_{1if}\Delta E\pi_{t-if} + \sum_{i=0}^{l}(\tau_{2if}^{+}\Delta WTI_{t-if}^{+} + \tau_{2if}^{-}\Delta WTI_{t-if}^{-}) + \sum_{i=0}^{m}\tau_{3if}\Delta INF_{t-if} \\ &+ \sum_{i=0}^{n}\tau_{4if}\Delta GDP_{t-if} + \sum_{i=0}^{p}\tau_{5if}\Delta EPU_{t-if} + \sum_{i=0}^{q}\tau_{6if}\Delta Du_{t-if} + \sum_{i=0}^{r}\tau_{7if}\Delta(WTI * Du)_{t-1f} \\ &+ \kappa_{if}ect_{t-1f} + \psi_{tf} ,\end{aligned} \quad (9)$$

where

$$ect_{t-1f} = E\pi_{t-1f} - \lambda_{0f} - \lambda_{1f}^{+}WTI_{t-if}^{+} - \lambda_{1f}^{-}WTI_{t-if}^{-} - \lambda_{2f}INF_{t-1f} - \lambda_{3f}GDP_{t-1f} - \lambda_{4f}EPU_{t-1f} - \lambda_{5f}Du_{t-1f} - \lambda_{6f}(WTI * Du)_{t-1f}\,. \tag{10}$$

Long run coefficients are $\lambda_{0f} = -\frac{\Omega_f}{\omega_{1f}}$, $\lambda_{1f}^{+} = -\frac{\omega_{2f}^{+}}{\omega_{1f}}$, $\lambda_{1f}^{-} = -\frac{\omega_{2f}^{-}}{\omega_{1f}}$, $\lambda_{2f} = -\frac{\omega_{3f}}{\omega_{1f}}$, $\lambda_{3f} = -\frac{\omega_{4f}}{\omega_{1f}}$, $\lambda_{4f} = -\frac{\omega_{5f}}{\omega_{1f}}$, $\lambda_{5f} = -\frac{\omega_{6f}}{\omega_{1f}}$, $\lambda_{6f} = -\frac{\omega_{7f}}{\omega_{1f}}$. ω_{2f}^{+} and ω_{2f}^{-} indicate the impact of increasing and decreasing oil prices on inflation expectations in the long run. ω_{6f} shows the impact difference of oil price shock before and after the epidemic. ω_{7f} expresses the impact change on oil price shock after the outbreak.

3. Preliminary Results

3.1 Descriptive Statistics

The oil price change has an important impact on the economic development of China and the United States. As important economies in the world, China and the United States are important importers of crude oil. As the second largest importer of oil and crude oil in the world, the U.S. import of oil was 12 MMb/d[6] in 2010 and 9.1 MMb/d in 2019, of which 9.2 MMb/d and 6.8 MMb/d of which were crude oil. Since 2001, China's crude oil imports have been rising for 20 consecutive years. In 2017, China's crude oil imports reached 8.4 million barrels per day, making it the country with the largest total crude oil imports.

The COVID-19 outbreak had a huge impact on China and the United States, not only in oil imports but also in oil prices, GDP, inflation, and EPU index. The United States imported about 7.86 MMb/d of petroleum in 2020, which included 5.88 MMb/d of crude oil and 1.98 MMb/d of non-crude petroleum liquids and refined petroleum products. These were the lowest levels of imports of total petroleum and crude petroleum products. oil since 1991. According to data released by the National Bureau of Statistics of China, China's crude oil imports in 2021 fell from 542 million tons in 2020 to 512.98 million tons, a drop of 5.4%. This also means that China's crude oil imports have declined for the first time in 20 years. In 2020, international oil prices reached the lowest level in decades, and in April 2020, the year-on-year decline in global crude oil demand reached the lowest level since 1995. In 2021, international oil prices continue d to rise, reaching the highest level since 2008. Not only that, but GDP growth has also been seriously affected. In the 10 years from 2010 to 2019, the average annual growth rate of GDP in the United States was 2.25%, and the average economic growth rate in China during the same period was 7.68%. However, affected by the epidemic, the GDP of China and the United States fell by 4.8% and 6.8% respectively in the first quarter of 2020. Simultaneously, the year-on-year inflation rate in the United States increased by 14.1%, and the inflation rate in the second quarter reached 2.1%. In the first quarter of 2020, the year-on-year inflation rate in China was lower than that of the previous quarter, but it was still at 4.36%. The rise in energy and food prices caused by the pandemic has led to rising inflationary pressures in many countries. EPU has also risen significantly. The EPU of the United States in the second quarter of 2020 was as high as 417.3, an increase of 88.1% over the previous quarter. China's EPU growth in the first quarter of 2020 also reached 100.0%. Therefore, the epidemic has greatly exacerbated the uncertainty of the change in oil prices and even the development of the world economy. All economies should study the difference in the impact of the oil shock before and after the epidemic.

To sum up, in the benchmark model, this paper uses 2010-2021 U.S. and China quarterly households' inflation expectations, oil price shocks, inflation, GDP and EPU indices, as well as a dummy variable that represents structural breakpoint and an interactive variable to show the change on the oil prices after the COVID-19 outbreak. Table 1 shows the mean, variance, minimum and maximum values of all variables as follows:

[6] MMb/d means a million barrels per day.

Table 1: Descriptive statistics

	U.S.				China			
Variable	Mean	Std.	Minimum	Maximum	Mean	Std.	Minimum	Maximum
Quarterly data								
Infex	0.0300	0.0054	0.0233	0.0483	0.0230	0.0105	-0.0002	0.0543
WTI	-1.299	0.372	-2.221	-0.777	-0.606	0.388	-1.549	-0.062
Inflation	0.0186	0.0104	-0.0011	0.0529	0.0242	0.0137	0.0017	0.0658
GDP	4.266	0.057	4.169	4.380	5.253	0.134	4.984	5.472
EPU	129.886	71.586	61.336	451.504	191.887	113.104	75.909	499.250
Du	0.14	0.357	0.000	1.000	0.167	0.377	0.000	1.000
$WTI \times Du$	-0.239	0.595	-2.221	0.000	-0.161	0.385	-1.549	0.000
Monthly data								
Infex	0.0300	0.0057	0.0210	0.0490	0.0230	0.0105	-0.0028	0.0558
WTI	-1.304	0.382	-2.724	-0.711	-0.607	0.399	-2.067	0.013
Natural gas	3.092	0.828	1.648	5.867	11.453	2.984	6.668	19.665
Gasoline	2.094	0.638	0.631	3.465	1.572	0.242	0.851	2.128
Inflation	0.0197	0.0127	-0.0023	0.0710	0.0244	0.0139	-0.0053	0.0669
GDP	4.242	0.031	4.188	4.299	3.284	0.107	3.058	3.449
EPU	129.743	78.914	50.289	555.325	233.208	259.607	0.000	1425.160

3.2 Unit Root Test

As mentioned earlier, to use ARDL and Nonlinear ARDL models to reflect the long-term and short-term effects and asymmetry of oil price shocks and other factors on inflation expectations, we need to satisfy the variables' stationarity at I(0) or I(1) or a mixture of the two.

Table 2: U.S. stationarity tests results without structural breaks

	Constant			Constant & Trend		
Variable	ADF	Phillips-Perron	KPSS	ADF	Phillips-Perron	KPSS
Level						
Infex	-0.732	-0.870	0.222	-0.178	-0.502	0.213^{**}
WTI	-1.571	-1.612	1.560^{***}	-2.040	-2.073	0.182^{**}
Inflation	-2.340	-1.867	0.179	-2.227	-1.806	0.162^{**}
GDP	0.279	0.184	1.690^{***}	-3.186	-3.640^{**}	0.042^{***}
EPU	-2.918^{*}	-2.967^{**}	0.385^{*}	-3.000	-3.057	0.304^{***}
Du	-0.350	-0.378	1.080^{***}	-1.318	-1.386	0.373^{***}
WTI$\times Du$	-1.200	-1.442	1.030^{***}	-2.049	-2.320	0.332^{***}
1st diff.						
Infex	-5.341^{***}	$-5.661 * **$	0.253	-5.465^{***}	-5.848^{***}	0.128^{*}
WTI	-6.792^{***}	-6.792^{***}	0.089	-6.737^{***}	-6.737^{***}	0.074
Inflation	-4.180^{***}	-5.456^{***}	0.161	-4.248^{***}	-5.613^{***}	0.074
GDP	-5.284^{***}	-8.270^{***}	0.068	-5.267^{***}	-8.225^{***}	0.051
EPU	-6.890^{***}	-6.890^{***}	0.043	-6.816^{***}	-6.816^{***}	0.025
Du	-6.782^{***}	-6.782^{***}	0.219	-6.955^{***}	-6.955^{***}	0.050
WTI$\times Du$	-7.797^{***}	-7.797^{***}	0.083	-7.800^{***}	-7.800^{***}	0.029

To examine the order of integration among the underlying variables in the absence of structural breakpoints, we applied the augmented Dickey–Fuller test (ADF) of Dickey and Fuller (1979), the Phillips–Perron test (PP) of Phillips and Perron (1988) and Kwiatkowski–Phillips–Schmidt–Shin test (KPSS) proposed by Kwiatkowski et al.

(1992). As the test results shown in Tables 2 and 3, all the quarterly variables in China and the United States are stationary at the I(1) level and none of the variables are stationary at the I(2) level. Therefore, inflation expectations, oil price shocks, inflation rates, GDP, and EPU indices are all non-stationary data, and we can only analyze the regression relationship of non-stationary variables when these variables are guaranteed to be cointegrated.

However, this paper focuses on the impact of the epidemic as an important structural breakpoint, thus confirming that the impact of oil price shocks on inflation expectations is different before and after the epidemic, and the above unit root tests are not qualified to capture any structural breaks in the data. In order to avoid the potential misleading caused by this limitation, this paper introduces both the Perron unit root test (Perron, 1997) and the ZA test (Zivot & Andrew, 2002) to perform a unit root test with structural breaks on the quarterly data of variables in the United States and China. The results in Tables 4 and 5 show that, despite some variables being even stationary at I(0), the results of the tests with and without structural breaks resemblance.

Given that all variables satisfy the stationarity requirement, these results apply to both the ARDL model and Nonlinear ARDL model, meaning that both models can conveniently capture sequences with mixed integration orders.

Table 3: China stationarity tests results without structural breaks

	Constant			Constant & Trend		
Variable	ADF	Phillips-Perron	KPSS	ADF	Phillips-Perron	KPSS
Level						
Infex	-2.372	-2.647*	0.668**	-2.868	-3.071	0.171**
WTI	-1.581	-1.596	1.590***	-1.934	-1.944	0.189**
Inflation	-1.914	-2.304	0.417*	-2.148	-2.886	0.098
GDP	-1.793	-1.967	2.450***	-3.647**	-3.603**	0.282***
EPU	-0.601	-1.495	0.807***	-1.645	-3.256*	0.186**
Du	-0.388	-0.414	1.190***	-1.433	-1.489	0.398***
WTI$\times Du$	-1.554	-1.728	0.737**	-2.354	-2.406	0.215**
1st diff.						
Infex	-4.381***	-7.794***	0.068	-4.383***	-7.713***	0.069
WTI	-6.645***	-6.645***	0.102	-6.608***	-6.608***	0.077
Inflation	-4.697***	-5.296***	0.057	-4.663***	-5.204***	0.054
GDP	-7.174***	-7.174***	0.279	-7.400***	-7.400***	0.080
EPU	-4.530***	-9.641***	0.090	-4.451***	-9.515***	0.074
Du	-6.782***	-6.782***	0.204	-6.924***	-6.924***	0.047
WTI$\times Du$	-3.726***	-4.917***	0.084	-4.381***	-4.855***	0.056

Table 4: U.S. stationarity tests results with structural breaks

Variable	Constant				Constant & Trend			
	Level		1st diff.		Level		1st diff.	
	PPU	ZA	PPU	ZA	PPU	ZA	PPU	ZA
Infex	-1.816	-1.332	-6.309***	-6.358***	-3.910	-3.661	-6.563***	-7.566***
WTI	-4.037	-4.125	-7.422***	-7.365***	-3.880	-2.599	-7.590***	-7.060***
Inflation	-2.541	-3.197	-5.822**	-5.895***	-3.730	-3.195	-6.179**	-6.104***
GDP	-5.076*	-3.981	-8.110***	-8.202***	-5.157	-3.487	-10.173***	-8.761***
EPU	-4.670	-4.738*	-6.901***	-6.103***	-6.624	-3.913	-7.008***	-6.239***
Du	-9.26E+15***	-5.670***	-7.406***	-7.495***	-4.55E+14***	-4.327*	-8.828***	-6.979***
WTI$\times Du$	-18.777***	-6.295***	-7.886***	-7.980***	-63.885***	-4.206*	-7.886***	-7.771***

Table 5: China stationarity tests results with structural breaks

Variable	Constant				Constant & Trend			
	Level		1st diff.		Level		1st diff.	
	PPU	ZA	PPU	ZA	PPU	ZA	PPU	ZA
Infex	-3.488	-3.511	-5.399**	-7.489***	-4.487	-3.213	-6.143**	-7.468***
WTI	-3.888	-3.971	-7.321***	-7.217***	-3.745	-2.513	-7.472***	-6.920***
Inflation	-3.092	-4.783*	-7.163***	-5.525***	-2.941	-4.935***	-6.508***	-6.064***
GDP	-6.437***	-4.151	-7.922***	-7.920***	-5.811**	-3.750	-7.832***	-7.998***
EPU	-3.352	-4.808**	-8.729***	-7.754***	-2.298	-4.088	-8.643***	-7.843***
Du	-3.412	-5.769***	-7.419***	-7.507***	-3.455	-3.924	-11.987***	-6.906***
WTI$\times Du$	-12.533***	-12.686***	-2.74E+14***	-5.263***	-22.200***	-4.340*	-7.589***	-5.427***

3.3 Cointegration Test

The results of the unit root test show that almost all the underlying variables are stationary at I(1), that is, the horizontal series data is non-stationary. To further confirm the regression relationship, we need to test the cointegration between variables. According to the boundary test method in the ARDL-ECM, the null hypothesis of no cointegration in Eq.2 is $H_0\colon \Phi_{1f} = \Phi_{2f} = \Phi_{3f} = \Phi_{4f} = \Phi_{5f} = \Phi_{6f} = \Phi_{7f} = 0$. By comparing the critical value of the F statistic given by Pesaran et al[7]. with the actual test results, we can choose whether to reject the null hypothesis. The specific principle is that if the actual F value is lower than the lower limit, it means that the null hypothesis is accepted, that is, there is no cointegration relationship between the variables; and when the actual F value exceeds the upper limit, we will reject the null hypothesis, indicating that there is a cointegration relationship between variables; if the F value is between the lower and upper values, it indicates that there is insufficient evidence to draw a conclusion. The cointegration test in Table 6 shows that the US data has an F-statistic of 10.804 > I(1) critical value = 4.43, which is significant at the 1% level, and similarly, China data has an F-statistic of 31.336 > I(1) critical value = 4.43, significant at the 1% level. Therefore, the co-integration test results both help us reject the null hypothesis, concluding that there is a co-integration and long-run relationship between the variables in both countries.

Table 6: The result of cointegration bound test

Dependent variable	F-statistics	Lower-bound (99%)	Upper-bound (99%)	Conclusion
Inflation expectation	U.S. 10.804*** China 31.336***	3.15	4.43	Cointegration

[1] Null hypothesis: No level relationship($H_0 : \phi_{1f} = \phi_{2f} = \phi_{3f} = \phi_{4f} = \phi_{5f} = \phi_{6f} = \phi_{7f} = 0$).

Based on the above tests of the stationarity and cointegration of variables in the United States and China, the ARDL-ECM and Nonlinear ARDL model will further help us analyze the impact of multiple factors on inflation expectations before and after the COVID19 epidemic.

4. Benchmark Empirical Analysis

4.1 U.S.

To reflect the effect of COVID-19 outbreak on the oil price shocks in limited data, we introduce a dummy variable, which means that we consider the difference in the impact of oil price shocks on inflation expectations between the two sub-periods. Taking into account the specific time when the United States was affected by the epidemic, we define the structural breakpoints as the second quarter in 2020 and the third month in 2020 in

[7] The authors performed boundary tests for both F and t statistics. Since the conclusions of the two data are consistent, the t-test results are not shown in this paper, but can be provided by the authors upon request.

quarterly and monthly samples, that is, the quarterly sample in the United States contains two sub-periods (2010Q1 to 2020Q1 and Q2 2020Q2 to 2021Q4), the monthly sample also includes two sub-periods (January 2010 to February 2020 and March 2020 to December 2021).

4.1.1 ARDL-ECM Results

According to the long-term cointegration between variables in the United States and the optimal lag option of AIC and SIC, we obtained the regression results of the American ARDL error correction model. Table 7 shows the results for the US benchmark model.

Given that oil price dynamics have an important impact on inflation, and inflation expectations have an anchoring effect on inflation, scholars have also devoted more enthusiasm to studying the relationship between oil price dynamics and inflation expectations. As a result, more research has emerged on the transmission mechanism of the impact of oil price changes on inflation expectations. Badel and McGillicuddy (2015) propose that with a tighter synchronization of all sources of oil price movements and inflation expectations, the correlation of American breakeven inflation expectations with oil prices in 2008-2015 is higher.

Table 7: U.S. ARDL Error Correction Model benchmark results

Regressors	Regressand ($\Delta Infex$)	
	Coefficient	Prob.
Panel A: Short-run estimates		
$Infex_{t-1}$	0.447**	0.003
$Infex_{t-2}$	-0.315*	0.015
WTI_t	0.006***	0.000
$Inflation_t$	0.072	0.133
GDP_t	-0.287***	0.000
GDP_{t-1}	0.061	0.171
GDP_{t-2}	0.105*	0.016
EPU_t	-9.00E-06	0.307
Du_t	0.056***	0.000
$WTI \times Du_t$	0.028***	0.000
$\Delta Infex_{t-1}$	0.315*	0.015
ΔGDP_t	-0.264**	0.001
ΔGDP_{t-1}	-0.202**	0.005
ΔGDP_{t-2}	-0.098	0.128
Constant	0.132*	0.016
Panel B: Long-run estimates		
WTI	0.007**	0.001
Inflation	0.083	0.094
GDP	-0.026	0.051
EPU	-1.04E-05	0.314
Du	0.065***	0.000
$WTI \times Du$	0.032***	0.000
Panel C: Diagnostic test		
R^2	0.916	
$Adjusted\ R^2$	0.889	
DW	2.221	
BG LM test	2.433	0.119
IM test	45.000	0.430
BPG test	6.010	0.014
Ramsey RESET test	4.070	0.016

[1] * 1% level of significance, ** 5% level of significance, *** 10% level of significance.
[2] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation.
[3] IM test is Information Matrix Test used for model determination.
[4] BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity.
[5] Ramsey RESET is the Ramsey Regression Equation Specification Error Test for stability.
[6] Optimal lag selection based on AIC.

As shown in the table above, the overall quarterly data from 2010 to 2021 shows that the oil price shock has a significant impact on American households' inflation expectations in the short and long term. It has increased inflation expectations by 6% in the short-term and 7% in the long term, which is closely related to the consumption structure of American households. The main energy source of electricity consumption and transportation is oil so the rise in oil prices reduces the disposable income of American households, especially low-income families with more pressure during the epidemic, which also directly increases households' inflation expectations. Hammoudeh and Reboredo (2018) explore the non-linear impact of oil prices on US inflation expectations in different periods, arguing that the impact in the medium term is more significant than in the long term. After the outbreak, the level of U.S. households' inflation expectations increased by 5.6% in the short term and 6.5% in the long term due to insufficient output and disrupted logistics during the epidemic. The impact of oil price shocks on inflation expectations is also more significant after the epidemic. Compared with 2010-2019, oil price shock causes inflation expectations to increase by 2.8% and 3.2% in the short and long term after COVID-19 outbreak respectively.

With the outbreak of the COVID-19 epidemic in 2020, the world economies have been affected to varying degrees, and changes in inflation expectations also vary according to national conditions. Based on a survey of German citizens' inflation expectations since 2019, Coleman and Nautz (2020) propose that household inflation expectations during the epidemic are higher than the actual average inflation rate in Germany in the past. Rusiadi (2020) finds from the data of emerging market countries in 2019-2020 that the epidemic affects adaptive inflation expectations, and residents in emerging market countries have higher inflation expectations and lower purchasing power. Kapoor (2020) points out that the epidemic is with a rise in inflation expectations in India, followed by negative growth. As one of the most important energy sources for economic production and daily life, the historic rise in the oil price will further delay economic recovery and increase residents' living pressures and inflation expectations. Therefore, in the short term, the oil price shock has a positive impact on U.S. inflation expectations, and this impact has increased after the epidemic. By monitoring U.S. inflation expectations, Apergis and Apergis (2021) find that inflation expectations and their volatility are positively affected by the Covid-19 pandemic, which may signal a risk of inflation expectations breaking out of their anchors. Sharif (2020) analyzes the relationship between the spread of COVID-19 in the United States and the shock of oil price volatility in a time-frequency framework, explaining that geopolitical risks and economic policy uncertainty make the two more closely related.

By studying the relationship between the rise in oil prices during the epidemic and American households' inflation, Lee (2021) finds that the rise in oil prices will increase inflation expectations by increasing wage and the price of goods. In this paper, the lagged inflation expectations $E\pi_{t-1}$ and $E\pi_{t-2}$ have positive and negative effects on inflation expectations, respectively, where the impact of $E\pi_{t-1}$is more significant. A 1% increase in lagged inflation expectations will lead to a 44.7% increase in inflation expectations. This is the preliminary evidence that adaptive expectations and inflation expectations are adjusted due to past deviations, and also the persistent impact of price levels on current household inflation expectations. Inflation expectations are also affected by inflation rates and EPU over the same period, but as Cavallo, et, al. (2017) confirm, information frictions play a central role in the formation of household inflation expectations, with the lag of this friction, the impact is not significant. By contrast, the effect of GDP is more pronounced, with its magnitude and importance varying by different lag periods. The growth of GDP in the same period will effectively balance the price level, thereby reducing inflation expectations, and the continuous increase of GDP increases the confidence of residents, thereby further reducing their inflation expectations.

The diagnostic test in panel C shows that there is no autocorrelation problem between the variables. The BPG test shows heteroskedasticity in the data. However, given that we use the White test in the informatrix test to show no heteroscedasticity existence, and the method explains the consistent standard errors and covariances, heteroscedasticity is not a major issue from a statistical adequacy point of view. The Ramsey REST test indicated that the stability of the model could not be demonstrated at the 5% statistical level of significance, so to further test the stability of the estimates, we also performed CUSUM and CUSUMSQ, the results are shown in Figure 1 (see Appendix B). The CUSUM and CUSUMSQ parametric stability tests of inflation expectations show that the overall sample from 2010-2021 both remains within the 5% significance bound and therefore, the parameter estimates are stable.

4.1.2 Nonlinear ARDL Results

Combined with the analysis of the ARDL model, we know that the oil price shock increases the inflation expectation, especially after the outbreak of COVID19 outbreak. Moreover, we will use the Nonlinear ARDL model to explore the significance of the asymmetry of increasing and decreasing oil prices on inflation expectations, and the difference in the asymmetries of positive and negative oil price shocks before and after the epidemic. In order to achieve linear and nonlinear ARDL research for small samples, we improve the model by introducing dummy variables and interactive variables, to ensure the sample size and compare the differences before and after the structural break. This article mainly uses ARDL and Nonlinear ARDL models to estimate the asymmetric impact of oil price shocks on inflation expectations before and after the epidemic. The results are shown in Table 8:

Table 8: U.S. NARDL quarterly benchmark results

Regressors	Regressand ($\Delta Infex$)	
	Coefficient	Prob.
Panel A: Short-run estimates		
$Infex_{t-1}$	-1.808***	0.000
WTI^{+}_{t-1}	0.067***	0.000
WTI^{-}_{t-1}	0.019***	0.000
$Inflation_{t-1}$	0.084	0.397
GDP_{t-1}	-0.535**	0.002
EPU_{t-1}	-3.21E-05	0.163
Du_{t-1}	0.064***	0.000
$WTI \times Du_{t-1}$	0.035**	0.001
$\Delta Infex_{t-1}$	0.797**	0.003
$\Delta Infex_{t-2}$	0.575**	0.002
ΔWTI^{+}_{t}	0.032***	0.000
ΔWTI^{+}_{t-1}	-0.034*	0.011
ΔWTI^{+}_{t-2}	-0.027	0.006
ΔWTI^{+}_{t-3}	-0.013	0.106
ΔWTI^{+}_{t-4}	-0.012	0.080
ΔWTI^{-}_{t}	-0.008*	0.050
ΔWTI^{-}_{t-1}	-0.023**	0.001
ΔWTI^{-}_{t-2}	-0.017**	0.008
ΔWTI^{-}_{t-3}	-0.014**	0.003
ΔWTI^{-}_{t-4}	-0.014**	0.006
$\Delta Inflation_{t}$	0.221	0.069
ΔGDP_{t}	-0.129	0.156
ΔDu_{t-1}	-0.085**	0.003
$\Delta WTI \times Du_{t-1}$	-0.034**	0.002
Constant	2.294**	0.001
Panel B: Long-run estimates		
WTI^{+}	0.004	0.665
WTI^{-}	0.006**	0.003
Inflation	0.237**	0.003
GDP	-0.025	0.805
EPU	-4.10E-05*	0.040
Du	0.025***	0.000
$WTI \times Du$	0.143	0.742
Panel C: Diagnostic test		
R^2	0.939	
$Adjusted\ R^2$	0.828	
$F statistic$	13.587***	
$Wald - short$	9.490**	
$Wald - long$	14.265**	
DW	2.437	
JB test	0.565	0.754
BG LM test	1.002	0.447
BPG test	1.684	0.146
Ramsey RESET test	1.562	0.263

[1] Significant at 10% (*), 5% (**), and 1% (***).
[2] The F-statistic is calculated by the Wald test (with $H_0 : \omega_{1f} = \omega^{+}_{2f} = \omega^{-}_{2f} = \omega_{3f} = \omega_{4f} = \omega_{5f} = \omega_{6f} = \omega_{7f}$) and compared with the upper bound critical value. $Wald\ short$ and $Wald\ long$, respectively, represent the F-statistics used by the Wald test to assess asymmetry in the short run (with $H_0 : \sum_{i=1}^{l} \tau^{+}_{2f} = \sum_{i=1}^{l} \tau^{-}_{2f}$) and long run (with $H_0 : \frac{\omega^{+}_{2f}}{\omega_{1f}} = \frac{\omega^{-}_{2f}}{\omega_{1f}}$).
[4] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation. JB test is the Jarque–Bera test for residual normality distribution. BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity. Ramsey RESET is the Ramsey Regression Equation Specification Error Test for stability.

Consistent with the results of the ARDL error correction model, in the short term, both positive and negative shocks to oil prices have a significant positive impact on inflation expectations, which is in line with the assumption of asymmetry in oil price shocks, that is, the effect of the increase on the oil price is greater than that of negative oil prices. As we can see, the positive oil price shock causes inflation expectations to rise by 6.7% in the short term, and even the negative oil price shock brings 1.9% increase. In particular, the increase in oil prices over the same period will directly lead to a 3.2% increase in inflation expectations, while the decline in oil prices will only reduce inflation expectations by 0.8%. In the long run, this asymmetry is also obvious. Though the impact of positive oil price shocks is not significant, it is still difficult for negative oil price shocks to reverse the rising trend of inflation expectations. It should be pointed out that oil price increases with longer lags do not have a significant effect on inflation expectations, although they reduce inflation expectations. In the nonlinear model, whether in the long-term or the short-term, the effect of the dummy variable and the interactive variable is significant, indicating that the oil price shock has a positive impact on inflation expectations, which is strengthened during the epidemic.

The effect of the inflation rate and EPU on inflation expectations is still present but not significant. Short-term and long-term GDP growth can still reduce consumer inflation expectations, and the lagged GDP will affect the decline in residents' inflation expectations. For example, the lagged GDP_{t-1} can even reduce residents' inflation expectations by 53.5%. The difference with the ARDL result is that in the short term, the lag period of inflation expectations $E\pi_{t-1}$ has a significant negative impact on inflation expectations, but this still reflects the adjustment of adaptive expectations and inflation expectations due to past deviations.

Panel C demonstrates that the variables do not have problems with autocorrelation or heteroskedasticity, and the Ramsey REST test confirms that the model passes the standard test. More importantly, we examine the cointegration of the NARDL model and the asymmetry of oil price shocks in the short and long term, concluding that we can reject the null hypothesis of cointegration at the 1% significance level. Therefore, the positive impact and asymmetry of the 2010-2020 US oil price shock on inflation expectations can be confirmed by ARDL and Nonlinear ARDL models.

4.2 China

Similar to the data processing method in the United States, we consider the overall sample and introduce a dummy variable of structural disruption to compare the effects of oil price shocks before and after the epidemic. Due to the early start of the epidemic and the economic damage in China, we have the first quarter in 2020 and the second month in 2020 to split the quarterly and monthly samples respectively, that is, the quarterly sample in China contains two sub-periods (2010Q1- 2019Q4 and 2020Q1-2021Q4), the monthly sample also includes two sub-periods (January 2010 to January 2020 and February 2020 to December 2021).

4.2.1 ARDL-ECM Results

According to the long-term cointegration relationship between variables in China and the optimal lags of AIC and SIC, we obtained the ARDL error correction model results of China's quarterly benchmark model, which are shown in Table 9 as follows.

As shown in Table 9, the overall quarterly data for 2010-2021 shows that China, like the US, is also significantly positively affected by the oil price shock on households' inflation expectations in the short and long term, the positive impact is less though. A 1% increase in oil prices will increase Chinese inflation expectations by 1.1% in the short term, and about 0.4% in the long run. This can also be explained by the consumption structure and consumption concept of Chinese residents, and China’s isolation policy for COVID-19. In 2021, the per capita electricity consumption in China was 4989KWh compared to 12220KWh in the United States. Chinese households’ electricity consumption grew by 5.9% year-on-year in 2020, while the consumption of gasoline used for travel has fallen by 3.53% year-on-year. Therefore, the impact of oil price shock on residents' disposable income is positive but limited. Yu (2022) studies the time-frequency dynamics of spillover effects between oil price shocks and global economic performance, and proposes that the recent outbreak of COVID-19 indicates that oil prices fluctuate significantly during the crisis, and that the impact of the epidemic on oil prices could even cause a serious impact on economic activities. Rafiuddin (2021) uses GCC member country data to show that although there is not much correlation in the short term, the impact of the global pandemic crisis on oil price shocks is significant in the medium and long term.

The above conclusions are also verified by the significant negative effect of the dummy variable. After the outbreak of the epidemic, the level of Chinese residents' inflation expectations decreased by 6.6% in the short term and 2.5% in the long term, and the negative impact of oil price shocks on inflation expectations was also more significant after the epidemic. Compared with 2010-2019, the impact of oil price shocks after COVID-19 outbreak on inflation expectations was reduced by 8.3% and 3.1% in the short and long term, respectively. This fully reflects that Chinese residents' reliance on oil prices has decreased significantly based on the less use of transportations according to the isolation policy. Therefore, with the decreasing consumption of oil products, the impact of oil prices on household inflation expectations has also declined.

Table 9: China ARDL Error Correction Model benchmark results

Regressors	Regressand ($\Delta Infex$)	
	Coefficient	Prob.
Panel A: Short-run estimates		
$Infex_{t-1}$	-0.452***	0.001
$Infex_{t-2}$	-0.706***	0.000
$Infex_{t-3}$	-0.325**	0.006
$Infex_{t-4}$	-0.167	0.115
WTI_t	0.011***	0.000
$Inflation_t$	-0.015	0.895
$Inflation_{t-1}$	0.492***	0.000
GDP_t	-0.061	0.353
GDP_{t-1}	0.300**	0.005
GDP_{t-2}	-0.378***	0.000
EPU_t	2.65E-05*	0.029
EPU_{t-1}	4.75E-05**	0.002
EPU_{t-2}	3.60E-05*	0.014
Du_t	-0.066***	0.000
$WTI \times Du_t$	-0.083***	0.000
$\Delta Infex_{t-1}$	1.198***	0.000
$\Delta Infex_{t-2}$	4.92E-01**	0.002
$\Delta Infex_{t-3}$	0.167	0.115
$\Delta Inflation_t$	-0.492***	0.000
ΔGDP_t	0.078	0.257
ΔGDP_{t-1}	0.378***	0.000
ΔEPU_t	-8.35E-05***	0.000
ΔEPU_{t-1}	-3.60E-05*	0.014
Constant	0.762***	0.000
Panel B: Long-run estimates		
WTI	0.004***	0.000
Inflation	0.180***	0.000
GDP	-0.052***	0.000
EPU	4.15E-05***	0.000
Du	-0.025***	0.000
$WTI \times Du$	-0.031***	0.000
Panel C: Diagnostic test		
R^2	0.920	
$Adjusted\ R^2$	0.878	
DW	1.650	
BG LM test	0.542	0.462
IM test	44.000	0.429
BPG test	1.720	0.190
Ramsey RESET test	4.320	0.014

[1] * 1% level of significance, ** 5% level of significance, *** 10% level of significance.
[2] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation.
[3] IM test is Information Matrix Test used for model determination.
[4] BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity.
[5] Ramsey RESET is the Ramsey Regression Equation Specification Error Test for stability.
[6] Optimal lag selection based on AIC.

It can be seen that the Chinese inflation expectations are more dependent on the lagged inflation expectations $E\pi_{t-1}$ and $E\pi_{t-2}$. Interestingly, long-duration lagged inflation expectations have a significant negative impact on current inflation expectations. Part of the reason is that according to the Chinese government's macroeconomic regulation policies, Chinese residents tend to trust the government to maintain its stability after a prolonged period of inflation. Another part of the reason is that China's inflation expectations also have adaptive expectations and inflation expectations are adjusted due to past deviations. According to the results, inflation expectations are also significantly affected by the lagged inflation rate INF_{t-1}, the lagged GDP_{t-2}, and the lagged EPU_{t-1}. The positive effects of the inflation rate and EPU and the negative effects of GDP are in line with the law of economic development.

The diagnostic tests in panel C show that there are no problems with autocorrelation and heteroskedasticity between variables. The Ramsey REST test showed that the model did not pass the standard test at the 5% statistical level of significance, so to further test the stability of the estimates, we also performed CUSUM and CUSUMSQ, the results are shown in Figure 2 (see Appendix B). The CUSUM and CUSUMSQ parametric stability tests of inflation expectations show that the overall sample in 2010-2021 is briefly out of bounds, but the subject remains within the 5% significance bound, so the parameter estimates can be considered stable.

4.2.2 Nonlinear ARDL Results

Nasir et al. (2020) apply the Nonlinear ARDL model to the assessment of the relationship between oil price dynamics and inflation expectations in New Zealand and the United Kingdom, and found that changes in oil prices have asymmetric effects on inflation expectations, while the exchange rate, money supply, Output growth, unemployment, and fiscal deficit/surplus also play a role in this pass through. Similarly, based on the Nonlinear ARDL model, we further explore the asymmetry of positive and negative oil price shocks and the change in the impact of oil price shocks after the epidemic. The results are shown in Table 10:

Table 10: China NARDL quarterly benchmark results

Regressors	Regressand ($\Delta Infex$)	
	Coefficient	Prob.
Panel A: Short-run estimates		
$Infex_{t-1}$	-1.898***	0.000
WTI^{+}_{t-1}	0.037***	0.000
WTI^{-}_{t-1}	0.010***	0.000
$Inflation_{t-1}$	0.588***	0.000
GDP_{t-1}	-0.196***	0.000
EPU_{t-1}	4.26E-05**	0.002
Du_{t-1}	-0.063***	0.000
$WTI \times Du_{t-1}$	-0.051***	0.000
$\Delta Infex_{t-1}$	0.651***	0.000
$\Delta Infex_{t-2}$	0.127	0.152
$\Delta Infex_{t-3}$	-0.036	0.487
ΔWTI^{+}_{t}	0.024***	0.000
ΔWTI^{+}_{t-2}	-0.005	0.209
ΔWTI^{+}_{t-3}	0.015**	0.002
ΔWTI^{-}_{t-1}	0.002	0.537
ΔWTI^{-}_{t-2}	0.011**	0.002
ΔWTI^{-}_{t-3}	0.007*	0.030
$\Delta Inflation_{t}$	-0.066	0.174
ΔGDP_{t}	-0.226	0.000
ΔGDP_{t-1}	0.169	0.268
ΔGDP_{t-2}	-0.161**	0.007
ΔGDP_{t-3}	-0.649***	0.000
ΔGDP_{t-4}	-0.296***	0.000
ΔDu_{t-1}	0.048***	0.000
Constant	1.037***	0.000
Panel B: Long-run estimates		
WTI^{+}	-0.014**	0.001
WTI^{-}	0.004**	0.001
Inflation	0.145**	0.001
GDP	0.023	0.285
EPU	6.51E-05***	0.000
Du	0.003	0.143
$WTI \times Du$	-0.104	0.354
Panel C: Diagnostic test		
R^2	0.993	
$Adjusted\ R^2$	0.981	
$Fstatistic$	65.905***	
$Wald - short$	22.537***	
$Wald - long$	28.812***	
DW	2.897	
JB test	1.384	0.501
BG LM test	2.774	0.097
BPG test	0.373	0.988
Ramsey RESET test	0.425	0.739

[1] Significant at 10% (*), 5% (**), and 1% (***).
[2] The F-statistic is calculated by the Wald test (with $H_0 : \omega_{1f} = \omega^{+}_{2f} = \omega^{-}_{2f} = \omega_{3f} = \omega_{4f} = \omega_{5f} = \omega_{6f} = \omega_{7f}$) and compared with the upper bound critical value. $Wald\ short$ and $Wald\ long$, respectively, represent the F-statistics used by the Wald test to assess asymmetry in the short run (with $H_0 : \sum_{i=1}^{l} \tau^{+}_{2f} = \sum_{i=1}^{l} \tau^{-}_{2f}$) and long run (with $H_0 : \frac{\omega^{+}_{2f}}{\omega_{1f}} = \frac{\omega^{-}_{2f}}{\omega_{1f}}$).
[3] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation. JB test is the Jarque–Bera test for residual normality distribution. BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity. Ramsey RESET is the Ramsey Regression Equation Specification Error Test for stability.

In the Nonlinear ARDL model, which explores the asymmetry of oil price shocks, we reach a conclusion similar to that of the United States, that is, in the short term, the impact of positive and negative oil prices on inflation expectations is asymmetric, and the positive oil price change plays a bigger role on inflation expectations than the negative change. As we can see from the table, a positive oil price shock causes inflation expectations to rise by 3.7% in the short term, while a negative oil price shock also gives a positive impact which is only 1.0%

though. In particular, the increase in oil prices over the same period directly increases the inflation expectation by 2.4%, and the lagged decline in oil prices also significantly increases inflation expectations by up to 1.1%. In the long run, this asymmetry also exists. Although the rate of increase is not obvious, the shock of negative oil prices is still working on the increase of inflation expectations. In the short term, the dummy variable and the interactive variables are also important in China. After the COVID-19 outbreak, the oil price shock harms inflation expectations, the impact is not significant in the long term though.

The inflation rate and EPU have a very significant positive impact on China's inflation expectations both in the short and long term, indicating that the rise in Chinese residents' inflation expectations is affected by the pass-through of inflation and economic policy uncertainty during the epidemic. However, oil prices not only do not lead to an increase in expectations, but even had the opposite effect due to the reduction in consumer demand. With all the significant effects GDP brings inflation expectation are positive. Changes in GDP with different lag periods have different effects on inflation expectations. For example, the lagged GDP_{t-3} even reduces households' inflation expectations by 64.9%.

The diagnostic tests in panel C demonstrate that the variables do not have problems with autocorrelation or heteroskedasticity, and the Ramsey REST test confirms that the model passes the standard test. According to the boundary and asymmetry tests, we can reject the cointegration null hypothesis at a significant level of 1% and reject the null hypothesis of symmetry at the 1% significance level. The negative impact and asymmetry of China's oil price shock on inflation expectations from 2010 to 2020 can be confirmed by ARDL and Nonlinear ARDL models.

Last but not least, the Nonlinear ARDL model has a better fit for both the US and China quarterly data than the ARDL model, which further shows that the asymmetric effect of oil price shocks on inflation expectations is more in line with the current state of economic development in the U.S. and China.

5. Robustness Check

In this section, we will apply monthly data from the US and China for robustness checks. As described in the previous section, we expanded the US and China data into the overall sample and two subsamples, the subsamples are January 2010-February 2020 and March 2020-December 2021 in the US, and January 2010-January 2020 and February 2020-December 2021 in China. Because of the supplementation of data and the setting of subsamples, we no longer need to use dummy variables and interactive variables but draw conclusions by directly comparing the results of the two subsamples.

Before this, we also perform unit root tests and boundary tests for the monthly data, and the results are shown in Figures A1-A5 (in Appendix A). The results also prove that all variables are stationary at I(0) or I(1), and there is cointegration between variables.

5.1 Causality Test

We cannot conclude the causal relationship between oil price shocks and inflation expectations although we have explored the linear impact and nonlinear symmetry of oil price shocks in the benchmark model. Therefore, we use the Toda-Yamamoto Granger causality test proposed by Toda and Yamamoto (1995). Compared with the classical Granger test, the advantages of the Toda and Yamamoto process are given as follows: First, the Granger test can give spurious regressions on aggregate variables for functions with time lags. Second, the F statistic can only be used when the variables are cointegrated. Third, the Toda and Yamamoto tests for Granger non-causality are based on the modified Wald test (MWald) and the seemingly uncorrelated regression model (SUR model). Thus, the Toda and Yamamoto procedure minimizes the risk of determining the optimal lag order for each variable, and it works for all variables with or without stationarity and cointegration.

However, the Toda-Yamamoto test cannot capture the effect of the presence of structural breakpoints on causality. To make up for this deficiency, we conduct this test also in the subsamples. The specific test results are shown in Table 11.

The null hypothesis of the test is that there is no causality between the oil price shock and inflation expectations. When the p-value is less than 0.5, we have reason to reject the null hypothesis. As shown in the results of the table above, only in the COVID-19 regime, did the oil price shock causes inflation expectations. While the oil price shock is the cause of inflation expectations in all the Chinese samples. On the contrary, except for the COVID-19 regime, other samples does not reflect that inflation expectations can cause oil price change. This exception may be due to that the impact of the pandemic and inflation expectations has reduced demand for oil, thereby affecting its price.

Table 11: Toda-Yamamoto causality test results

Null hypothesis	Country	Sample	*Optimal VAR lag length* (k+dmax)	*Wald* (Chi-square)	Prob.	Causality
WTI $\neq>$ Infex	U.S.	*Full sample*	3	3.388	0.336	*No causality*
		Pre-COVID19	3	24.646	0.000	Yes
		COVID19	5	10.596	0.060	*No causality*
	China	*Full sample*	10	22.434	0.013	Yes
		Pre-COVID19	17	30.910	0.021	Yes
		COVID19	7	2913.082	0.000	Yes
Infex $\neq>$ WTI	U.S.	*Full sample*	3	1.223	0.748	*No causality*
		Pre-COVID19	3	1.533	0.675	*No causality*
		COVID19	5	2.778	0.734	*No causality*
	China	*Full sample*	10	10.916	0.364	*No causality*
		Pre-COVID19	17	17.730	0.406	*No causality*
		COVID19	7	91.891	0.000	Yes

[1] Lag lengths have been selected according to AIC criteria.
[2] $\neq>$ notation on the table expressed the hypothesis that there is no causality relation between two variables in the shown direction.

5.2 U.S.

Table 12 is the ARDL error correction model results.

Table 12: U.S. ARDL Error Correction Model monthly results

Regressors	Full sample		Regressors	Pre-COVID-19		Regressors	COVID-19	
	Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.
Panel A: Short-run estimates								
$Infex_{t-1}$	0.657***	0.000	$Infex_{t-1}$	0.593***	0.000	$Infex_{t-1}$	-0.555**	0.001
$Infex_{t-2}$	0.119	0.165	WTI_t	0.003**	0.006	$Infex_{t-2}$	-0.135	0.211
WTI_t	0.008***	0.000	$Inflation_t$	0.188**	0.008	$Infex_{t-3}$	0.378**	0.001
WTI_{t-1}	-0.007***	0.000	$Inflation_{t-1}$	-0.165*	0.020	WTI_t	0.025***	0.000
$Inflation_t$	0.082**	0.005	GDP_t	-0.014	0.253	$Inflation_t$	-0.055	0.542
GDP_t	-0.005	0.686	EPU_t	-1.76E-06	0.749	$Inflation_{t-1}$	0.664***	0.000
EPU_t	4.57E-06	0.147	$\Delta Inflation_t$	0.175*	0.012	GDP_t	-0.269**	0.001
$\Delta Infex_{t-1}$	-0.119	0.165	Constant	0.074	0.152	GDP_{t-1}	-0.174**	0.003
ΔWTI_{t-1}	0.007***	0.000				GDP_{t-2}	-0.091*	0.045
Constant	0.026	0.606				GDP_{t-3}	-0.092*	0.012
						EPU_t	-7.75E-06	0.243
						$\Delta Infex_{t-1}$	-0.243*	0.044
						$\Delta Infex_{t-2}$	-0.378**	0.001
						$\Delta Inflation_t$	-0.664***	0.000
						ΔGDP_t	0.358***	0.000
						ΔGDP_{t-1}	0.183***	0.001
						ΔGDP_{t-2}	0.092*	0.012
						Constant	2.754***	0.000
Panel B: Long-run estimates								
WTI	0.002	0.638	WTI	0.007**	0.003	WTI	0.019***	0.000
Inflation	0.365***	0.001	Inflation	0.049	0.494	Inflation	0.464***	0.000
GDP	-0.022	0.686	GDP	-0.029	0.310	GDP	-0.478***	0.000
EPU	2.04E-05	0.165	EPU	-3.83E-06	0.778	EPU	-5.90E-06	0.243
Panel C: Diagnostic test								
R^2	0.816		R^2	0.750		R^2	0.991	
Adjusted R^2	0.807		*Adjusted* R^2	0.737		*Adjusted* R^2	0.982	
DW	1.968		DW	2.028		DW	2.938	
BG LM test	0.263	0.608	BG LM test	0.081	0.775	BG LM test	7.641	0.006
IM test	52.500	0.029	IM test	38.280	0.074	IM test	22.000	0.400
BPG test	11.120	0.001	BPG test	20.900	0.000	BPG test	0.160	0.686

[1] * 1% level of significance, ** 5% level of significance, *** 10% level of significance.
[2] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation.
[3] IM test is Information Matrix Test used for model determination.
[4] BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity.
[5] Optimal lag selection based on AIC.

Consistent with the conclusion of the benchmark ARDL-ECM, the full sample gives us positive and significant effects from the oil price shock in the short term, with an impact level of 8.0%. The effects of lagged inflation expectations and inflation on inflation expectations are similar to the benchmark results. The difference is that, in the long run, the oil price shock is no longer the factor that significantly affects inflation expectations, but the inflation rate is.

In the two subsamples, we can also see that the impacts of oil price shocks on inflation expectations are equally positive and significant in the short and long term. The impact of oil price shocks on inflation expectations under the COVID-19 regime has increased significantly, which is from 0.3% to 2.5% in the short term, from 0.7% to 1.9% in the long run, which also shows the importance of the COVID19 outbreak as a structural breakpoint. Besides, the oil price shock has a more significant effect on inflation expectations in the long run under the pre-COVID19 regime, and during the epidemic, inflation expectations are also significantly affected by inflation and GDP.

Table 13 shows a robustness test for the asymmetry of positive and negative oil price shocks using the Nonlinear ARDL model.

Table 13: U.S. NARDL Model monthly results

Regressors	Full sample		Regressors	Pre-COVID-19		Regressors	COVID-19	
	Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.
Panel A: Short-run estimates								
$Infex_{t-1}$	-0.400***	0.000	$Infex_{t-1}$	-0.959***	0.000	$Infex_{t-1}$	-4.064***	0.000
WTI^{+}_{t-1}	0.007***	0.000	WTI^{+}_{t-1}	-0.010**	0.006	WTI^{+}_{t-1}	0.087***	0.000
WTI^{-}_{t-1}	0.003**	0.006	WTI^{-}_{t-1}	0.007***	0.000	WTI^{-}_{t-1}	0.097***	0.000
$Inflation_{t-1}$	0.080*	0.011	$Inflation_{t-1}$	0.190**	0.001	$Inflation_{t-1}$	1.886***	0.000
GDP_{t-1}	-0.140**	0.003	GDP_{t-1}	0.562***	0.000	GDP_{t-1}	-0.107	0.097
EPU_{t-1}	-1.77E-05*	0.011	EPU_{t-1}	2.26E-05*	0.021	EPU_{t-1}	2.69E-04***	0.000
$\Delta Infex_{t-1}$	-0.104	0.256	$\Delta Infex_{t-1}$	0.371**	0.006	$\Delta Infex_{t-1}$	1.723***	0.000
ΔWTI^{+}_{t}	0.017**	0.003	$\Delta Infex_{t-2}$	0.401**	0.003	ΔWTI^{+}_{t}	-0.043**	0.001
ΔWTI^{+}_{t-1}	-0.001	0.913	$\Delta Infex_{t-3}$	0.300*	0.014	ΔWTI^{+}_{t-1}	-0.051***	0.000
ΔWTI^{-}_{t}	-0.001	0.892	$\Delta Infex_{t-4}$	0.218*	0.045	ΔWTI^{+}_{t-2}	0.010**	0.002
ΔWTI^{-}_{t-1}	-0.002	0.726	$\Delta Infex_{t-5}$	0.337**	0.002	ΔWTI^{-}_{t}	0.190***	0.000
ΔWTI^{-}_{t-2}	-0.008	0.065	ΔWTI^{+}_{t}	0.004	0.578	$\Delta Inflation_{t}$	0.721***	0.000
$\Delta Inflation_{t}$	0.201**	0.008	ΔWTI^{+}_{t-1}	0.024***	0.000	$\Delta Inflation_{t-1}$	-2.017***	0.000
ΔGDP_{t}	-0.091	0.108	ΔWTI^{+}_{t-2}	-0.002	0.713	ΔGDP_{t}	0.064	0.116
ΔGDP_{t-1}	0.069	0.266	ΔWTI^{+}_{t-3}	0.001	0.865	ΔEPU_{t-1}	-1.77E-04***	0.000
ΔGDP_{t-2}	0.093	0.113	ΔWTI^{+}_{t-4}	0.018**	0.004	Constant	0.454	0.096
ΔEPU_{t}	-8.66E-06	0.192	ΔWTI^{+}_{t-5}	0.006	0.288			
ΔEPU_{t-1}	1.03E-05	0.176	ΔWTI^{+}_{t-6}	-0.004	0.425			
ΔEPU_{t-2}	6.08E-06	0.400	ΔWTI^{+}_{t-7}	0.009	0.132			
Constant	0.599**	0.003	ΔWTI^{+}_{t-8}	-0.002	0.750			
			ΔWTI^{-}_{t}	0.006	0.248			
			$Inflation_{t}$	0.039	0.633			
			$Inflation_{t-1}$	-0.084	0.347			
			$Inflation_{t-2}$	0.017	0.839			
			$Inflation_{t-3}$	-0.142	0.091			
			ΔGDP_{t}	-0.186	0.156			
			ΔGDP_{t-1}	-0.644	0.006			
			ΔGDP_{t-2}	-0.789**	0.001			
			ΔGDP_{t-3}	-0.595**	0.005			
			ΔGDP_{t-4}	-0.604**	0.002			
			ΔGDP_{t-5}	-0.538**	0.005			
			ΔGDP_{t-6}	-0.376*	0.043			
			ΔGDP_{t-7}	-0.267	0.088			
			ΔGDP_{t-8}	-0.124	0.309			
			ΔEPU_{t}	4.36E-06	0.592			
			ΔEPU_{t-1}	-1.99E-05*	0.050			
			ΔEPU_{t-2}	-8.21E-06	0.381			
			ΔEPU_{t-3}	-5.05E-06	0.551			
			ΔEPU_{t-4}	-2.45E-05**	0.003			
			ΔEPU_{t-5}	-1.85E-05*	0.031			
			Constant	-2.328***	0.000			
Panel B: Long-run estimates								
WTI^{+}	0.015***	0.000	WTI^{+}	-0.005	0.506	WTI^{+}	0.021*	0.050
WTI^{-}	0.008**	0.006	WTI^{-}	0.009***	0.000	WTI^{-}	0.042	0.159
Inflation	0.175	0.011	Inflation	0.136*	0.045	Inflation	0.363**	0.001
GDP	-0.277**	0.005	GDP	0.446*	0.049	GDP	-0.221	0.223
EPU	-2.98E-05*	0.046	EPU	3.23E-05*	0.045	EPU	1.80E-05	0.318
Panel C: Diagnostic test								
R^2	0.368		R^2	0.651		R^2	0.999	
$Adjusted\ R^2$	0.269		$Adjusted\ R^2$	0.457		$Adjusted\ R^2$	0.996	
$F statistic$	4.601**		$F statistic$	9.708***		$F statistic$	313.481***	
$Wald\ short$	13.177***		$Wald\ short$	22.645***		$Wald\ short$	6.155	
$Wald\ long$	10.427**		$Wald\ long$	15.756***		$Wald\ long$	6.228	
DW	2.023		DW	2.024		DW	3.343	
JB test	77.408	0.000	JB test	49.732	0.000	JB test	0.333	0.847
BG LM test	0.428	0.653	BG LM test	3.334	0.010	BG LM test	74.628	0.082
BPG test	1.267	0.218	BPG test	0.847	0.713	BPG test	0.926	0.612
$Ramsey\ RESET$	2.384	0.055	$Ramsey\ RESET$	3.083	0.010	$Ramsey\ RESET$	1.816	0.465

[1] Significant at 10% (*), 5% (**), and 1% (***).
[2] The F-statistic is calculated by the Wald test (with $H_0 : \omega_{1f} = \omega^{+}_{2f} = \omega^{-}_{2f} = \omega_{3f} = \omega_{4f} = \omega_{5f} = \omega_{6f} = \omega_{7f}$) and compared with the upper bound critical value. $Wald\ short$ and $Wald\ long$, respectively, represent the F-statistics used by the Wald test to assess asymmetry in the short run (with $H_0 : \sum_{i=1}^{l} \tau^{+}_{2f} = \sum_{i=1}^{l} \tau^{-}_{2f}$) and long run (with $H_0 : \frac{\omega^{+}_{2f}}{\omega_{1f}} = \frac{\omega^{-}_{2f}}{\omega_{1f}}$).
[3] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation. JB test is the Jarque–Bera test for residual normality distribution. BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity. Ramsey RESET is the Ramsey Regression Equation Specification Error Test for stability.

In the short-term and long-term of the overall sample, both positive and negative oil prices have a significant positive impact on inflation expectations, and the magnitude of positive shocks is greater than that of negative shocks, which more intuitively proves price stickiness, and also shows the asymmetry of oil prices. Interestingly, in the results of the two subsamples, the positive effect of negative oil price shocks on inflation expectations even exceeds that of positive oil price shocks, which further reflects the significantly positive effect of oil price shocks and the more obvious price stickiness. The asymmetry is further amplified in the monthly data.

Similarly, we also conduct the robustness test on the Chinese data. See Tables 14 and 15.

Table 14: China ARDL Error Correction Model monthly results

Regressors	Full sample		Regressors	Pre-COVID-19		Regressors	COVID-19	
	Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.
Panel A: Short-run estimates								
$Infex_{t-1}$	1.428***	0.000	$Infex_{t-1}$	1.264***	0.000	$Infex_{t-1}$	-0.616***	0.000
$Infex_{t-2}$	-0.467***	0.000	$Infex_{t-2}$	-0.462***	0.000	WTI_t	0.018***	0.000
$Infex_{t-3}$	-0.711***	0.000	$Infex_{t-3}$	-0.709***	0.000	WTI_{t-1}	-0.009**	0.003
$Infex_{t-4}$	0.936***	0.000	$Infex_{t-4}$	0.915***	0.000	WTI_{t-2}	0.040***	0.000
$Infex_{t-5}$	-0.406***	0.000	$Infex_{t-5}$	-0.542***	0.000	$Inflation_t$	0.339***	0.000
WTI_t	-0.002	0.484	WTI_t	0.002**	0.004	$Inflation_{t-1}$	-0.558***	0.000
WTI_{t-1}	0.003	0.393	$Inflation_t$	0.104**	0.003	$Inflation_{t-2}$	0.453***	0.000
WTI_{t-2}	-0.006*	0.034	$Inflation_{t-1}$	-0.010	0.821	$Inflation_{t-3}$	0.751***	0.000
WTI_{t-3}	0.009**	0.002	$Inflation_{t-2}$	0.085*	0.020	$Inflation_{t-4}$	0.337***	0.000
WTI_{t-4}	-0.005**	0.007	GDP_t	-0.077*	0.040	GDP_t	0.199***	0.000
$Inflation_t$	0.039	0.276	GDP_{t-1}	0.058	0.113	GDP_{t-1}	0.040***	0.005
$Inflation_{t-1}$	-0.036	0.459	EPU_t	2.04E-06*	0.049	GDP_{t-2}	-0.419***	0.000
$Inflation_{t-2}$	0.124**	0.002	EPU_{t-1}	7.21E-07	0.484	GDP_{t-3}	0.118**	0.003
GDP_t	-0.048	0.109	EPU_{t-2}	1.95E-06	0.068	GDP_{t-4}	-0.619***	0.000
GDP_{t-1}	0.086*	0.029	$\Delta Infex_{t-1}$	0.773***	0.000	EPU_t	8.32E-06***	0.000
GDP_{t-2}	-0.126**	0.008	$\Delta Infex_{t-2}$	0.342***	0.000	EPU_{t-1}	8.68E-06***	0.000
GDP_{t-3}	0.080	0.051	$\Delta Infex_{t-3}$	-0.393***	0.000	EPU_{t-2}	1.53E-05***	0.000
EPU_t	1.36E-06	0.135	$\Delta Infex_{t-4}$	0.510***	0.000	EPU_{t-3}	2.57E-06**	0.001
$\Delta Infex_{t-1}$	0.648***	0.000	$\Delta Inflation_t$	-0.057	0.150	EPU_{t-4}	-5.48E-06***	0.000
$\Delta Infex_{t-2}$	0.181*	0.011	$\Delta Inflation_{t-1}$	-0.079*	0.032	ΔWTI_t	-0.031***	0.000
$\Delta Infex_{t-3}$	-0.530***	0.000	ΔGDP_t	-0.079*	0.027	ΔWTI_{t-1}	-0.040***	0.000
$\Delta Infex_{t-4}$	0.406***	0.000	Constant	0.070***	0.000	$\Delta Inflation_t$	-0.983***	0.000
ΔWTI_t	-0.001	0.781				$\Delta Inflation_{t-1}$	-1.541***	0.000
ΔWTI_{t-1}	0.002	0.246				$\Delta Inflation_{t-2}$	-1.088***	0.000
ΔWTI_{t-2}	-0.004*	0.028				$\Delta Inflation_{t-3}$	-0.337***	0.000
ΔWTI_{t-3}	0.005**	0.007				ΔGDP_t	0.881***	0.000
$\Delta Inflation_t$	-0.088*	0.029				ΔGDP_{t-1}	0.920***	0.000
$\Delta Inflation_{t-1}$	-0.124**	0.002				ΔGDP_{t-2}	0.501***	0.000
ΔGDP_t	-0.040	0.168				ΔGDP_{t-3}	0.619***	0.000
ΔGDP_{t-1}	0.046	0.083				ΔEPU_t	-2.11E-05***	0.000
ΔGDP_{t-2}	-0.080	0.051				ΔEPU_{t-1}	-1.24E-05***	0.000
Constant	0.026*	0.034				ΔEPU_{t-2}	2.91E-06**	0.003
						ΔEPU_{t-3}	5.48E-06***	0.000
						Constant	2.369***	0.000
Panel B: Long-run estimates								
WTI	-0.005	0.156	WTI	0.004**	0.002	WTI	0.030***	0.000
Inflation	0.575***	0.000	Inflation	0.355***	0.000	Inflation	0.818***	0.000
GDP	-0.035*	0.035	GDP	-0.030***	0.000	GDP	-0.422***	0.000
EPU	6.19E-06	0.122	EPU	6.30E-06**	0.001	EPU	1.82E-05***	0.000
Panel C: Diagnostic test								
R^2	0.968		R^2	0.964		R^2	1.000	
Adjusted R^2	0.964		*Adjusted* R^2	0.959		*Adjusted*R^2	0.9996	
DW	1.853		DW	2.187		DW	2.641	
BG LM test	1.923	0.166	BG LM test	3.326	0.068	BG LM test	9.294	0.002
IM test	139.000	0.460	IM test	116.000	0.456	IM test	23.000	0.402
BPG test	33.310	0.000	BPG test	77.700	0.000	BPG test	2.410	0.121

[1] * 1% level of significance, ** 5% level of significance, *** 10% level of significance.
[2] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation.
[3] IM test is Information Matrix Test used for model determination.
[4] BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity.
[5] Optimal lag selection based on AIC.

According to the overall sample in Table 14, oil price shocks have a negative but insignificant impact on inflation expectations in the short and long term. The lagged inflation expectations exert a persistent and significant positive impact, although the short-term impact varies with the choice of lag period. In the two subsamples, the oil price shock has a positive impact on inflation expectations in the long run, while the rise in oil prices under the epidemic regime has a significant negative impact on inflation expectations, which is consistent with the conclusion of the benchmark model.

Table 15: China NARDL Model monthly results

Regressors	Full sample		Regressors	Pre-COVID-19		Regressors	COVID-19	
	Coefficient	Prob.		Coefficient	Prob.		Coefficient	Prob.
Panel A: Short-run estimates								
$Infex_{t-1}$	-0.222***	0.000	$Infex_{t-1}$	-0.480***	0.000	$Infex_{t-1}$	-0.545***	0.000
WTI^+_{t-1}	-2.44E-03**	0.004	WTI^+_{t-1}	5.11E-04	0.667	WTI^+_{t-1}	-0.044***	0.000
WTI^-_{t-1}	1.20E-03	0.097	WTI^-_{t-1}	3.75E-03***	0.000	WTI^-_{t-1}	-0.004	0.393
$Inflation_{t-1}$	0.087***	0.000	$Inflation_{t-1}$	0.145***	0.000	$Inflation_{t-1}$	0.760***	0.000
GDP_{t-1}	0.027**	0.008	GDP_{t-1}	0.009	0.438	GDP_{t-1}	1.268***	0.000
EPU_{t-1}	8.46E-06**	0.001	EPU_{t-1}	8.77E-06***	0.000	EPU_{t-1}	-8.76E-06**	0.002
$\Delta Infex_{t-1}$	0.608***	0.000	$\Delta Infex_{t-1}$	0.783***	0.000	$\Delta Infex_{t-1}$	-0.324**	0.001
$\Delta Infex_{t-2}$	0.347***	0.000	$\Delta Infex_{t-2}$	0.539***	0.000	$\Delta Infex_{t-2}$	0.298**	0.002
$\Delta Infex_{t-3}$	-0.876***	0.000	$\Delta Infex_{t-3}$	-0.985***	0.000	ΔWTI^+_t	-0.067***	0.000
$\Delta Infex_{t-4}$	0.579***	0.000	$\Delta Infex_{t-4}$	0.854***	0.000	ΔWTI^-_t	0.024**	0.006
$\Delta Infex_{t-5}$	0.339**	0.004	$\Delta Infex_{t-5}$	0.579***	0.000	ΔWTI^-_{t-2}	-0.027***	0.000
$\Delta Infex_{t-6}$	-0.689***	0.000	$\Delta Infex_{t-6}$	-1.150***	0.000	$\Delta Inflation_t$	0.369***	0.000
$\Delta Infex_{t-7}$	0.306**	0.001	$\Delta Infex_{t-7}$	0.535***	0.000	$\Delta Inflation_{t-1}$	-0.874***	0.000
$\Delta Infex_{t-8}$	0.228*	0.015	$\Delta Infex_{t-8}$	0.473**	0.001	$\Delta Inflation_{t-2}$	-0.286**	0.002
$\Delta Infex_{t-9}$	-0.175*	0.044	$\Delta Infex_{t-9}$	-0.676***	0.000	ΔGDP_t	1.229**	0.002
ΔWTI^+_t	0.005	0.220	$\Delta Infex_{t-10}$	0.167*	0.045	ΔEPU_t	-4.19E-06**	0.003
ΔWTI^+_{t-1}	0.008*	0.041	$\Delta Infex_{t-11}$	0.206*	0.011	Constant	-4.301***	0.000
ΔWTI^+_{t-2}	0.002	0.498	$\Delta Infex_{t-12}$	-0.238**	0.001			
ΔWTI^+_{t-3}	0.006*	0.036	ΔWTI^+_t	0.005	0.174			
ΔWTI^+_{t-4}	0.004	0.174	ΔWTI^+_{t-1}	0.012***	0.000			
ΔWTI^+_{t-5}	0.007*	0.017	ΔWTI^+_{t-2}	5.55E-05	0.985			
ΔWTI^+_{t-6}	0.003	0.282	ΔWTI^+_{t-3}	0.005	0.083			
ΔWTI^+_{t-7}	0.004	0.184	ΔWTI^+_{t-4}	0.011**	0.001			
ΔWTI^+_{t-8}	-3.84E-04	0.890	ΔWTI^+_{t-5}	0.011***	0.000			
ΔWTI^+_{t-9}	0.008**	0.008	ΔWTI^+_{t-6}	0.004	0.154			
ΔWTI^+_{t-10}	0.003	0.312	ΔWTI^+_{t-7}	0.002	0.537			
ΔWTI^-_t	-0.001	0.632	ΔWTI^+_{t-8}	0.010***	0.000			
$Inflation_t$	0.023	0.475	ΔWTI^+_{t-9}	0.011***	0.000			
$Inflation_{t-1}$	-0.106**	0.005	ΔWTI^+_{t-10}	0.006*	0.025			
ΔGDP_t	-0.046	0.105	ΔWTI^+_{t-11}	0.001	0.605			
ΔGDP_{t-1}	-0.014	0.615	ΔWTI^+_{t-12}	0.004	0.169			
ΔGDP_{t-2}	-0.126***	0.000	ΔWTI^-_t	0.003	0.174			
ΔGDP_{t-3}	-0.035	0.311	$Inflation_t$	0.045	0.056			
ΔEPU_t	7.80E-07	0.423	ΔGDP_t	-0.104***	0.000			
ΔEPU_{t-1}	-8.11E-06**	0.003	ΔGDP_{t-1}	-0.173**	0.001			
ΔEPU_{t-2}	-8.46E-06**	0.001	ΔGDP_{t-2}	-0.117*	0.047			
ΔEPU_{t-3}	-8.62E-06**	0.001	ΔGDP_{t-3}	-0.094	0.100			
ΔEPU_{t-4}	-9.12E-06***	0.000	ΔGDP_{t-4}	-0.048	0.264			
ΔEPU_{t-5}	-8.55E-06**	0.001	ΔEPU_t	1.34E-06*	0.043			
ΔEPU_{t-6}	-6.93E-06**	0.003	ΔEPU_{t-1}	-6.88E-06***	0.000			
ΔEPU_{t-7}	-6.87E-06**	0.001	ΔEPU_{t-2}	-5.83E-06***	0.000			
ΔEPU_{t-8}	-6.28E-06**	0.001	ΔEPU_{t-3}	-4.03E-06**	0.003			
ΔEPU_{t-9}	-4.99E-06**	0.004	ΔEPU_{t-4}	-2.53E-06*	0.014			
ΔEPU_{t-10}	-2.28E-06	0.179	ΔEPU_{t-5}	-1.09E-06	0.103			
ΔEPU_{t-11}	-7.09E-08	0.961	Constant	-0.018	0.633			
ΔEPU_{t-12}	-4.73E-07	0.641						
Constant	-0.083*	0.013						
Panel B: Long-run estimates								
WTI^+	-7.96E-03	0.069	WTI^+	8.32E-03**	0.008	WTI^+	-0.080	0.559
WTI^-	-7.37E-03	0.063	WTI^-	5.24E-03**	0.003	WTI^-	0.026	0.875
Inflation	0.564***	0.000	Inflation	0.326***	0.000	Inflation	0.884	0.469
GDP	-0.032	0.415	GDP	-0.058*	0.011	GDP	1.785	0.720
EPU	5.21E-06	0.322	EPU	4.79E-06	0.084	EPU	-1.44E-05	0.721
Panel C: Diagnostic test								
R^2	0.884		R^2	0.944		R^2	1.000	
$Adjusted\ R^2$	0.820		$Adjusted\ R^2$	0.904		$Adjusted\ R^2$	0.998	
$F statistic$	7.913***		$F statistic$	15.556***		$F statistic$	526.459***	
$Wald\ short$	14.071***		$Wald\ short$	7.246**		$Wald\ short$	45.758**	
$Wald\ long$	21.394***		$Wald\ long$	9.078**		$Wald\ long$	78.541**	
DW	1.830		DW	1.633		DW	2.879	
JB test	1.119	0.571	JB test	1.313	0.519	JB test	0.675	0.713
BG LM test	1.035	0.428	BG LM test	0.946	0.511	BG LM test	23.956	0.143
BPG test	1.377	0.102	BPG test	0.934	0.590	BPG test	0.310	0.949
$Ramsey\ RESET$	5.880	0.000	$Ramsey\ RESET$	0.575	0.748	$Ramsey\ RESET$	132.744	0.061

[1] Significant at 10% (*), 5% (**), and 1% (***).
[2] The F-statistic is calculated by the Wald test (with $H_0: \omega_{1j} = \omega^+_{2j} = \omega^-_{2j} = \omega_{3j} = \omega_{4j} = \omega_{5j} = \omega_{6j} = \omega_{7j}$) and compared with the upper bound critical value. Wald short and Wald long, respectively, represent the F-statistics used by the Wald test to assess asymmetry in the short run (with $H_0: \sum_{i=1}^{q} \tau^+_{2j} = \sum_{i=1}^{q} \tau^-_{2j}$) and long run (with $H_0: \frac{-\omega^+_{2j}}{\omega_{1j}} = \frac{-\omega^-_{2j}}{\omega_{1j}}$).
[3] DW is Durbin–Watson Statistic and BG is Breusch-Godfrey LM Test used for residual autocorrelation. JB test is the Jarque–Bera test for residual normality distribution. BPG is Breusch-Pagan-Godfrey Test used for heteroskedasticity. Ramsey RESET is the Ramsey Regression Equation Specification Error Test for stability.

It is worth noting in Table 15 that positive oil prices in the full sample negatively impact inflation expectations in the short term, while negative oil prices increase inflation expectations. This can be explained by the sub-sample.

Under the pre-COVID19 regime, both positive and negative oil prices have a positive impact on inflation expectation, and the impact of negative oil prices is more significant, which fully reflects the asymmetry of positive and negative oil price shocks, that is, the impact of positive oil prices on inflation expectations is relatively greater than that of negative oil price. Under the COVID19 mechanism, oil price shock has a significant negative impact on China's inflation expectations, which once again reflects the asymmetry of positive and negative oil price shocks, but in the overall sample, the role of negative impact is even more significant because of the outbreak, which also explains the long-term results of the overall sample that both positive and negative oil price shocks have a negative, although insignificant, impact on inflation expectations.

Based on the above robustness check, we have once again verified that the impact of oil prices on inflation expectations has changed after COVID-19 outbreak. At the same time, it is confirmed that the asymmetry of positive and negative oil price shocks exists in the United States and China. However, the positive effect of the positive oil price shock after the epidemic is strengthened in the United States, and the negative effect of China's negative oil price shock is more obvious.

6. Further Discussion

The asymmetric impact of crude oil prices on the households’ inflation expectations is essentially a shock of energy prices. Changes in crude oil prices act more directly on the energy sector and the prices of refined products, which in turn raise residents' expectations of future price levels by increasing the prices of oil products. Ultimately, crude oil prices have an impact on the inflation expectations of the population. More generally, increases in crude oil prices have a more significant impact on inflation expectations by generating price volatility in oil products than the impact of decreases. For example, gasoline prices have risen sharply and swiftly following a rise in crude oil prices-such as occurred in 1999 and 2000 and during the Gulf War in 1990 in America. This asymmetric relationship between crude oil and product prices within the energy sector may also have an asymmetric impact on other macroeconomic variables.

The impact of oil price change is important, where both supply- and demand-level shocks may be responsible for its asymmetric effects. Oil, as an essential basic energy source and industrial raw material, directly affects the functioning of the economy and the consumption structure and quality of residents’ lives. The impact of supply-side shocks caused by oil price changes on economic variables is not as significant in China as the impact of demand shocks. However, China, as the world's largest oil importer, is very dependent on oil. Supply shocks from higher oil prices can directly affect GDP growth and the timely replenishment of market output, which in turn affects price levels and residents' inflation expectations. In terms of demand shocks, oil price fluctuations from demand shocks can boost the economy and, conversely, increase inflation and further raise residents' inflation expectations. The impact of falling oil prices is more in terms of raising demand and boosting economic development, which in turn raises residents' inflation expectations. Thus, there is an asymmetry in the change of inflation expectations caused by the rise and fall of oil prices.

The impact of positive and negative changes in oil prices on economic uncertainty is asymmetric. The increase in oil prices leads to an increase in economic uncertainty, which affects the development of macroeconomics and the stability of financial markets. These fluctuations can affect the sustainability and stability of the population's consumption and investments and may also cause the energy market to raise preventive energy reserves and speculative activity in financial markets, which can lead to higher production costs and higher price levels. Inflation expectations are more likely to increase in an unstable economic environment and thus react asymmetrically to increases and decreases in oil prices.

7. Conclusion

The primary objective of this study is to figure out the asymmetry effects of oil price changes on U.S. and China household inflation expectations after COVID-19 outbreak. By adopting the ARDL model and the Nonlinear ARDL model to explore the dynamic relationship between oil price shocks and household inflation expectations, we analyze the data from the first quarter of 2010 to the fourth quarter of 2021. To verify the applicability of the models, we confirm the stationarity and cointegration relationships in the short and long term by unit root tests and boundary tests, and also apply diagnostic tests to demonstrate the absence of autocorrelation, heteroscedasticity, and stability issues, thereby increasing the credibility of the conclusions. In the robustness test, we use the Toda-Yamamoto causality test to reflect the causal relationship between the oil price shock and inflation expectations from January 2010 to December 2021, and further through the comparison of sub-samples in different regimes to check the reliability of the conclusions of the benchmark model as follows.

1. The outbreak of COVID-19 has changed the impact of oil price dynamics on household inflation expectations. The positive impact of oil prices in the U.S. has been amplified, while diminished in China.

2. There are asymmetric effects from positive and negative oil price changes. Consistently, before the COVID-19 outbreak, inflation expectations in both the U.S. and China were more affected by positive oil price shocks than negative oil price shocks, so there is an interesting phenomenon that negative oil price shocks raised inflation expectations, while in the COVID-19 regime, the asymmetry persists despite changes between positive and negative shocks.t

3. Finally, the asymmetry of the oil price shock between the United States and China has diverged in the wake of the pandemic. The role of the positive oil price shock in the United States has been further strengthened after the epidemic, while in China, on the contrary, the role of the negative oil price shock is more significant after the outbreak, so there is an interesting phenomenon that the positive oil price shock reduces household inflation expectations.

According to the empirical analysis, we can see the similarities in the economic development of the United States and China, but also recognize the differences in economic development between the two countries due to the impact of the epidemic. On the one hand, this is related to differences in the epidemic isolation policies in the two countries, and on the other hand, it is also related to the households' consumption structure of the two countries. Under the current situation of rising oil prices and the urgent need for economic recovery, how to optimize the production structure and stabilize residents' inflation expectations is a problem that both countries need to solve, and it is also of great significance to the sustainable development of the two countries' economies.

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References

Apergis, E., & Apergis, N. (2021, September 02). Inflation expectations, volatility and Covid-19: evidence from the US inflation swap rates. *Applied economics letters*, *28*(15), 1327-1331. https://doi.org/10.1080/13504851.2020.1813245

Armantier, O., Kosar, G., Pomerantz, R., Skandalis, D., Smith, K., Topa, G., & Van der Klaauw, W. (2020). Inflation Expectations in Times of COVID-19. Working Paper. *Liberty Street Economics*. Federal Reserve Bank of New York.

Armantier, O., Topa, G., Van der Klaauw, W., & Zafar, B. (2016). How Do People Revise Their Inflation Expectations? *Liberty Street Economics*. Federal Reserve Bank of New York.

Badel, A., & McGillicuddy, J. (2015). Oil Prices and Inflation Expectations: Is There a Link? *The Regional Economist*. Federal Reserve Bank of St. Louis. https://doi.org/10.20955/wp.2015.034

Baker, Scott R., Bloom, N., & Davis, Steven J. (2016, November 01). Measuring economic policy uncertainty. *The Quarterly journal of economics*, *131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Bohi, D. R. (1991). On the Macroeconomic Effects of Energy Price Shocks. *Resources and Energy, 13*(2), 145-162. https://doi.org/10.1016/0165-0572(91)90012-R

Bresnahan, T. F., & Ramey, A. V. (1993). Segment Shifts and Capacity Utilization in the US Automobile Industry. *American Economic Review*, *83*, 213-218.

Cao, Y., & Shapiro, A. H. (2016, June). Energy's Impact on Inflation Expectations. Federal Reserve Bank of San Francisco. *Economic Letters*.

Carlson, J., & Parkin, M. (1975). Inflation Expectations. *Economica*, *42*(166), 123-138. https://doi.org/10.2307/2553588

Cavallo, A., Cruces, G., & Perez-Truglia, R. (2017, July 1). Inflation Expectations, Learning, and Supermarket Prices: Evidence from Survey Experiments. *American economic journal. Macroeconomics*, *9*(3), 1-35. https://doi.org/10.1257/mac.20150147

Ciccarelli, M., & Garcia, J. A. (2015, October 08). International Spillovers in Inflation Expectations. *Policy File*. https://doi.org/10.2139/ssrn.2675051

Coibion, O., & Gorodnichenko, Y. (2015). Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation. *Am. Econ. J. Macroecon.*, *7*, 197-232. https://doi.org/10.1257/mac.20130306

D'Acunto, F., Lee, U., Ospina, J., & Weber, M. (2021, May 1). Exposure to Grocery Prices and Inflation Expectations. *The Journal of political economy*, *129*(5), 1615-1639. https://doi.org/10.1086/713192

Davis, S. J., & Haltiwanger, J. (2001). Sectoral Job Creation and Destruction Responses to Oil Price Changes. *Journal of Monetary Economics, 48*(3), 465-512. https://doi.org/10.1016/S0304-3932(01)00086-1

Deepak Mohanty, Executive Director. (2012, November 9). Reserve Bank of India at S.P. Jain Institute of Management and Research, Mumbai.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc., 74,* 427-431. https://doi.org/10.1080/01621459.1979.10482531

Edelstein, P., & Kilian, L. (2009). How Sensitive are Consumer Expenditures to Retail Energy Prices? *Journal of Monetary Economics, 56*(6), 766-779. https://doi.org/10.1016/j.jmoneco.2009.06.001

Elder, J., & Serletis, A. (2010, September). Oil Price Uncertainty. *Journal of money, credit and banking, 42*(6), 1137-1159. https://doi.org/10.1111/j.1538-4616.2010.00323.x

Emeka, N., & Aham Kelvin Uko. (2016, January 1). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric Methods, 5*(4).

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987-1007. https://doi.org/10.2307/1912773

Engle, R. F., & Granger, C. W. J. (1987). Cointegration and error correction: Representation, estimation and testing. *Econometrica, 55*(2), 251-276. https://doi.org/10.2307/1913236

Eser, F., Karadi, P., Moretti, L., & Osbat, C. (2020). The Phillips Curve at the ECB. *European Central Bank*. Working Paper, No 2400. https://doi.org/10.2139/ssrn.3593363

Hammoudeh, S., & Reboredo, J. C. (2018, September). Oil price dynamics and market-based inflation expectations. *Energy economics, 75,* 484-491. https://doi.org/10.1016/j.eneco.2018.09.011

Istiak, K., & Alam, Md. R. (2019a). Oil prices, policy uncertainty and asymmetries in inflation expectations. *Journal of Economic Studies, 46*(2), 324-334. https://doi.org/10.1108/JES-02-2018-0074

Kapoor P. (2020). COVID-19 and its Likely Impact on the Indian Economy vis-a-vis Inflation, Inflation Expectations and Future Scenario. *Journal of Economics and Policy Analysis, 1*(1), 95-104.

Kilian, L. (2008). Exogenous Oil Supply Shocks: How Big are They and How Much Do They Matter for the US Economy? *The Review of Economics and Statistics, 90*(2), 216-240. https://doi.org/10.1162/rest.90.2.216

Kilian, L., & Zhou, X. Q. (2021, November 1). The Impact of Rising Oil Prices on U.S. Inflation and Inflation Expectations in 2020-23. *Policy File*. https://doi.org/10.2139/ssrn.3980337

Kortelainen, M., Paloviita, M., & Viren, M. (2011). Observed inflation forecasts and the new Keynesian macro model. *Economics letters, 112*(1), 88-90. https://doi.org/10.1016/j.econlet.2011.03.023

Lagarde, C. (2020, June 4). ECB President Press Conference. *European Central Bank*. Retrieved from https://www.ecb.europa.eu/press/pressconf/2020/html/ecb.is200604~b479b8cfff.en.html

Lagoa, S. (2017). Determinants of inflation differentials in the euro area: is the New Keynesian Phillips Curve enough? *J. Appl. Econ., 20*(1), 75-103. https://doi.org/10.1016/S1514-0326(17)30004-1

Lee, I. (2021, October 01), Oil could surge above $100 in the event of a cold winter - and spark inflation that drives the next macro crisis, BofA says. *Markets Insider.*

Li, Y., & Guo, J. (2022). The asymmetric impacts of oil price and shocks on inflation in BRICS: A multiple threshold nonlinear ARDL model. *Applied Economics, 54*(12), 1377-1395. https://doi.org/10.1080/00036846.2021.1976386

Liu, S., Wang, M. X., & Tan, Y. (2019). Stabilizing inflation expectations in China: Does economic policy uncertainty matter? *Green Finance, 1*(4), 429-441. https://doi.org/10.3934/GF.2019.4.429

Long, S., & Liang, J. (2018). Asymmetric and nonlinear pass-through of global crude oil price to China's PPI and CPI inflation. *Economic Research-Ekonomska Istraživanja, 31*(1), 240-251. https://doi.org/10.1080/1331677X.2018.1429292

Marfatia, H. A. (2018). Estimating the New Keynesian Phillips Curve for the UK: evidence from the inflation-indexed bonds market. *B.E. J. Macroecon, 18*(1), 1-18. https://doi.org/10.1515/bejm-2016-0005

Mihajlović, V., & Marjanović, G. (2020, January 2). Asymmetries in effects of domestic inflation drivers in the Baltic States: A Phillips curve-based nonlinear ARDL approach. *Baltic journal of economics, 20*(1), 94-116. https://doi.org/10.1080/1406099X.2020.1770946

Nasir, M. A., Balsalobre-Lorente, D., & Huynh, T. L. D. (2020, February). Anchoring inflation expectations in the face of oil shocks and in the proximity of ZLB: A tale of two targeters. *Energy economics*, *86*, 104662-13. https://doi.org/10.1016/j.eneco.2020.104662

Nie Q. (2023, February). The Impacts of Economic Growth on Per Capita Consumption - Based CO2 Emission Between China and United States. *International Journal of Business & Management Studies*, 4(2), 1-7. https://doi.org/10.56734/ijbms.v4n2a1

Nie, Q. (2023, January). Analysis of Economic Effects of The Establishment of The BRICS Free Trade Zone—Based on the GTAP-E Model. *Journal of Business and Social Science Review, 4*(1), 16-27. https://doi.org/10.48150/jbssr.v4no1.2023.a2

Pal, D., & Mitra, K. S. (2019). Asymmetric Oil Price Transmission to the Purchasing Power of the U.S. Dollar: A Multiple Threshold NARDL Modelling Approach. *Resources Policy, 64*, 101508. https://doi.org/10.1016/j.resourpol.2019.101508

Perron, P. (1997, October). Further evidence on breaking trend functions in macroeconomic variables. *Journal of Econometrics, 80*(2), 355-385. https://doi.org/10.1016/S0304-4076(97)00049-3

Pesaran, M. H., & Shin, Y. (1999). An autoregressive distributed lag modeling approach to cointegration analysis. In S. Strom (Ed.), *Econometrics and economic theory in the 20th century: The Ragnar Frisch centennial symposium* (pp. 371-413). Cambridge: Cambridge University Press. https://doi.org/10.1017/CCOL521633230.011

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001, May). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics (Chichester, England), 16*(3), 289-326. https://doi.org/10.1002/jae.616

Pfajfarabc, D. & Žakeljd, B. (2014, July). Experimental evidence on inflation expectation formation. *Journal of Economic Dynamics and Control, 44*, 147-168. https://doi.org/10.1016/j.jedc.2014.04.012

Phillips, P. C. B., & Perron, P. (1988, June). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Rafiuddin, A., Daffodils, J., Gaytan, J. C. T., & Sisodia, G. S. (2021, June 8). Trend of oil prices, gold GCC stocks market during COVID-19 pandemic: A WAVELET APPROACH. *International journal of energy economics and policy, 11*(4), 560-572. https://doi.org/10.32479/ijeep.11365

Rusiadi, R. (2020, December). The impact of COVID-19 changes in the adaptive expectation inflation model of emerging market countries. *International Proceeding of Law and Economic*, (S.l.), 25-33.

Sharif, A., Aloui, C., & Yarovaya, L. (2020, July). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International review of financial analysis*, 70, 101496. https://doi.org/10.1016/j.irfa.2020.101496

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. *In Festschrift in Honor of Peter Schmidt* (pp. 281-314). New York, NY: Springer. https://doi.org/10.1007/978-1-4899-8008-3_9

Tan, L., Wu, X. H., Guo, J., Santibanez-Gonzalez, & Ernesto, D. R. (2022, January). Assessing the Impacts of COVID-19 on the Industrial Sectors and Economy of China. *Risk analysis, 42*(1), 21-39. https://doi.org/10.1111/risa.13805

Toda, H. Y., & Yamamoto, T. (1995). Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. *Journal of Econometrics, 66*(1-2), 225-250. https://doi.org/10.1016/0304-4076(94)01616-8

Villar, A. J., & Joutz, L. F. (2006, October). The Relationship Between Crude Oil and Natural Gas Prices. *Energy Information Administration, Office of Oil and Gas.*

Xiao, Z. Y., & Chen, Y. B. (2004, November). China Inflation Expectation Research Data Method. *Journal of Finance Research,* 1-18.

Yu, M., et al. (2018, May). Research on the estimation of China inflation expectation based on VAR. *Scientific Decision*, 79-92.

Yu, Y., Guo, S. L., & Chang, X. C. (2022, March). Oil prices volatility and economic performance during COVID-19 and financial crises of 2007-2008. *Resources policy, 75*, 102531-102531. https://doi.org/10.1016/j.resourpol.2021.102531

Zhang, B. (2009, September). The Nature of Inflation Expectations and the Impact on Inflation in Our Country. *Journal of Finance Research*, 40-54.

Zhang, C. S. (2011). Inflation persistence, inflation expectations, and monetary policy in China. *Economic modelling*, *28*(1), 622-629. https://doi.org/10.1016/j.econmod.2010.06.009

Zhang, S. C., & Dang, C. (2016, January). Inflation Expectation Transformation Based on Central Bank Survey Data: Algorithmic Basis and Differences in Understanding. *Journal of Finance Review*, 1-12.

Zivot, E., & Andrews, D. W. K. (2002, January 1). Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *Journal of business and economic statistics*, *20*(1), 25-44. https://doi.org/10.1198/073500102753410372

Appendix A.

Table A1: U.S. monthly stationarity tests results without structural breaks

Variable	Sample	Constant			Constant & Trend		
		ADF	Phillips-Perron	KPSS	ADF	Phillips-Perron	KPSS
Level							
	full	-1.467	-1.898	0.709**	-1.368	-1.823	0.677***
Infex	sub_1	-2.759*	-3.094**	2.710***	-3.998**	-4.277***	0.237***
	sub_2	-0.421	-0.669	1.020***	-2.034	-2.535	0.017**
	full	-1.754	-1.954	2.230***	-2.213	-2.596	0.246***
WTI	sub_1	-1.320	-1.265	2.690***	-2.269	-2.205	0.369***
	sub_2	-1.218	-1.408	0.750***	-5.891***	-4.379**	0.137**
	full	-0.843	-0.258	0.589**	-1.042	-0.548	0.422***
Inflation	sub_1	-2.549*	-2.301	0.467**	-2.505	-2.242	0.430***
	sub_2	0.221	0.391	0.603**	-2.691	-2.936	0.145*
	full	-0.756	-0.997	3.560***	-4.011**	-4.448***	0.165**
GDP	sub_1	0.610	0.171	3.140***	-2.654	-5.158***	0.332***
	sub_2	-1.352	-1.759	0.699**	-5.354***	-4.313**	0.117
	full	-2.940**	-3.348**	0.625**	-3.093**	-3.497**	0.491***
EPU	sub_1	-4.051***	-4.081***	2.000***	-4.559***	-4.536***	0.561***
	sub_2	-1.971	-2.147	0.602**	-3.465*	-3.365*	0.184**
1st diff.							
	full	-9.933***	-14.390***	0.151	-9.997***	-14.425***	0.070
Infex	sub_1	-9.043***	-12.941***	0.039	-9.038***	-12.913***	0.025
	sub_2	-4.339***	-6.163***	0.082	-4.300***	-6.040***	0.065
	full	-7.957***	-9.057***	0.052	-7.944***	-9.023***	0.045
WTI	sub_1	-7.150***	-8.351***	0.076	-7.123***	-8.325***	0.072
	sub_2	-3.003**	-3.365**	0.114	-3.043	-3.259*	0.098
	full	-6.783***	-7.250***	0.428*	-7.016***	-7.390***	0.106
Inflation	sub_1	-6.572***	-8.117***	0.094	-6.564***	-8.084***	0.047
	sub_2	-2.237	-2.174	0.358*	-3.071	-2.501	0.092
	full	-8.099***	-10.628***	0.017	-8.070***	-10.586***	0.017
GDP	sub_1	-8.553***	-18.290***	0.042	-8.567***	-18.233***	0.024
	sub_2	-3.821***	-3.821***	0.137	-3.846***	-3.846***	0.095
	full	-7.443***	-9.145***	0.077	-7.427***	-9.141***	0.022
EPU	sub_1	-6.174***	-11.917***	0.041	-6.147***	-11.860***	0.024
	sub_2	-2.933*	-2.933*	0.166	-2.760	-2.760	0.166

Table A2: U.S. monthly stationarity tests results with structural breaks

Variable	Sample	Constant				Constant & Trend			
		Level		1st diff.		Level		1st diff.	
		PPU	ZA	PPU	ZA	PPU	ZA	PPU	ZA
Infex	full	-3.289	-2.443	-14.754***	-14.670***	-5.258	-4.533**	-14.771***	-14.688***
	sub_1	-4.790	-4.823**	-13.317***	-7.154***	-5.578*	-4.692**	-13.239***	-7.021***
	sub_2	-4.897	-4.982**	-7.613***	-6.474***	-4.603	-3.343	-7.593***	-6.177***
WTI	full	-4.310	-4.331	-9.691***	-9.686***	-4.217	-2.968	-9.711***	-9.487***
	sub_1	-5.262**	-5.273**	-9.164***	-7.979***	-5.218	-2.954	-9.121***	-6.911***
	sub_2	-8.085***	-7.114***	-12.552***	-4.687*	-7.330***	-8.746	-12.392***	-7.217***
Inflation	full	-2.128	-2.204	-7.527***	-7.212***	-4.170	-3.255	-7.917***	-7.652***
	sub_1	-3.596	-3.633	-8.791***	-4.798*	-3.558	-3.259	-8.753***	-4.486**
	sub_2	-3.578	-3.151	-4.691	-5.196**	-8.712***	-3.374**	-4.541	-4.887**
GDP	full	-6.284***	-5.784***	-10.975***	-7.740***	-12.261***	-4.132*	-11.581***	-7.931***
	sub_1	-3.731	-3.748	-12.761***	-12.457***	-3.981	-3.719	-12.754***	-12.269***
	sub_2	-14.183***	-5.594***	-11.431***	-4.742*	-12.146***	-4.905**	-11.531***	-11.047***
EPU	full	-6.207***	-5.179**	-9.229***	-9.172***	-7.841***	-4.363*	-9.194***	-9.127***
	sub_1	-6.233***	-6.245***	-9.324***	-8.304***	-6.228***	-5.404***	-9.403***	-8.183***
	sub_2	0.025	-0.122	-5.250***	-4.338	-1.761	-2.225	-5.600**	-5.799***

Table A4: China monthly stationarity tests results with structural breaks

Variable	Sample	Constant				Constant & Trend			
		Level		1st diff.		Level		1st diff.	
		PPU	ZA	PPU	ZA	PPU	ZA	PPU	ZA
Infex	full	-3.848	-2.643	-5.503**	-5.467***	-4.938	-2.380	-5.426*	-5.249***
	sub_1	-2.882	-1.477	-5.312**	-5.334***	-4.174	-2.524	-5.678**	-5.462***
	sub_2	-4.063	-3.966	-3.233	-3.893	-5.118	-4.559**	-3.209	-5.020***
WTI	full	-4.194	-4.214	-9.578***	-9.584***	-4.109	-2.979	-9.605***	-9.394***
	sub_1	-5.299**	-5.296**	-9.226***	-7.984***	-5.332*	-3.015	-9.180***	-6.958***
	sub_2	-5.535**	-3.718	-4.595	-3.672	-4.986	-3.694	-4.537	-7.404***
Inflation	full	-4.135	-4.203	-12.979***	-12.633***	-3.794	-3.588	-13.224***	-12.588***
	sub_1	-3.517	-3.018	-14.731***	-14.763***	-3.493	-2.810	-14.808***	-14.067***
	sub_2	-3.586	-2.588	-3.366	-5.565***	-3.798	-3.608	-3.367	-4.247*
GDP	full	-3.223	-3.204	-16.938***	-12.695***	-4.951	-4.981***	-19.331***	-11.738***
	sub_1	-0.956	-0.961	-15.929***	-9.164***	-1.539	-1.934	-15.971***	-8.987***
	sub_2	-4.940*	-3.074	-10.548***	-4.539	-4.242	-12.711***	-10.547***	-4.516**
EPU	full	-4.733	-4.750*	-14.242***	-13.846***	-5.688**	-3.949	-14.151***	-13.613***
	sub_1	-5.290**	-4.894**	-10.771***	-8.429***	-5.962**	-5.521***	-10.730***	-8.464***
	sub_2	-5.473**	-4.995**	-9.396***	-8.496***	-7.147***	-4.145*	-9.346***	-7.280***

Table A3: China monthly stationarity tests results without structural breaks

Variable	Sample	Constant			Constant & Trend		
		ADF	Phillips-Perron	KPSS	ADF	Phillips-Perron	KPSS
Level							
	full	-2.543	-2.473	0.781***	-3.187*	-2.848	0.198**
Infex	sub_1	-1.800	-2.257	1.260***	-1.528	-1.824	0.353***
	sub_2	-1.466	-1.013	0.662**	-2.555	-1.629	0.172**
	full	-1.746	-1.926	2.270***	-2.102	-2.473	0.256***
WTI	sub_1	-1.421	-1.340	2.750***	-2.201	-2.120	0.373***
	sub_2	-1.180	-1.455	0.730**	-3.842	-3.683**	0.073
	full	-2.156	-2.330	1.920***	-2.641	-3.003	0.399***
Inflation	sub_1	-1.529	-1.663	0.955***	-1.225	-1.624	0.317***
	sub_2	-2.398	-2.555	0.364*	-1.324	-1.448	0.176**
	full	-2.163	-0.680	3.590***	-2.665	-2.650	0.699***
GDP	sub_1	-5.241***	-1.348	3.040***	-1.224	-0.660**	0.693***
	sub_2	-1.577	-1.974	0.629**	-2.322	-1.902	0.169**
	full	-2.312	-5.194***	2.090***	-3.354*	-7.201***	0.295***
EPU	sub_1	-0.591	-4.472***	1.530***	-2.027	-6.825***	0.514***
	sub_2	-2.402	-3.141**	0.202	-2.368	-3.105	0.151
1st diff.							
	full	-5.111***	-6.554***	0.041	-5.112***	-6.529***	0.041
Infex	sub_1	-4.971***	-6.017***	0.195	-5.083***	-6.075***	0.048
	sub_2	-2.725**	-2.508	0.188	-3.630**	-2.415	0.188**
	full	-7.905***	-9.048***	0.060	-7.901***	-9.016***	0.047
WTI	sub_1	-7.132***	-8.420***	0.074	-7.101***	-8.385***	0.075
	sub_2	-3.041**	-3.449**	0.135	-3.174	-3.410*	0.098
	full	-12.408***	-12.408***	0.074	-12.369***	-12.369***	0.060
Inflation	sub_1	-5.604***	-13.023***	0.193	-5.649***	-13.037***	0.159**
	sub_2	-3.430**	-3.450**	0.348*	-4.043**	-3.813**	0.059
	full	-9.439***	-13.663***	0.047	-9.672***	-13.803***	0.030
GDP	sub_1	-7.426***	-14.713***	0.247	-9.012***	-15.753***	0.090
	sub_2	-3.986***	-5.155***	0.179	-3.839**	-5.396***	0.063
	full	-9.900***	-21.579***	0.022	-9.864***	-21.492***	0.022
EPU	sub_1	-8.308***	-23.454***	0.037	-8.383***	-23.424***	0.033
	sub_2	-4.266***	-7.292***	0.062	-4.124**	-7.041***	0.057

Table A5: The result of monthly data cointegration bound test

Test Statistic	Value			Signif.	I(0)	I(1)
k = 4	Full	Pre-COVID19	COVID19			
F-statistic						
U.S.	4.626**	6.662***	27.471***	10%	2.12	3.23
China	9.182***	12.153***	2339.351***	5%	2.45	3.61
				2.5%	2.75	3.99
				1%	3.15	4.43
t-statistic						
U.S.	-4.415**	-5.555***	-9.430***	10%	-2.57	-4.04
China	-6.475***	-7.323***	-98.259***	5%	-2.86	-4.38
				2.5%	-3.13	-4.66
				1%	-3.43	-4.99

[1] Null hypothesis: No level relationship.

Appendix B.

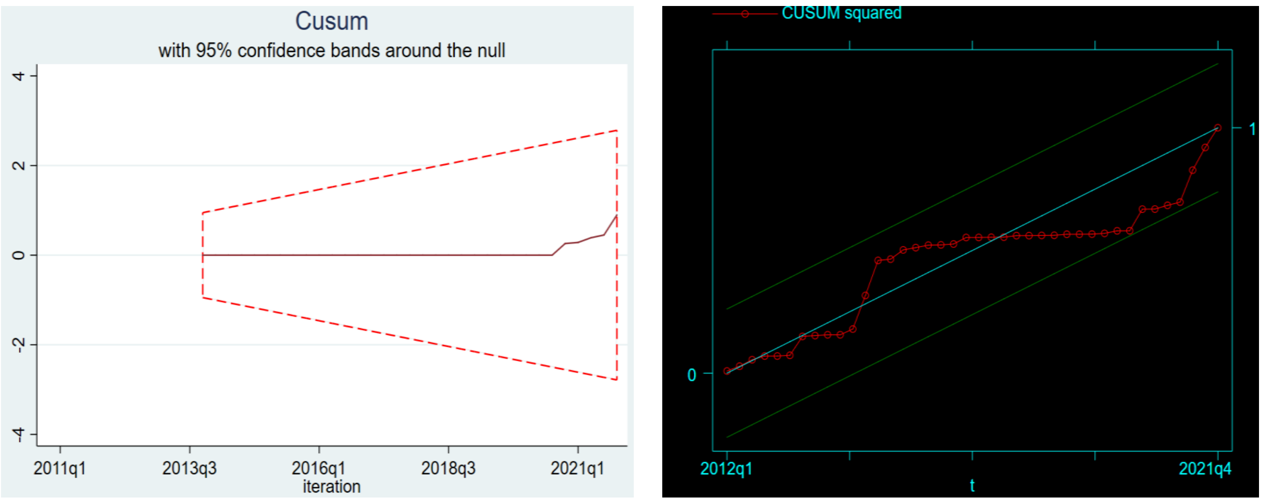

Figure B1. CUSUM and CUSUM Squared of U.S.

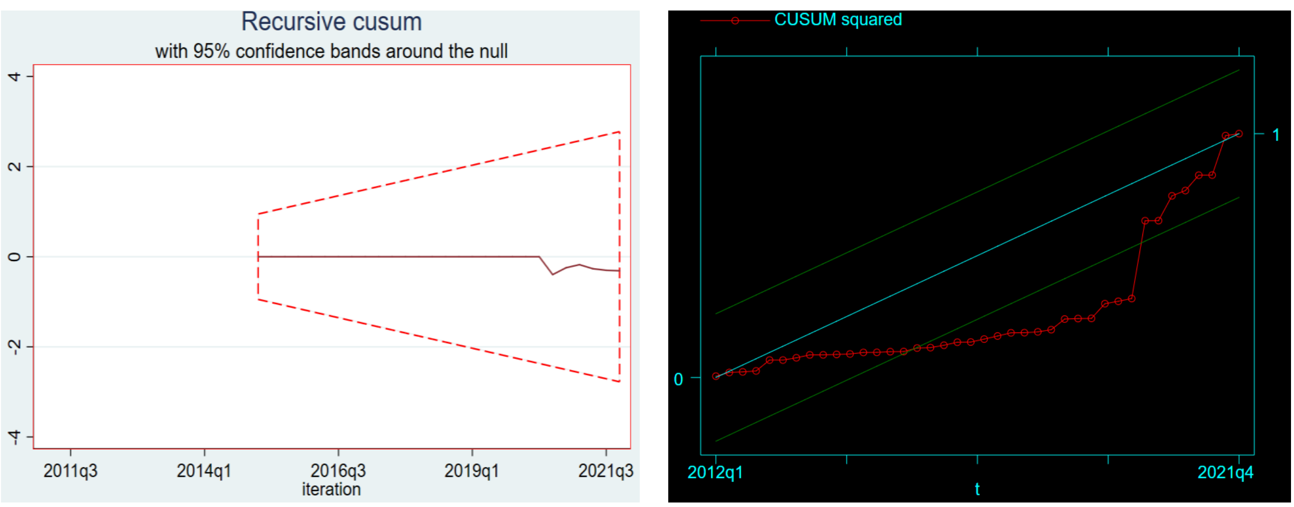

Figure B2. CUSUM and CUSUM Squared of China

Appendix C.

Chinese Inflation Expectations:

China's quarterly inflation expectations data are based on the quarterly survey from People's Bank of China, which is for all urban depositors across the country (the Urban Depositor Questionnaire Report of the Statistics and Analysis Department of People's Bank of China). This survey has been established since 1999 for more than 20,000 savings users in 50 different cities across the country. The survey content mainly covers the overall judgment of households on economic operation, savings and liabilities, household basic situation and consumption. With three options, i,e, up, unchanged and down, we can get residents' qualitative views on the change in CPI over the next three months, as well as the percentage of each option. The method in this paper to convert these qualitative data into quantitative indicators is C-P Method (Carlson and Parkin,1975). The basic principle is: Assuming that respondents' expectations for future price level changes are subject to a specific probability distribution, and there is a "sensibility interval" centered at 0. If the respondent's judgment on the price increase in the next period exceeds the range, "up" is selected, if it falls below the range, "down" selected, "unchanged" otherwise. Respondents' answers were symmetrical and normally distributed; and the average realized in the past was equal to the expected average. Given these assumptions above, quarterly and monthly thresholds and inflation expectations can be obtained. (Zhang & Dang, 2016) confirmed that from 2000 to 2014, the correlation between the year-on-year inflation expectation rate based on the C-P Method and the price expectation index reached 0.78. Xiao Zhengyan and Chen Yanbin (2004) used the CP method to achieve quantitative transformation of inflation expectations, and through research The long-term and short-term nature of expected outcomes, found that consumer cognitive biases have no effect on changes in actual and expected inflation rates, and inflation expectations are unbiased. Zhang Bei (2009) also used the C-P method to calculate chinese expected inflation more scientifically, and studied the impact of inflation expectations on actual inflation. In order to obtain the monthly data of China's inflation expectations, this paper adopts the method of (Yu, et al., 2018), and uses the arithmetic average of real interest rate and lagged inflation rate as the inflation expectation. Yu M et al. (2018) derived quarterly expected data on the deviation of lagged inflation rate, real interest rate, and output deviation from the expected target value by combining a VAR expectation model with additional forward-looking policy variables and a Kalman filter recursive algorithm The estimated results of China's inflation expectations from 2002 to 2014 are presented, and the subsequent test results show that the arithmetic average is unbiased, and the mean value of the expected error is zero and there is no auto-correlation.