World Oil Price Changes and Inflation in Indonesia: A Nonparametric Regression Approach

Indra Darmawan\textsuperscript{1,2}, Hermanto Siregar\textsuperscript{1,3}, Dedi Budiman Hakim\textsuperscript{1,3}, Adler Haymans Manurung\textsuperscript{1,4}

\textsuperscript{1}School of Business, IPB University, Indonesia  
\textsuperscript{2}STIE Indonesia Banking School, Indonesia  
\textsuperscript{3}Faculty of Economics and Management, IPB University, Indonesia  
\textsuperscript{4}School of Business, Bina Nusantara University, Indonesia

Email: \textsuperscript{1}indrad64@yahoo.com, \textsuperscript{2}hermansiregar@yahoo.com, \textsuperscript{3}dedihakim@gmail.com, \textsuperscript{4}adler.manurung@yahoo.com

\textsuperscript{*Corresponding author}

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\textbf{Abstract}

This study aims to investigate the effect of world oil price changes on inflation in Indonesia. We used a nonparametric regression approach that never been employed in previous studies, both domestically and internationally. This study shows that the second-order Epanechnikov kernel function is statistically significant in explaining the effect of world oil price changes on Indonesia's inflation. We found that the world oil price changes had a lower effect on Indonesia's inflation when its price below USD 100 per barrel, and its effect became higher when its price above USD 100 per barrel. These results have important implications for Bank Indonesia and Indonesia's government in response to the world oil price changes. The policies that aimed at reducing the effect of world oil price changes on inflation in Indonesia should consider the world oil price level.

\textbf{Keywords:} oil price changes, inflation, nonparametric approach, second-order Epanechnikov kernel function.

\textbf{How to Cite:}

Introduction

Since the discovery of a modern steam engine by James Watt, oil increase rapidly both for industry and transportation. Supported by the technological breakthrough in 20's century, oil has become an important energy source and plays an essential role in economies (Sek et al., 2015; Hesary et al., 2019). The essential role of oil prices in the economy occurs in the oil commodity market and financial markets. In other words, world oil price changes affect the economy through the oil commodity market and financial market.

From 2001 to 2017, world oil prices fluctuated in various volatility and trends. From January 2001 to March 2007, Brent oil prices fluctuated in low-range volatility. Its price increased by USD 36.50 per barrel, moving from USD25.64 to USD 62.14. From April 2007 to July 2008, Brent oil prices fluctuated in high-range volatility and increased by USD 71.76 per barrel, moving up from USD 67.40 to USD 133.90. From August 2008 to February 2009, Brent oil prices fluctuated in high-range volatility and decreased by USD 27.56 per-barrel, moving down from USD 70.80 to USD 43.24. From March 2009 to April 2011, Brent oil prices fluctuated in high-range volatility and increased by 130 percent, becomes USD 123.07 per barrel at the end of its period. From May 2011 to July 2014, Brent oil price fluctuated in low-range volatility with a slight decrease by 9.73 percentage becomes USD 106.98 per barrel in July 2014. From August 2014 to December 2017, Brent oil price fluctuated in high-range volatility and decreased by 37.48%, becomes USD 66.87 per barrel at the end of its period.

In the same period, inflation in Indonesia fluctuated in single-digit percentages, except for 2002 (10.03%), 2005 (17.17%), and 2008 (11.06%). One of the fundamental reasons for higher inflation in Indonesia in those periods (2002, 2005, and 2008) compared to other periods was the increase of the domestic fuel price in significant percentages. In 2002, the domestic fuel price increased by 52.20%, while in 2005 it increased by 37.16%, and in 2007 increased by 47.88%. Apart from those periods, Indonesia’s inflation fluctuated in single-digit percentage, where the lowest was in 2009 (2.78%), and the highest was in 2013 (8.38%). In the last three years, Indonesia’s inflation was 3.35% in 2015, 3.02% in 2016, and 3.61% in 2017. The Brent oil price and inflation in Indonesia from 2001 to 2017 as presented in Figure 1.

Hamilton (1983) is the first researcher to investigate the effect of oil price changes on U.S. macroeconomic indicators. He used a six-variable, they are (1) real GNP, (2) unemployment, (3) domestic prices (as a proxy of inflation), (4) wages, (5) import-prices, and (5) money supply (M1). He concluded that the increases in oil prices induce recession in the U.S. economy. It occurs because the increase in oil price increased uncertainty and raised the operating costs. After Hamilton’s study, many researchers investigated the effect of oil price changes on several macroeconomic indicators, especially inflation.
Qianqian (2011), using a vector error correction model (VECM), found a significant long-run relationship between oil price and China’s macroeconomic. She concluded that an increase of 1% of oil price changes statistically significant pushing-up inflation in China by 0.017%. Dias (2013) finds that an increase in oil price pushed higher inflation in the first two years, by 0.25% and 0.05% in the Portuguese economy. However, its effect was temporary. Since the third year, oil price shocks on inflation have reduced slowly, without long-term effects.

Gokmenoglu et al. (2015) employed the Johansen cointegration approach and Granger causality tests to find that the Johansen cointegration test confirms a long-run relationship among variables, but the Granger causality test showed no causality relationship between oil prices and inflation. Mukhtarov et al. (2019), using a vector error correction model (VECM), shows that increasing 1% in oil prices increases inflation in Azerbaijan by 0.58%.

Many researchers investigated the effect of oil price changes on inflation in a group of countries. Sek et al. (2015) investigated the effects of oil price changes on inflation in the high and low oil dependency countries. They find that oil price changes have different effects for these two groups of countries. Oil price changes directly impact the domestic inflation in the low oil dependency countries, but its impact is indirect for the high oil dependency countries. Raghavan (2015) using a structural vector autoregressive model (SVAR) to observe the effect of oil price shocks on the domestic economy of ASEAN-5 (Thailand, Malaysia, Singapore, Philippines, and Indonesia). The research shows that oil supply shocks significantly affect inflation on four net-oil importing economies but insignificant for Malaysia as a net oil-exporting economy. However, the inflationary effects of oil price shocks vary among the four net-oil importing countries depend on their oil self-sufficiency.

Morana (2016) employed a semiparametric dynamic conditional correlation model
(SP-DCC), estimated using the quasi-maximum likelihood (QML) approach, which shows that recession in the European countries triggered by the oil price hikes and slumps in European countries. The research concluded that the conditional correlation is sizeable, particularly on inflation, which shows that inflation positively links to the oil price shocks.

Brini et al. (2016) analyzed the impact of oil price shocks on inflation and real exchange rate in MENA-6 countries (Tunisia, Morocco, Algeria, Bahrain, Saudi Arabia, and Iran) from January 2000 to July 2015. Using a structural vector autoregressive model (SVAR), they found that the impulse response function (IRF) of inflation to shock to oil price has a smaller impact and absorbed by subsidized product prices' rigidity. Forecast error variance decomposition (FEVD) shows that oil price shocks significantly affect inflation for MENA-6 countries, except for Algeria and Iran. Bala & Chin (2018) investigated the effect of oil price changes on inflation in African OPEC member countries: Algeria, Angola, Libya, and Nigeria. They used an autoregressive distributed lag (ARDL) and found that both positive and negative oil price changes positively affect inflation in those countries. However, the impact of oil price changes was more significant when the oil price dropped. It means inflation increased in African OPEC countries when the oil price dropped. Zivkov et al. (2019) observe the effect of oil price changes on inflation in Central and Eastern European (CEE) countries: the Czech Republic, Poland, Hungary, Slovak, Lithuania, Latvia, Estonia, Romania, Bulgaria, Slovenia, and Croatia, from January 1996 to June 2018. By using a wavelet-based Markov switching approach, they found that transmission of oil price changes to inflation was relatively low. However, the most substantial impact was the longer-time horizon for most CEE countries. Therefore, they concluded that the indirect spillover effect was more intensive than the direct one.

Several researchers had conducted the relationship between oil price changes and inflation in Indonesia. Nizar (2012), using a vector autoregressive model (VAR), found that the oil price shocks increased Indonesia’s domestic inflation rate for a year and its response permanently since the second year. Artami & Hara (2010) conclude that both positive and negative oil price changes had a statistically insignificant effect on Indonesia’s inflation. Rostin et al. (2019) conclude that there are no long-run and short-run effects of crude oil price shocks on Indonesia’s inflation.

Several studies concluded that the effect of oil price changes on inflation is asymmetric. Nazarian & Amiri (2014) examined the effect of oil price shocks on Iran’s inflation from March 2003 to March 2013. Using a pass-through model, they found that the model can demonstrate the effect of oil price shocks on inflation with a large magnitude in the long-run. They conclude that the relationship is asymmetrical, wherein in the short-run, the relationship showed the positive and negative effects of oil price shocks. Lorusso & Peironi (2015) assessed the effect of oil price changes on the U.K. macroeconomy measured by GDP growth and inflation. They used a structural vector autoregressive (SVAR) model to observe the data from 1976 to 2014. They found that oil supply shocks significantly affect the U.K’s inflation, but shocks in oil demand have no significant effect. They concluded that the effect of oil supply shocks on the
U.K’s inflation is significant, which occurs because of the position of the U.K. as an oil producer country.

Luthfi et al. (2017) investigated the impact of oil price changes on Indonesia’s macroeconomic variables, measured by the inflation rate, real interest rate, GDP growth, and unemployment, on the pre and post-Asian financial crisis. By employing a vector autoregression model (VAR), they found there was an insignificant impact of oil price volatility, as net oil price decreased and increased to inflation for the period Q1.1984 to Q4.1997 (pre-crisis), but they were significant for the period 1998 to 2012 (post-crisis).

Khan & Malik (20161) investigated the pass-through of oil prices to the domestic price in Pakistan using Consumer Price Inflation (CPI) and Wholesales Price Inflation (WPI). By using the recursive vector autoregressive (VAR) model, their study showed that (1) the oil price has a moderate effect on inflation, (2) oil price pass-through is stronger in WPI than CPI, (3) the impact of oil pass-through is more pronounced in the period 2008 to 2015, and (4) oil prices have an asymmetric impact on domestic inflation in Iran.

Many studies conducted using various parametric approaches, both in Indonesia and outside Indonesia, the relationship between oil price and inflation had various conclusions. The different conclusion occurs because there are differences in the time horizon, source of oil price shocks, county’s position in the oil market, and the model. Therefore, investigating the effect of oil price changes on Indonesia by using different approaches is still relevant.

Based on the fluctuation of Brent oil prices and inflation in Indonesia, this study investigates the effect of world oil price changes on inflation in Indonesia from January 2001 to December 2017, using a nonparametric approach. A nonparametric is used as an alternative approach if the variables used did not fulfill the parametric approach’s requirement. However, a nonparametric approach based on general data assumptions, the validity of its procedure can be accountable (Daniel, 1989). Therefore, a nonparametric regression model used in this study can be a novelty to complete the literature that studied the behavior of inflation in Indonesia.

**Method**

The world oil price that we used in this study is Brent oil price, based on the fact that it is the largest crude oil produced and the most frequently traded in European, Middle East, and African oil markets. Approximately two-thirds of the oil productions in the world are from Brent oil. Brent oil trades in the broadest commodity futures market in the world, such as International Petroleum Exchange (IPE) in London, Dubai Mercantile Exchange (DME) in Dubai, Multi Commodity Exchange (MCX) in India, and Tokyo Commodity Exchange (TOCOM) in Tokyo, Japan. The Brent oil price data taken from the Federal Reserve Bank of St. Lois Economic Data Research (FRED). The data of inflation in Indonesia taken from The Economic of Indonesia Monthly Report published by The Central Bureau of Statistic of Indonesia. We analyze 204 monthly
data from January 2001 to December 2017, and sufficient to be analyzed using the regression approach. We analyzed data using Eviews 9.0 for descriptive analysis, ADF unit root test, heteroscedasticity and stability test, and ARCH LM test. To select optimum bandwidth and analyze the nonparametric regression function, we used the R application program version 3.6.1.

The characteristics of inflation's data from January 2001 to December 2017 tended to follow a normal distribution and had no ARCH effect; therefore, when we used the parametric approach, the estimation would be biased and inconsistent (Handerson & Souto, 2018). A nonparametric regression provides an alternative method for a weak identification assumption and minimizes misspecification (Cizek & Sadikoglu, 2019). When we use a nonparametric regression function, the relationship between two or more variables cannot predict sooner. Therefore, we could not use a specific regression function before we had valid information on the relationship function (Hardle, 1994).

We observed the relationship between inflation in Indonesia and Brent oil price using three alternatives nonparametric regression functions: general additive model, second-order Gaussian Kernel, and second-order Epanechnikove Kernel. To observe the relationship using second-order Gaussian Kernel and second-order Epanechnikove Kernel approaches, we employed the Naradaya-Watson (N-W) estimator due to its popularity, and it was easy to use. The regression function of the relationship between two variables should be assumed smooth and estimated based on the data given, which expressed by the following equation (1)

\[ y_i = m(x_i) + \epsilon_i, \text{ for } i = 1, 2, 3, ... n \]  

Where:
- \( y_i \) is inflation (INF) as a response variable
- \( x_i \) is Brent oil price (BOP) as a predictor variable.
- \( m \) is an unknown regression function

To select the best estimator, we estimate the optimum bandwidth using a smoothing regression technique, as De-Ullibarri (2015) suggested. This study used a kernel smoothing technique and an optimum bandwidth to control the bandwidth to ensure that the bandwidth is not under-smoothed or over-smoothed. It is important to control the bandwidth because an under smoothed bandwidth will cause the regression function to fluctuate and generate a rough estimation. Otherwise, an over-smoothed bandwidth will cause the regression function biased, and estimation cannot be accurate. Eubank (1988) defines a kernel regression function (\( K \)) with an optimum bandwidth (\( h \)) expressed in equation (2)

\[ K_h(x) = \frac{1}{h} K \left( \frac{x}{h} \right); -\infty < x < \infty \text{ dan } h > 0 \]  

Where:
- \( K \) is the kernel regression function.
- \( h \) is the optimum bandwidth
- \( x \) is the predictor variable (Brent oil price)
There are several kernel regression functions that we can use to observe the relationship between the response variable and predictor variables, such as Uniform, Triangle, Triweight, Cosinus, Gaussian, and Epanechnikov kernel regression functions. This study used a second-order Epanechnikov kernel function because it is popular and frequently used by many researchers. A second-order Epanechnikov kernel function defined as in equation (3)

\[ K(z) = \frac{3(1-z^2)}{4\sqrt{5}}, \text{where } z = (x_i - x)/h, \text{ for } h > 0 \quad (3) \]

The regression function of \( m(x) \) in equation (1) can be estimated using several estimator techniques, such as Naradaya-Watson (N-W), Priestley, and Gesser-Müller estimators. This study used Naradaya-Watson (N-W) estimator because many researchers more frequently use it. A Naradaya-Watson (N-W) estimator can be used to estimate the regression function of \( m(x) \) in equation (1) as a weighted kernel function, as presented in equation (4):

\[ \hat{m}(x) = \frac{\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right)y_i}{\sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right)} \quad (4) \]

Where:
- \( \hat{m}(x) \) is an N-W estimator
- \( K \) is the Kernel regression function
- \( h \) optimum bandwidth

We analyzed the relationship between Brent oil price and inflation in Indonesia using descriptive analysis and inference analysis. The descriptive analysis observes the characteristics of data using general statistic descriptive parametric. Inference analysis is used to estimate the relationship between inflation in Indonesia as a response variable and Brent oil price as the predictor variable.

We conducted several steps to analyze the relationship between inflation and oil price. Firstly, plotting the pairing value of inflation in Indonesia and Brent oil price using a scatterplot diagram. Secondly, estimating the optimum bandwidth for each alternative nonparametric regression function. Thirdly, selecting the best alternative nonparametric regression function. Finally, assessing the relationship between inflation in Indonesia and Brent oil price using the best model that we chose at the 3rd step.

Results and Discussion

The summary descriptive analysis of Brent oil price and inflation in Indonesia is present in Table 1. The maximum and minimum value of BOP show that Brent oil prices movement had a wide range but still in the expected range. On the other side, the minimum value of INF was negative, which indicates that there were several data set of inflation had negative values even the BOP value is positive. Based on the descriptive analysis, we could not use a parametric approach to analyze the relationship between inflation in Indonesia (INF) and Brent oil price (BOP).
The probability of the Jarque-Bera statistics parameter can test a null hypothesis, where each variable consider to have a normal distribution. Table 1 shows that the p-value of BOP and INF was equal to 0.000, which means BOP and the INF data did not support a normal distribution. Therefore, we had to reject the null hypothesis of each variable that had a normal distribution. Based on the descriptive analysis, we could predict the relationship between Brent oil price and Indonesia’s inflation using a parametric approach. If we still used the parametric approach to analyze the relationship, it could generate a spurious conclusion. Therefore, we used a nonparametric approach as an alternative approach to exploring the relationship between Brent oil price and inflation in Indonesia.

We conducted a preliminary test, such as a stationary test, heteroscedasticity test, and stability test, to analyze the relationship between inflation and the oil price. The results of the preliminary examination are as follow. The result of the stationary test using the Augmented Dickey-Fuller (ADF) unit root test for inflation in Indonesia (INF) and Brent oil price (BOP) is present in Table 2. Table 2 shows that inflation in Indonesia (INF) had $\tau$ statistic less than 1% critical value ($\alpha=0.01$) and p-value = 0.0000. It indicates that inflation in Indonesia was stationary in level(I/0). On the other side, the $\tau$ statistic and p-value of Brent oil price (BOP) exceeded a 5% critical value ($\alpha=0.05$), which indicates that Brent oil price was non-stationary in level, but stationary in a first different form (I/1).

### Table 1. Descriptive Statistics of Brent Oil Price and Inflation in Indonesia

<table>
<thead>
<tr>
<th>Statistics</th>
<th>BOP</th>
<th>INF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>66,46495</td>
<td>0,536422</td>
</tr>
<tr>
<td>Maximum</td>
<td>133,9000</td>
<td>8,700000</td>
</tr>
<tr>
<td>Minimum</td>
<td>18,60000</td>
<td>-0,450000</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>31,19502</td>
<td>0,794425</td>
</tr>
<tr>
<td>Skewness</td>
<td>0,326080</td>
<td>5,735764</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>1,888461</td>
<td>56,59053</td>
</tr>
<tr>
<td>Jarue-Bera</td>
<td>14,11708</td>
<td>25530,10</td>
</tr>
<tr>
<td>Probability</td>
<td>0,000860</td>
<td>0,000000</td>
</tr>
<tr>
<td>Observations</td>
<td>204</td>
<td>204</td>
</tr>
</tbody>
</table>

Source: Data processed using Eviews
Because INF and BOP had a different integration order, the relationship between these two variables model by using an autoregressive distributed lag (ARDL) model. This research conducted the heteroscedasticity and stability test for the ARDL model to ensure that the ARDL model was fit to analyze the relationship between inflation in Indonesia (INF) and Brent oil price (BPO).

We used the Breusch-Pagan-Godfrey test to observe heteroscedasticity and CUSUM and CUSUMSQ test to identify the ARDL model's stability. The results of the heteroscedasticity and stability test of the ARDL model as presented in Table 3. Table 3 shows that the ARDL model was unstable that caused by heteroscedasticity. Therefore, the ARDL model cannot analyze the relationship between inflation in Indonesia and the Brent oil price.

### Table 3 Heteroscedasticity and stability test for ARDL model

<table>
<thead>
<tr>
<th>Model</th>
<th>Heteroscedasticity</th>
<th>Stability test</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARDL Model</td>
<td>exist</td>
<td>Yes, No</td>
</tr>
</tbody>
</table>

Source: Data processed using Eviews

We use the ARCH effect test to observe the relationship between inflation in Indonesia and Brent oil price. It could be analyzed using the ARCH/GARCH approach. The ARCH LM test result for inflation in Indonesia and Brent oil price (BOP) shows in Table 4. By observing the probability of Chi-square and 5% critical value (=0.05), the ARCH LM test shows that Brent oil price (BOP) had an ARCH effect, while inflation in Indonesia (INF) had no ARCH effect. These results indicate that the ARCH/GARCH approach cannot analyze the relationship between inflation in Indonesia (INF) and Brent oil price (BOP).

### Table 4 ARCH LM test for inflation in Indonesia (INF) and Brent oil price (BOP)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs*R-squared</th>
<th>Prob.Chi-square</th>
<th>ARCH Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln.BOP</td>
<td>167.3117</td>
<td>0.0000</td>
<td>Yes</td>
</tr>
<tr>
<td>INF</td>
<td>0.003069</td>
<td>0.9558</td>
<td>No</td>
</tr>
</tbody>
</table>

Source: Data processed using Eviews

The preliminary test shows that the relationship between inflation in Indonesia (INF) and Brent oil price (BOP) could not be analyzed using a parametric approach. Therefore, we employed a nonparametric regression approach to explore the relationship between these two variables. We used several steps to analyze a nonparametric regression approach: (1) plotting its relationship, (2) calculating the optimum bandwidth, (3) selecting the best alternative model, and (4) estimating its relationship.

The first step in analyzing the relationship between inflation in Indonesia as the response variable and the Brent oil price as the predictor variable was to predict these two
variables’ relationship function. We used a scatterplot diagram to identify the relationship function between inflation in Indonesia as a response variable and Brent oil price as a predictor variable, as shown in Figure 3. Figure 3 shows that the relationship between inflation in Indonesia and Brent oil price from 2001 to 2017 did not offer a specific function. Therefore, we had no information to identify and model the relationship between inflation in Indonesia and Brent oil price using a particular regression function. Based on this fact, we analyzed the relationship between inflation in Indonesia and Brent oil price using a nonparametric regression approach.

![Figure 3. Scatterplot Diagram of BOP and INF for the Period of 2001 – 2017](image)

We used three alternatives nonparametric regression functions to analyze the relationship between inflation in Indonesia and Brent oil price; they are (1) general additive model, (2) second-order Gaussian kernel model, and (3) second-order Epanechnikov kernel model. The second-order Gaussian kernel and second-order Epanechnikov kernel model required optimum bandwidth information, while this information no need for the general additive model. The optimum bandwidth is selected automatically using an R-studio program, as shown in Table 5. The optimum bandwidth is 3.973047 for the second-order Gaussian kernel model and 3.009644 for the second-order Epanechnikov kernel model. This optimum bandwidth uses to regress the relationship between the response variable (inflation) and the predictor variable (Brent oil price) for each model.

<table>
<thead>
<tr>
<th>Non-Parametric Regression Model</th>
<th>Bandwidth</th>
<th>R-squared</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>General additive model</td>
<td>-</td>
<td>0.0204</td>
<td>0.346</td>
</tr>
<tr>
<td>Second-order Gaussian kernel model</td>
<td>3.973047</td>
<td>0.1007</td>
<td>0.088</td>
</tr>
<tr>
<td>Second-order Epanenchikov kernel model</td>
<td>3.009644</td>
<td>0.1081</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Source: Data processed using R-studio

To select the best nonparametric regression model, we observed three alternative models and selected using two criteria: R-squared and p-value, indicating the model’s
explanatory power. Table 5 shows the R-squared and the p-value resulted from the regression process for each model. The R-squared criterion for the second-order Gaussian kernel model and second-order Epanechnikov kernel model was equal to 10 percent, indicates that the variation of Brent oil price can explain a 10 percent variation of inflation. The rest variation of inflation in Indonesia define by other factors that exclude the Brent oil price. Although the R-squared for these two models was low enough, it was better than the R-squared for the general additive model.

Table 5 also shows that the p-value of the General additive model (0.346) was higher than 10 percent, which means this model was statistically insignificant in 90% confidence level. The p-value of the second-order Gaussian Kernel model was 0.088, and the second-order Epanechnikov Kernel model was 0.018. It means that the second-order Epanechnikov Kernel model was statistically significant in a 95% confidence level. In comparison, the second-order Gaussian kernel model was statistically significant in a 90% confidence level. Using the p-value criteria, we employ the second-order Epanechnikov Kernel function model to analyze the relationship between inflation in Indonesia and Brent oil price.

The relationship between inflation in Indonesia (INF) and Brent oil price (BOP) is observed using the second-order Epanechnikov kernel model and estimated using a Naradaya-Watson’s estimator. The Naradaya-Watson (N-W) estimator is used because it is frequently used to estimate a nonparametric regression function. By using sample size (n) = 204, the regression function of m(xi), as shown in equation (4), can be estimated using equation (5).

\[ \hat{m}(x) = \frac{\sum_{i=1}^{n} K(\frac{x-x_i}{h})Y_i}{\sum_{i=1}^{n} K(\frac{x-x_i}{h})} \]  

which,

\[ K(z) = \frac{3(1-z^2)}{4\sqrt{5}}, \text{where}, z = (x_i - x)/h, h > 0 \]  

By substituting the value of K(z) into the regression function of \( \hat{m}(x) \) in equation (5), the second-order Epanechnikov kernel function between inflation in Indonesia and Brent oil price formulated as equation (7)

\[ \hat{m}(x) = \frac{5h^2 \sum_{i=1}^{204} x_i^2 Y_i - (h+1)^2 \sum_{i=1}^{204} x_i^2 Y_i + 2(h+1)x \sum_{i=1}^{204} x_i Y_i - x^2 \sum_{i=1}^{204} Y_i}{5h^2 - (h+1)^2 \sum_{i=1}^{204} x_i^2 + 2(h+1)x \sum_{i=1}^{204} x_i Y_i - x^2} \]  

Where:

\[ \sum_{i=1}^{204} Y_i = 109,43; \quad \sum_{i=1}^{204} x_i^2 Y_i = 538473,99; \quad \sum_{i=1}^{204} x_i^2 = 13558,84; \quad \sum_{i=1}^{204} x_i = 1098733,39; \quad h = 3.009644, \]

By replacing the value of \( \sum_{i=1}^{204} Y_i, \sum_{i=1}^{204} x_i, \sum_{i=1}^{204} x_i^2, \sum_{i=1}^{204} x_i^2 Y_i, \sum_{i=1}^{204} x_i Y_i, \) and \( h \) into equation (7), the relationship between inflation in Indonesia (INF) and Brent oil price could be estimated using the following equation (8).

\[ \text{INF} = \frac{-8612286.5 + 55010.3 \text{BOP} - 99.4 \text{BOP}^2}{-17664195.6 + 108732.\text{the 14630352 BOP} - \text{BOP}^2} + \varepsilon \]  

http://journal.uinjkt.ac.id/index.php/signifikan
https://doi.org/10.15408/sjie.v10i1.19010
To interpret the relationship between inflation and oil price, we drew this relationship into a two-dimensional diagram, where Indonesia's inflation mark on the vertical axis and Brent oil price draw on the horizontal axis. We calculated the value of inflation for each value of Brent oil price using equation (8), starting from the Brent oil price of USD 1 per barrel to USD 140 per barrel. The plotting of the value of inflation and Brent oil price shows in Figure 4.

Figure 4 shows that the relationship between inflation in Indonesia and Brent oil prices tends to follow exponentially. An increase in Brent oil price forcing Indonesia’s inflation to follow the exponential function in the second-order Epanechnikov kernel function, as shown in equation (8). The intercept of its function is 0.004875, which indicates that if the Brent oil price was equal to USD 0 per barrel, Indonesia’s inflation rate per month is 0.4875 percent. Without considering the oil price, the inflation rate per month in Indonesia is 0.4785 percent. Figure 4 also informed us that Indonesia’s inflation rate increases slowly when the oil price below USD 100 per-barrel and becomes high when the oil price above USD.100 per barrel.

When Brent oil price is below USD 100 per barrel, increasing USD 1 on Brent oil price will increase the inflation rate per month in Indonesia by 0.001289%. However, when the Brent oil price above USD 100 per-barrel, increasing USD 1 affects inflation rate increase by 0.1541%, higher than when the oil price below USD 100 per barrel. This result implies that when the oil price below USD 100 per barrel, increasing USD 10 on oil price will push up Indonesia’s inflation by 0.01289%. Meanwhile, when the price is above USD 100 per barrel, an increase in the same amount on oil price will push up Indonesia’s inflation by 1.541%. In other words, when the oil price below USD 100 per barrel, it affect Indonesia’s inflation by a lower rate. On the other side, the oil price above USD 100 per-barrel affects Indonesia’s inflation at a higher rate.

This study’s result is in line with the result of the studies conducted by Nizar (2012) and Luthfi et al. (2017), although they used a parametric approach different from the
model used in this study. The nonparametric model also can be giving us information on
the behavior of the relationship. By plotting the predictor and response variables’ values
into a diagram, as shown in Figure 3, a nonparametric model gives us more detailed
information about the relationship between these variables. Therefore, we conclude that
the nonparametric model used in this study can be considered an alternative approach
to observe the relationship between oil price changes and inflation in Indonesia, and
the result of this approach as good as a parametric approach.

This study is in line with almost all international studies conducted before, such as
Qianqian (2011) in China, and Dias (2013) in Portuguese, although their studies used a
parametric approach. The same conclusion between this study and those occurs because
all these countries have the same oil market position as net-oil importing countries. This
conclusion supports Raghavan (2015), which concluded that oil price shocks significantly
affect inflation on net-oil importing economies.

This study’s result is also in line with the previous study conducted in Indonesia
by Nizar (2012) and Luthfi et al. (2017). Although this study uses a different approach
from those, all of these studies conclude that oil price changes significantly affect inflation
in Indonesia. Due to the resulting study conducted by Lutfhi, Senevirathne & Kaneko
(2017) and Khan & Malik (2016), this same conclusion occurs because all of these
studies analyzed data on the same time horizon that is, in a post-financial crisis (1998).
The effect of oil price changes on inflation could be occurred because of the asymmetric
effect of oil price changes on the economy, caused by the position of a country in the
oil market and the time horizon used to analyze (Khan & Malik, 2016). These two
considerations are relevant to the result of this study, in which, from 2001 to 2017,
Indonesia became a net oil importing country.

On the other side, this study’s result differs from Gokmenoglu et al. (2015), which
concluded that the Granger causality test confirms no causality relationship between oil
price and Turkey’s inflation. The different result occurs because the Granger causality test
has limitations. One of the Granger causality test limitations is “all causal relationships
remain constant in their direction over time”. Therefore, only the strengths relations
changes but never the general direction. This study’s result is also different from Artami
& Hara (2018) and Rostin et al. (2019) that oil price changes have no significant effect
on inflation in Indonesia. The different results between this study and Artami & Hara
(2018) exist because they employed a different proxy for the oil price, where they used
actual oil prices in Indonesia as an independent variable that consisting of the price
subsidy policy. Because the government employs the price’s oil subsidy policy to reduce
oil price changes’ impact on the general price level, the effect of oil price changes on
inflation is statistically insignificant. The different result between this study and Rostin
et al. (2019) occurs because of the Aostin et al. (2019). As Sek et al. (2015) concluded,
in ARDL format, oil price changes indirectly affect inflation in high oil dependency
countries. Therefore, the ARDL model cannot observe the direct effect of oil price
changes on Indonesia’s inflation as a high oil dependency country.
Conclusion

The second-order Epanechnikov kernel function as a nonparametric model can use as an alternative approach to estimating the relationship between the world oil price and inflation in Indonesia. The regression of the second-order Epanechnikov kernel function shows that the oil price changes on inflation in Indonesia tend to follow exponentially, with the critical level of oil price at USD 100 barrel. Our study shows that the effect of world oil price changes on Indonesia's inflation depends on the oil price level. If the oil price is below USD 100 per barrel, oil price changes will lower inflation in Indonesia. However, when its price is above USD 100 per barrel, its effect becomes higher.

This conclusion is giving important consequences on the implementation of the government and Bank Indonesia's policy. Because the oil price changes have a lower effect on inflation when its prices are below USD 100, as long as the oil price is at this price, the government and Bank Indonesia do not need to over-react to manage inflation due to oil price changes. Bank Indonesia and the government need to be concerned about managing inflation in response to the oil price changes when its price is above USD 100 per barrel.

References


