Testing for Asymmetries in the Response of GDP to Oil Price Shocks Using MIDAS Regressors

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Major Paper presented to the
Department of Economics of the University of Ottawa
in partial fulfillment of the requirements of the M.A. Degree
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Ottawa, Ontario
December 6, 2016

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Introduction

There is an ongoing debate regarding how GDP reacts to an oil price shock. Previous studies looking at this have found evidence for both symmetric and asymmetric responses, but these results vary depending on the method of testing. A symmetric shock is one that induces the same reaction in terms of magnitude to price increases as it does to price decreases, while an asymmetric shock is one that does not. Consequently, an oil price shock will be symmetric if a positive increase in oil prices decreases output the same amount a decrease in prices of equal magnitude would increase output. Until recently, most research has been in consensus that the reaction of real GDP to an oil price shock is asymmetric. Results supporting this have followed a general model proposed by Hamilton (2003) and (2011). Another method of testing however, proposed by Kilian and Vigfusson (2011a) and (2011b), has provided results that challenge the conclusion of asymmetries.

The frequencies of GDP and oil prices differ. GDP is only available in quarterly values while oil prices are available at various frequencies such as daily or monthly, depending on the type of measure used. In the case of Hamilton's and Kilian and Vigfusson's tests, the oil prices they use are the Refiner's Acquisition Cost (RAC) of crude imported oil and the Producer Price Index (PPI) of crude petroleum, which both come in monthly frequencies. To put all the data in the same frequency, they average monthly values into quarterly.

The purpose of this paper is to test for the presence of asymmetry obtained in Hamilton (2011) and to evaluate the impact of the method of time-averaging of the oil price data on his conclusions. This will be done by building on his model through the use of MIDAS regressors. In the process, we expand the data set to include more observations.

The rest of this paper is designed as follows: Section 1 will discuss the theory behind the potential existence of symmetric or asymmetric shocks, Section 2 will provide an overview of the two methods of testing for asymmetries, as well the literature in favor of each. Section 3 will develop the AR U-MIDAS model that will be used to test for asymmetries, Section 4 will discuss the data being used, in Section 5 we will compare the strength of the simply averaged model and the AR U-MIDAS regression for various lag specifcations, Section 6 will involve testing for asymmetries and comparing the results of the models, and Section 7 will be the conclusion.

Section 1: Overview of Asymmetries

Oil price shocks will have a direct effect on both the demand and the supply channels of the economy. On the demand side, they will affect the purchasing power of households, as discussed in Kilian and Vigfusson (2011b). Specifically, following an unexpected increase in the price of imported oil, households from oil-importing economies will experience a decrease in purchasing power, brought on by income being transferred out of the country. Households from oil exporting economies, on the other hand, will experience an increase in purchasing power from an influx of foreign currency. The impact of a change in purchasing power is symmetric for both oil importing and oil exporting countries, as noted in Herrera et al. (2013).

On the supply side, for an oil importing country, a positive (negative) oil price shock will result in a decrease (increase) in the supply of goods whose production is energy intensive. For an oil exporting country, the effect of a price shock will vary depending on the characteristics of the economy. Herrera et al. (2013*)* note that the effect of an oil price increase will primarily depend on three things: the percentage of aggregate GDP the oil sector accounts for, the response time of production to the shock, and productivity spillovers between oil and non-oil industries. Following a positive price shock, firms will transfer their labour and capital from high energy to low energy sectors where they can be more productive, which will ultimately decrease output due to lower levels of production. The more reliant an economy's GDP is on imported oil, the more negatively it will be affected. For oil producing countries on the other hand, higher global oil prices will lead to an increase in energy production. Evidence for this is found in Bjørnland and Thorsrud (2015), who show that booms in the energy sector lead to productivity spillovers on the non-oil sectors (with construction, business services and real estate are the most stimulated sectors), which ultimately leads to higher output.

In theory, the effects mentioned above result in a symmetric response. In reality however, additional factors following a price change may amplify the impact of a price shock. The most common explanations in literature for the origins of the additional effects are: reallocation costs, uncertainty, and monetary policy. The next three paragraphs will discuss each in detail.

The first reason for asymmetries comes from uncertainties about future oil prices. Using a partial equilibrium model, Bernanke (1983) notes that uncertainty (high volatility in oil price) can lead businesses to postpone their purchases of durable goods, ultimately leading to economic contractions. In addition, he finds that this effect is particularly strong when expenditures are irreversible, since firms may react to this by choosing to wait for additional information before investing scarce resources. Elder et al. (2010) find that the effect of volatility in the price of oil on investment, durables consumption, and aggregate output is statistically significant. According to Edelstein and Kilian (2009), uncertainty about the future can also lead to precautionary savings and a decrease in GDP from lower levels of consumption. The impact of uncertainty is not conclusive in literature, however. It has been argued by Kilian and Vigfusson (2011a) and Herrera (2011) that savings decisions following shocks are symmetric, and so although a shock will affect the decisions of consumers, impacts from positive and negative shocks will have the same magnitude.

The second reason for asymmetries is that oil price shocks can lead to costly intra-sectoral and intersectoral reallocations of labour and capital, which have recessionary impacts (Davis, 1987). Following an oil price increase, as was stated above, expenditures in high energy sectors may be transferred to lower energy sectors where they can be more productive. In order for oil shocks to be symmetric, this transition would have to occur smoothly without any inefficiencies. If this is not the case, however, then these factors of production will be temporarily out of service and aggregate output will be negatively affected. For example, Lougani (1986) and Hamilton (1988) find that unemployment following a price shock can be caused by workers transitioning between sectors or waiting for conditions to improve before returning to work. Kilian et al. (2011a) notes that for an oil-importing country, reallocation costs will increase the recessionary impacts of an oil price increase, and they will reduce the expansionary impacts following an oil price decrease. In contrast, for an oil-exporting country, reallocation costs will increase the recessionary impacts of an oil price decrease. Reallocation can also occur within a sector- a high energy firm can be lead to switch to more energy efficient means of production following a positive price shock (see Davis and Haltiwanger, 2001). If there is a sudden decrease in the price of oil, the impact of reallocation will partially offset the higher output which results from increased purchasing power.

A theoretical argument for asymmetries arises from the consequences of the monetary policy decisions of the Federal Reserve in the face of price shocks. Bernanke (1997) writes that the Federal Reserve will raise interest rates to a greater extent following an unexpected oil price increase, but not following unexpected price decreases, which can ultimately lead to asymmetry. This has been challenged by authors such as Hamilton and Herrera (2004) and Kilian and Vigfusson (2011a), which find little evidence to justify the claim. Rather, they find that the effects of monetary policy are not as strong as predicted by Bernanke because the impact of shocks are not instantaneous -although interest rates are usually altered immediately following a shock, the effects of oil shocks do not occur until many months later.

Section 2: Methods to Test for Asymmetries

Strategies to evaluate the presence of asymmetries involve using non-linear transformations of oil prices in GDP models. This paper will use the three-year oil price specification introduced by Hamilton (2003), which has the form:

$$\varphi_t = \max\{0, X_t - max\{X_{t-1}, \dots, X_{t-12}\}\}$$

Where X_t is the natural logarithm of the price of oil (either real or nominal). The purpose of φ_t is to capture a nonlinear reaction to oil price shocks. This specification gives a value of zero when there is a price decrease. Including this variable as one of the regressors will account for correctional price increases. As Hamilton (1996) points out, for an increase in prices to have a deterring effect on consumers, it needs to be large enough to offset a previous decline. For example, a 10% increase in prices will not have much of an impact if it follows a 20% decrease. Consequently, what is important is price increases that come following a period where prices were stable. This specification implies asymmetry since it assumes a net decrease in price does not induce a reaction at all from individuals, and so consumers react differently to positive and negative oil shocks.

There are two common methods of testing for asymmetries in literature. The method to test for asymmetries that we will follow is a slope based test proposed by Hamilton (2003). He tests for asymmetries using the following model:

$$y_t = \alpha + \sum_{i=1}^{p} \phi_i \, y_{t-i} + \sum_{i=1}^{p} \beta_i x_{t-i} + \sum_{i=1}^{p} \gamma_i \varphi_{t-i} + \varepsilon_t$$

where y_t is real GDP growth and x_t is the growth in the nominal PPI of crude petroleum oil. The existence of asymmetries is evaluated using a Wald Test to estimate the null hypothesis: $\gamma_1 = \cdots = \gamma_p$ =0. Hamilton recommends setting $p = 4$.

Another method for testing was proposed by Kilian and Vigfusson (2011a) and consists of a Wald test based on the following impulse response functions:

$$x_t = \alpha_1 + \sum_{i=1}^{p} \beta_{11_i} x_{t-i} + \sum_{i=1}^{p} \beta_{12_i} y_{t-i} + \varepsilon_{1,t}$$

$$y_t = \alpha_2 + \sum_{i=0}^{p} \beta_{21_i} x_{t-i} + \sum_{i=1}^{p} \beta_{22_i} y_{t-i} + \sum_{i=0}^{p} \gamma_i \varphi_{t-i} + \varepsilon_{2,t}$$

Where x_t is the real RAC, y_t is the same as in Hamilton's model, and φ_t is the shock measure.

Based on papers by Lee et al. (1995), Balke et al. (2002), and Hamilton (1996, 2003, 2011), the consensus until recently has been that the economy's response to oil price shocks is asymmetric. Furthermore, Carlton et al. (2010) and Ravazzolo and Rothman (2010) have also found asymmetry when they test using real-time data. For an oil importing country, Hamilton (2008) shows that if the production function is continuous and differentiable in energy input, small changes in oil prices won't significantly affect output. An et al. (2013) find evidence of asymmetry using a factor augmented vector auto regressive (FAVAR) model.

In contrast, Kilian and Vigfusson (2011a) failed to reject the null hypothesis of symmetry. However, when they conducted their analysis to include two standard deviation shocks, they could detect asymmetry. Using the approach of Kilian and Vigfusson (2011a), Herrera et al. (2011) test the impact of oil price shocks on industrial production and find evidence for symmetry at the aggregate level for regular shocks, and some evidence for asymmetry for large shocks. Asymmetry is found at the disaggregate level for all the NAICS industries, and it is only in the industries of non-durables where the null hypothesis of symmetry is not rejected. Herrera et al. (2013) expand their previous analysis to test for asymmetries in 18 OECD countries, and find little evidence for nonlinearities, for countries that are both oil importers and exporters.

There are a number key differences in how the variables are specified in Hamilton's model and Kilian and Vigfusson's model. Hamilton tests for asymmetries using the nominal producer price index (PPI) of crude petroleum and Kilian and Vigfusson use the real refiner's acquisition cost (RAC) of imported petroleum. When the RAC is used instead of the PPI, Hamilton's model does not reject the null of asymmetry. This calls into question the previously accepted conclusion of asymmetry since there is no compelling reason to use PPI instead of RAC, and so if the asymmetry found in Hamilton's model using the PPI reflect the true economic situation, it should be possible to replicate these results using the RAC.

The goal of this paper is to help enforce Hamilton's conclusions considering the issues recently brought up by Kilian and Vigfusson and to check the implications of time averaging data on the accuracy of Hamilton's model. We will do so by focusing on Hamilton's model and adjusting it to include MIDAS regressors in the place of the time averaged oil prices and shock measure. To determine if these changes improve forecasting ability, we will compare the RMSE of the model with time averaged data, to the AR U-MIDAS at various lag specifications. Next, we will compare the fit of the AR U-MIDAS model and the simply averaged model at various lag specifications using the Akaike, Schwarz, and Hannan-Quinn information criterion (AIC, SIC, HQ respectively). Finally tests for asymmetries will be conducted on the AR U-MIDAS and the simply averaged model at these lag specifications.

Section 3: Developing the AR U-MIDAS regression model

First proposed by Ghysels et al. (2004), MIDAS regressions have become increasingly attractive as a forecasting tool (see examples of research in the paragraph below) since they permit the explained variable to be forecasted using higher frequency regressors, making it possible to exploit all available data. As previously mentioned, data for oil prices and GDP are of different frequencies, so when testing for asymmetries, one would have to incorporate time averaging, or step weighting, so that the frequencies are the same for all variables in the regression. This can result in the loss of potentially valuable information when it comes to forecasting. Consequently, there is reason to believe that MIDAS regressions can lead to improvements in the forecasting of GDP using oil prices. GDP is only available in quarterly values, so previous examinations have resorted averaging monthly price and shock variables into quarterly values.

Using the notation from Ghysels et al. (2004), a MIDAS regression with one explanatory variable can expressed in the form:

$$Y_t^l = \beta_0 + \beta_1 B\left(L^{\frac{1}{h}};\ \theta\right) X_t^h + \varepsilon_t \qquad (1)$$

Where Y_t^l is the lower frequency variable, X_t^h is the higher frequency variable, $B\left(L^{\frac{1}{h}};\ \theta\right) = \sum_{k=0}^{K} B(k;\ \theta) L^{\frac{k}{h}}$, $L^{\frac{1}{h}}$ is the lag operator such that $L^{\frac{1}{h}} x_t^h = x_{t-\left(\frac{1}{h}\right)}$, K is the number of lags of the higher frequency variable that are used to estimate one period of the lower frequency variable, B$(k;\theta)$ is a function that determines the weights for intertemporal aggregation, θ is a vector the individual weights, and h represents the number of periods of the higher frequency variable that are contained in one period of the lower frequency variable. For example, if we are estimating quarterly data using monthly data, then h=3.

The simple MIDAS regression can be extended to the multivariate form without any issues (Ghysels et al, 2007). The general MIDAS equation can thus be written as:

$$Y_{t+k}^l = \mathrm{B}_0 + \sum_{i=1}^{K} \sum_{j=1}^{L} \mathrm{B}_{ij} \left(L^{\frac{1}{h_i}};\ \theta\right) X_t^{h_i} + \varepsilon_t$$

Where Y, X, and ε are n-dimensional vectors, and Y is the lower frequency explained variable and X is the higher frequency explanatory variable. With regards to the coefficients, B_0 is a matrix of n dimensions, and B_{ij} are n x n matrices of polynomials parameterized by θ . L is the number of periods of the higher frequency X variable that we want to equal one period of lower frequency Y variable and K is equal to the number of regressors in the equation (either lags or individual explanatory variables). Foroni and Marcellino (2013) note that since each indicator is modelled with its individual parameterization, explanatory variables do not need to have the same frequency either.

<u>3.1: Using an Almon Exponential Lag or a U-MIDAS for the MIDAS Regression</u>

There are several different ways in which the function $B(k;\theta)$ in (1) can be defined. Some of these are: a polynomial specification with step functions, the normalized Beta probability density function, and a normalized exponential Almon lag polynomial. Ghysels et al. (2007) provide an overview of each. As will be discussed below, the exponential Almon lag polynomial and the U-MIDAS parameterizations have provided the best results for economic forecasting. These specifications take the form: $B(k;\theta) = \frac{e^{\theta_1 k + \cdots \theta_Q k^Q}}{\sum_k^K e^{(\theta_1 k + \cdots \theta_Q k^Q)}}$ and $B(k;\theta) = \theta_0 + \theta_1 L + \cdots \theta_{k-1} L^{k-1}$, respectively.

Foroni et al. (2011) forecast US and Euro GDP using MIDAS and compare various polynomial specifications. They find that when forecasting quarterly data using monthly data, the U-MIDAS will yield better results than the exponential Almon lag specification, while the exponential Almon lag specification is better suited for forecasting quarterly data using daily data. This is because it allows for estimation incorporating large numbers of lags, but does not result in parameter proliferation. The appeal of U-MIDAS in contrast, is that it is much more flexible than the exponential Almon lag specification, but it leads to parameter proliferation. The exponential Almon lag has a nonlinear specification, so the parameters need to be estimated using nonlinear least squares, while the U-MIDAS' specification is linear, so the parameters can be estimated using OLS. Since monthly data is being used to forecast quarterly data, this paper will make use of the U-MIDAS, following the results of earlier research.

3.2: Aggregation Issues

Ghysels et al. (2004) note that directly inserting the autoregressive components into the MIDAS regression can result in seasonality between the dependent variable and some of its regressors, regardless if the regressors experience seasonal effects themselves. Clements and Galvao (2008) resolve this issue by incorporating autoregressive dynamics into the MIDAS regression. They assume that X_t^h and Y_t^l share the same autoregressive dynamics so that the dynamics on Y_t can be interpreted as a common factor. Based on this assumption, the general MIDAS equation can be rewritten with an autoregressive term as:

$$Y_t = \beta_0 + \lambda Y_{t-d} + \beta_1 B\left(L^{\frac{1}{h}};\theta\right)(1-\lambda L^d)X_t^h + \varepsilon_t$$

A problem with this method is that a common factor does not always exist, and it can be cumbersome to compute (Clements and Galvao, 2008). Andreous et al. (2010) also note that the lag variable is subject to geometrically declining spikes, which can lead to seasonality as well.

In contrast, more recent literature, such as Foroni and Marcellino (2013), argues that when using a U-MIDAS specification, it is not necessary to use a common factor restriction, and so inputting the regressor directly will not lead to any issues. The results from Duarte (2014) support this conclusion. Duarte (2014) shows that in terms of one period ahead forecasts, the AR U-MIDAS consistently outperforms the Common Factor (CF) MIDAS the majority of the time. This author argues that directly inputting the autoregressive term can be a successful alternative to using a common factor MIDAS regression.

3.3: The Model Set up

The form of the AR U-MIDAS used to test for asymmetries will be:

$$y_t^l = \alpha + \sum_{i=1}^{\rho} \emptyset_i \, y_{t-i} + \sum_{r_1=0}^{R_1-1} \omega_{1+r_1}^{1} x_{t-\tau-r_1}^{m_j} + \sum_{r_2=0}^{R_2-1} \omega_{1+r_2}^{2} \varphi_{t-\tau-r_2}^{m_j} + \varepsilon_t$$

Where R_1 is the total number of lags on x_t (either the nominal or the real oil price change), R_2 is the number of lags on φ_t (the shock measure), and τ is fixed and is the number of lags we start at. For the following tests, τ will equal four to imitate lagging one quarter. Since the components θ_i are not normalized, they do not sum to one, so there are no β_i coefficients to estimate. Since we want to replicate the model while remaining as much as possible in line with the economic theory Hamilton uses to reach his conclusions, the previous twelve months will be used to forecast one quarter of GDP change. Thus, $R_1=R_2=12$. In addition, following Hamilton, ρ =4. In total, estimating this regression using OLS will result in 29 coefficients (the constant, twelve parameters for the price change and 12 coefficients for the shock measure, and four coefficients for real GDP growth). Consequently, our equation will take the following form:

$$y_t^q = \alpha + \sum_{i=1}^{4} \emptyset_i \, y_{t-i} + \sum_{r_1=0}^{11} \omega_{1+r_1}^{1} x_{t-4-r_1}^{m} + \sum_{r_2=0}^{11} \omega_{1+r_2}^{2} \varphi_{t-4-r_2}^{m} + \varepsilon_t \qquad (2)$$

Testing for asymmetries will be done using a likelihood ratio and comparing the restricted and unrestricted models. The unrestricted model will be the same as in equation 2, while the restricted model will not contain the MIDAS coefficients of φ_τ.

Section 4: The Data

As mentioned earlier, the choice of oil price used in the regression has a significant impact on the results. Since it is unclear which price specification is better to use, forecasting quarterly real GDP growth will be done using the nominal and real prices of the refiner's acquisition cost (RAC) of imported crude oil and the producer price index (PPI) of crude petroleum. For the simply-averaged model, oil prices will be converted to quarterly values, while for the AR U-MIDAS they will be kept as monthly. Oil prices are retrieved from the United States' Bureau of Labor Statistics, while GDP values are from the Federal Reserve Bank of St. Louis. Initially, Hamilton (2003) tested for asymmetries using nominal PPI. He argued that if one believes that the primary effects of oil price shocks come through the change in the price consumers pay for gasoline, then PPI is a better option since the two prices are more highly correlated. Mork (1989), however, argues that PPI may not accurately capture the effects of oil shocks since it can be subject to government controls which will affect its natural value. He suggests instead to use the RAC. This view is also supported by Kilian and Vigfusson (2011b). They argue that it is necessary to incorporate the price of imported oil, since oil price shocks tend to arise from events in the global market. It is also unclear whether nominal or real prices are better suited for this model. Hamilton (2011) argues that the nominal price is more fitting than the real. This is because the nominal price may more accurately capture the threshold decisions of individuals being influenced by uncertainty, which can lead to asymmetries. Kilian and Vigfusson (2011a) in contrast argue that it makes more sense to use the real price of oil since theoretical models that are based on asymmetric responses use real prices not nominal ones. Nominal prices will be deflated using the CPI. Hamilton (2011) also points out that using CPI as a deflator can lead to measurement errors.

The sample periods tested will include 1974Q4-2007Q4 and1974Q4-2016Q2 for PPI and 1978Q2-2007Q4 and 1978Q2-2016Q2 for RAC. There is a structural break in the data in 1973, as noted by Kilian and Vigfusson (2009) and so forecasting from an earlier date for PPI can lead to incorrect results. This is not an issue for RAC since it only became available in 1974. The sample for the RAC starts in 1978 since three years are required to calculate the shock measure.

Section 5: Comparing the Forecasting Strength of the Simply Averaged Model and the AR U-MIDAS Model at alternate lag specifications

Table 1 shows the RMSE for the simply averaged model with quarterly lag specifications of 1, 2, 4, 5, and 6 on x_t and φ_τ . Table 2 shows the RMSE for the AR U-MIDAS regression with lag specifications of 3, 6, 12, 15, 18, and 21 months on x_t and φ_τ . For both the AR U-MIDAS and the simply averaged model, 4 quarter lags are used for the autoregressive component. Comparing the results from these two tables we see that the RMSE for the AR U-MIDAS is smaller than the RMSE for the simply averaged model for all data sets, as well as prices, when compared over the same forecasting period. This is true for both nominal and real PPI and RAC. These results suggest that forecasting GDP with oil prices can be improved by conducting the forecast with the use of MIDAS regressors instead of averaging the data into quarters.

Table 1: RMSE for The Simply Averaged Model Regression with 4 Quarter Lags on GDP and Various Quarterly Lags on x_t and φ_t

Sample	**Oil Measure**	**Price Adjustment**	**1 Quarter Lag**	**2 Quarter Lags**	**4 Quarter Lags**	**5 Quarter Lags**	**6 Quarter Lags**
1974Q4-2016Q3	PPI	Nominal	0.006897	0.006877	0.006585	0.006505	0.006452
1974Q4 2007Q4	PPI	Nominal	0.007015	0.006999	0.006638	0.006596	0.006562
1974Q4-2016Q3	PPI	Real	0.006858	0.006839	0.006723	0.006379	0.006328
1974Q4 2007Q4	PPI	Real	0.006983	0.006964	0.006553	0.006500	0.006462
1978Q2 2016Q3	RAC	Nominal	0.006820	0.006724	0.006555	0.006537	0.005947
1978Q2 2007Q4	RAC	Nominal	0.006952	0.006883	0.006700	0.006699	0.006005
1978Q2 2016Q3	RAC	Real	0.006779	0.006683	0.006583	0.006528	0.005974
1978Q2 2007Q4	RAC	Real	0.006906	0.006856	0.006984	0.006726	0.006052

Table 2: RMSE for MIDAS regressions with 4 Quarter Lags on GDP and Various Monthly Lags

Sample	**Oil Measure**	**Price Adjustment**	**3 Monthly Lags**	**6 Monthly Lags**	**12 Monthly Lags**	**15 Monthly Lags**	**18 Monthly Lags**
1974Q4-2016Q3	PPI	Nominal	0.006787	0.006702	0.006051	0.005977	0.005957

1974Q4 2007Q4	PPI	Nominal	0.006822	0.006700	0.005979	0.005889	0.005764
1974Q4-2016Q3	PPI	Real	0.006772	0.006626	0.005838	0.005736	0.005729
1974Q4 2007Q4	PPI	Real	0.006832	0.006720	0.005880	0.005768	0.005688
1978Q2 2016Q3	RAC	Nominal	0.006679	0.006628	0.006343	0.005665	0.005593
1978Q2 2007Q4	RAC	Nominal	0.006787	0.006742	0.006374	0.005456	0.005274
1978Q2 2016Q3	RAC	Real	0.006686	0.006796	0.005910	0.005791	0.005533
1978Q2 2007Q4	RAC	Real	0.006795	0.006766	0.005889	0.005764	0.005350

There is no clear consensus in the literature on the correct lag specification to use when defining the model. Hamilton (2011) recommends lagging 4 quarters while Kilian and Vigfusson (2011a) recommend 6 quarter lags, while also including the contemporaneous values for the oil price and shock measure (from t=0 to t-6). As Hamilton (2011) explains, if the true number of lags is 4, then adding more lags will reduce the strength of the forecast, but if the true model contains more than 4 lags, then it can be argued that leaving them out of his estimation may have led him to falsely conclude that shocks are asymmetric in some situations. The tables below compare the AIC, SIC and HQ for the two models with different lag specifications. For each test, the number of lags on GDP is four quarters. The columns for 12 lags in table 4 shows the three information criterion for the AR U-MIDAS regression with 12 monthly lags. The regressors for this specification take into account the same time frame as the regressors in Hamilton's model do (one year), and so this specification provides our base of comparison.

Tables 3-5: AIC SIC BIC, and HQ for Simply Averaged Model at Lag Specifications 1-8

Table 3:

Sample	Oil Measure	Price Adjustment	1 Lags AIC	1 Lags SIC	1 Lags HQ	2 Lags AIC	2 Lags SIC	2 Lags HQ
1974Q4-2016Q3	PPI	Nominal	-7.031993	-6.901828	-6.979166	-7.014052	-6.846697	-6.946131
1974Q4 2007Q4	PPI	Nominal	-6.976224	-6.824101	-6.914407	-6.950883	-6.755296	-6.871404
1974Q4-2016Q3	PPI	Real	-7.043344	-6.913179	-6.990517	-7.025074	-6.857718	-6.957153
1974Q4 2007Q4	PPI	Real	-6.985427	-6.833303	-6.923610	-6.960907	-6.765319	-6.881428
1978Q2 2016Q3	RAC	Nominal	-7.049260	-6.913576	-6.994157	-7.051704	-6.876505	-6.980549
1978Q2 2007Q4	RAC	Nominal	-6.985658	-6.825615	-6.920649	-6.971893	-6.765039	-6.887875
1978Q2 2016Q3	RAC	Real	-7.059073	-6.921030	-7.003000	-7.061543	-6.884058	-6.989449
1978Q2 2007Q4	RAC	Real	-6.995324	-6.831847	-6.928941	-6.976202	-6.766016	-6.890852

Table 4:

Sample	Oil Measure	Price Adjustment	3 Quarter Lags AIC	3 Quarter Lags SIC	3 Quarter Lags HQ	4 Lags AIC	4 Lags SIC	4 Lags HQ
1974Q4-2016Q3	PPI	Nominal	-7.016403	-6.811858	-6.933388	-7.053313	-6.811578	-6.955205
1974Q4 2007Q4	PPI	Nominal	-6.947880	-6.708828	-6.850738	-6.996376	-6.713860	-6.881572
1974Q4-2016Q3	PPI	Real	-7.042825	-6.838279	-6.959810	-7.089625	-6.847890	-6.991517

1974Q4 2007Q4	PPI	Real	-6.969447	-6.730395	-6.872305	-7.022441	-6.739926	-6.907638
1978Q2 2016Q3	RAC	Nominal	-7.030847	-6.815793	-6.943501	-7.049375	-6.794120	-6.945696
1978Q2 2007Q4	RAC	Nominal	-6.942967	-6.688804	-6.839742	-6.956681	-6.654703	-6.834046
1978Q2 2016Q3	RAC	Real	-7.044601	-6.827676	-6.956486	-7.039907	-6.783541	-6.935772
1978Q2 2007Q4	RAC	Real	-6.950169	-6.693276	-6.845853	-6.932835	-6.629233	-6.809552

Table 5:

Sample	Oil Measure	Price Adjustment	5 Quarter Lags			6 Quarter Lags		
			AIC	SIC	HQ	AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-7.054003	-6.775078	-6.940801	-7.046559	-6.730444	-6.918264
1974Q4 2007Q4	PPI	Nominal	-6.979022	-6.653043	-6.846557	-6.959372	-6.589928	-6.809244
1974Q4-2016Q3	PPI	Real	-7.093015	-6.814090	-6.979814	-7.085127	-6.769012	-6.956832
1974Q4 2007Q4	PPI	Real	-7.008424	-6.682444	-6.875958	-6.990179	-6.620736	-6.840051
1978Q2 2016Q3	RAC	Nominal	-7.027904	-6.732097	-6.907748	-7.189635	-6.852920	-7.052856
1978Q2 2007Q4	RAC	Nominal	-6.921722	-6.571412	-6.779472	-7.104406	-6.705240	-6.942333
1978Q2 2016Q3	RAC	Real	-7.030648	-6.734841	-6.910492	-7.180551	-6.843835	-7.043771
1978Q2 2007Q4	RAC	Real	-6.913489	-6.563180	-6.771240	-7.088732	-6.689565	-6.926658

Table 6:

Sample	Oil Measure	Price Adjustment	8 Quarter Lags		
			AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-7.018307	-6.627812	-6.859825
1974Q4 2007Q4	PPI	Nominal	-6.929243	-6.472872	-6.743791
1974Q4-2016Q3	PPI	Real	-7.061227	-6.670732	-6.902745
1974Q4 2007Q4	PPI	Real	-6.961573	-6.505202	-6.776121
1978Q2 2016Q3	RAC	Nominal	-7.164274	-6.744652	-6.993801
1978Q2 2007Q4	RAC	Nominal	-7.091414	-6.592920	-6.889054
1978Q2 2016Q3	RAC	Real	-7.157477	-6.737855	-6.987004
1978Q2 2007Q4	RAC	Real	-7.071650	-6.573155	-6.869290

Tables 7-12: AIC, SIC and HQ for the AR U-MIDAS at Various Monthly Lag Selections

Table 7:

Sample	Oil Measure	Price Adjustment	3 Lags			4 Lags		
			AIC	SIC	HQ	AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-7.016709	-6.812164	-6.933695	-7.00079	-6.75906	-6.90268
1974Q4 2007Q4	PPI	Nominal	-6.971827	-6.732776	-6.874686	-6.95896	-6.67644	-6.84415
1974Q4-2016Q3	PPI	Real	-7.020995	-6.816450	-6.937981	-7.00527	-6.76354	-6.90717
1974Q4 2007Q4	PPI	Real	-6.969036	-6.729984	-6.871894	-6.95831	-6.6758	-6.84351
1978Q2 2016Q3	RAC	Nominal	-7.036765	-6.819840	6.948651	-7.01418	-6.75782	-6.91005
1978Q2 2007Q4	RAC	Nominal	-6.962874	-6.705980	6.858557	-6.965911	-6.802433	-6.899528
1978Q2 2016Q3	RAC	Real	-7.042023	-6.825098	-6.953909	-7.019833	-6.881789	-6.963760
1978Q2 2007Q4	RAC	Real	-6.935921	-6.679027	-6.831604	-6.959813	-6.796335	-6.893430

Table 8:

Sample	Oil Measure	Price Adjustment	6 Monthly Lags			7 Monthly Lags		
			AIC	SIC	HQ	AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-6.970464	-6.654349	-6.842169	-6.97983	-6.62652	-6.83644
1974Q4 2007Q4	PPI	Nominal	-6.917819	-6.548376	-6.767691	-6.94013	-6.52723	-6.77234

1974Q4-2016Q3	PPI	Real	-6.993255	-6.677139	-6.864960	-7.01835	-6.66504	-6.87496
1974Q4 2007Q4	PPI	Real	-6.911838	-6.542395	-6.761710	-6.93898	-6.52608	-6.77119
1978Q2 2016Q3	RAC	Nominal	-6.974157	-6.638909	-6.837981	-6.84235	-6.39863	-6.66217
1978Q2 2007Q4	RAC	Nominal	-6.875182	-6.478164	-6.713966	-6.95268	-6.57799	-6.80048
1978Q2 2016Q3	RAC	Real	-6.998327	-6.663079	-6.862150	-6.83755	-6.39383	-6.65737
1978Q2 2007Q4	RAC	Real	-6.868140	-6.471122	-6.706923	-6.95438	-6.57969	-6.80218

Table 9: AIC, SIC and HQ for 9 and 10 monthly lag specifications

Sample	Oil Measure	Price Adjustment	9 Lags			10 Lags		
			AIC	SIC	HQ	AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-6.95754	-6.52985	-6.78396	-7.06601	-6.60114	-6.87734
1974Q4 2007Q4	PPI	Nominal	-6.92315	-6.42331	-6.72004	-7.00333	-6.46003	-6.78255
1974Q4-2016Q3	PPI	Real	-7.00126	-6.57357	-6.82768	-7.13014	-6.66526	-6.94147
1974Q4 2007Q4	PPI	Real	-6.93553	-6.4357	-6.73242	-7.03921	-6.49591	-6.81844
1978Q2 2016Q3	RAC	Nominal	-6.94247	-6.4889	-6.75823	-6.92532	-6.43231	-6.72506
1978Q2 2007Q4	RAC	Nominal	-6.83227	-6.29513	-6.61415	-6.80901	-6.22516	-6.57193
1978Q2 2016Q3	RAC	Real	-6.93229	-6.47872	-6.74805	-6.92126	-6.42825	-6.721
1978Q2 2007Q4	RAC	Real	-6.8118	-6.27465	-6.59368	-6.76277	-6.17892	-6.52568

Table 10 AIC, SIC and HQ for 11 and 12 monthly lag specifications

Sample	Oil Measure	Price Adjustment	11 Lags			12 Lags		
			AIC	SIC	HQ	AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-7.05506	-6.55299	-6.8513	-7.031825	-6.492570	-6.812969
1974Q4 2007Q4	PPI	Nominal	-6.98588	-6.39912	-6.74744	-6.965185	-6.334958	-6.709085
1974Q4-2016Q3	PPI	Real	-7.11996	-6.6179	-6.9162	-7.103472	-6.564216	-6.884616
1974Q4 2007Q4	PPI	Real	-7.02335	-6.43659	-6.78491	-6.998536	-6.368309	-6.742436
1978Q2 2016Q3	RAC	Nominal	-6.92482	-6.39237	-6.70854	-6.906410	-6.334516	-6.674108
1978Q2 2007Q4	RAC	Nominal	-6.81722	-6.18666	-6.56117	-6.785697	-6.108431	-6.510681
1978Q2 2016Q3	RAC	Real	-6.89544	-6.36299	-6.67916	-7.045224	-6.470827	-6.811895
1978Q2 2007Q4	RAC	Real	-6.76219	-6.13163	-6.50614	-6.939988	-6.259057	-6.663510

Table 11: AIC, SIC and HQ for 13 and 15 monthly lag specifications

Sample	Oil Measure	Price Adjustment	13 Monthly Lags			15 Monthly Lags		
			AIC	SIC	HQ	AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-7.01574	-6.43929	-6.78179	-6.985029	-6.334203	-6.720892
1974Q4 2007Q4	PPI	Nominal	-6.94717	-6.27347	-6.6734	-6.905242	-6.144623	-6.596155
1974Q4-2016Q3	PPI	Real	-7.08698	-6.51054	-6.85303	-6.946494	-6.185876	-6.637408
1974Q4 2007Q4	PPI	Real	-6.97644	-6.30275	-6.70268	-6.946494	-6.185876	-6.637408
1978Q2 2016Q3	RAC	Nominal	-6.88935	-6.27801	-6.64103	-7.051662	-6.358425	-6.770058
1978Q2 2007Q4	RAC	Nominal	-6.78169	-6.05772	-6.48771	-6.991135	-6.169321	-6.657454
1978Q2 2016Q3	RAC	Real	-6.85877	-6.24744	-6.61045	-7.004430	-6.308142	-6.721573

1978Q2 2007Q4	RAC	Real	-6.72672	-6.00274	-6.43273	-6.876176	-6.049884	-6.540711

Table 12: AIC, SIC and HQ for 24 monthly lag specifications

Sample	Oil Measure	Price Adjustment	24 Monthly Lags		
			AIC	SIC	HQ
1974Q4-2016Q3	PPI	Nominal	-6.86261	-5.87707	-6.46263
1974Q4 2007Q4	PPI	Nominal	-6.75815	-5.60635	-6.2901
1974Q4-2016Q3	PPI	Real	-6.95252	-5.96698	-6.55254
1974Q4 2007Q4	PPI	Real	-6.80546	-5.65367	-6.33742
1978Q2 2016Q3	RAC	Nominal	-7.15008	-6.08632	-6.71791
1978Q2 2007Q4	RAC	Nominal	-6.80546	-5.65367	-6.33742
1978Q2 2016Q3	RAC	Real	-7.09584	-6.03208	-6.66367
1978Q2 2007Q4	RAC	Real	-7.01713	-5.75207	-6.50365

By looking at Tables 7-12, we can see that the fit of the AR U-MIDAS regression can be improved by decreasing the number of lags used to 3, 6, or 10, with a specification of 6 monthly lags providing weaker results than 3 or 10. If a lag specification of 15, 18, 21, 24 months is used, the fit of the model will decrease. We note that a lag specification of 10 months will lower the AIC, SIC, and HQ for every period for real and nominal PPI and nominal RAC, but will lower the accuracy of the model when we are using real RAC. Comparing the information criterion for the estimation with 10 monthly lags with the estimation using 3 monthly lags, we see that the AIC is lower for both real and nominal PPI estimations when 10 monthly lags is used, but the SIC and HQ are all higher. For the estimation using the RAC (real and nominal) the three criterions are smaller when 3 lags are used. This suggests that specifying 10 monthly lags may be better suited for forecasting using PPI, while 3 monthly lags could be better when we are using RAC. To determine if this is the case we test the null hypothesis H_0: $\omega^1_4 = \cdots \omega^1_{10} = \omega^2_4 = \cdots \omega^2_{10} = 0$ on the regression:

$$y_t^q = \alpha + \sum_{i=1}^{4} \phi_i \, y_{t-i} + \sum_{r_1=0}^{9} \omega^1_{1+r_1} x^m_{t-4-r_1} + \sum_{r_2=0}^{9} \omega^2_{1+r_2} \varphi^m_{t-4-r_2} + \varepsilon_t$$

Table 13 summarizes these results. We see that for PPI, 10 monthly lags will better specify the regression than 3.

Table 13:

Sample	Oil Measure	Price Adjustment	P-value
1974Q4-2016Q3	PPI	Nominal	0.00094637
1974Q4 2007Q4	PPI	Nominal	0.00376938
1974Q4-2016Q3	PPI	Real	0.00002470
1974Q4 2007Q4	PPI	Real	0.00065666
1978Q2 2016Q3	RAC	Nominal	0.69877532
1978Q2 2007Q4	RAC	Nominal	0.78446457

1978Q2 2016Q3	RAC	Real	0.82885350
1978Q2 2007Q4	RAC	Real	0.93190857

Similarly, the strength of the simply averaged model can be improved by lagging 1 or 2 quarters instead of 4. The forecasting accuracy with real and nominal RAC is improved by reducing the number of quarterly lags of the oil price and shock measure regressors to 1 or 2, while the AIC and HQ are increased when these lag specifications are used if estimating is done with nominal or real PPI. Specifying 6 quarter lags will increase the fit of the model when the RAC (nominal or real) is used, but will decrease the fit when PPI is used. Specifying 3, 5, or 8 quarter lags will reduce the power of the model. These results show the importance of considering how differences in the price of oil will affect how many lags should be used to model the regression.

Section 6: Testing for Asymmetries

Evaluating the presence of asymmetries using the AR U-MIDAS is done with a likelihood ratio test to test the null hypothesis of symmetry: H_0: $\omega_1^2 = \omega_2^2 = \cdots = \omega_K^2 = \mathbf{0}$, where k is the number of monthly lags. For Hamilton's simply averaged model, he tests the null hypothesis of symmetry H_0: $\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = \mathbf{0}$ using a Wald Test. Table 10 compares the results for the tests using Hamilton's model with simple data averaging for high frequency variables and the results computed using the AR U-MIDAS model with twelve monthly lags (K=12) and 4 quarterly lags on the autoregressive component.

Table 10: P-Values for The Simply Averaged Model and the AR U-MIDAS for One Year Lags and No Contemporaneous variables

Sample	**Oil Measure**	**Price Adjustment**	**P-Values**	
			Simply AVG Model	**AR U-MIDAS**
1974Q4-2016Q3	PPI	Nominal	0.0004	0.00000783
1974Q4 2007Q4	PPI	Nominal	0.0024	0.00013222
1974Q4-2016Q3	PPI	Real	0.0000	0.00000005
1974Q4 2007Q4	PPI	Real	0.0005	0.00001835
1978Q2 2016Q3	RAC	Nominal	0.0048	0.01373712
1978Q2 2007Q4	RAC	Nominal	0.0831	0.10702817
1978Q2 2016Q3	RAC	Real	0.0057	0.00006849
1978Q2 2007Q4	RAC	Real	0.1370	0.00091448

When testing from the earliest possible period following the structural break in 1973, the p-values for both the significance of the resulting coefficients for real and nominal PPI suggest asymmetry at a significance level less than 0.001% for the sample periods stopping at the fourth quarter of 2007, and for those continuing until the second period of 2016. The p-values from testing for the significance of the coefficients of Hamilton's time averaged model also suggest asymmetry for these periods at a significance level less than 0.01%. Like in Hamilton's test, the p-values become less significant for the tests using the RAC. In line with Kilian and Vigfusson's results, Hamilton's model is not able to reject the null hypothesis of symmetry for the period of 1978Q2 to 2007Q4 for both real and nominal values of RAC. The AR U-MIDAS fails to reject the null of asymmetry only for the specification with the real RAC, not the nominal RAC. Extending the data set to 2016Q3, however, results in a rejection of the null hypothesis of symmetry. This is the case for Hamilton's test as well as for the AR U-MIDAS. Kilain and Vigfusson (2011) argue that if data from the financial crisis is included (information following 2007Q4), then all evidence of asymmetries disappear. Our results show that this is not the case. This suggests that the differences in the results found by Kilian and Vigfusson (2011) may be caused by loss in accuracy due to a smaller sample size or from averaging the monthly data into quarterly values.

Both the simply averaged model and the AR U-MIDAS regression, when tested using one year lag specifications on their regressors, suggest that asymmetry is probable. However, these models are not able to explain the lack of asymmetry for the periods 1978Q2 to 2007Q4 when real RAC is used. As Section 5 showed, a one year lag specification may not be ideal and so it is possible that asymmetry can be detected for this period using the RAC if a different lag specification is used.

6.1: Testing for Asymmetries using Different Lag Specifications

This section will test for the null of symmetry using different lag specifications on the AR U-MIDAS and the OLS model with simple averaging. The resulting p-values for the tests using the AR U-MIDAS are summarized in Tables 11, and 12, while Table 13 reports the p-values for the tests using the simply averaged model.

For tests with the AR U-MIDAS, when 6 and 10 monthly lags are used, the null of symmetry is not rejected if the regression is done using the real or nominal RAC, while if the PPI (real or nominal) is used, the null of symmetry is rejected. If the number of lags is increased to 15, 18, or 21 the AR U-MIDAS detects asymmetry using the RAC specification.

As section 5 showed, specifying 3 monthly lags will lead to better results when the RAC is used to rather than the PPI. For the 3-month lag specification, asymmetry is detected at the 5% level for all periods except when the nominal RAC is used to forecast during the period 1978Q2 to 2007Q4, which detects asymmetry at the 7% level. Similarly, the simply averaged model at one quarter lags can detect asymmetry using both the PPI and the RAC.

Tables 11 and 12: Asymmetry Tests using the AR U-MIDAS at Various Lag Specifications

Table 11:

Sample	Oil Measure	Price Adjustment	P-Values			
			3 lags	6 lags	10 lags	15 lags
1974Q4-2016Q3	PPI	Nominal	0.00145055	0.00325927	0.00000384	0.00004077
1974Q4 2007Q4	PPI	Nominal	0.01113233	0.01994634	0.00010377	0.00096255
1974Q4-2016Q3	PPI	Real	0.00098846	0.00064373	0.00000004	0.00000019
1974Q4 2007Q4	PPI	Real	0.01110360	0.02420786	0.00001154	0.00011153
1978Q2 2016Q3	RAC	Nominal	0.00283814	0.01526349	0.02666422	0.00000808
1978Q2 2007Q4	RAC	Nominal	0.06604106	0.24424740	0.21386765	0.00005097
1978Q2 2016Q3	RAC	Real	0.00288291	0.00438216	0.02767977	0.00163378
1978Q2 2007Q4	RAC	Real	0.02114497	0.13630098	0.34205911	0.01767687

Table 12:

Sample	Oil Measure	Price Adjustment	P-Values	
			18 lags	21 lags
1974Q4-2016Q3	PPI	Nominal	0.00033829	0.00099884
1974Q4 2007Q4	PPI	Nominal	0.00119358	0.00383649
1974Q4-2016Q3	PPI	Real	0.00000337	0.00000793
1974Q4 2007Q4	PPI	Real	0.00030520	0.00056949
1978Q2 2016Q3	RAC	Nominal	0.00031312	0.00049411
1978Q2 2007Q4	RAC	Nominal	0.00055569	0.00258630
1978Q2 2016Q3	RAC	Real	0.00385780	0.00024001
1978Q2 2007Q4	RAC	Real	0.01809642	0.00327951

Table 13: Asymmetry Tests various lag specifications simply averaged model

Sample	Oil	Price	P-Values

	Measure	Adjustment	1 lag	2 lags	3 lags	5 lags	6 lags
1974Q4-2016Q3	PPI	Nominal	0.0011	0.0033	0.0018	0.0002	0.0003
1974Q4 2007Q4	PPI	Nominal	0.0123	0.0337	0.0177	0.0033	0.0078
1974Q4-2016Q3	PPI	Real	0.0004	0.0013	0.0002	0.0000	0.0000
1974Q4 2007Q4	PPI	Real	0.0052	0.0149	0.0040	0.0006	0.0011
1978Q2 2016Q3	RAC	Nominal	0.0011	0.0013	0.0036	0.0062	0.0029
1978Q2 2007Q4	RAC	Nominal	0.0248	0.0557	0.0990	0.1185	0.1705
1978Q2 2016Q3	RAC	Real	0.0015	0.0008	0.0017	0.0048	0.0042
1978Q2 2007Q4	RAC	Real	0.0308	0.0447	0.0732	0.1310	0.2080

Section 7: Conclusion

This paper tested for asymmetries in the real GDP's response to oil price shocks by using an AR U-MIDAS regression and various lag specifications to improve the forecasting strength of the model proposed in Hamilton (2003) and (2011). The purpose of this exercise was to assess the issues brought up by Kilian and Vigfusson (2011a) and (2011b), and to see if they are alleviated when a more statistically suitable model is used. The issues of concern were that Hamilton's aggregated OLS model could not detect asymmetries when the RAC oil price specification is used to test from 1974Q4 to 2007Q4. By incorporating different lag specifications and using the AR U-MIDAS, it was possible to find evidence of asymmetries for both the nominal and real RAC for the periods 1978Q2 to 2007Q4 and 1978Q2 to 2016Q3. Furthermore, no evidence was found contradicting the previous conclusions of asymmetry when the PPI is used for testing. In addition, it was found that when testing is conducted using the AR U-MIDAS PPI, using a 10 month lag specification is the optimal amount, while when testing is done using the RAC, a lag specification of 3 months will be best. Consequently, for both the PPI and the RAC, when the fit of the model is improved, evidence of asymmetries can be found.

An interesting extension to this paper would be to incorporate the MIDAS regressor into Kilian and Vigfusson's impulse response based method of testing to see how this affects their results.

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