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Improving the predictive ability of oil for inflation: An ADL-MIDAS Approach

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Abstract

This paper attempts to improve the predictive ability of oil for inflation by incorporating mixed data sampling regression model into the autoregressive distributed lag model. The efficiency of the conventionally used models, which are based on same frequency of variables, is challenged on the basis of the concealed information in low frequency series. Using data covering OECD countries, we find that the ADL-MIDAS seems to outperform all the other competing models, a feat attributable to the integration of more information from a higher frequency oil price series in the forecast of a low frequency inflation series. In addition, including oil price in inflation model produces more accurate results than the model that excludes it.

JEL Classification: C53, E31, E37

Keywords: OECD countries, ADL-MIDAS, Inflation forecasts, Forecast evaluation

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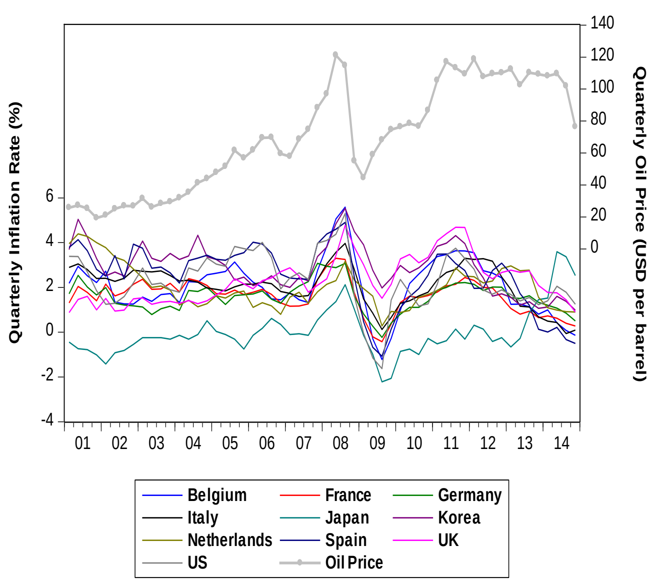
1.0 Introduction

The need to produce accurate inflation forecast is considered a necessary condition for effective monetary policy decisions and in forming expectations about the future direction of policy thrusts. The increasing evidence on the role of oil price in producing accurate inflation forecast is a major motivation for this work. We are particularly motivated by two papers - Coibion and Gorodnichencko (2015) and Salisu et al. (2017a,b) both of which justify the significant role of oil price in the modeling of inflation. For instance, Coibion and Gorodnichencko (2015) argue, among other things, that the increase in inflation during the global financial crisis was driven largely by increases in oil prices. A clearer demonstration of the comovement between oil price and inflation is also illustrated in Figure 1. Although there are several other studies on inflation forecasting (see for example, Ascari and Marrocu, 2003 Canova, 2007; Stock and Watson, M., 2008); however, all these studies do not account for the role of oil price and Salisu et al. (2017b) demonstrate that forecasting inflation this way may produce less desirable results (see also Chen et al., 2014).

Figure1: Oil Price & Inflation



Source: Salisu et al. (2017a)

In this paper, we attempt to take a departure from the existing literature on inflation forecasting including those that involve oil-inflation forecasting. Specifically, we examine how the predictive ability of oil price in inflation forecast can be enhanced through the use of mixed data sampling (MIDAS) regression models which allow for mixed data frequencies in the one regression model. The idea is to capture potentially useful information available at higher frequencies (in this case, oil price) in the forecasting of inflation. Hitherto the development of MIDAS regressions, the estimation and forecasting of models were constrained to include variables sampled on same frequency. However, with more recent developments in time series analyses, it is now becoming increasingly feasible to incorporate data from different frequencies in the same regression model (see Ghysels *et al*., 2002; Ghysels *et al*., 2006a and Andreou *et al*., 2010). This approach has been prominently applied to forecast output growth (see Clements and Galavao, 2009; Foroni and Marcellino, 2014; Barsoum and Stankiewicz, 2015). However, virtually all the studies on inflation forecasting involve the use of uniform data frequency. The few exceptions however are Clements and Galavao (2006) and Li et al. (2015) which consider high frequency series in forecasting inflation. Nonetheless, to the best of our knowledge, no study has applied the MIDAS approach to account for the role of higher frequency oil price in inflation forecasting. Specifically, we consider the Autoregressive Distributed Lag Mixed Data Sampling (ADL-MIDAS) regression model. Unlike other versions of autoregressive/distributed lag models (with uniform frequency) such as Random Walk and Autoregressive Distributed Lag (ARDL) models, the ADL-MIDAS regression model allows for more dynamics but with fewer parameters. The response to the higher frequency explanatory variables is modelled using highly parsimonious distributed lag polynomials, as a way of preventing the proliferation of parameters that might otherwise result, and as a way of side-stepping difficult issues to do with lag-order selection (Clements and Galavao, 2006). In other words, modelling the coefficients on the lagged explanatory variables as a distributed lag function allows for long lags with only a small number of parameters needing to be estimated (Clements and Galavao, 2006).

In addition, we consider a large sample of countries using OECD data in order to render more useful generalizations on the subject. For the purpose of robustness, we also compare the forecast performance of the ADL-MIDAS approach with models involving uniform frequency such as the Random Walk model and the ARDL model specified for both the demand-side (Phillips curve based) model and the supply side variant.

The rest of the paper is structured as follows: Section 2 provides the model set up including the forecast performance measures and data issues. In Section 3, we present and discuss the results while Section 4 concludes the paper.

2.0 The Model and Data

The data utilized cover quarterly consumer price index (cpi) and industrial production index and monthly benchmark crude oil price $(oilp)$, with West Intermediate Texas (WTI) and Brent prices used as proxies. We cover all the thirty-five (35) OECD countries over the period of 2000 to 2016. The log-transformed series is subdivided for estimation and forecast purposes, with periods 2001 to 2014 used as in-sample estimation and forecast, while the remaining period (2015 to 2016) is used for the out-of-sample forecast. The competing models are discussed in subsequent sub-sections.

2.1 ADL-MIDAS approach

Mixed data sampling (MIDAS) regression is a flexible class of time series models that incorporates variables sampled at different frequencies into one regression model. It is characterized by response and predictor variables sampled at lower and higher frequencies, respectively (*see* Forsberg and Ghysels, 2006; Clements and Galavao, 2006; Kotze, 2007; Tay, 2007; Alper *et al*., 2008 and Bai *et al*., 2009). A special case of the MIDAS regression, the ADL-MIDAS regression model (see Ghysels *et al*., 2009, Andreou *et al*., 2013b and Ghysels, 2016), incorporates lagged dependent, and current and lagged independent variables. It projects a low frequency series at some horizon, unto its one or more time lags and a higher frequency dependent variable. The model for the oil price-inflation nexus follows the Van Hoang et al. (2016)[1] and is specified in ADL-MIDAS form as given below:[2]

$$\pi_t = c + \sum\nolimits_{j=1}^{2} \alpha_j \pi_{t-j} + \sum\nolimits_{j=0}^{3} \beta_j p_{4t-j} + \varepsilon_t \tag{1}$$

where the dependent variable, π_t is defined by $\log\left(cpi_t / cpi_{t-1}\right)$; the independent variable, p_t is defined by $\log\left(oilp_t / oilp_{t-1}\right)$; c represents the constant; α_j and β_j represent the midas lag structure for the dependent and independent variables, respectively; and the disturbance term, $\varepsilon \sim N(0,1)$. The equation (1) is a basic ADL-MIDAS model for a single explanatory variable.

2.2 Autoregressive Distributed Lag (ARDL) approach

As previously noted, we also consider a battery of models with uniform frequency in order to further verify and validate the plausibility of using mixed data frequencies when forecasting inflation. One of the prominent models used in the literature to analyze the oil price-inflation nexus is the ARDL by Pesaran and Shin (1995) and Pesaran et al. (1996b) model (see Van Hoang et al., 2016 and Salisu et al., 2017). This model incorporates the lagged dependent, and the current and lagged independent variables as regressors in a time series regression model. An ARDL (m,n) model is specified below:

$$\pi_t = \alpha + \sum_{i=1}^{m} \delta_i \pi_{t-i} + \sum_{j=0}^{n} \gamma_j p_{t-j} + \varepsilon_t \tag{2}$$

[1] The inflation model specified this way plays a high premium on the supply side factor(s) than the Demand side (Phillips curve based) factor(s).

[2] Please see Clements and Galavao (2006) for more expositions on the specification details of the ADL-MIDAS.

The variables have been defined previously. The parsimonious model obtained via the Hendry general-to-specific approach is used for forecasting. Note that equation (2) is the ARDL version of the supply-side (oil-based) Inflation model which is also expressed in ADL-MIDAS form in equation (1).

We further consider the Demand-side (Phillips curve-based) Inflation model that captures output-inflation tradeoffs. This model has remained a workhorse when dealing with Inflation forecasting and most studies often times compare its performance with time series models. The model is also expressed in ARDL form in order to facilitate its comparison with other models.

$$\pi_t = \alpha + \sum_{i=1}^{p} \delta_i \pi_{t-i} + \sum_{j=0}^{q} \gamma_j y_{t-j} + \varepsilon_t \tag{3}$$

where y_t is the output proxied by industrial production index and other variables have been previously defined.

2.3 Random Walk Model (RWM)

Another commonly employed time series forecast model, the random walk model, specifies a series as a function of its own lag and trivially, variables on both sides of the equation have the same frequency level. Two likely scenarios of RWM are considered - the random walk with and without drift. The model is given as

$$\pi_t = \mu + \pi_{t-1} + \varepsilon_t \tag{4}$$

where π_t and ε_t are as defined previously and μ is the drift parameter such that $\mu = 0$, $\mu < 0$ and $\mu > 0$ imply no drift, negative and positive drifts, respectively.

2.4 Forecast Measures

As customary when forecasting, we employ the Root Mean Square Error (RSME) to evaluate the forecast performance of the models considered in this study. If we define the full-sample period as $t = T+1,....,T+m,$[3] where T is the in-sample period while m is the forecast horizon, then the RMSE for the two sub-periods can be calculated as follows:

In-Sample: $$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\hat{\pi}_t - \pi_t\right)^2} \quad (5a)$$

Out-of-Sample: $$RMSE = \sqrt{\frac{1}{m}\sum_{t=T+1}^{T+m}\left(\hat{\pi}_t - \pi_t\right)^2} \quad (5b)$$

The lower the RMSE, the better the forecast performance and thus, the model with the least RMSE among the competing models is considered the best inflation forecast model.

3.0 Results and Discussion

Table 1 below presents the forecast performance for ADL-MIDAS in comparison with the four other competing models - the traditional ARDL for the demand side (Phillips curve-based) and supply side (cost-push/oil based) inflation models, the Random Walk Model with Drift (RWWD) and without Drift (RWWOD). For each of the models, we analyze the in-sample and out-of-sample ($m = 4$ and $m = 8$) forecast accuracy. Also, we utilize the WTI oil price for the main analyses while the Brent oil price is considered for robustness. The figures in Table 1 represent the root mean square errors corresponding to the estimation and forecast periods for each model and each country. While all the values are close to zero, indicating a high forecast precision for all the competing models, the model that consistently has the least RMSE in the most cases considered is preferred.

The number of times each model is preferred over other competing models is presented in Table 2. In the table, which shows the frequency distribution of forecast performance

[3] Please see Ghysels, 2016 for the ADL-MIDAS forecast horizon construct.

for each model considered, the order of performance seems to follow a similar pattern, with the best and worst performed models being ADL-MIDAS and RWWOD, respectively. This performance is consistent across the models regardless of the forecast sample periods considered. In other words, both ADL-MIDAS and ARDL models (ARDL-1 & ARDL-2) outperformed the random walk models in forecasting inflation.

Table 1: Inflation Forecast Performance Using RMSE

COUNTRY	IN-SAMPLE					OUT-OF-SAMPLE									
						ADL-MIDAS		ARDL-1		ARDL-2		RWWD		RWWOD	
	ADL-MIDAS	ARDL-1	ARDL-2	RWWD	RWWOD	$m=4$	$m=8$	$m=4$	$m=8$	$m=4$	$m=8$	$m=4$	$m=8$	$m=4$	$m=8$
Australia	0.0035	0.0054	0.0055	0.0058	0.0089	0.0008	0.0030	0.0018	0.0037	0.0040	0.0053	0.0035	0.0043	0.0045	0.0048
Austria	0.0039	0.0040	0.0041	0.0042	0.0065	0.0041	0.0040	0.0035	0.0030	0.0073	0.0065	0.0070	0.0062	0.0065	0.0063
Belgium	0.0041	0.0039	0.0049	0.0051	0.0069	0.0029	0.0029	0.0056	0.0054	0.0026	0.0032	0.0028	0.0031	0.0043	0.0051
Canada	0.0047	0.0046	0.0059	0.0062	0.0077	0.0040	0.0041	0.0048	0.0044	0.0060	0.0064	0.0053	0.0051	0.0061	0.0060
Chile	0.0071	0.0073	0.0083	0.0083	0.0113	0.0052	0.0043	0.0123	0.0098	0.0048	0.0038	0.0051	0.0041	0.0111	0.0094
Czech	0.0081	0.0083	0.0081	0.0085	0.0101	0.0040	0.0036	0.0052	0.0043	0.0072	0.0056	0.0068	0.0051	0.0042	0.0040
Denmark	0.0046	0.0046	0.0048	0.0048	0.0066	0.0031	0.0038	0.0035	0.0039	0.0050	0.0051	0.0054	0.0050	0.0039	0.0035
Estonia	0.0070	0.0085	0.0089	0.0095	0.0127	0.0101	0.0080	0.0085	0.0072	0.0110	0.0089	0.0128	0.0101	0.0081	0.0065
Finland	0.0045	0.0045	0.0046	0.0048	0.0061	0.0030	0.0030	0.0032	0.0032	0.0055	0.0049	0.0056	0.0050	0.0032	0.0036
France	0.0035	0.0034	0.0039	0.0041	0.0056	0.0030	0.0037	0.0027	0.0032	0.0069	0.0063	0.0063	0.0060	0.0051	0.0052
Germany	0.0026	0.0027	0.0030	0.0032	0.0050	0.0012	0.0020	0.0020	0.0024	0.0044	0.0043	0.0046	0.0043	0.0036	0.0042
Greece	0.0102	0.0123	0.0124	0.0138	0.0153	0.0145	0.0150	0.0098	0.0093	0.0147	0.0153	0.0143	0.0151	0.0122	0.0132
Hungary	0.0085	0.0101	0.0103	0.0100	0.0141	0.0067	0.0071	0.0107	0.0103	0.0128	0.0114	0.0125	0.0113	0.0080	0.0075
Iceland	0.0106	0.0115	0.0084	0.0114	0.0169	0.0092	0.0077	0.0083	0.0081	0.0072	0.0070	0.0098	0.0093	0.0074	0.0066
Ireland	0.0070	0.0067	0.0086	0.0087	0.0097	0.0053	0.0067	0.0115	0.0107	0.0092	0.0093	0.0080	0.0087	0.0064	0.0072
Israel	0.0074	0.0079	0.0090	0.0090	0.0102	0.0056	0.0056	0.0051	0.0060	0.0103	0.0094	0.0105	0.0094	0.0082	0.0072
Italy	0.0024	0.0029	0.0033	0.0034	0.0056	0.0021	0.0033	0.0024	0.0037	0.0056	0.0058	0.0053	0.0054	0.0029	0.0030
Japan	0.0051	0.0047	0.0051	0.0052	0.0052	0.0037	0.0034	0.0058	0.0050	0.0040	0.0039	0.0038	0.0039	0.0038	0.0040
Korea	0.0047	0.0049	0.0055	0.0056	0.0090	0.0043	0.0049	0.0058	0.0058	0.0050	0.0044	0.0054	0.0047	0.0034	0.0037
Latvia	0.0102	0.0136	0.0135	0.0132	0.0167	0.0155	0.0143	0.0169	0.0147	0.0142	0.0125	0.0141	0.0124	0.0101	0.0097
Luxembourg	0.0045	0.0040	0.0055	0.0052	0.0074	0.0033	0.0047	0.0038	0.0032	0.0058	0.0058	0.0059	0.0061	0.0053	0.0054
Mexico	0.0064	0.0064	0.0066	0.0066	0.0119	0.0080	0.0077	0.0070	0.0066	0.0076	0.0082	0.0077	0.0080	0.0079	0.0097
Netherlands	0.0051	0.0052	0.0053	0.0053	0.0071	0.0079	0.0068	0.0080	0.0068	0.0096	0.0082	0.0096	0.0082	0.0091	0.0077
New Zealand	0.0041	0.0044	0.0052	0.0052	0.0077	0.0043	0.0037	0.0045	0.0041	0.0068	0.0055	0.0068	0.0052	0.0038	0.0036
Norway	0.0067	0.0073	0.0073	0.0073	0.0087	0.0054	0.0057	0.0028	0.0039	0.0036	0.0044	0.0032	0.0073	0.0068	0.0081
Poland	0.0066	0.0069	0.0069	0.0069	0.0089	0.0062	0.0066	0.0075	0.0074	0.0090	0.0085	0.0090	0.0085	0.0044	0.0051
Portugal	0.0069	0.0073	0.0070	0.0072	0.0089	0.0076	0.0078	0.0070	0.0061	0.0103	0.0097	0.0113	0.0109	0.0107	0.0104
Slovakia	0.0111	0.0118	0.0118	0.0119	0.0147	0.0057	0.0070	0.0089	0.0092	0.0107	0.0100	0.0106	0.0102	0.0037	0.0037
Slovenia	0.0095	0.0095	0.0096	0.0102	0.0128	0.0085	0.0094	0.0046	0.0055	0.0138	0.0143	0.0133	0.0131	0.0091	0.0102
Spain	0.0076	0.0120	0.0105	0.0099	0.0117	0.0090	0.0115	0.0094	0.0082	0.0168	0.0163	0.0151	0.0152	0.0134	0.0143
Sweden	0.0056	0.0054	0.0057	0.0059	0.0067	0.0022	0.0018	0.0058	0.0056	0.0048	0.0037	0.0046	0.0036	0.0034	0.0039
Switzerland	0.0049	0.0063	0.0065	0.0065	0.0066	0.0047	0.0042	0.0008	0.0026	0.0047	0.0052	0.0061	0.0056	0.0051	0.0049
Turkey	0.0259	0.0301	0.0290	0.0333	0.0403	0.0166	0.0127	0.0199	0.0180	0.0151	0.0169	0.0156	0.0150	0.0218	0.0203
UK	0.0049	0.0047	0.0050	0.0051	0.0076	0.0053	0.0053	0.0030	0.0024	0.0073	0.0063	0.0070	0.0061	0.0046	0.0050
USA	0.0052	0.0051	0.0074	0.0075	0.0092	0.0036	0.0034	0.0029	0.0032	0.0089	0.0073	0.0082	0.0066	0.0071	0.0066

Note: Root Mean Square Error (RMSE), Autoregressive Distributed Lag Mixed Data Sampling (ADL-MIDAS), Autoregressive Distributed Lag (ARDL), Random Walk with and without drift (RWWD and RWWOD). Also, ARDL-1 is for the oil-based (cost-push) inflation model while ARDL-2 represents the Phillips curve based (demand-pull) inflation model. m is the m^{th} period ahead forecast.

Table 2: Frequency Distribution of Forecast Performance

	ADL-MIDAS	ARDL-1	ARDL-2	RWWD	RWWOD
In-Sample Forecast					
ADL-MIDAS	-	23:12	34:1	35:0	35:0
ARDL-1		-	29:6	30:5	34:1
ARDL-2			-	27:8	35:0
RWWD				-	35:0
RWWOD					-
Out-of-Sample Forecast $m=4$					
ADL-MIDAS	-	22:13	28:7	28:7	25:10
ARDL-1		-	26:9	27:8	20:15
ARDL-2			-	19:16	25:10
RWWD				-	27:8
RWWOD					-
Out-of-Sample Forecast $m=8$					
ADL-MIDAS	-	21:14	30:5	32:3	24:11
ARDL-1		-	26:9	27:8	19:16
ARDL-2			-	24:11	27:8
RWWD				-	24:11
RWWOD					-

Note: *Each cell has "a : b" format such that "a" represents the number of times the model on the row outperformed "b" the model on the column.*

3.1 ADL-MIDAS vs ARDL-1 (Oil-Based)

Table 3 presents the percentage comparison of each model with the benchmark model, which in this case is the ADL-MIDAS. In comparison with ARDL-1, which incorporates oil in forecasting inflation, ADL-MIDAS is preferred since it consistently outperformed the former with 66%, 63% and 60%, for the in-sample, and out-of-sample $(m=4)$ and $(m=8)$, respectively. Although both models consist of same variables, ADL-MIDAS which incorporates mixed data regression provides a better forecast for inflation as more information is available from the high frequency oil price series.

3.2 ADL-MIDAS vs ARDL-2 (Phillips curve-Based)

The traditional Phillips curve, a supply side - ARDL model (described as ARDL-2 in this paper) that is frequently used in forecasting inflation, incorporates the industrial production index, which is measured on the same frequency as inflation. In comparison with ADL-MIDAS, it underperforms the latter in approximately 97%, 80% and 86% for in-sample and out-of-sample $(m=4)$ and $(m=8)$, respectively. A comparison between ARDL-1 (oil-based) and ARDL-2 (Phillips curve-based) models, which are both based on variables having same frequencies, confirms the importance of oil price in the forecast of inflation (Table 2). In addition, incorporating at a higher frequency of oil price than the inflation series produces even more accurate forecast performance (Table 3).

3.3 ADL-MIDAS vs RWM

The two variants of RWM (RWWD & RWWOD) are also compared with the benchmark model (ADL-MIDAS) in Table 3 and are observed to underperform the benchmark, with (100% & 100%), (80% & 71%) and (91% & 69%) in the in-sample and out-of-sample $(m=4)$ and $(m=8)$ forecast, respectively. The performance of ADL-MIDAS is clearly evident and confirmed especially, in the in-sample forecast with an overwhelming 100% preference over both variants of RWM.

Table 3: Percentage comparison with the Benchmark model

	ARDL-1	ARDL-2	RWWD	RWWOD
IN-SAMPLE	$\downarrow$66%	$\downarrow$97%	$\downarrow$100%	$\downarrow$100%
OUT-OF-SAMPLE $(m=4)$	$\downarrow$63%	$\downarrow$80%	$\downarrow$80%	$\downarrow$71%
OUT-OF-SAMPLE $(m=8)$	$\downarrow$60%	$\downarrow$86%	$\downarrow$91%	$\downarrow$69%

Note: $\downarrow$ indicates the percentage decrease relative to the benchmark model

3.4 Robustness Checks

Table 4 checks the robustness of the result using Brent as a proxy for oil price and compares the models (ADL-MIDAS and ARDL-1), which incorporate oil price as a regressor. The forecast performance mirrors the result obtained when WTI was used to proxy oil price. This feat implies that regardless of the proxy used for oil price, the performance of the ADL-MIDAS remains consistent in the in-sample forecast periods (Tables 4 & 5). For the out-of-sample forecast periods ($m=4$ and $m=8$), ADL-MIDAS outperformed all the other models except ARDL-1, where it was marginally outperformed. Here, the best and worst performed models are ADL-MIDAS and RWWOD, respectively, which confirms the results obtained earlier using WTI.

Table 4: Inflation Forecast Performance **(Using Brent)**

COUNTRY	IN-SAMPLE		OUT-OF-SAMPLE			
	ADL-MIDAS	ARDL-1	ADL-MIDAS		ARDL-1	
			$m=4$	$m=8$	$m=4$	$m=8$
Australia	0.0036	0.0052	0.0017	0.0030	0.0015	0.0036
Austria	0.0037	0.0040	0.0037	0.0036	0.0036	0.0029
Belgium	0.0039	0.0036	0.0031	0.0031	0.0060	0.0058
Canada	0.0045	0.0047	0.0059	0.0056	0.0028	0.0036
Chile	0.0065	0.0072	0.0064	0.0062	0.0124	0.0103
Czech	0.0079	0.0083	0.0035	0.0035	0.0050	0.0042
Denmark	0.0045	0.0045	0.0032	0.0039	0.0033	0.0037
Estonia	0.0068	0.0085	0.0116	0.0097	0.0085	0.0071
Finland	0.0045	0.0045	0.0029	0.0029	0.0032	0.0031
France	0.0034	0.0034	0.0036	0.0034	0.0028	0.0032
Germany	0.0024	0.0026	0.0017	0.0020	0.0019	0.0022
Greece	0.0099	0.0128	0.0120	0.0131	0.0109	0.0102
Hungary	0.0083	0.0101	0.0071	0.0083	0.0107	0.0103
Iceland	0.0106	0.0113	0.0082	0.0072	0.0062	0.0061
Ireland	0.0068	0.0067	0.0078	0.0079	0.0123	0.0117
Israel	0.0072	0.0076	0.0067	0.0060	0.0081	0.0090
Italy	0.0023	0.0028	0.0025	0.0033	0.0022	0.0035
Japan	0.0050	0.0049	0.0045	0.0039	0.0036	0.0033
Korea	0.0050	0.0048	0.0045	0.0039	0.0053	0.0057
Latvia	0.0102	0.0136	0.0153	0.0142	0.0165	0.0144
Luxembourg	0.0042	0.0037	0.0043	0.0046	0.0041	0.0034
Mexico	0.0062	0.0062	0.0094	0.0083	0.0071	0.0065
Netherlands	0.0051	0.0052	0.0082	0.0070	0.0079	0.0067
New Zealand	0.0040	0.0043	0.0051	0.0045	0.0039	0.0039
Norway	0.0071	0.0073	0.0040	0.0054	0.0030	0.0040
Poland	0.0066	0.0069	0.0062	0.0066	0.0074	0.0073
Portugal	0.0067	0.0075	0.0068	0.0065	0.0076	0.0064
Slovakia	0.0111	0.0118	0.0057	0.0071	0.0091	0.0093
Slovenia	0.0092	0.0097	0.0072	0.0075	0.0051	0.0056
Spain	0.0072	0.0139	0.0075	0.0100	0.0133	0.0104
Sweden	0.0055	0.0054	0.0016	0.0020	0.0056	0.0054
Switzerland	0.0049	0.0065	0.0046	0.0040	0.0016	0.0026
Turkey	0.0257	0.0301	0.0196	0.0153	0.0197	0.0181
UK	0.0047	0.0042	0.0043	0.0043	0.0036	0.0032

USA	0.0044	0.0049	0.0064	0.0058	0.0043	0.0042

Table 5: Frequency Distribution of Forecast Performance

	ADL-MIDAS	ARDL-1	ARDL-2	RWWD	RWWOD
In-Sample Forecast					
ADL-MIDAS	-	28:7	34:1	35:0	35:0
ARDL		-	26:9	30:5	34:1
Out-of-Sample Forecast $m = 4$					
ADL-MIDAS	-	17:18	26:9	27:8	25:10
ARDL		-	28:7	29:6	22:13
Out-of-Sample Forecast $m = 8$					
ADL-MIDAS	-	17:18	29:6	30:5	24:11
ARDL		-	28:7	28:7	20:15

4.0 Conclusion

This study has examined the predictive ability of oil price in inflation forecast and further shown the forecast improvement by the inclusion of a higher frequency oil price, which is made possible by the mixed data sampling regression technique. The ADL-MIDAS regression structure employs all the available information in the high frequency oil price series, rather than constrained averages employed by the conventional models that are based on same frequency for variables. The limitations imposed by data paucity and/or unequal frequency of available data are addressed appropriately using ADL-MIDAS, with better estimates in comparison to the existing conventional models.

References

Alper, C. E., Fendoglu, S. and Saltoglu, B., 2008. Forecasting Stock Market Volatilities Using MIDAS Regression: An Application to the Emerging Markets. *MPRA Paper No. 7460.*

Andreou, E., Ghysels, E. and Kourtellos, A., 2010. Regression Models with Mixed Sampling Frequencies. *Journal of Econometrics*, 158, 246 - 261.

Andreou, E., Ghysels, E. and Kourtellos, A., 2013. Should macroeconomic forecasters look at daily financial data? *Journal of Business and Economic Statistics*, 31, 240 - 251.

Ascari, G., Marrocu, E., 2003. Forecasting inflation: A comparison of linear Phillips curve models and nonlinear time series models. Working Paper CRENoS 200307, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.

Atkeson, A., Ohanian, L., 2001. Are Phillips curves useful for forecasting inflation? Federal Reserve Bank of Minneapolis Quarterly Review 25(1), 2–11.

Bai, J., Ghysels, E. and Wright, J., 2009. State space models and MIDAS regression. *Working Paper,* NY Fed, UNC and John Hopkins.

Barsoum, F., Stankiewicz, S., 2015. Forecasting GDP growth using mixed-frequency models with switching regimes. International Journal of Forecasting, 31(1), 33-50.

Canova, F., 2007. G-7 inflation forecasts: Random walk, Phillips curve, or what else? Macroeconomic Dynamics 11, 1-30.

Chen, Y., Turnovsky, J. S., Zivot, E., 2014. Forecasting inflating using commodity price aggregates. Journal of Econometrics 185, 117-134.

Clements, M. P., Galavao, A. B., 2006. Macroeconomic Forecasting with mixed Frequency Data: Forecasting US output growth and inflation. *Warwick Economic Research Paper No. 773.* University of Warwick.

Clements, M. P., Galvão, A. B., 2009. Forecasting US output growth using leading indicators : an appraisal using MIDAS models. Journal of Applied Econometrics, 24, 7, 1187-1206.

Coibion, O., Gorodnichencko, Y., 2015. Is the Phillips curve alive and well after all? inflation expectation and the missing disinflation. American Economic Journal: Macroeconomics 7(1), 197–232.

Forsberg, L., Ghysels, E., 2006. Why do absolute returns predict volatility so well? *Journal of Financial Econometrics,* 6*,* 31-67*.*

Ghysels, E., Ozkan, N., 2015. Real-time forecasting of the US federal government budget: A simple mixed frequency data regression approach. International Journal of Forecasting, 31(4), 1009-1020.

Ghysels, E., Sinko, A., Valkanov, R., 2006. MIDAS regression: Further results and new directions. *Econometric Reviews,* 26, 53-90.

Ghysels, E., Sinko, A., Valkanov, R., 2009. Granger Causality Tests with Mixed Data Frequencies. *Discussion Paper, UNC.*

Ghysels, E., Santa-Clara, P., Valkanov, R., 2002. The MIDAS touch: Mixed Data Sampling Regression. *Working Paper UNC and UCLA.*

Ghysels, E., 2016. MIDAS Matlab Toolbox.

Kotze, G. L., 2007. Forecasting Inflation with High Frequency Asset Price Data. *Working Paper.* University of Stellenbosch.

Li, X., Shang, W., Wang, S. and Ma, J. (2015). A MIDAS modelling framework for Chinese inflation index forecast incorporating Google search data. Electronic Commerce Research and Applications, 14(2), 112-125.

Salisu, A.A., Isah, K.O., Oyewole, O.J., Akanni, L.O., 2017a. Modelling oil price-inflation nexus: The role of asymmetries. Energy, 125, 97-106.

Salisu, A.A., Ademuyiwa, I., Isah, K.O., 2017b. Rethinking the Phillips curve. CEAR Working Paper No. 22.

Stock, J., Watson, M., 2008. Phillips curve inflation forecast. NBER Working Paper 4322.

Tay, A. S., 2007. Mixed Frequencies: Stock Returns as a Predictor of real Output Growth. *Discussion Paper,* SMU.

Van Hoang, T.H., Lahiani, A., Heller, D., 2016. Is gold a hedge against inflation? New evidence from a nonlinear ARDL approach. Economic Modelling, 54, 54–66.