How do Housing Returns in Emerging Countries Respond to Oil Shocks? A MIDAS Touch

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Abstract

In this study, we utilize the recent oil shock data of Baumeister and Hamilton (2019) to analyze how housing returns in China, India and Russia respond to different oil shocks. Given the available data for the relevant variables, the MIDAS approach which helps circumvent aggregation problem in the estimation process is employed. We also extend the MIDAS framework to account for nonlinearities in the model. Expectedly, the housing returns of the countries considered respond differently to the variants of oil shocks. More specifically, we find that the housing returns of India and China which are net oil-importing countries do not seem to possess oil risk hedging characteristics albeit with the converse for Russia which is a major net oil-exporter. We also find that modeling with the MIDAS framework offers better predictability than other variants with uniform frequency.

Keywords: Housing return, Oil shock, MIDAS regression, Nonlinearities, Forecasting

JEL classification: C12, C22, Q41, Q47, R12, R31

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1. Introduction

Housing market variables, and in particular house price, is considered as leading indicators for not only advanced economies, but also for emerging markets (Gupta and Hartley, 2013; Aye et al., 2014). Given this, there exist a large number of studies, primarily dealing with advanced economies, that has aimed to predict housing market movements based on a wide-variety of models and predictors (see, Rahal, 2015; Kishor and Marfatia, 2018; and Hassani et al., 2019; for detailed reviews). In this regard, a burgeoning literature has started to analyze the impact of oil prices and shocks on house (real estate) price movements (see for example, Chan et al., (2011), Breitenfellner et al., (2015), Khiabani (2015), Antonakakis et al., (2016), Nazlioglu et al., (2016), Agnello et al., (2017), Killins et al., (2017), Kilian and Zhou (2018), Aye et al., (2019)).[1]

These studies highlight at least six channels underlying the relationship between house and oil (energy) prices. First, recessionary impact of oil price increases is likely to dampen the demand for housing, and hence, reduce its price. But while this is true for an oil importing country, for an oil exporter, increases in oil prices is likely to cause a boom in the economy, and thus increase housing prices. Second, oil price increases, irrespective of an oil exporter and importer, are likely to increase construction and operational building costs, which might push house prices up due to a decline in the supply of housing. Third, tighter monetary policy to curb the pressure induced by oil price increases on headline inflation is likely to reduce liquidity from the housing market and hence, result in a fall in house prices due to a decline in demand for housing. Fourth, if in the wake of inflation, housing is used as a hedge, the inflationary-effect of oil prices might actually end up increasing housing demand and hence, raise its price. Fifth, following oil price hikes, investment opportunities in the oil (energy) sector, in the wake of its financialization, might lead to portfolio allocation away from housing, and thus affect its demand and price negatively. Finally, both the oil and housing markets are likely to be driven by common factors such as economic growth and/or monetary policy.

Note that, barring Khiabani (2015) who analyzed the Iranian housing market, rest of the abovementioned studies have concentrated on the real estate market of advanced economies, when analyzing the impact of oil price movements. Against this backdrop, the objective of this paper is to extend this literature by considering three emerging countries namely, China, India and Russia. Given that the literature has shown oil price movements to have differential impact on the housing sector of oil exporters and importers, our choice of these three economies were quite natural, with China and India being the two largest oil importing countries (ranked first and third respectively, with 20.2% and 9.7% of total crude oil imports), and Russia being the second largest oil exporter (The World Factbook).[2] In addition, given the observation that oil price

[1] In this regard, note that, Kaufmann et al., (2011) identified a significant long-run relationship between household expenditures on energy and US mortgage delinquency rates, and hence, postulated a direct role for energy prices in the 2008 financial crisis.
[2] https://www.cia.gov/library/publications/the-world-factbook/rankorder/2242rank.html.

movements can have different impact on the economy depending on the cause of the oil price change (Kilian, 2009; Kilian and park, 2009), we analyze the impact of structural oil shocks (oil-specific supply and demand, inventory accumulation, and global demand), rather than oil price per se, on the housing prices.

As far as the econometric framework is concerned, given that the housing price data of China, India and Russia are only available at quarterly frequency, while the oil shocks are monthly, we use a mixed frequency approach to analyze the impact of these shocks. The Mixed Data Sampling (MIDAS) approach allows us to avoid loss of information that would have resulted by averaging the oil shocks to lower frequency (Clements and Galvao, 2008; Foroni and Marcellino, 2013; Das et al., forthcoming) – an observation we highlight through our results as well. To the best of our knowledge, this is the first paper to use MIDAS modeling approach in predicting (both in- and out-of-sample) quarterly house price movements of emerging markets, based on the information contained in alternative structural oil shocks available at the higher (monthly) frequency. The remainder of the paper is organized as follows: Section 2 discusses the methodology, while Section 3 presents the data and results, with Section 4 concluding the paper.

2. Methodology

As earlier noted, one of the contributions of this study is the consideration of a predictive model that accommodates mixed data frequencies conventionally described as the Mixed Data Sampling (MIDAS) regressions.[3] Essentially, we utilize both quarterly and monthly data frequencies for the predicted and predictor series respectively thus allowing for more robust information in the estimation process.[4] The ADL-MIDAS[5] variant of MIDAS regressions which accommodates the described data frequencies in the estimation process is formulated.[6] Also, there are different variants of the MIDAS regression models based on how the high frequency regressors are handled in a predictive model with a low frequency regressand. There is the Flat weight aggregation approach (*see* e.g., Asimakopoulos et al., 2013), which involves equal weights for the aggregation of the high frequency data. In our case; where the oil shocks are monthly series, while the housing return series is quarterly; the Flat weight approach implies equal weights on each month. However, one of the shortcomings of this approach is that the estimators may be biased if the true weighting scheme is not that of equal weights and this affects the forecasting accuracy of the model (Asimakopoulos et al., 2013). Another variant of the MIDAS regression is the Unrestricted MIDAS (U-MIDAS) (see Foroni et al., 2011), which does not require the aggregation of high frequency observations in order to convert to low frequency. A typical representation for oil shock-housing return nexus using the U-MIDAS

[3] See (Forsberg and Ghysels, 2006; Alper et al., 2008; Bai et al., 2009; Barsoum and Stankiewicz, 2015; Jung, 2017) for arguments in support of such modelling structure that allows the predictor and predicted variables to be sampled at different data frequencies.
[4] Some of the computational advantages of using the MIDAS regressions are documented in Salisu and Ogbonna (2019).
[5] ADL-MIDAS regression is the Autoregressive Distributed Lag – Mixed Data Sampling regression.
[6] Studies such as Ghysels et al. (2009); Andreou et al. (2013); Albu et al. (2015); Ghysels (2016); Salisu and Ogbonna (2017) document succinct explanations of the ADL-MIDAS regression model.

framework can be expressed as (see also Asimakopoulos et al., 2013; Salisu and Ogbonna, 2019):

$$hr_{t+1}^{Q} = \gamma_0 + \sum_{i=0}^{N_M-1} \gamma_i s_{N_M-i,t}^{M} + \varepsilon_{t+1}^{Q} \qquad (1)$$

where hr is the real housing return; s is the oil shock using the four oil shocks proposed by Baumeister and Hamilton (2019); N_M denotes the number of months in a quarter, while Q and M are the quarterly and monthly data frequencies, respectively. Unlike the Flat weight aggregation approach, the U-MIDAS does not require any assumption on the weights attached to each month and is therefore considered to be unrestricted. Notwithstanding the attraction(s) to the U-MIDAS, it however suffers the problem of parameter proliferation. For instance, there are four parameters to be estimated for quarterly/monthly data in which one coefficient is estimated for each month and one for the constant. The parameter proliferation becomes severe if the gap between the low and high frequencies widens, or if the number of lags of each month increases. We thus opt for the ADL-MIDAS model proposed by Ghysels et al. (2006), which does not require any assumption on the weights for aggregation of high frequency variables (as in the Flat weight aggregation MIDAS variant) and it also helps to circumvent the problem of parameter proliferation inherent in the U-MIDAS. In addition, the ADL-MIDAS allows for dynamics in both the predicted and predictor series. Evidently, most economic time series tend to exhibit persistence, and therefore allowing for dynamics in both the predicted and the predictor series may offer more robust estimates. The exponential Almon lag polynomial proposed by Ghysels et al. (2007) which can take many shapes is adopted as the weighting scheme. The estimated ADL-MIDAS model for oil shock-housing return nexus is specified as follows with the lag structure (p_{hr}^{Q}, q_{s}^{M}):[7]

$$hr_{t+1}^{Q} = \lambda + \sum_{i=0}^{p_{hr}^{Q}-1} \alpha_i hr_{t-i}^{Q} + \beta \sum_{i=0}^{q_s^M-1} \cdot \sum_{j=0}^{N_M-1} w_{i+j*N_M}(\phi^M) s_{N_M-j,t-i}^{M} + \zeta_{t+1} \qquad (2)$$

where p_{hr}^{Q} and q_s^M denote the number of lags of the quarterly (low) and monthly (high) frequency variables, respectively. $w_i(\phi^H)$ is a weighting structure of a two parameter exponential Almon lag polynomial expressed as:

$$w_i(\phi^H) = w_i(\phi_1\phi_2) = \frac{e^{(\phi_1 i+\phi_2 i^2)}}{\sum_{i=0}^{k} e^{(\phi_1 i+\phi_2 i^2)}} \qquad (3)$$

For the purpose of analyses, each of the oil shocks namely oil supply shocks, economic activity shocks, oil consumption demand shocks and oil inventory demand shocks is singly captured in the predictive model as expressed in equation (2). The predictability of real housing returns is tested on the basis of oil shock given that the null hypothesis, $H_0 : \beta = 0$ is rejected.

For completeness, we also consider an alternative model that shares similar features with the ADL-MIDAS except for the data frequency. This is described as the Autoregressive Distributed Lag [ARDL(*p,q*)] model proposed by Pesaran and Shin (1999) and Pesaran et al. (2001). While

[7] The specification is also in line with Asimakopoulos et al. (2013), Albu et al. (2015) and Salisu and Ogbonna (2019).

the ADL-MIDAS model allows for mixed data frequencies, the ARDL model only accommodates uniform frequency. The consideration of the latter helps us to evaluate the behaviour of the nexus when the uniform frequency assumption is imposed despite the availability of alternative data frequencies. The underlying intention is to test whether the nexus is sensitive to the choice of data frequency or predictive model.[8]

$$\Delta hr_t = c + \sum_{i=1}^{p-1} \phi_i \Delta hr_{t-i} + \sum_{i=0}^{q-1} \varphi_i \Delta s_{t-i} + \theta\left[hr_{t-1} - \{\alpha + \delta s_{t-1}\}\right] + \xi_t \qquad (4)$$

where Δ is the first difference operator and parameters with this operator capture the short run effect while those without same are for long run estimates. The regressand (hr) and regressor (s) are as previously defined. The optimal lags for the ARDL model are determined on the basis of the Schwartz Information Criterion (AIC), where the model with the least SIC is considered parsimonious and the corresponding lag structure producing such model is the optimal lag, and is therefore used for the predictability analyses. Since the ARDL and ADL-MIDAS are similar except for the data frequency of the regressor(s) and also for consistency, we maintain the same lag structure for both models, where the optimal lag is determined using the ARDL (Salisu and Ogbonna, 2019).

Further analyses involving the consideration of structural breaks and nonlinearities are also rendered as complementary analyses. This idea is motivated by related studies justifying the role of same when analyzing oil price dynamics (see for example, Hamilton, 2011; Narayan and Gupta, 2015; Salisu and Isah, 2017; Salisu et al., 2019a). In addition, we allow for the role of macroeconomic variables such as industrial production growth, real effective exchange rate growth and real interest rate as another form of robustness test in the analyses of oil shock-housing return nexus (see also Salisu et al., 2019a). Also, some forecast analyses are also conducted to assess how much of information in oil shocks can be used to forecast future housing returns. The forecast performance of the ADL-MIDAS model is compared with the ARDL model as well as the historical average model using both single and pairwise forecast measures involving the root mean square error and Clark and West (2007) test of forecast equality.

3. Data and Results

3.1 Data and preliminary analyses

Three countries namely China, India and Russia, are considered for the analyses of the relationship between oil shocks and housing returns. Quarterly data frequency is utilized for real housing returns, while monthly data are used for the predictors. As mentioned earlier, the predictors involve four variants of oil shocks, as well as, other standard macroeconomic variables used in the literature on predicting housing returns. Specifically, the variables employed in this paper are Real Housing Returns, Real Effective Exchange Rate Returns,

[8] Although, there are studies that have examined the role of data frequency in predictability (such as Ferraro et al., 2015; Narayan and Liu, 2015; Narayan and Sharma, 2015; Salisu and Adeleke, 2016; Salisu et al., 2016, Salisu et al., 2019b; Tule et al., 2019) however, the analyses still involve uniform frequency. The only exception is the work of Salisu and Ogbonna (2019).

Industrial Production Growth, Real Interest Rate (i.e., short-term interest rate minus the CPI-based inflation rate), oil supply shocks, economic activity shocks, oil consumption demand shocks, and oil inventory demand shocks. Note that as our econometric approach requires mean-reverting data, usage of the returns-based series ensured stationarity. Based on data availability, our sample covers the period 1999Q2 to 2018Q4 for China, 2002Q1 to 2018Q2 for India and 2001Q2 and 2018Q4 for Russia. Data on the untransformed real house variables were derived from various sources, with real house prices coming from the Organization for Economic Co-operation and Development (OECD) house price database, while the other domestic macroeconomic variables are obtained from the Global Insight database of IHS, and real effective exchange rates from the Bank for International Settlements. As far as the oil shocks are concerned, we obtain them from the recent study by Baumeister and Hamilton (2019).[9] These authors revisit the studies of Kilian (2009) and Kilian and Park (2009) by formulating a less restrictive framework that incorporates uncertainty about the identifying assumptions of structural vector autoregressions, and in the process derive more accurate estimates of the structural oil shocks.

Some descriptive statistics are rendered to provide general information about the variables of interest (see Table 1). Both quarterly and monthly frequencies are used in the descriptive analyses except for real housing return series which is only available on quarterly basis. Starting with real housing returns, it is observed that India has the highest returns on housing investment followed by China while Russia has the least. Conversely however, in terms of volatility judging by the standard deviation value, Russia seems to report the highest magnitude followed by India while China has the least. Among the oil shocks, the oil consumption demand shock has both the highest mean and standard deviation values regardless of the data frequency. Interestingly, only the oil consumption demand shock is positive among the variants of oil shocks irrespective of the data frequency. This appears to suggest some level of asymmetries in the oil shocks thus justifying the argument by Kilian (2009) and Kilian and Park (2009) that not all oil shocks are the alike. Therefore, disentangling oil shocks will be necessary when analyzing the macroeconomic effects of oil shocks. This is one of the motivations for the choice of the variants of oil shocks in this study. Since oil shock is global, the data scope for China is used for its descriptive statistics as it has the widest coverage relative to other selected countries.

For the selected macroeconomic variables, the results are mixed for the two data frequencies. Indian seems to be less stable relative to others judging by the real interest rate and industrial production growth when the quarterly data frequency is used while the same conclusion is only reached for real interest rate when monthly data frequency is used. Thus, the choice of data frequency may influence the outcome of the oil shock-housing returns nexus. This conclusion about the role of data frequency is not new. A number of studies have also reported same although not from the perspective of our study (see footnote 9).

[9] We thank Professor Christiane Baumeister for kindly providing us with the data of the underlying oil shocks.

As conventional for time series analyses, we also perform unit root test using the ADF test and the GARCH based unit root test proposed by Narayan and Liu (2015) [NL hereafter]. One of the merits of the latter is that it is suitable for series with trending behavior, structural breaks and conditional heteroscedasticity. A cursory look at Figures 1, 2 and 3 seems to support the need to account for these features in the test regression. Regardless of the choice of unit root test, the null hypothesis of unit root is rejected for all the series.

Table 1: Descriptive statistics and unit root test

	Descriptive Statistics						Unit Root Test					
Quarterly Frequency	Mean			Standard Deviation			ADF Test			NL Test		
	China	India	Russia	China	India	Russia	China	India	Russia	China	India	Russia
Real Housing Returns	0.815	1.663	0.640	1.413	3.393	5.464	-4.822 [a,#]	-8.104 [a]	-6.264 [a]	-7.832 [a]	-6.807 [a]	-3.397 [a]
Real Effective Exchange Rate Returns	-0.129	-0.210	0.017	1.337	1.430	3.419	-9.358 [a]	-6.992 [a]	-11.716 [a]	-9.097 [a]	-7.081 [a]	-9.222 [a]
Industrial Production Growth	0.140	4.323	4.417	2.054	4.858	4.519	-9.103 [a]	-2.433	-1.952	-13.849 [a]	-12.861 [a]	-6.947 [a]
Real Interest Rate	1.834	2.712	0.216	6.204	8.201	5.517	-6.231 [a]	-8.098 [a]	-5.952 [a]	-12.059 [a]	-8.844 [a]	-6.514 [a]
Oil supply shocks	-0.241			1.352			-8.266 [a]			-8.756 [a]		
Economic activity shocks	-0.098			0.496			-8.875 [a]			-4.517[a]		
Oil consumption demand shocks	0.462			3.477			-9.212 [a]			-8.641[a]		
Oil inventory demand shocks	-0.340			1.026			-10.726 [a]			-9.094 [a]		
Monthly Frequency												
Real Effective Exchange Rate Returns	0.108	0.030	0.135	1.375	1.576	3.057	-11.328 [a]	-10.932 [a]	-10.113 [a]	-11.025 [a]	-11.835 [a]	-9.703 [a]
Industrial Production Growth	-0.012	0.467	0.187	2.572	5.616	6.946	-13.593 [a]	-10.817 [a]	-17.014 [a]	-16.337 [a]	-22.540 [a]	-15.086 [a]
Real Interest Rate	1.592	0.206	-0.757	7.129	9.168	7.160	-14.798 [a]	-10.436 [a]	-7.463 [a]	-12.467 [a]	-11.947 [a]	-7.774 [a]
Oil supply shocks	-0.163			1.263			-14.687 [a]			-13.551 [a]		
Economic activity shocks	-0.024			0.529			-14.294 [a]			-12.733[a]		
Oil consumption demand shocks	0.188			3.355			-15.358 [a]			-13.479[a]		
Oil inventory demand shocks	-0.100			0.996			-15.545 [a]			-11.899 [a]		

Note: ADF test is the Augmented Dickey Fuller test; NL test is the Narayan and Liu test; All the variables are expressed in natural logs; all variables are integrated of order zero I(0) i.e. they are stationary at level; a, b, c indicate the rejection of the null hypothesis of a unit root at 1%, 5% and 10%, respectively.

Figure 1: Graphs for Real Housing Returns and the various shocks [China]

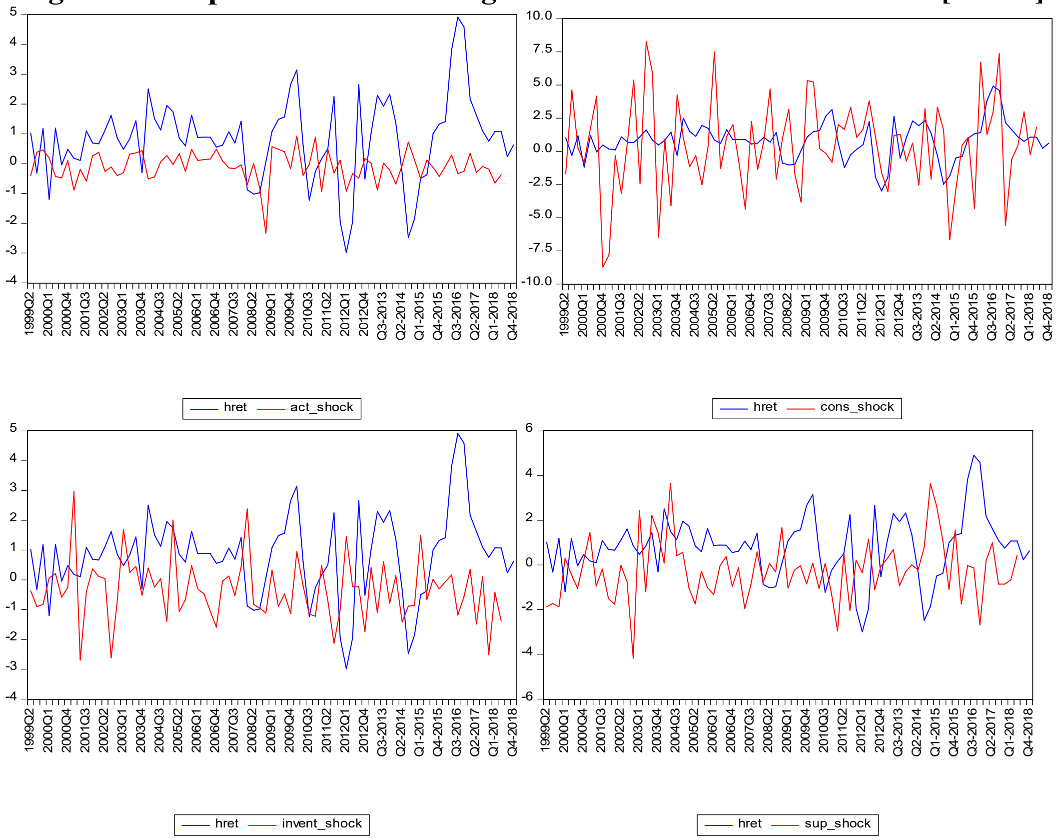


Figure 2: Graphs for Real Housing Returns and the various shocks [India]

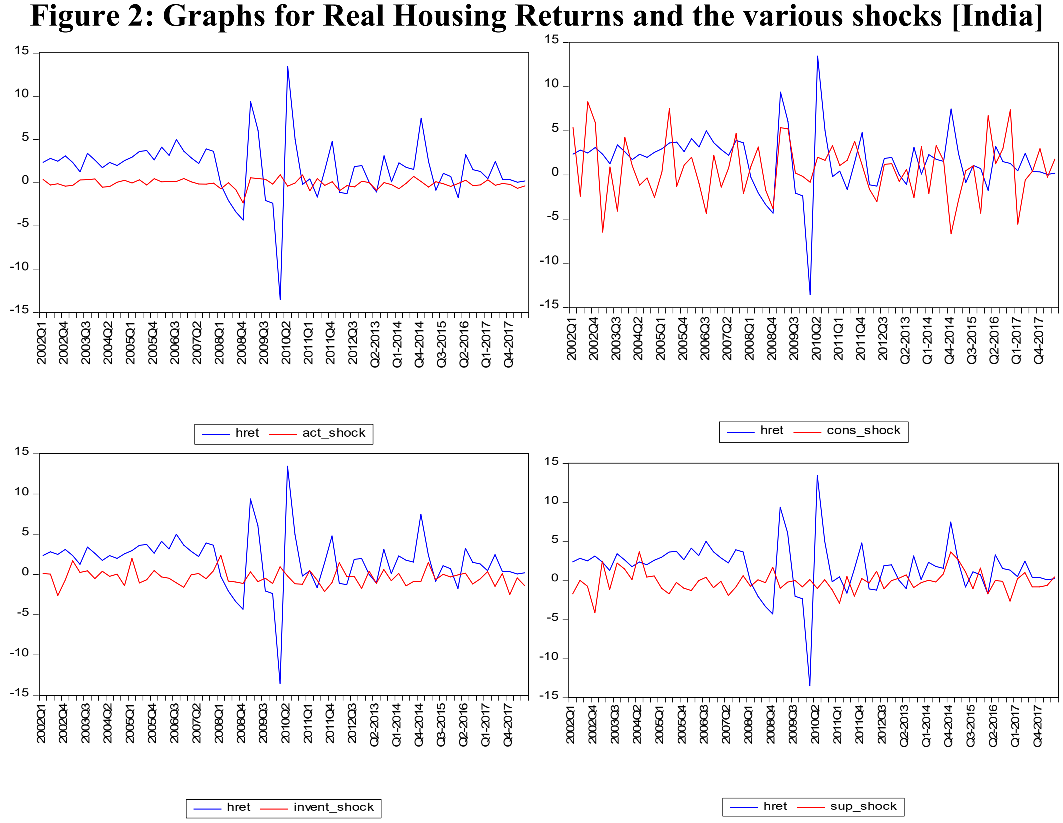
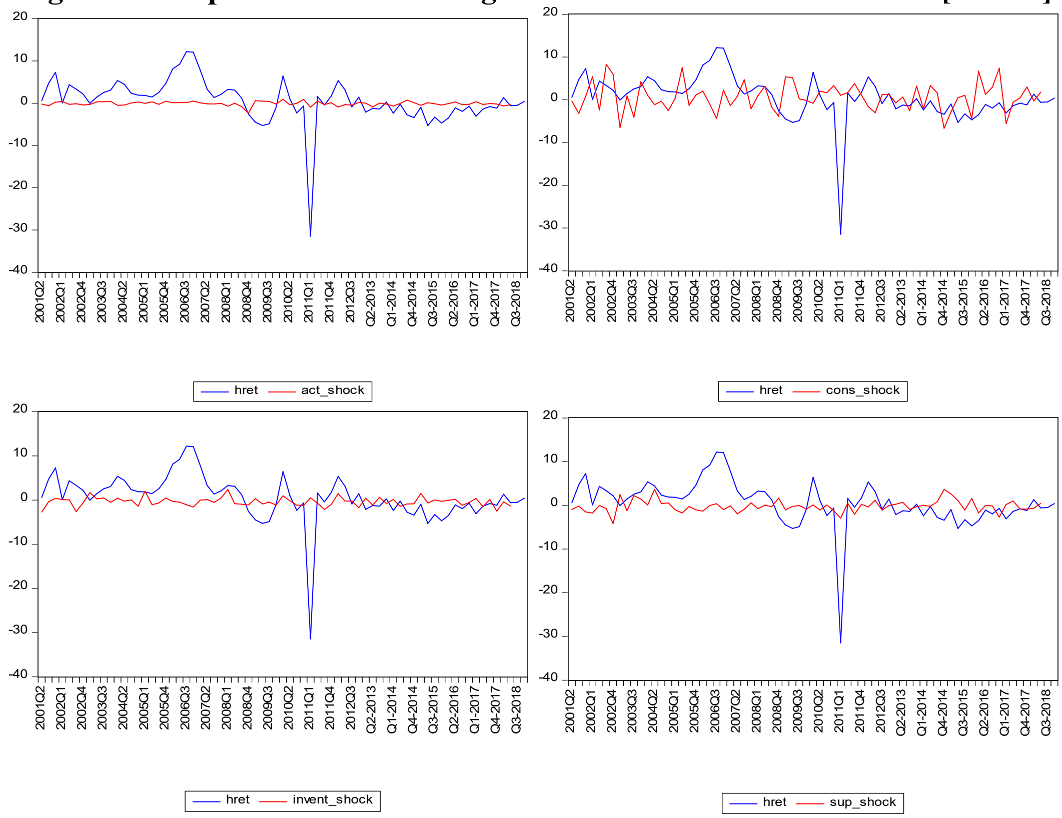


Figure 3: Graphs for Real Housing Returns and the various shocks [Russia]



Note: Real Housing Returns = hret; Oil supply shocks = sup_shock; Economic activity shocks = activity_shock; Oil consumption demand shocks = cons_shock; Oil inventory demand shocks = invent_shock.

3.2 Discussion of main results

3.2.1 How sensitive are housing returns to oil shocks?

The reaction of the housing market to oil shocks may be dependent on whether the shock is supply- or demand-driven (see Killins et al., 2017; among others). This intuition is also in line with the works of Kilian (2009) and Kilian and Park (2009) which assume that not all shocks are the same and therefore there may be need to disentangle into demand and supply shocks with further extensions by Baumeister and Hamilton (2019) as earlier mentioned. Thus, we begin our analyses with the oil supply shock. Table 2 presents the predictability results of oil supply shock (OSS) for real housing return (RHR) using both the conventional ARDL model and different constructs of the MIDAS model. This is presented for three different countries – China, India and Russia. Different variants of the MIDAS constructs comprise a control variable or a dummy variable depicting a structural break or asymmetry (positive and negative). Although, not found to be statistically significant in predicting RHR, the estimated coefficients of the OSS variable for China and India are negative, while that of Russia is positive, using the ARDL model construct. On the MIDAS construct, the Almon polynomial distributed lag (PDL) weighting is adopted given that it is the natural candidate for mixed frequency weighting. The results in the second, third, fifth and sixth columns of Table 2 show the PDL coefficients for the higher frequency variable. In contrast with the conventional ARDL model, we find OSS to significantly predict RHR given the statistical significance of one or both polynomial distributed lag coefficients (PDL01 and PDL02), especially with respect to China. Thus, the consideration of a higher frequency for the predictor variable seems to enhance predictability (see also Salisu and Ogbonna, 2017; 2019). However, the OSS does not predict RHR in India and Russia except when negative asymmetry is incorporated into the model. This may seem to validate the role of nonlinearity in the analysis of oil price effect (see also Hamilton, 2011; Narayan and Gupta, 2015; Salisu and Isah, 2017; Salisu et al., 2019a). It also corroborates the stance of differing strength of the relationship between global oil prices and housing prices for net oil exporting countries than the net oil importing countries (see Killins, 2017).

Also noted from Table 2 is the fact that the oil supply shock is generally found to have a negative and linearly increasing effect with increased lags on real housing returns, especially with regard to the case of China, in all the considered constructs except when positive asymmetry is incorporated in the MIDAS model. This result lends support to the standpoint of Antonakakis et al. (2016) that oil shocks negatively impact the real estate market. In addition, given the depth of economic activities in China, an increase in oil price occasioned by oil supply shock will generally lead to higher prices of goods and services thus fuelling a higher inflation. Consequently, the inflation-adjusted housing return is expected to decline more so that the real estate in China does not seem to have inflation hedging ability (see Chu and Sing, 2004; Zhou and Clements, 2010). Conversely, we find that for India which shares similar characteristics with China, the estimated coefficient is found to be positive, it is also linearly decreasing, and when negative, the estimated coefficients increased linearly. Therefore, the explanation of the underlying economics of the findings for China cannot suffice here. Nonetheless, the evidence can be justified on the grounds that most of the housing assets in India are obtained through loan with about 90 percent of property purchase done through a loan.[10] Thus, the demand for loanable funds to finance real estate in India is more likely to be inelastic and that explains why this asset class is considered to possess inflation hedging property. In essence, if inflation rises due to oil supply shock, the effect is captured in terms of a higher cost of capital which may have very minimal impacts on the demand for loanable funds to finance real estate in India. Thus, even if inflation is rising, the nominal returns on real estate may rise even higher than inflation implying that the real return may be independent of inflation.

In the case of Russia, the estimated coefficients are generally positive and linearly decreasing with increased lags except when positive asymmetry is incorporated. This outcome for Russia is in agreement with our expectation for an oil exporting country. A shock to oil supply will deepen foreign reserves of an oil exporting country with increased cash flows to the financial sector which ultimately makes the supply of loanable funds for investment purpose cheaper. With an improved investment climate, the prices of goods and services may be lower and thus, the real returns on investment including housing will increase.

Table 3 presents the predictability result of Economic Activity Shock (EAS) for Real Housing Return (RHR) using similar features as those in Table 2. The EAS is found to have a positive and significant effect on RHR in the case of Russia, when the ARDL model is considered. The negative and positive effects of EAS on RHR in the case of China and India, respectively, were not statistically significant. However, on the MIDAS construct, we find some significant levels of predictability of EAS for RHR, when EAS occurring at a higher frequency is incorporated, across the three countries. This further confirms the importance of the mixed frequency regression and its role in improving predictability (see Salisu and Ogbonna, 2017; 2019). The EAS is generally found to have a negative and linearly increasing effect, with increasing lags, on real housing returns (RHR), especially, with regard to China and India, while for the case of Russia, except when the positive asymmetry is incorporated, is generally positive and mostly linearly increasing, with increasing lags. The stance of negative impact as observed in the case of China and India lends support to Antonakakis et al. (2016), while the case of positive impact

[10] The Economic Times, retrieved from https://economictimes.indiatimes.com/realty-trends/property-is-the-best-hedge-against-inflation/articleshow/13732806.cms?from=mdr

supports Killins (2017) findings. In terms of the underlying economic intuition, a demand-oriented oil shock are associated with economic downturns which may lower the demand for oil and therefore its negative effect on real housing returns for non-oil exporting countries such as China and India is not unexpected. However, for Russia, during the crisis of demand-driven oil shock, oil producing countries usually cut back oil supply to moderate the level of oil price and therefore its impact may fizzle out in the long run. More so, Russia is a well-diversified net oil-exporter and by extension the impact of demand-oriented oil shocks may not adversely affect its cash flow. Therefore, the real estate in Russia may serve as a good hedge against demand-oriented oil risk while the converse seems to be the case for China and India.

Another alternative oil shock considered is the oil consumption demand shock (OCDS) which is that part of oil demand shock that is associated with the household demand. The OCDS predictability for RHR, as presented in Table 4, a similar feat is observed in the ARDL model construct with OCDS as the independent variable. This variable does not seem to possess the inherent features that are capable of mirroring the variation in the RHR series, across the countries considered. On the MIDAS model framework however, a number of significant polynomial distributed lags are found in the MIDAS model constructs for India. Like the EAS, we find evidence of negative and linearly increasing coefficients of the OCDS in India, while there is no evidence of statistically significant effect of OCDS when China and Russia are analyzed. In other words, the housing returns in India are more susceptible to oil consumption shock than those of China and Russia.

The last alternative oil shock is the Oil Inventory Demand Shock (OIDS) which is also the part of oil demand shock that is associated with the real sector of the economy. The predictability results are presented in Table 5, following similar features as with the previous predictability tables. Regardless of the choice of model, the OIDS does not seem to influence housing returns for all the countries considered. By comparing the results of both the OCDS and the OIDS with the oil demand shock (EAS), it does appear that partitioning the latter into both consumption- and investment-oriented demand shocks tends to diminish the influence of the aggregate (economy-wide) oil demand shock. Without prejudice to the contribution of Baumeister and Hamilton (2019), our findings suggest that the approach of Kilian (2009) and Kilian and Park

(2009) may suffice for the analysis of oil shock-housing returns nexus. Even when we control for relevant macroeconomic variables such as real effective exchange rate, industrial production growth and real interest rate, the results about the relationship between oil shock and housing returns substantially remain the same.

Table 2: Predictability of oil supply shock (OSS) for real housing return (RHR)

MODEL	OSS					
	INDEPENDENT VARIABLE			CONTROL VARIABLE		
	PDL01	PDL02	Coefficient	PDL01	PDL02	Coefficient
China						
ARDL			-0.1299(0.1147)			
MIDAS (Baseline)	-0.1437(0.0944)	0.0504***(0.0180)	-0.0934			
MIDAS (IPG)	-0.1345*(0.0791)	0.0331***(0.0121)	-0.1014	0.3125***(0.1106)	-0.0607***(0.0195)	0.2517
MIDAS (REERR)	-0.0968(0.0834)	0.0305**(0.0128)	-0.0664	-0.0467(0.1250)	-0.0081(0.0431)	-0.0548
MIDAS (RIR)	-0.1386(0.0895)	0.0363**(0.0137)	-0.1023	-0.0135(0.0132)	0.0034(0.0022)	-0.0101
MIDAS (Negative Asymmetry)	-0.0961**(0.0446)	0.0193**(0.0089)	-0.0768			
MIDAS (Positive Asymmetry)	0.5026**(0.2294)	-0.2521**(0.1146)	0.2505			
MIDAS (Break dummy)	-0.1048(0.0938)	0.0451**(0.0177)	-0.0597			
India						
ARDL			-0.0520(0.3965)			
MIDAS (Baseline)	0.5398(0.3670)	-0.1154(0.0700)	0.4244			
MIDAS (IPG)	0.5244(0.3580)	-0.1090(0.0684)	0.4154	0.1012(0.1674)	-0.0886(0.0602)	0.0127
MIDAS (REERR)	-0.7980(0.7353)	0.5926(0.3650)	-0.2054	-0.444*(0.2353)	0.1119**(0.0447)	-0.3320
MIDAS (RIR)	-0.4363(0.7287)	0.3370(0.3628)	-0.0993	0.0427(0.0316)	0.0002(0.0048)	0.0429
MIDAS (Negative Asymmetry)	0.5033*(0.2724)	-0.1426*(0.0777)	0.3607			
MIDAS (Positive Asymmetry)	-0.1677(0.1218)	0.0275(0.0202)	-0.1401			
MIDAS (Break dummy)						
Russia						
ARDL			0.7209(0.5739)			
MIDAS (Baseline)	0.1175(0.5363)	-0.1058(0.1102)	0.0117			
MIDAS (IPG)	0.3318(0.5425)	-0.1223(0.1090)	0.2096	0.2538(0.1581)	0.0030(0.0121)	0.2568
MIDAS (REERR)	0.5174(0.5761)	-0.1713(0.1152)	0.3462	0.0321(0.1562)	0.0302(0.0329)	0.0623
MIDAS (RIR)	0.1463(0.5451)	-0.1048(0.1110)	0.0415	-0.2817(0.2701)	0.1325(0.1198)	-0.1492
MIDAS (Negative Asymmetry)	3.9075*(2.0697)	-2.5825*(1.3786)	1.3250			
MIDAS (Positive Asymmetry)	-1.0427(1.2406)	0.5105(0.6194)	-0.5322			
MIDAS (Break dummy)	0.2012(0.5106)	-0.1113(0.1037)	0.0900			

Note: The statistical significance of the estimated coefficients are indicated by ***, ** and *, respectively, for 1%, 5% and 10% levels. The figures in parentheses are the standard errors of the estimated coefficients. PDL01 and PDL02 represent the first and second Almon polynomial distributed lag (PDL) weighting. The terms in parentheses on the first column indicate the additional features and/or control variables included in the MIDAS framework.

Table 3: Predictability of EAS for RHR

MODEL	EAS					
	INDEPENDENT VARIABLE			CONTROL VARIABLE		
	PDL01	PDL02	Coefficient	PDL01	PDL02	Coefficient
China						
ARDL			-0.0463(0.3076)			
MIDAS (Baseline)	-0.6172**(0.2400)	0.2070**(0.0779)	-0.4101			
MIDAS (IPG)	-0.6441***(0.2171)	0.2263***(0.0700)	-0.4177	0.3967***(0.1054)	-0.0730***(0.0186)	0.3237
MIDAS (REERR)	-0.7231***(0.2332)	0.2459***(0.0749)	-0.4773	-0.1538***(0.0534)	0.0153**(0.0071)	-0.1385
MIDAS (RIR)	-0.6209***(0.2314)	0.2330***(0.0758)	-0.3879	-0.0174(0.0114)	0.0036**(0.0014)	-0.0138
MIDAS (Negative Asymmetry)	-0.4022(0.3816)	0.1623(0.1527)	-0.2399			
MIDAS (Positive Asymmetry)	-0.6054*(0.3553)	0.2408*(0.1422)	-0.3645			
MIDAS (Break dummy)	-0.6069**(0.2420)	0.2060**(0.0789)	-0.4009			
India						
ARDL			1.1868(1.0065)			
MIDAS (Baseline)	-1.3393***(0.3991)	0.2457***(0.0549)	-1.0936			
MIDAS (IPG)	-1.5162***(0.4015)	0.2798***(0.0572)	-1.2364	-0.2516(0.1885)	0.2661*(0.1329)	0.0144
MIDAS (REERR)	-1.5785***(0.3966)	0.2645***(0.0539)	-1.3139	-0.2291(0.2179)	0.0905*(0.0464)	-0.1386
MIDAS (RIR)	-1.2408***(0.4004)	0.2252***(0.0576)	-1.0156	-0.0641(0.0507)	0.0251(0.0152)	-0.0390
MIDAS (Negative Asymmetry)	5.2417(5.0188)	-3.4814(3.3469)	1.7603			
MIDAS (Positive Asymmetry)	-0.5885**(0.2372)	0.0903**(0.0366)	-0.4982			
MIDAS (Break dummy)	-1.2787***(0.4230)	0.2367***(0.0575)	-1.0419			
Russia						
ARDL			3.2087**(1.3509)			
MIDAS (Baseline)	0.4272(1.2008)	0.2424(0.3968)	0.6696			
MIDAS (IPG)	1.3770**(0.6744)	-0.1653*(0.0942)	1.2116	-0.7070(0.4866)	0.5162(0.3650)	-0.1908
MIDAS (REERR)	1.3108*(0.7270)	-0.1741*(0.1009)	1.1366	0.0087(0.1588)	0.0181(0.0220)	0.0268
MIDAS (RIR)	0.2357(1.2354)	0.2833(0.4017)	0.519	-0.3109(0.2655)	0.1442(0.1181)	-0.1667
MIDAS (Negative Asymmetry)	1.0840***(0.3652)	-0.1653***(0.0563)	0.9186			
MIDAS (Positive Asymmetry)	-0.5494(0.3468)	0.0828(0.0534)	-0.4666			
MIDAS (Break dummy)	1.4147**(0.6419)	-0.1871**(0.0899)	1.2276			

Note: The statistical significance of the estimated coefficients are indicated by ***, ** and *, respectively, for 1%, 5% and 10% levels. The figures in parentheses are the standard error of the estimated coefficient. PDL01 and PDL02 represent the first and second Almon polynomial distributed lag (PDL) weighting. The terms in parentheses on the first column indicate the additional features and/or control variables included in the MIDAS framework.

Table 4: Predictability of OCDS for RHR

	OCDS					
MODEL	**INDEPENDENT VARIABLE**			**CONTROL VARIABLE**		
	PDL01	**PDL02**	**Coefficient**	**PDL01**	**PDL02**	**Coefficient**
			China			
ARDL			-0.0008(0.0524)			
MIDAS (Baseline)	0.0058(0.0296)	-0.0035(0.0040)	0.0023			
MIDAS (IPG)	0.0235(0.0296)	0.0009(0.0044)	0.0244	0.4451***(0.1237)	-0.0805***(0.0212)	0.3645
MIDAS (REERR)	-0.0402(0.0417)	0.0180*(0.0107)	-0.0222	-0.1552**(0.0582)	0.0176**(0.0077)	-0.1376
MIDAS (RIR)	-0.0287(0.0406)	0.0152(0.0105)	-0.0134	-0.0234**(0.0111)	0.0041**(0.0016)	-0.0193
MIDAS (Negative Asymmetry)	0.0761(0.0729)	-0.0302(0.0291)	0.0460			
MIDAS (Positive Asymmetry)	-0.0354(0.0377)	0.0100(0.0107)	-0.0254			
MIDAS (Break dummy)						
			India			
ARDL			0.2090(0.1933)			
MIDAS (Baseline)	0.1174(0.2203)	-0.1988*(0.1034)	-0.0814			
MIDAS (IPG)	0.1109(0.2122)	-0.198*(0.099)	-0.0871	0.1800(0.1532)	-0.11*(0.0546)	0.0700
MIDAS (REERR)	0.1196(0.2134)	-0.199*(0.0994)	-0.0794	-0.4015*(0.2134)	0.0956**(0.0398)	-0.3059
MIDAS (RIR)	0.2039(0.2175)	-0.2105**(0.1006)	-0.0066	-0.0248(0.0538)	0.0204(0.0166)	-0.0043
MIDAS (Negative Asymmetry)	-0.1559(0.1023)	0.0312(0.0203)	-0.1247			
MIDAS (Positive Asymmetry)	0.4679(0.3729)	-0.2350(0.1862)	0.2329			
MIDAS (Break dummy)						
			Russia			
ARDL			-0.0545(0.2582)			
MIDAS (Baseline)	0.2062(0.1534)	-0.0077(0.0217)	0.1985			
MIDAS (IPG)	0.2469(0.1520)	-0.0091(0.0219)	0.2378	-0.9695*(0.4827)	0.7501**(0.3649)	-0.2194
MIDAS (REERR)	0.0858(0.1883)	0.0080(0.0349)	0.0939	0.0949(0.1507)	0.0054(0.0215)	0.1003
MIDAS (RIR)	0.1999(0.1633)	-0.0058(0.0226)	0.1941	-0.3413(0.2649)	0.1621(0.1177)	-0.1792
MIDAS (Negative Asymmetry)	0.4602(0.3653)	-0.1812(0.1457)	0.2790			
MIDAS (Positive Asymmetry)	-0.1025(0.1368)	0.0220(0.0302)	-0.0805			
MIDAS (Break dummy)	0.1236(0.1446)	0.0024(0.0204)	0.1260			

Note: The statistical significance of the estimated coefficients are indicated by ***, ** and *, respectively, for 1%, 5% and 10% levels. The figures in parentheses are the standard error of the estimated coefficient. PDL01 and PDL02 represent the first and second Almon polynomial distributed lag (PDL) weighting. The terms in parentheses on the first column indicate the additional features and/or control variables included in the MIDAS framework.

Table 5: Predictability of OIDS for RHR

MODEL	OIDS					
	INDEPENDENT VARIABLE			CONTROL VARIABLE		
	PDL01	PDL02	Coefficient	PDL01	PDL02	Coefficient
			China			
ARDL			0.0441(0.1564)			
MIDAS (Baseline)	0.2867(0.2408)	-0.0096(0.1066)	0.2771			
MIDAS (IPG)	0.2015(0.2263)	0.0238(0.0991)	0.2253	0.3672***(0.1076)	-0.0659***(0.0190)	0.3013
MIDAS (REERR)	0.1897(0.2432)	0.0242(0.1066)	0.2139	-0.1057*(0.0559)	0.0113(0.0070)	-0.0944
MIDAS (RIR)	0.3376(0.2306)	-0.0278(0.1020)	0.3098	-0.0196*(0.0104)	0.0036**(0.0014)	-0.0160
MIDAS (Negative Asymmetry)	0.3183**(0.1586)	-0.1054*(0.0528)	0.2129			
MIDAS (Positive Asymmetry)	-0.1023(0.1800)	0.0401(0.0718)	-0.0622			
MIDAS (Break dummy)						
			India			
ARDL			-0.0211(0.5466)			
MIDAS (Baseline)	0.5318(0.4038)	-0.0017(0.0545)	0.5301			
MIDAS (IPG)	0.4984(0.3997)	0.0051(0.0566)	0.5035	0.0295(0.1763)	-0.0698(0.0619)	-0.0403
MIDAS (REERR)	0.2744(0.4155)	0.0218(0.0511)	0.2962	-0.3313(0.2422)	0.0872*(0.0468)	-0.2441
MIDAS (RIR)	-1.4764(0.9452)	1.0583**(0.4418)	-0.4181	-0.0693(0.0549)	0.0445**(0.0169)	-0.0248
MIDAS (Negative Asymmetry)	-2.0295**(0.9029)	0.8142**(0.3611)	-1.2153			
MIDAS (Positive Asymmetry)	0.3386(0.2263)	-0.0682(0.0452)	0.2704			
MIDAS (Break dummy)						
			Russia			
ARDL			-0.9275(0.8124)			
MIDAS (Baseline)	-1.2410(1.0508)	0.4472(0.3529)	-0.7938			
MIDAS (IPG)	-1.3203(1.0698)	0.3922(0.3111)	-0.9281	0.1982(0.1702)	0.0166(0.0156)	0.2148
MIDAS (REERR)	-1.3506(1.0468)	0.4624(0.3487)	-0.8882	0.1510(0.1521)	0.0019(0.0213)	0.1529
MIDAS (RIR)	-1.4881(1.1061)	0.6099(0.3819)	-0.8782	0.5880(0.7117)	-0.4369(0.4625)	0.1511
MIDAS (Negative Asymmetry)	1.9754(1.7954)	-0.9745(0.8976)	1.0010			

MIDAS (Positive Asymmetry)	-1.7596*(0.9075)	0.6945*(0.3623)	-1.0651
MIDAS (Break dummy)	-0.7730(0.5479)	-0.0091(0.0653)	-0.7821

Note: The statistical significance of the estimated coefficients are indicated by ***, ** and *, respectively, for 1%, 5% and 10% levels. The figures in parentheses are the standard error of the estimated coefficient. PDL01 and PDL02 represent the first and second Almon polynomial distributed lag (PDL) weighting. The terms in parentheses on the first column indicate the additional features and/or control variables included in the MIDAS framework.

Table 6: RMSE results for OSS

	OSS											
	CHINA				INDIA				RUSSIA			
Model	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	1.2906	0.6862	2.6908	2.7119	3.7762	4.5531	3.2663	2.6908	6.0497	0.7590	1.5932	1.4548
HA	1.3081	0.7440	2.7282	2.8242	3.7902	2.6908	1.9188	1.6773	6.0001	2.1513	2.4740	2.2476
MIDAS (Baseline)	1.0786	0.4409	1.9383	2.1214	3.6819	2.6049	1.9729	1.9880	5.6808	1.9094	3.1050	2.7314
MIDAS (IPG)	0.9976	0.8225	2.1595	2.2282	3.4953	2.8319	2.2227	2.2835	5.3954	1.0667	2.5595	2.2965
MIDAS (REERR)	1.0466	1.0129	1.7662	1.9504	3.4276	4.1507	3.3296	2.7466	5.3951	3.6359	5.3500	4.8024
MIDAS (RIR)	1.0427	0.9331	2.0222	2.0593	3.4683	4.0563	2.9069	2.9320	5.6616	1.6396	2.6211	2.4002
MIDAS (NA)	1.1805	0.3886	2.8788	2.9758	3.6180	1.9397	1.6659	1.9064	5.2478	1.5065	1.6491	2.5497
MIDAS (PA)	1.2104	0.9746	3.2411	3.2077	3.6800	2.1926	1.6707	1.8874	5.3968	1.9564	2.7188	2.9764
MIDAS(Break)	1.0288	0.4105	2.4230	2.7392	-	-	-	-	4.9124	1.7439	2.5206	2.0584

Note: HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

3.2.2 How useful is oil shock in forecasting housing returns?

The model adequacy of the different variants of the MIDAS-based model and the ARDL model along with the historical average model is analyzed subsequently using the Root Mean Square Error (RMSE) for the different oil shock alternatives. The in-sample and out-of-sample forecast performance are analytically examined. Considering the oil supply shock as the predictor in the MIDAS construct in comparison with the conventional ARDL and historical average models, for the in-sample period, the baseline MIDAS model outperforms both, having the least RMSE across the three countries. While this feat is replicated in the out-of-sample forecast performance for China, the same cannot be said for the out-of-sample performance in India and Russia, since there seems to be no clear consistent out-performance of any one model across the periods ahead forecast horizons (see the first three models in Table 6). The further incorporation of control variables improves the forecast performance of the MIDAS-based model in the in-sample but worsens same in the out-of-sample. This feat is observed across China, India and Russia. Also, MIDAS-based models incorporating, separately, positive and negative asymmetries do not outperform the baseline MIDAS model in the in-sample but do in the out of sample periods in the case of China and Russia. A comparison between both asymmetries showed the MIDAS-based model with negative asymmetry to consistently out-perform that incorporating the positive asymmetry. Our findings are in consonance with extant findings (see Tsai, 2015; Sakaki, 2019), which suggest the plausibility of "asymmetry" effect of positive and negative oil shocks on stock returns. These differing stances could be further observed under different periods – prior to crisis period, during crisis period and after crisis period. Another interesting feat is the role of structural breaks in improving the forecast performance of the MIDAS-based model. More evidenced in the case of Russia, the MIDAS-based model that accounts for structural break consistently out-performs, both in the in-sample and out-of-sample of the MIDAS-based model that ignores it, while the case of China only reveals out-performance in the in-sample and 2-quarters ahead forecast horizons. The importance of incorporating structural breaks in a model is herein validated as previously opined the work by Salisu et al. (2019b).

The model adequacy check, similar to those applied in Table 5 above, is employed to examine the MIDAS-based models that incorporate alternative oil shocks, which include EAS (Table 7), OCDS (Table 8) and OIDS (Table 9). On the adoption of EAS as an alternative oil shock series, the baseline MIDAS model is only observed to consistently out-perform the ARDL and historical average models across all consider sample periods in the case of Russia only, while the data favoured ARDL and historical average models in the cases of China and India, respectively. It is however observed that the incorporation of some control variables improved the in-sample forecast performance of the MIDAS-based model across the three countries. However, in the out-of-sample periods, MIDAS-based models incorporating REERR, IPG and RIR out-performed the baseline MIDAS model in China, India and Russia respectively. The incorporation of structural breaks improves the baseline MIDAS model across the sample periods for India and Russia, while it improved only the in-sample forecast for China (see the results in Table 7). Also, positive asymmetry seems to have lower RMSE than the negative asymmetry in the cases of India and Russia, while the reverse is the case for China.

Under the OCDS alternative (see Table 8), a consistent out-performance of the baseline MIDAS model over the ARDL and historical average models is observed across the three countries. However, for the out-of-sample performance, data supports the baseline MIDAS model in the China case, ARDL in the case of Russia and historical average model in the case of India. Although, as seen in earlier oil shock alternatives, the incorporation of control variables reduces the RMSE in the in-sample periods in all three countries, it does not replicate same in the out-of-sample periods. This stance is also evident when structural break is accounted for in the case of Russia. MIDAS-based model incorporating positive asymmetry seem to have lower RMSE compared to those incorporating negative asymmetry in the cases of China and Russia.

For the OIDS alternative, the baseline MIDAS model consistently out-performed ARDL and historical average models in both the in-sample and out-of-sample periods when China is considered, while it only replicated the out-performance feat in the in-sample for India and Russia. Generally, the incorporation of control variable is only observed to improve the in-sample forecast performance of the MIDAS-based models in the cases of China, India and Russia. Accounting for structural is also observed to improve the in-sample forecast of the MIDAS-based model whenever structural breaks are observed in the series, as seen in the case of Russia. Models incorporating negative asymmetry were found to have lower RMSE compared to those incorporating positive asymmetry as seen in the cases of India and Russia, while the reverse is the case for China. However, all the aforementioned stances would be further subjected to a pairwise comparison test – the Clark and West (see Tables 10 - 13).

Table 7: RMSE results for EAS

Model	EAS											
	CHINA				INDIA				RUSSIA			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	1.3108	0.6072	2.6889	2.7920	3.6662	2.7603	1.9881	1.7152	5.5184	0.2233	2.5660	2.1863
HA	1.3081	0.7440	2.7282	2.8242	3.7902	2.6908	1.9188	1.6773	6.0001	2.1513	2.4740	2.2476
MIDAS (Baseline)	1.3086	0.6613	2.7826	2.8142	3.1082	4.2664	3.1020	2.6453	5.6649	1.4282	1.7389	1.7631
MIDAS (IPG)	1.0857	0.6298	2.7618	2.8020	2.9733	3.7148	2.6829	2.2052	5.4931	2.1539	1.7363	2.3625
MIDAS (REERR)	1.1438	0.5232	2.1123	2.2126	2.8785	4.6636	3.5983	2.9930	5.4060	2.1215	3.9346	4.6759
MIDAS (RIR)	1.1668	0.7180	2.8963	2.9599	3.0045	3.8390	3.0518	2.6249	5.6408	0.9165	1.1406	1.3986
MIDAS (NA)	1.2601	1.1759	3.2494	3.3797	3.7138	2.5476	2.1387	1.8574	4.9267	0.0427	0.9725	1.4401
MIDAS (PA)	1.2605	1.0301	3.1298	3.2943	3.5310	3.0422	2.1643	1.9068	5.2559	1.8112	1.8599	2.4550
MIDAS(Break)	1.2406	0.9053	3.0188	3.0722	3.0890	4.2168	3.0586	2.6300	4.9379	1.1427	1.5567	1.4021

Note: HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

Table 8: RMSE results for OCDS

	OCDS											
	CHINA				INDIA				RUSSIA			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	1.3080	0.6201	2.6912	2.7964	3.7443	3.5463	2.7090	2.2424	5.9789	0.7420	1.6056	1.4813
HA	1.3081	0.7440	2.7282	2.8242	3.7902	2.6908	1.9188	1.6773	6.0001	2.1513	2.4740	2.2476
MIDAS (Baseline)	1.3033	0.0759	2.3764	2.4092	3.3707	4.0040	2.8578	2.4543	5.7509	2.5863	2.5646	2.8219
MIDAS (IPG)	1.0932	1.1638	3.2109	3.2617	3.1394	4.5197	3.3200	2.8036	5.4333	3.4582	2.4482	3.5387
MIDAS (REERR)	1.1720	0.3239	2.3609	2.4945	3.1352	4.5502	3.3213	2.8078	5.4878	2.8667	4.8737	5.0737
MIDAS (RIR)	1.1670	0.4541	3.0383	3.0669	3.1937	4.7394	3.4788	2.9733	5.7079	2.7534	2.4138	2.9284
MIDAS (NA)	1.2472	1.1500	3.3118	3.4186	3.6506	2.6425	1.9580	1.6397	5.3409	3.3825	3.0534	4.1805
MIDAS (PA)	1.2560	1.0504	3.2699	3.4428	3.6894	3.2105	2.3972	1.9667	5.4215	2.5770	3.1055	3.7547
MIDAS(Break)	-	-	-	-	-	-	-	-	4.9616	3.1568	2.6850	2.2893

Note: HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

Table 9: RMSE results for OIDS

Model	OIDS											
	CHINA				INDIA				RUSSIA			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	1.3072	0.6123	2.6905	2.7976	3.7797	4.4856	3.2176	2.6532	6.0363	1.2478	1.1899	1.1666
HA	1.3081	0.7440	2.7282	2.8242	3.7902	2.6908	1.9188	1.6773	6.0001	2.1513	2.4740	2.2476
MIDAS (Baseline)	1.2132	0.5220	2.5086	2.6109	3.6300	4.0862	3.1325	2.6902	5.9458	2.0925	2.1416	2.1605
MIDAS (IPG)	1.0384	0.5115	2.5340	2.6371	3.4230	4.1795	3.2493	2.8470	5.4724	1.6821	2.2026	2.2220
MIDAS (REERR)	1.1350	0.4175	2.1083	2.2893	3.4704	4.1649	3.1134	2.6401	5.4775	2.7840	4.8871	4.9831
MIDAS (RIR)	1.0863	0.4838	2.5660	2.6975	3.1674	3.1456	3.2567	2.9859	5.7286	1.1375	0.9603	0.8808
MIDAS (NA)	1.2128	1.1115	3.3052	3.3255	3.5591	1.1680	1.5687	1.4291	5.3967	2.1094	1.9941	2.6448
MIDAS (PA)	1.2495	1.0902	3.1584	3.2909	3.6620	2.1150	1.6957	1.5223	5.2555	2.3466	2.2491	2.8568
MIDAS(Break)	-	-	-	-	-	-	-	-	4.8627	4.4500	4.0322	3.8049

Note: HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

Table 10: C&W results for OSS

Model	OSS											
	CHINA				INDIA				RUSSIA			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	1.0327***	1.4689	4.6215	3.8107*	1.5618	18.417	9.2163	5.983	11.8014***	-1.4258	-2.7724	-2.1464
HA	0.9984***	1.6141*	4.9029*	4.5838*	1.6316	0.4904	0.695**	-0.161	7.8859***	11.7313	3.072	1.9974
MIDAS (Baseline)	-	-	-	-	-	-	-	-	-	-	-	-
MIDAS (Break)	0.0684	0.2535	2.4971	3.4923**	-	-	-	-	-0.5606	-0.5487	-2.656	-1.8213
MIDAS (IPG)	0.1098	1.0160	1.2340	1.1953	0.0063	1.3817	1.3224	1.5293	0.3076	-1.7804	-1.9122	-1.3797
MIDAS (Asymmetry)	0.1285	-0.3876	-1.9154	-1.2186	0.1148	-0.6739	0.4715	0.4112	0.1975	-1.3173**	-3.3673	-1.0022
MIDAS (REERR)	0.1305	1.4816	-0.215	-0.0601	1.238	13.681	9.6255	6.3589	-1.0776	15.277	26.0955	21.7791*
MIDAS (RIR)	0.1266	1.2290	0.6424	0.3016	0.844	12.853	7.510	7.922	0.4339	-0.7939	-	-1.4492

	1	2	1				2.4858

Note: ***, ** and * respectively represent statistical significance at 1%, 5% and 10% level. HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

On the Clark and West pairwise test, we compare all the contending models with the MIDAS (baseline) model except for the case of "asymmetry" consideration, where the MIDAS model with negative asymmetry is compared to the MIDAS model with positive asymmetry. In each case of comparison (see Tables 9 - 12), a positive and significant value suggests the preference in favour of the baseline or positive asymmetry, as in the case where asymmetry is considered. For the models with OSS as a predictor, we find the baseline MIDAS model to significantly out-perform the ARDL and historical averages in the in-sample forecast for China and Russia, but not in the case of India. The out-performance of the baseline MIDAS model over the other variants in the in-sample periods were however not statistically significant. The feat of out-performance of the baseline model is not evident in the out-of-sample periods for all three countries. We also do not find any consistency in the out-performance of the positive asymmetry model over the negative asymmetry model, as the values in all the considered sample periods for the three countries, except 2-quarters ahead forecast horizon for Russia, were statistically not significant. Our findings here confirm Kilian (2009) stance that oil shocks are not likely to be similar. This may be attributed to the nature and source of the oil shocks and the sample period investigated. In addition, the incorporation of structural break(s) only improved forecast performance over the baseline in the case of the 6-quarters ahead forecast horizon for China. This implies that where structural breaks are inherent in a series, they should be captured in the predictive model (see Salisu et al. 2019b).

Similar feats are also observed in the other oil shock alternatives (see Tables 10 - 12), as we find the baseline MIDAS model to out-perform the contending models in the in-sample period. Interestingly, a common feat across the alternative oil shock series is that the incorporation of control variables seems not to improve the result of the baseline MIDAS model. Also, the baseline MIDAS model with OSS as the main predictor variable seems to out-perform those incorporating other alternatives. This aligns with the submission of Broadstock and Filis (2014) and Sakaki (2019) that returns respond more to supply-side shocks than other sources of shocks. Accounting for structural breaks inherent in the series is only found to improve the baseline MIDAS model in the out-of-sample cases (see results in Table 10 - 12). Generally, we find consistent out-performance of the baseline MIDAS model over all other contending models mostly in the in-sample periods.

Table 11: C&W results for EAS

Model	EAS											
	CHINA				INDIA				RUSSIA			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	0.1235	-0.0657	-0.4906	-0.0998	9.8311^{**}	-5.3312	-1.8410	-0.8170	2.4422	0.6862	6.2667	3.8908
HA	0.1159	0.1276	-0.2775	0.0834	9.4024^{**}	-7.6174^{*}	-3.8414	-2.4214	8.2636^{***}	4.3214	4.5391^{**}	2.9418^{*}
MIDAS (Baseline)	1.2269^{***}	1.288^{***}	5.2262	4.4350^{*}	0.1170	15.4398	8.8382	6.3562	5.6200^{**}	2.3001	-2.7567	-1.7715
MIDAS (Break)	-0.0652	0.4419	1.446^{*}	1.6017^{**}	0.0090	-0.3705	-0.2218	-0.0378	0.3777	-0.2173	0.0550	-0.4983
MIDAS (IPG)	-0.1667	0.0015	-0.089	-0.0306	0.0027	-3.2790	-1.6697	-1.1186	-0.1877	3.1887	1.4214	4.2479
MIDAS (Asymmetry)	0.1370	0.3524	0.7923	0.5972	3.139^{***}	-2.0905	2.0326	1.2541	-1.3024	-0.1095	-0.6492	-2.1569^{*}
MIDAS (REERR)	-0.0786	-0.1404	-2.8292	-2.6460^{*}	-0.0157	3.7352	3.941^{**}	2.4103^{*}	0.4492	4.624	18.6987	28.450^{**}
MIDAS (RIR)	-0.0320	0.0828	0.6606	0.8671^{**}	-0.0021	-2.3330	0.7837	0.9424	0.4805	-0.9245	-1.3455	-0.8103

Note: ***, ** and * respectively represent statistical significance at 1%, 5% and 10% level. HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

Table 12: C&W results for OCDS

Model	OCDS											
	CHINA				INDIA				RUSSIA			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	0.0670	0.763	1.866^{*}	2.305^{**}	5.7473^{***}	-1.447	2.1046	1.1785	6.3242^{***}	-0.4336	-0.7887	-2.1739
HA	0.0710	1.090	2.1579^{*}	2.5279^{***}	6.2311^{***}	-4.465	-1.927	-0.6127	6.6351^{**}	19.1716^{*}	12.1065^{*}	6.2984
MIDAS (Baseline)	1.0382^{***}	0.061	2.2322	1.805	1.0272	13.127	6.3167	5.7693	5.4463^{*}	6.4519	0.653	3.8125
MIDAS (Break)	-	-	-	-	-	-	-	-	-0.5996	3.8662	3.0688	1.1774
MIDAS (IPG)	-0.0909	2.650	5.847^{*}	5.890^{**}	-0.0497	4.6617	3.4007	2.4174	-0.8451	6.5046	2.9781	8.3267
MIDAS (Asymmetry)	0.0051	0.2355	0.3108	-0.1305	0.9034	-1.8355	0.2153	0.4066	0.0669	5.9347	0.9183	5.3037
MIDAS (REERR)	0.0355	0.2131	0.028	0.5206	-0.0996	5.0013	3.3063	2.1680	-0.6115	4.3974	28.3395	26.8539

MIDAS (RIR)	-0.0107	0.4137	4.1123	4.1167*	-0.0543	6.9715	5.2436	4.7470*	0.5374	1.1242	-0.3975	0.9617

Note: ***, ** and * respectively represent statistical significance at 1%, 5% and 10% level. HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

Table 13: C&W results for OIDS

Model	OIDS											
	CHINA				**INDIA**				**RUSSIA**			
	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6	In-Sample	H-2	H-4	H-6
ARDL	0.3973*	0.165	1.008	1.0692*	2.2727**	3.609	3.024	1.9829	2.6717*	0.5315	-0.2228	1.9728
HA	0.4014*	0.374	1.235	1.2328*	2.3642**	-6.268	-3.609	-2.6382	1.3677	1.1946	2.1708	1.3947
MIDAS (Baseline)	0.7806**	0.977	3.314	3.0160*	2.1276**	12.898	10.900	6.7159	7.6915***	7.5204	0.3705	1.2612
MIDAS (Break)	-	-	-	-	-	-	-	-	1.3026	50.376	41.951*	39.6217***
MIDAS (IPG)	-0.0976	0.008	0.140	0.1604	-0.0042	0.9247	0.9610	1.1484*	0.3049	-0.9123	4.1886	2.8873
MIDAS (Asymmetry)	-0.0074	0.154	1.026	0.2905	0.4726	-1.9654**	0.4532	0.3512	3.2546	0.9169	0.8087	1.9154
MIDAS (REERR)	-0.0555	-0.087	-1.688	-1.4569*	0.1035	0.9592	0.2632	0.1078	-0.7065	5.0670*	28.8268	30.0385**
MIDAS (RIR)	-0.0165	-0.031	0.299	0.4714*	1.3813	-5.8496	2.8871	3.3938	-1.1547	-2.1235	-1.9795	-1.3439

Note: ***, ** and * respectively represent statistical significance at 1%, 5% and 10% level. HA=Historical Average; NA=Negative Asymmetry; PA=Positive Asymmetry.

4.0 Conclusion

In this study, we analyze whether housing returns respond to oil shocks and by extension whether the former possess risk hedging characteristics against the latter. We employ the MIDAS approach which allows for mixed data frequencies in the predictability of economic relationships. Also, we utilize data covering China, India and Russia which thus allowing us to offer empirical evidence from the perspective of the BRICS regional bloc. Although, it may not be valid for a wider generalization, the selection in a way helps us to analyze the response of housing returns to oil shocks from the perspective oil exporting (Russia) and oil importing countries (China and India). The definition of oil shocks follows the categorization rendered by Baumeister and Hamilton (2019) where oil shocks are decomposed into four variants namely oil supply shocks, economic activity shocks, oil consumption demand shocks, and oil inventory demand shocks. Essentially, Baumeister and Hamilton (2019) extend the demand- and supply-oriented oil shocks of Kilian (2009) and Kilian and Park (2009) to include other (more) specific oil shocks relating to consumption- and inventory demand-oriented oil shocks. The predictability of each of these variants is distinctly evaluated for all the countries considered.

Our findings can be summarized in two-fold. First, our results suggest that housing returns respond differently to the variants of oil shocks. More importantly, we find that the housing returns of the net oil-exporting country may serve as a good hedge again oil price risk while the same cannot be said for the net oil-importing countries involving China and India. Second, the MIDAS framework offers better predictability than other model variants such as the ARDL and historical averages and ignoring the inherent feature of the former may lead to wrong conclusions. Finally, future studies may extend the analyses to a wider scope that captures more representative countries for oil exporting and oil importing groups to be able to offer a more convincing generalization about oil shock-housing returns nexus.

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