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Is the Response of the Bank of England to Exchange Rate Movements Frequency-Dependent?

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Abstract

In this paper, we estimate a Small Open Economy Dynamic Stochastic General Equilibrium (SOEDSGE) model of the United Kingdom (UK), with the main focus being to test the hypothesis whether the Bank of England (BoE) responds to (frequency-dependent) exchange rate movements or not. For our purpose, we use an extended quarterly data set spanning the period of 1986:Q1 to 2018:Q1, which in turn includes the zero lower bound situation, and also estimate the SOEDSGE model based on observable data decomposed into its frequency components, under the presumption that central banks is more comfortable in responding to to long-term fundamental movements in exchange rates. We find that the BoE not only responds to exchange rate movements in a statistically significant manner, but also

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that it primarily focuses on long-term movements of currency depreciations more strongly than short-term fluctuations of the same.

Keywords: Small Open Economy DSGE Model, Monetary Policy Rule, Exchange Rate, Structural Estimation, Bayesian Analysis, Wavelets

JEL Classification: C32, E52, F41.

1. Introduction

The United Kingdom (UK), just like the United States (US), is a major player in the world economy, with monetary policy decisions of the Bank of England (BoE) being of interest to both academicians and financial markets. Given this, what variables determine the interest rate-setting behaviour of the BoE is, understandably, an important question. While the role of the output-gap and inflation rate in determining the policy rate of the BoE, and central banks across the world, is well-accepted along the lines of the Taylor-rule (Taylor (1993)), whether information in exchange rate movements should also be accounted for remains a debatable issue.

UK is a natural resource exporter, and hence, domestic business cycle fluctuations are likely to have substantial international relative price components. In addition, monetary policy is partly transmitted to the real economy through its effect on the exchange rate. The BoE therefore may have a specific interest in explicitly reacting to and smoothing exchange rate movements as a predictor of domestic volatility. However, based on various alternative econometric approaches (for example, single-equation interest rate rules, structural vector autoregressions (SVARs), Small Open Economy Dynamic Stochastic General Equilibrium (SOEDSGE) models), evidence regarding that the BoE responds to (nominal) exchange rate movements is mixed (see for example, Lubik and Schorfheide (2007), Dong (2013), Bjornland and Halvorsen (2014)). [1]

Low frequency movements in exchange rates are likely to be tied with fundamentals more than high-frequency movements of the same, which in turn could be associated with speculation, and hence (harder to predict) random behaviour (Rapach and Wohar (2002), Balke, Ma, and Wohar (2013)), Caraiani (2017)). Given this, it is possible that central bankers find it more comfortable to respond to long-term (i.e., low-frequency) movements of the exchange rate rather than its corresponding short-term fluctuations. With this hypothesis in mind, the objective of this paper is to revisit the question of whether the BoE respond to exchange rate movements, with us now analyzing not only the aggregate nominal effective exchange rate depreciations, but also its various frequency components. Given the well-known econometric issues associated with single-equation rule-type and atheoretical VAR approaches in light of the Lucas Critique (Lucas (1976)), we estimate the SOEDSGE model of Lubik and Schorfheide (2007) for the UK to provide an answer to our question, over the period of 1986:Q1 to 2018:Q1. While, closed-economy frequency-based models for the US economy has been estimated before (see, Caraiani (2015)for a detailed discussion in this regard), to the best of our knowledge, this is the first attempt to estimate a SOEDSGE model in both time and frequency-domains to determine whether the BOE's response to exchange rate movements is contingent on its frequency components.

[1]But, some evidence in favor of the fact that the BoE does weigh in exchange rate movements in its interest rate decisions can be observed when one allows for structural regime-switches (see for example, Chen and Macdonald (2012), and Alstadheim, Bjornland, and Maih (2013)).

The remainder of the paper is organized as follows: Section 2 lays out the basics of the SOEDSGE and the frequency decomposition of the data using wavelet, Section 3 presents the data and results, with Section 4 concluding the paper.

2. Theoretical and Empirical Frameworks

In this section, we introduce the open-economy DSGE model used in the empirical analysis, and detail the wavelet filtering method used to decompose the observable data series used in the estimation of the DSGE model.

2.1. An Open Economy DSGE Model

The model we use is one of the reference models used in the past to answer to the question whether the central banks react or not to exchange rates, Lubik and Schorfheide (2007). The model is a simplified version of the reference model in Gali and Monacelli (2005).

$$\begin{aligned} y_t = E_t y_{t+1} - (\tau + \alpha\ (2-\alpha)\ (1-\tau))\ (R_t - E_t \pi_{t+1}) - \rho_z\, z_t - \\ \alpha\ (\tau + \alpha\ (2-\alpha)\ (1-\tau))\ E_t \Delta q_{t+1} + \alpha\ (2-\alpha)\ \frac{1-\tau}{\tau}\, E_t \Delta y^*_{t+1} \end{aligned} \tag{1}$$

The first equation is an open economy IS curve. Here, y_t is the output, R_t the nominal interest rate, π_t the domestic inflation, q_t the terms of trade and y^*_t the foreign output. The parameter α is the import share, while τ is the intertemporal substitution elasticity.

$$\pi_t = \beta E_t \pi_{t+1} + \alpha\beta E_t \Delta q_{t+1} - \alpha \Delta q_t + \frac{\kappa}{\tau + \alpha\ (2-\alpha)\ (1-\tau)}\ (y_t - \bar{y}_t) \tag{2}$$

Equation 2 is the open economy economy equivalent of a New Keynesian Phillips curve. Here $\bar{y}$ is the potential output, i.e. that level of output when prices nominal rigidities are missing. The parameter κ is determined by factors like labor supply and demand elasticities or by price stickiness. The potential output is defined below, in equation 3.

$$\bar{y}_t = -\alpha \frac{(1-\tau)\ (2-\alpha)}{\tau} y_t^* \tag{3}$$

$$\pi_t = \Delta e_t + \Delta q_t\ (1-\alpha) + \pi_t^* \tag{4}$$

Equation 4 above shows the link between domestic inflation π_t, nominal exchange rate e_t, terms of trade q_t as well as foreign inflation, denoted by π_t^*.

$$R_t = \rho_r R_{t-1} + (1-\rho_r)\left(\psi_1 \pi_t + \psi_2 y_t + \psi_3 \Delta e_t\right) + \epsilon_{r3_t} \tag{5}$$

The last equation, equation 5, introduces a standard Taylor, modified to include the reaction to exchange rate movements. The parameter ρ_r characterizes the degree of interest rate smoothing, while ψ_1, ψ_2, ψ_3 correspond to inflation, output and exchange rate movements.

$$\Delta q_t = \rho_q \Delta q_{t-1} + \epsilon_{q_t} \tag{6}$$

Following the original paper, Lubik and Schorfheide (2007), changes in terms of trade are assumed to follow an AR(1) process, equation 6. Finally, AR(1) processes are also assumed for world technology, z_t, foreign output y_t^* and foreign inflation π_t^*, see equations 7-9.

$$z_t = \rho_z \, z_{t-1} + \epsilon_{z_t} \tag{7}$$

$$y_t^* = \rho_{y^*} y_{t-1}^* + \epsilon_{y_t^*} \tag{8}$$

$$\pi_t^* = \rho_{\pi^*} \pi_{t-1}^* + \epsilon_{\pi_t^*} \tag{9}$$

2.2. Wavelet Decomposition

A known issue in estimating DSGE model is that the filtering of the series must not use forward information, but only the backward observations to derive the current filtered value. This is a known issue for several filtering methods, including the double-sided Hodrick-Prescott filter. In the context of wavelets, the standard filtering using wavelets suffers from the same deficiency. To address this shortcoming, we use the redundant wavelet transform, see Aussem, Campbell, and Murtagh (1998) and Zheng, Starck, Campbell, and Murtagh (1999). This approach has already been used in Caraiani (2017) to forecast exchange rate on different frequencies.

The approach we use is based on the redundant Haar Wavelet Transform. The main advantage being that it performs the time-scale decomposition using only the previous data-points. Below, we present the algorithm for general redundant discrete wavelet transform, which is also known as *the à trous wavelet transform*.

We start from a series $c_0(k)$. The initial series is decomposed into wavelets components, as well as a smooth component. At each scale j the latter is denoted by

$c_j(k)$. The initial series can be written as the scalar product at samples k of the function $f(x)$ and the scaling function $\phi(x)$.

$$c_0(k) =< f(x), \phi(x-k) > \tag{10}$$

The scalar function is selected such that the following equation holds (also known as the dilation equation)

$$\frac{1}{2}\phi(\frac{x}{2}) = \sum_l h(l)\phi(x-l) \tag{11}$$

h stands for the low-pass filter, corresponding to ϕ_x. Based on these equations, we can derive the smooth component at resolution j for any observation k as follows:

$$c_j(k) = \frac{1}{2^j} < f(x), \phi\frac{(x-k)}{2^j} > \tag{12}$$

For two consecutive resolutions, the difference between them can be denoted by w_j. Thus, we obtain:

$$w_j(k) = c_{j-1}(k) - c_j(k) \tag{13}$$

This can also be written as:

$$w_j(k) = \frac{1}{2^j} < f(x), \psi\frac{(x-k)}{2^j} > \tag{14}$$

Thus, we obtained the discrete wavelet transform using the *the à trous* algorithm. ψ denotes wavelet function given by:

$$\frac{1}{2}\psi(\frac{x}{2}) = \phi(x) - \frac{1}{2}\phi(\frac{x}{2}) \tag{15}$$

Using this algorithm, we can decompose the initial series as the sum of wavelet components w_j and a smooth component c_p:

$$c_0(k) = c_p + \sum_{j=1}^{p} w_j(k) \tag{16}$$

3. Empirical Analysis

3.1. Data

The SOEDSGE model is fitted to data on output growth, inflation, nominal interest rates, exchange rate changes, and terms of trade changes. We consider seasonally adjusted quarterly data for the UK covering the period of 1986:Q1 to 2018:Q1. The series were obtained (primarily) from the Main Economic Indicators (MEI) database of the Organisation for Economic Co-operation and Development (OECD). The output series is real GDP in per-capita terms, inflation is computed using the Consumer Price Index. The nominal interest rate is a short-term rate. However, given the zero lower bound situation of the monetary policy instrument in the wake of the "Great Recession", we use the shadow short rate developed by Wu and Xia (2016), based on its availability, over the period of 1990 (till the end of the sample), and the regular short-term-rate prior to that. Note that, the shadow short rate is the nominal interest rate that would prevail in the absence of its effective lower bound, with it derived by modeling the (three-factors) term structure of the yield curve, and has been shown by Wu and Xia (2016) to be a close approximation of the short-term rate during the conventional periods of monetary policy decision-making. As nominal exchange rate variable we use a nominal trade-weighted exchange rate index, whereas the terms of trade are measured as the (natural log) ratio of export and import price indices. We de-mean the data prior to estimation.

3.2. Estimating the DSGE Model across Time and Frequency

We provide estimations for the DSGE model for both the aggregate demeaned series, as well as the wavelet components. Although there is some effort to estimate structural equations along different wavelet components, see Gallegati, Gallegati, Ramsey, and Semmler (2011), or structural DSGE models, see Caraiani (2015), a problem that negatively affected previous work was the fact that the wavelet decomposition did not take into account the forward character of standard wavelet transform. In contrast, in this paper, we use a redundant wavelet transform based on the Haar wavelet that is purely backward looking.

In Table 1, we first provide estimations for the aggregate series. We also provide estimations for the wavelet components, W_1 to W_4 in Tables 2 to 5. Each component W_i captures the changes in the interval $[2^i, 2^{i+1}]$. Thus the W_1 component measures the dynamics between 2 and 4 quarters while the W_4 component does the same for the changes between 16 and 32 quarters (4 to 8 years). Based on the results, we make the following two main observations:

First from Table 6, using the marginal data densities obtained under the models allowing for response of the interest rate to exchange rate movements and then restricting it to zero, we find that the former (unrestricted) model has a better fit than the restricted version of the same, with the results holding for not only the aggregate data, but also in the cases of the wavelet components ($W1$, W_2, W_3 and W_4). In terms of the Bayes factor reported in the same table, we can say that the unrestricted model performs significantly better for the aggregate series, and the wavelet components W_2, W_3 and W_4, with the highest gain obtained under the longest frequency considered (W_4), i.e., at changes in exchange rates at between 16 and 32 quarters.[2]

Second, when comparing the results across Tables 1 to 5, we observe that, for some of the parameters, there is a tendency to move in certain patterns across the different frequencies. For example, the autocorrelation coefficients are stronger at detail W_4 as compared to detail W_1. The coefficient attached to inflation is also weaker at the first detail W_1, while there is also a tendency toward stronger responses of the interest rate to exchange rate, although for the latter case, this is not verified for W_4. The results are similar in essence with the findings in the previous related work, like Caraiani (2015) or Sala (2015). It must be noted however, that Caraiani (2015) did not find a clear pattern for the Taylor rule coefficients, but mostly for structural parameters related to the behavior of households and firms in the New Keynesian DSGE model used by the author.

In sum, we can draw two main conclusions: (a) The marginal densities of the DSGE model increases for the frequency-based estimations when compared to the aggregate series, with the fit increasing massively in a consistent manner as the

[2]Using the original data span of Lubik and Schorfheide (2007) ending in 2003, the biggest gain in terms of the Bayes factor was observed under the aggregate series, with the results available upon request from the authors. Clearly then, over the recent periods, the BoE has started to respond more strongly to the exchange rate depreciations, and in particular to long-frequency movements of the same.

BoE targets lower frequency movements in the exchange rate, and; (b) While, the response of interest rate to exchange rate movements is the strongest under the aggregate series (which makes sense given that the original data series is the sum of all four frequency components),[3] the explanatory power of the structural model to explain the behavior of the economy of the UK, especially in terms of the BoE responding to exchange rate depreciations, particularly at longer horizons, is much higher than not responding at all.

4. Conclusions

The existing literature provides mixed evidence in terms of whether the BoE responds to exchange rate movements or not. Given this, we revisit this question, but now we analyze not only aggregate nominal effective exchange rate depreciations, but also its various frequency components, with the belief that low- frequency movements in exchange rates are likely to be tied with fundamentals more than high-frequency movements of the same, and hence, central bankers might find it more comfortable to respond to such long-term fluctuations. We estimate a SOEDSGE model to provide an answer to our question, over the extended period (relative to existing studies) of 1986:Q1 to 2018:Q1, which in turn, also include the zero lower bound period of the interest rates. Unlike the conflicting evidence in existing studies, we find

[3]This observation, though statistically insignificant as in Bjornland and Halvorsen (2014), is also verified when we compare the impulse response of the interest rate to an exchange rate shock for the aggregate and wavelet-decomposed data series, obtained from a VAR model, whereby the shock is identified using a Choleski decomposition (i.e., with a recursive ordering of output growth, inflation, terms of trade changes, nominal interest rates, and exchange rate changes). Complete details of these results are available upon request from the authors.

evidence that the BoE not only responds to exchange rate movements in a statistically significant manner (likely driven by the extended sample), but also the fact that it primarily focuses on long-term movements of currency depreciations more strongly than short-term fluctuations of the same.

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Table 1: Results from Metropolis-Hastings for Aggregate Series

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
κ	gamma	0.500	0.2500	0.474	0.1046	0.3078	0.6327
ψ_1	gamma	1.500	0.5000	3.120	0.3418	2.5576	3.6670
ψ_2	gamma	0.250	0.1500	0.095	0.0273	0.0492	0.1390
ψ_3	gamma	0.250	0.1500	0.237	0.0601	0.1380	0.3350
τ	beta	0.500	0.2000	0.239	0.0448	0.1666	0.3074
ρ_r	beta	0.500	0.1000	0.801	0.0292	0.7560	0.8496
ρ_q	beta	0.400	0.2000	0.060	0.0386	0.0031	0.1139
ρ_{π^*}	beta	0.800	0.1000	0.426	0.0648	0.3197	0.5327
ρ_{y^*}	beta	0.900	0.1000	0.996	0.0033	0.9918	1.0000
ρ_z	beta	0.200	0.0500	0.582	0.0073	0.5729	0.5897
ϵ_r	invg	0.500	4.0000	0.167	0.0205	0.1339	0.1991
ϵ_q	invg	1.500	4.0000	0.543	0.0344	0.4862	0.5980
ϵ_{y^*}	invg	1.500	4.0000	0.461	0.1151	0.2900	0.6317
ϵ_{π^*}	invg	0.500	4.0000	1.402	0.0892	1.2563	1.5461
ϵ_z	invg	1.000	4.0000	0.385	0.0458	0.3087	0.4553

Table 2: Results from Metropolis-Hastings for W1 Component

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
κ	gamma	0.500	0.2500	2.804	0.4439	2.0656	3.5245
ψ_1	gamma	1.500	0.5000	1.926	0.4362	1.1912	2.6131
ψ_2	gamma	0.250	0.1500	0.666	0.3300	0.1516	1.2275
ψ_3	gamma	0.250	0.1500	0.096	0.0341	0.0401	0.1499
τ	beta	0.500	0.2000	0.652	0.0668	0.5472	0.7676
ρ_r	beta	0.500	0.1000	0.430	0.0694	0.3166	0.5439
ρ_q	beta	0.400	0.2000	0.025	0.0180	0.0012	0.0492
ρ_{π^*}	beta	0.800	0.1000	0.135	0.0256	0.1025	0.1703
ρ_{y^*}	beta	0.900	0.1000	0.125	0.0426	0.0551	0.1885
ρ_z	beta	0.200	0.0500	0.117	0.0267	0.0755	0.1618
ϵ_r	invg	0.500	4.0000	0.131	0.0194	0.1005	0.1612
ϵ_q	invg	1.500	4.0000	0.394	0.0250	0.3522	0.4336
ϵ_{y^*}	invg	1.500	4.0000	0.643	0.2161	0.3406	0.9760
ϵ_{π^*}	invg	0.500	4.0000	0.751	0.0497	0.6696	0.8298
ϵ_z	invg	1.000	4.0000	0.544	0.1379	0.3275	0.7702

Table 3: Results from Metropolis-Hastings for W2 Component

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
κ	gamma	0.500	0.2500	1.429	0.2410	1.0274	1.7964
$\psi 1$	gamma	1.500	0.5000	2.751	0.4167	2.0531	3.3984
$\psi 2$	gamma	0.250	0.1500	0.185	0.0992	0.0300	0.3305
$\psi 3$	gamma	0.250	0.1500	0.161	0.0437	0.0902	0.2321
τ	beta	0.500	0.2000	0.713	0.0674	0.6068	0.8246
ρ_r	beta	0.500	0.1000	0.562	0.0612	0.4588	0.6575
ρ_q	beta	0.400	0.2000	0.319	0.1018	0.1580	0.4865
ρ_{π^*}	beta	0.800	0.1000	0.456	0.0611	0.3559	0.5568
ρ_{y^*}	beta	0.900	0.1000	0.749	0.0509	0.6670	0.8321
ρ_z	beta	0.200	0.0500	0.241	0.0373	0.1817	0.3025
ϵ_r	invg	0.500	4.0000	0.094	0.0133	0.0725	0.1132
ϵ_q	invg	1.500	4.0000	0.198	0.0090	0.1863	0.2108

(Continued on next page)

Table 3: (continued)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
ϵ_{y^*}	invg	1.500	4.0000	0.777	0.3060	0.3912	1.2052
ϵ_{π^*}	invg	0.500	4.0000	0.477	0.0297	0.4283	0.5253
ϵ_z	invg	1.000	4.0000	0.263	0.0537	0.1791	0.3481

Table 4: Results from Metropolis-Hastings for W3 Component

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
κ	gamma	0.500	0.2500	0.378	0.0778	0.2536	0.5016
$\psi 1$	gamma	1.500	0.5000	2.769	0.4317	2.0326	3.4240
$\psi 2$	gamma	0.250	0.1500	0.179	0.0769	0.0484	0.3062
$\psi 3$	gamma	0.250	0.1500	0.175	0.0473	0.0960	0.2471
τ	beta	0.500	0.2000	0.690	0.0692	0.5749	0.8069
ρ_r	beta	0.500	0.1000	0.668	0.0423	0.6000	0.7414
ρ_q	beta	0.400	0.2000	0.708	0.1219	0.5238	0.9107
ρ_{π^*}	beta	0.800	0.1000	0.831	0.0423	0.7592	0.9013
ρ_{y^*}	beta	0.900	0.1000	0.914	0.0385	0.8552	0.9816
ρ_z	beta	0.200	0.0500	0.437	0.0335	0.3840	0.4927
ϵ_r	invg	0.500	4.0000	0.076	0.0072	0.0641	0.0873
ϵ_q	invg	1.500	4.0000	0.189	0.0025	0.1863	0.1922
ϵ_{y^*}	invg	1.500	4.0000	0.804	0.2895	0.3758	1.2188
ϵ_{π^*}	invg	0.500	4.0000	0.227	0.0143	0.2039	0.2504
ϵ_z	invg	1.000	4.0000	0.179	0.0246	0.1402	0.2164

Table 5: Results from Metropolis-Hastings for W4 Component

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
κ	gamma	0.500	0.2500	0.285	0.0514	0.2019	0.3716
ψ_1	gamma	1.500	0.5000	2.604	0.2640	2.2327	2.9773
ψ_2	gamma	0.250	0.1500	0.035	0.0177	0.0072	0.0621
ψ_3	gamma	0.250	0.1500	0.054	0.0248	0.0146	0.0934
τ	beta	0.500	0.2000	0.571	0.0635	0.4682	0.6735
ρ_r	beta	0.500	0.1000	0.521	0.0431	0.4685	0.5917
ρ_q	beta	0.400	0.2000	0.566	0.1345	0.3478	0.7560
ρ_{π^*}	beta	0.800	0.1000	0.918	0.0271	0.8730	0.9614
ρ_{y^*}	beta	0.900	0.1000	0.979	0.0135	0.9608	0.9999
ρ_z	beta	0.200	0.0500	0.323	0.0479	0.2577	0.3903
ϵ_r	invg	0.500	4.0000	0.072	0.0048	0.0636	0.0794
ϵ_q	invg	1.500	4.0000	0.189	0.0022	0.1863	0.1915
ϵ_{y^*}	invg	1.500	4.0000	0.498	0.1400	0.2987	0.7116
ϵ_{π^*}	invg	0.500	4.0000	0.080	0.0050	0.0723	0.0885
ϵ_z	invg	1.000	4.0000	0.355	0.0808	0.2407	0.4824

Table 6. Bayes Factors

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	-389.94	198.3	474.65	597.42	711.97
Marginal Data Densities ($\psi_3 = 0$)	-397.72	197.8	466.55	573.23	611.09
Bayes Factor	2381.810	1.708	3291.13	exp(24.18)	exp(100.87)