Is the response of the bank of England to exchange rate movements frequency-dependent?•

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A B S T R A C T

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:Q2 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. We fnd that the BoE not only responds to exchange rate movements in a statistically signifcant manner, but also that it primarily focuses on long-term movements of currency depreciations more strongly than short-term fuctuations of the same. In general, our results are also confrmed for three other developed infation-targeters namely, Australia, Canada and New Zealand.

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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 fnancial 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 infation 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 fuctuations are likely to have substantial international relative price components. In addition, monetary policy is partly transmitted to the real economy through its efect on the exchange rate. The BoE therefore may have a specifc 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),

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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 et al., 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.

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).[2] The model is a simplified version of the reference model in Gali and Monacelli (2005).

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

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.

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

Eq. (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 Eq. (3).

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

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

Eq. (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.

$$R_t = \rho_r R_{t-1} + (1-\rho_r)(\psi_1 \pi_t + \psi_2 y_t + \psi_3 \Delta e_t) + \epsilon^r_t \tag{5}$$

The last equation, Eq. (5), introduces a standard Taylor rule, 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, Eq. (6). Finally, AR(1) processes are also assumed for world technology, z_t, foreign output y^*_t and foreign inflation π^*_t, see Eqs. (7)–(9).

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$$z_t \quad \rho_z z_{t-1} \quad \epsilon_t^z \tag{7}$$

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

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

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 et al. (1998) and Zheng et al. (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:

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

Summing up, although the wavelet have been used extensively in empirical macroeconomics, and recently in estimating DSGE models, up to now the wavelets used in filtering the series were not purely backward looking. As such, this questions the significance of results, especially for the case of estimating DSGE models for which data series should be filtered only on the basis of backward observations.

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:Q2 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

Table 1
Estimated parameters: corresponding equations and meaning.

κ	Phillips Curve	Slope Coefficient
ψ_1	Taylor Rule	Reaction to inflation
ψ_2	Taylor Rule	Reaction to output
ψ_3	Taylor Rule	Reaction to exchange rate
τ	IS Curve	Intertemporal substitution elasticity
ρ_r	Taylor Rule	Interest rate smoothness
k	Taylor Rule	Parameter for augmented Taylor rule
ρ_q	AR(1) exchange rate	Persistence in exchange rate
ρ_{π^*}	AR(1) foreign inflation	Persistence in foreign inflation
ρ_{y^*}	AR(1) foreign output	Persistence in foreign output
ρ_z	AR(1) productivity	Persistence in productivity
ϵ_r	Taylor rule	Monetary Policy Shock
ϵ_q	AR(1) exchange rate	Exchange rate shock
ϵ_{y^*}	AR(1) foreign output	Foreign output shock
ϵ_{π^*}	AR(1) foreign inflation	Foreign inflation shock
ϵ_z	AR(1) productivity	Productivity Shock

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 demean 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 et al. (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. The filtration was done for each series individually, pretty much like in the case of standard filtering methods used in preparing data series for estimating a DSGE model (be it first difference, backward HP filtering or band-pass filters), see Table 1 for definitions and explanations of the parameters.

In Table 2, we first provide estimations for the aggregate series. We also provide estimations for the wavelet components, W_1 to W_4 in Tables 4–7. 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 8, 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

Table 2
Results from Metropolis–Hastings for Aggregate Series - baseline Taylor rule.

	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							

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.[3]

Second, when comparing the results across Tables 2 and 4 tbl0005 tbl0006–7, 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.

Third, compared to the case of the estimates of the original paper by Lubik and Schorfheide (2007), we found that there is a stronger coefficient attached to inflation in our paper as compared to the original paper (we discuss here only the aggregate series, not the details for which there is no correspondence in the original paper), however the coefficients for output gap and exchange rate depreciation are much closer. When the same data sample was used as in the original paper, the estimates for output gap and exchange rate are basically the same, while the estimated parameter for inflation is much closer, though still higher.

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 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),[4] 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. Further results and robustness

In this section we further consider several robustness exercises as well as further analysis. First, we take into consideration an augmented Taylor rule. In the second step, we also look whether there is variation in the responses of interest rate to exchange rate coefficients.

4.1. An augmented Taylor rule

We further employ an augmented Taylor rule following the contribution in Lansing and Ma (2017).[5] The Taylor rule in Eq. (5) is replaced with the following specification:

$$R_t = \rho_r R_{t-1} + (1-\rho_r)(\psi_1\pi_t + \psi_2 y_t + \psi_3(\Delta e_t + k\Delta e_{t-1} + (1-k)^*(\pi_t - \pi_t^*))) + \epsilon_t^r \tag{17}$$

Here the coefficient k gives a combination between a standard Taylor rule for $k = 1$, corresponding to the paper by Lubik and Schorfheide (2007), and a Taylor rule augmented to take into account deviations from power purchasing parity, as in Lansing and Ma (2017). Since our model does not feature the price levels, we slightly departed from Lansing and Ma (2017) and used the difference between domestic and foreign inflation rates, given that the DSGE model estimation is not based on levels data. We re-estimated our model for the aggregate series, with the results for the wavelet decomposed components available at request.

Our results (see Table 3 for the estimates for aggregate series and Table 9 for Bayes factors) indicate that the model featuring an augmented Taylor rule outperforms the model with a baseline Taylor rule that does not feature an exchange rate, but it does not outperform the model with the Taylor rule extended with the exchange rate.

4.2. Sub-sample analysis

In this section, we analyze whether there is any time variation in the responses of monetary policy (through the nominal interest rate) to the exchange rate modifications. Given the limited data-sample, we choose to split the available sample between 1986:Q2 and 2018:Q1 into two equal sub-samples, one between 1986:Q2 and 2002:Q1 and one between 2001:Q2 and 2018:Q1. However, these periods roughly correspond to the Great Moderation, and, respectively to the Great Recession and its aftermath (we can also include a few years before the crisis to take into account the buildup in the boom). We have estimated the model for both the aggregate series and the 4 different wavelet details (with the results available at request).

However, we focus here on the main research question and discuss only whether there is time-variation in the responses of

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Table 3
Results from Metropolis–Hastings for Aggregate Series - extended Taylor rule.

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
κ	gamm	0.500	0.2500	0.466	0.0990	0.3105	0.6237
$\psi 1$	gamm	1.500	0.5000	3.125	0.3356	2.5653	3.6597
$\psi 2$	gamm	0.250	0.1500	0.096	0.0272	0.0526	0.1418
$\psi 3$	gamm	0.250	0.1500	0.137	0.0349	0.0795	0.1925
τ	beta	0.500	0.2000	0.234	0.0419	0.1673	0.3000
ρ_r	beta	0.500	0.1000	0.805	0.0285	0.7593	0.8509
ρ_q	beta	0.400	0.2000	0.060	0.0383	0.0043	0.1136
ρ_{π^*}	beta	0.800	0.1000	0.406	0.0629	0.3050	0.5120
ρ_{y^*}	beta	0.900	0.1000	0.996	0.0033	0.9915	1.0000
ρ_z	beta	0.200	0.0500	0.582	0.0071	0.5732	0.5897
k	beta	0.800	0.1500	0.761	0.1517	0.5434	0.9961
ϵ_r	invg	0.500	4.0000	0.164	0.0199	0.1325	0.1958
ϵ_q	invg	1.500	4.0000	0.544	0.0345	0.4859	0.5990
ϵ_{y^*}	invg	1.500	4.0000	0.450	0.1061	0.2878	0.6042
ϵ_{π^*}	invg	0.500	4.0000	1.400	0.0876	1.2565	1.5435
ϵ_z	invg	1.000	4.0000	0.390	0.0438	0.3185	0.4620

Table 4
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 5
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
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							

Table 6
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 7
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 8
Bayes factors: basic Taylor rule.

	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)

Table 9
Bayes factors: extended Taylor rule.

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	−391.06	192.56	473.7	591.00	620.65
Marginal Data Densities ($\psi_3 = 0$					

monetary policy to exchange rate movements. First, Table 12 documents the time variation in the ψ_3 parameter in the Taylor rule. We notice a lower value in the mean posterior mean for the second sub-sample. However, we also notice a spike in the response at W3 (corresponding to the business cycle component), higher than for the other samples. Overall, there is not much that variation in the

Table 10
Bayes factors: sub-sample 1.

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	−252.95	37.68	190.96	275.37	316.40
Marginal Data Densities ($\psi_3 = 0$)	−255.10	28.6	188.37	272.32	318.15
Bayes Factor	8.621	8607.91	13.28	20.93	0.173

sample results.

We also analyze whether the Bayes Factors change along the two sub-samples, see Tables 10 and 11. We find that the findings remain the same for the first sub-sample, except for the low frequency detail W4 (which is anyway lower than business cycle frequencies). At the same time, for the latter sub-sample, although the are aggregate evidences which are again verified, it seems that BoE responded to closer to business cycle movements in exchange rate (W2 and especially W3), and less for W1 or W4.

4.3. Results for Australia, Canada and New Zealand

The original results in Lubik and Schorfheide (2007) also include estimation and the comparison of Bayesian factors for further three countries of Australia, Canada and New Zealand. Given this, we too report here the of Bayesian factors that allows us to test whether central banks in these countries reacts to exchange rate changes or not. Tables 13–15 report the Bayes factor for Australia, Canada and New Zealand, respectively, with the complete estimation results available upon request from the authors.

The results indicate a rejection of the hypothesis that the central bank targets exchange rate movements too only for the aggregate series for Australia. For the details, W1 to W4, of Australia as well as the aggregate series and details of Canada and New Zealand (except detail W1), the hypothesis of no reaction to exchange rate movements is strongly rejected. Hence in general, like the BoE, the central banks of other major inflation targeters of Australia, Canada and New Zealand also tends to react to longer-run exchange rate movements.

5. Relation to previous literature

In this section, we further discuss the main implications of results from two perspectives: the findings in the related literature, as well as possible policy implications.

There is a rapidly developing literature on the use of wavelets in empirical macroeconomic work, however, summarizing it, is beyond the scope of this article. However, more closely related to the purpose of this article we can mention the contributions by Sala (2015), who estimated a DSGE model in different frequencies by augmenting the likelihood function of a DSGE model with frequency components. More closely related to this paper, Caraiani (2017) applied the wavelet decomposition to the series usually employed in the estimation of a DSGE model and estimated a DSGE model along different frequencies (as well as in time). More recently, Gallegati et al. (2019) applied a similar approach as in Caraiani (2015) and estimated a medium-sized DSGE model featuring financial frictions.

The present paper innovated through in two dimensions: the use of backward-looking wavelet filtering and the focus on the open-economy issues. As such, not only that it improved on the filtering side, but it also added new findings regarding the frequency dependence of the reaction function of interest rate to exchange rate movements.

A pertinent question is whether there are additional empirical evidences to support the DSGE based findings here. We would like to point first to a related paper on testing whether central banks in selected small open economies react or not to exchange rate movements, see Caraiani (2013). The results are pretty much the same as in this paper, and they are robust to using a baseline model as in Lubik and Schorfheide (2007) or adding additional open-economy features (e.g. incomplete pass-through).

Furthermore, a more empirical paper that adds more support to our findings is due to Aguiar-Conraria et al. (2018). Here, the authors, using a waveleted based approach to study the Taylor rule, found that the relationships between the policy rate and inflation and the output gap differs along both time and frequency. Although their study was focused solely on the case of the United States, it nevertheless adds up to the already available evidences regarding the Taylor rule behavior in time and frequency.

Table 11
Bayes factors: sub-sample 2.

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	−158.74	135.30	251.6	292.20	342.39
Marginal Data Densities ($\psi_3 = 0$					

Table 12
Variation in responses to exchange rate movements.

Sample	Aggregate Series	W1	W2	W3	W4
Full Sample	0.237	0.096	0.161	0.175	0.054
	[0.1380; 0.3350]	[0.0401; 0.1499]	[0.0902; 0.2321]	[0.0960; 0.2471]	[0.0146; 0.0934]
Sub-sample 1	0.223	0.105	0.129	0.137	0.091
	[0.0795; 0.3624]	[0.0303; 0.1737]	[0.0493; 0.2096]	[0.0560; 0.2173]	[0.0164; 0.1648]
Sub-sample 2	0.178	0.083	0.139	0.244	0.084
	[0.0645; 0.2753]	[0.0200; 0.1448]	[0.0639; 0.2142]	[0.1345;0.3446]	[0.0191; 0.1338]

Table 13
Bayes factors: basic Taylor rule: Australia.

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	−761.84	51.51	398.85	546.22	1041.21
Marginal Data Densities ($\psi_3 = 0$)	−661.61	30.5	252.63	529.43	939.84
Bayes Factor	0.000	exp(20.9)	exp(146.2)	exp(16.7)	exp(101.3)

Table 14
Bayes factors: basic Taylor rule: Canada.

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	−270.47	372.6	594.40	805.60	1168.75
Marginal Data Densities ($\psi_3 = 0$)	−378.03	293.6	501.71	756.95	1143.06
Bayes Factor	exp(107)	exp(79)	exp(92)	exp(48.6)	25.69

Table 15
Bayes factors: basic Taylor rule: New Zealand.

	Aggregate	W1	W2	W3	W4
Marginal Data Densities ($\psi_3 > 0$)	−394.3	463.02	695.95	1042.97	1312.13
Marginal Data Densities ($\psi_3 = 0$					

6. 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:Q2 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 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.

From a policy perspective, the main implication of our analysis is that, if the exchange rate depreciation was ignored in the interest-rate setting behavior by the BoE, then it would end up putting incorrect weights on the other components of the rule, and in the process impact the macroeconomy more strongly while trying to achieve its inflation-target. In addition, if we take into acount the in-sample evidence of the model's ability to explain movements of key macroeconomic variables, then ignoring the exchange rate movements is likely to produce relatively poor forecasts.

In general, our results are also confirmed for other developed inflation targeters namely, Australia, Canada and New Zealand. Given this, as part of future research, it would be interesting to extend our analysis to emerging countries that target inflation.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jmacro.2019.103187

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