

Beckmann, Joscha; Reitz, Stefan

Conference Paper

Information Rigidities and Exchange Rate Expectations

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session:
Exchange Rates, No. B18-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Beckmann, Joscha; Reitz, Stefan (2018) : Information Rigidities and Exchange Rate Expectations, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2018: Digitale Wirtschaft - Session: Exchange Rates, No. B18-V3, ZBW - Leibniz-Informationszentrum Wirtschaft, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/181628>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Information Rigidities and Exchange Rate Expectations*

Joscha Beckmann[†] Stefan Reitz[‡]

March 1, 2018

Abstract

Sluggish adjustment of expectations to new information is rational in an environment characterized by information costs and signal-to-noise problems. This paper investigates the role of such information rigidities for exchange rate expectations using data from Consensus Economics for eight emerging and industrial economies from 1999 until 2015. Our results provide strong support for this view showing that the inclusion of forecast updates largely accounts for otherwise detected biases in expectation errors. Moreover, we detect little evidence for a systematic effect of fundamentals or uncertainty measures on exchange rate disagreement. Structural shocks do not appear to lead to any systematic increase in disagreement which illustrates the importance of noisy information models.

Keywords: Exchange rates, Expectations, Disagreement
JEL: F31, F37, G17

*Corresponding author:

[†]Ruhr University of Bochum, Chair for International Economics, D-44801 Bochum, e-mail: joscha.beckmann@rub.de, and Kiel Institute for the World Economy, Kiellinie 66, 24105 Kiel.

[‡]University of Kiel, Institute for Quantitative Business and Economics Research, Heinrich-Hecht-Platz 9, 24098 Kiel, stefan.reitz@qber.uni-kiel.de, and Kiel Institute for the World Economy, Kiellinie 66, 24105 Kiel.

1 Introduction

Understanding and forecasting exchange rates remains one of the central areas of research in international economics due to its importance for portfolio allocation and policy making. Rigorous empirical evidence on market participants' exchange rate forecasts are available only since the mid-1980s. The growing interest in survey data of exchange rate forecasts in this period can be understood against the backdrop of empirical evidence rejecting the joint hypothesis of uncovered interest parity and Rational Expectations (REH) (Fama, 1984). Numerous studies such as Blake et al. (1986), Dominguez (1986), and Chinn and Frankel (1984) all reject unbiasedness and efficiency of exchange rate forecasts contained in survey data.¹ Comprehensive surveys on related studies and theoretical explanations for the weak statistical performance of professional forecasts are provided by, among others, Lewis (1995), Engel (1996), MacDonald (2000), and Jongen et al. (2008). The authors also stress the fact that although mean forecasts are often not useful for predicting exchange rates, professional expectations potentially contain useful information. For instance, taking the established link between predictability of returns on financial markets and expectation errors of professionals into account (Bacchetta and van Wincoop, 2006), the weak performance of professional exchange rate forecasters is also not surprising and does not necessarily imply irrational behavior of forecasters. Moreover, Beckmann and Czudaj (2017) have illustrated a potential contradiction between statistical and economic measures for large number currencies after the financial crises.² Their findings show that relying on survey expectations for currency trading is superior to simple momentum and carry trade

¹Together with strong evidence pointing towards substantially differing information sets among foreign exchange practitioners (Taylor and Allen, 1992) these results spurred the development of heterogeneous expectations models (Frankel and Froot, 1986).

²Recent findings by Cavusoglu and Neveu (2016) provide slightly more encouraging forecasting results by taking the most optimistic and pessimistic as a measure of disagreement into account.

benchmarks even if unbiasedness is rejected.

More recently, the rejection of unbiasedness and information efficiency of survey forecasts has been investigated in the context of imperfect information models in which agents face different kinds of information rigidities. For instance, Coibion and Gorodnichenko (2016) have highlighted the importance of information rigidities in the expectation formation process for inflation and GDP. The theoretical foundations are provided by Mankiw and Reis (2002), who propose a model in which the information set of agents is adjusted only infrequently due to information costs and Sims (2003) who stresses the fact that available information typically consists of noisy signals about the true state of the economy. Coibion and Gorodnichenko (2016) show that both approaches, sticky and noisy information models, can be tested in a unified framework.

Following this strategy, our study is the first to analyze the role of information frictions for exchange rates at the aggregated level. We rely on data from Consensus Economics for 10 economies from 1999 until 2015. We start by assessing the role of information rigidities for mean exchange rate forecasts. Controlling for a large variety of exchange rate fundamentals our estimations robustly reveal a significant influence of information rigidities. Remarkably, the magnitude of information rigidity hardly differs across the different currencies in the data set. Moreover, lagged exchange rate changes are also a significant driver of expectations, possibly reflecting the importance of heterogeneity in signal-noise ratios.

Since noisy and sticky information models have different implications for the disagreement across forecasters our results also inform about their relative importance on foreign exchange markets. We proceed by analyzing subsamples before conducting a regression- and Bayesian VAR-based analysis of disagreement among forecasters.³ In

³Sarno et al. (2015) also rely on consensus economics survey data when testing the scapegoat approach by Bacchetta and van Wincoop (2008, 2010), which argues that different fundamentals matter at different points in time. However, they do not rely on disagreement data and focus on a

line with noisy information models, we find that exchange rate disagreement does not systematically react to fundamental shocks.

The remainder of this paper is organized as follows. The next chapter briefly recaptures the theoretical analysis of information rigidities in the context of exchange rates based on Coibon and Gorodnichenko (2012, 2015), providing testable hypothesis for both mean forecasts and disagreement among forecasters. Chapter three provides data and empirical results. Section 4 concludes.

2 Theoretical framework

This section derives the estimation equations to investigate the influence of information rigidities of both the mean forecasts error and forecast disagreement among survey participants.

2.1 Information rigidities and mean forecast errors

Coibon and Gorodnichenko (2015) show how information rigidities from two different sources, information stickiness and noisy information, can enter the expectation formation process. In case of information stickiness it is assumed that due to costs of information acquisition a forecaster remains inattentive in each period with probability λ , but adjusts to full information and forms rational expectations with probability $(1 - \lambda)$. Under these circumstances forecaster's i time t prediction of the time $t + h$ exchange rate ($E_t s_{t+h}$) remains unchanged with probability λ^h . Aggregation across agents leads to a weighted average of current and past full-information predictions of the exchange rate

$$F_t s_{t+h} = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j} s_{t+h} \quad (1)$$

survey, which ranks the importance of different fundamentals.

Since

$$F_{t-1}s_{t+h} = (1 - \lambda) \sum_{j=0}^{\infty} \lambda^j E_{t-j-1}s_{t+h} \quad (1')$$

time t average forecast can be written as the weighted sum of the lagged average forecast and time t rational expectation:

$$F_t s_{t+h} = (1 - \lambda) E_t s_{t+h} + \lambda F_{t-1} s_{t+h}. \quad (2)$$

Full information rational expectations imply that

$$s_{t+h} = E_t s_{t+h} + u_{t,t+h}, \quad (3)$$

where $u_{t,t+h}$ is the rational expectation error orthogonal to available information at time t . In contrast, the aggregate prediction error of the partially inattentive forecasters is given by

$$s_{t+h} - F_t s_{t+h} = \frac{\lambda}{1 - \lambda} (F_t s_{t+h} - F_{t-1} s_{t+h}) + u_{t,t+h}, \quad (4)$$

which contains a predictable component arising from the time t update of aggregate expectations. In fact, the higher the probability of forecasters being inattentive the stronger is the systematic bias of forecast errors. In contrast, with decreasing λ the forecasting error converges to its rational expectation counterpart. Coibion and Gorodnichenko (2015) stress that this model assumes a single λ for all forecasters, so that equation (4) applies for any economic variable and forecast horizon.

Predictable forecasting errors can also appear if forecasters fully update their information set, but the time series to be forecasted contains an unobservable noisy component. In case of foreign exchange markets, forecasters are concerned with the lower-frequency trends of the exchange rate. Forecasters are supposed to observe an idiosyncratic signal

$$y_{it} = s_t + \epsilon_{it}, \quad (5)$$

where ϵ_{it} is an independent identically distributed disturbance term. The exchange rate signals are used to update the exchange rate forecast via the Kalman filter

$$F_{it}s_t = Gy_{it} + (1 - G)F_{it-1}s_t, \quad (6)$$

where G represents the Kalman gain. Using the fact that $F_{it}s_{t+h} = \rho^h F_{it}s_t$ and averaging across forecasters leads to

$$s_{t+h} - F_t s_{t+h} = \frac{1 - G}{G} (F_t s_{t+h} - F_{t-1} s_{t+h}) + u_{t+h,t}. \quad (7)$$

As a result, the influence of the forecast revision on the ex post forecast error is strong if the exchange rate signal is weak forcing forecasters to rely more on their recent prediction. Since the size of the noise component depends on the specific times series the estimation results on the importance of noisy information may differ across forecasted variables.

Equation (4) and (7) reveal that both forms of information rigidity, information stickiness and noisy information, share the same econometric model

$$s_{t+h} - F_t s_{t+h} = \alpha + \beta_0 (F_t s_{t+h} - F_{t-1} s_{t+h}) + u_{t+h,t}. \quad (8)$$

Thus, the model can be applied to test the null hypothesis of rational expectations against the alternative of both forms of information rigidities. However, given the set of survey participants the β_0 coefficient should be constant across forecasting variables in case of dominance of information stickiness, but is expected to vary in case of dominance of signal-to-noise problems as the quality of signals depend on the macroeconomic variable.

In the empirical section of the paper Equation (8) is augmented by two components. Firstly, as considered in Coibion and Gorodnichenko (2015), forecast updates might be based on heterogeneous signal-to-noise ratios across survey participants, implying that

lagged values of the variable being forecasted also exhibit predictive power with regard to forecast revisions. In this spirit, we augment Equation (8) by lagged exchange rate changes.

$$s_{t+h} - F_t s_{t+h} = \alpha + \beta_0(F_t s_{t+h} - F_{t-1} s_{t+h}) + \phi(\Delta s_{t-1}) + u_{t+h,t}. \quad (9)$$

where the coefficient ϕ is related to the average Kalman gain across professionals.

Secondly, Equation (8) can be augmented by a vector z_t of control variables for which the literature has revealed the potential ability to predict the forecasting error. We include changes in the interest rate and industrial production differential and inflation rates relative to the US.⁴ Thus, aside from testing the relevance of information rigidities for the determination of the forecast error itself, the inclusion of control variables also reveals whether the forecast revisions fully capture their predictive content. If this is the case then estimating

$$s_{t+h} - F_t s_{t+h} = \alpha + \beta_0(F_t s_{t+h} - F_{t-1} s_{t+h}) + \phi(\Delta s_{t-1}) + \gamma z_{t-1} + u_{t+h,t}. \quad (10)$$

should result in a significant β_0 , but in an insignificant γ -vector of estimated coefficients for the control variables in z_t .⁵

Since the dataset provided by Consensus Forecasts includes 1-month, 3-month and 12-month forecasts, two-step ahead forecasts are unavailable. Thus, for $h=1$ we have

⁴The chosen set of fundamentals is partly due to data availability but is sufficient to incorporate considerations of conventional exchange rate models such as the monetary approach, uncovered interest parity or purchasing power parity. See Sarno and Taylor (2005) for a comprehensive overview of fundamental exchange rate models.

⁵Chinn and Frankel (1984) were the first to analyze the predictive power of exchange rate expectations based on a related linear regressions of the kind $s_{t+h} - s_t = a_1 + a_2(F_t(s_{t+h}) - s_t) + E_{t+k}$. Jongen et al. (2008) summarize the empirical evidence and also reject the hypothesis of unbiased exchange rate expectations, implying significant prediction errors, a finding which will be critically discussed further below.

to replace $F_{t-1}(s_{t+1})$ by $F_{t-2}(s_{t+1})$ leading to the following equation:

$$s_{t+1} - F_t s_{t+1} = \alpha + \beta_0(F_t s_{t+1} - F_{t-2} s_{t+1}) + \phi(\Delta s_{t-1}) + \gamma z_{t-1} + u_{t+1,t}. \quad (11)$$

A competitor hypothesis to explain the predictability of forecast errors has been established by referring to forecasters tendency to smooth their predictions over time (Andrade and Bihan, 2013). Coibion and Gorodnichenko (2015) derive the forecast smoothing from an intertemporal maximization problem, which contains both discounted expected future forecast errors and expected future forecast revisions. The first-order condition under full information rational expectations (no information rigidities) can be estimated using

$$\begin{aligned} s_{t+1} - F_t s_{t+1} = & \alpha + \beta_0(F_t s_{t+1} - F_{t-1} s_{t+1}) + \\ & \beta_1(F_{t-1} s_{t+1} - F_{t-2} s_{t+1}) + u_{t+1,t}. \end{aligned} \quad (12)$$

where β_0 is expected to be negative, while β_1 should be positive. The sign restriction arise from the intertemporal trade-off of adjustment costs to new information. If, for instance, a forecaster decides to ignore current exchange rate observation for the sake of smoothing, tomorrows expectation adjustment will have to be a lot stronger in order to keep track of the exchange rate trend. Given the frequency of the dataset's forecasts, we modify equation (12) for $h = 1$.

$$\begin{aligned} s_{t+1} - F_t s_{t+1} = & \alpha + \beta_0(F_t s_{t+1} - F_{t-2} s_{t+1}) + \\ & \beta_1(F_{t-2} s_{t+1} - F_{t-11} s_{t+1}) + \phi(\Delta S_{t-1}) + \gamma z_{t-1} + u_{t+1,t}. \end{aligned} \quad (13)$$

We have also estimate alternative specifications where the forecast smoothing terms is modelled as $F_{t-2}(s_{t+1}) - F_{t-3}(s_t)$, that is the update in 3-month forecasts. Such a specification leaves our findings unchanged.

2.2 Disagreement among forecasters

Earlier work by Coibion and Gorodnichenko (2012) also demonstrates that both models of information rigidities have different implications for the forecast disagreement, which is captured by a dispersion measure of forecasts among survey participants. In particular, forecast disagreement among participants should rise after any economic shock in case of a sticky information model, while disagreement does not respond to shocks in a noisy information model (except in the case heterogeneous signal-to-noise ratios).

We therefore also estimate the following equation of the forecast disagreement D_t , measured as the absolute difference between the strongest and the weakest forecast ($abs(F_{t+1,strongest} - F_{t+1,weakest})$):

$$D_t = \alpha + \beta D_{t-1} + \gamma' z_t + \epsilon' un_t + u_{t+h,t}, \quad (14)$$

where the vector z_t includes changes in the industrial production and interest rate differential and relative inflation rates. The vector un_t is included to account for additional possible determinants of exchange rates disagreements. We adopt the Chicago Board Options Exchange volatility index (VIX), domestic and foreign economic policy uncertainty provided by Baker et al. (2015) and oil price shocks according to Hamilton (1995). Equation (14) is estimated for $h = 1$ and $h = 12$. Estimation results for $h = 3$ are also available upon request.

3 Data and Preliminary Tests

Survey data on exchange rate expectations is obtained from Consensus Economics. The fact that names of forecasters are published in the monthly issues of Consensus economics results in a reputation effect which assures that survey data is considered to be the most adequate measure of expectations. Our main sample runs from 1999:1

until 2015:12. We follow standard procedures in the literature and calculate the geometric mean in order to aggregate exchange rate expectations (Jongen et al., 2008). In addition, we are also interested in the disagreement among FX forecasters for the G7 currencies for which we use the absolute difference between strongest and weakest forecast as a measure of disagreement. A similar measure has been considered by Cavusoglu and Neveu (2015). The forecasts we consider are provided on the second monday of each month. Forecasters are therefore unaware of the exchange rate at the end of the month where the forecast is provided. The last observable exchange rate change therefore corresponds to the difference between the end of the previous months and the survey date.

Data on spot exchange rates, inflation, industrial production, VIX, and short-term interest rates are obtained from Datastream. We also include the Economic Policy Uncertainty Index (EPU) provided by Baker et al. (2013), which is based on text-searching in the large newspapers for both the US and the domestic economy. Oil price shocks are calculated according to Hamilton (1995).

In a preliminary step, we conducted various unit root tests to assure that no spurious regressions are estimated. Both, the forecast error $s_{t+1} - F_t(s_{t+1})$ and the forecast updates $F_t(s_{t+1}) - F_{t-2}(s_{t+1})$ and $F_{t-2}(s_{t+1}) - F_{t-11}(s_{t+1})$ are clearly stationary, implying a cointegrating relationship between realized and expected exchange rates as well as between expectations across different horizons. Thus, OLS estimates can be adopted since all control variables are stationary.

4 Empirical Results

4.1 FX Expectations and information rigidities

As a starting point, we compare different estimates for the information rigidity coefficient β_0 in Equation (11) for specifications with and without control variables summarized in z_{t-1} . The detailed results are available upon request but the findings show that the rigidity estimate is mostly significant and positive. The magnitude of the coefficient only slightly decreases once lagged exchange rate changes and the other controls are included, implying that the results we describe in the following are robust to alternative specifications. As discussed in the next section, this is also the case if we control for autocorrelation based on a slightly different empirical setting.

Table 1 provides estimations for the specification including controls. Except for the euro/dollar exchange rates as a borderline case, the regressions provide a significant and positive estimate for β_0 . It is also remarkable that the magnitude hardly differs across the different currencies under observation. As expected, the control variables are often insignificant. That implies that the forecast error remains unaffected by fundamentals. In line with noisy information models, lagged exchange rate changes are highly significant reflecting the fact that signal-to-noise ratios vary across survey participants.

While Table 1 has provided estimations for the expectation updates between $t - 3$ and $t - 1$ and the forecast error in t , we now focus on Equation (13) which additionally includes the expectation update between $t - 12$ and $t - 3$ for t . We do not observe any evidence for forecast smoothing. The significance of β_0 hardly changes while the absolute magnitude slightly decreases. β_1 is either insignificant or enters with a negative sign. The second finding is potentially explained by remaining serial correlation and our limited data availability in the sense that the only forecast smoothing we can

account takes place over a difference of nine months. Another explanation is that the high amount of noisy information leads to a quick diminish of previous forecasts when expectations are formed. As previously outlined, we have also conducted estimates where we model the forecast update as $F_{t-2}(s_{t+1}) - F_{t-3}(s_t)$ for $h = 1$ and alternative specifications.⁶ This also does not provide any evidence for forecast smoothing.

Taking our sample into account, a natural question is whether the degree of information rigidities is subject to structural changes. To shed some light on this issue, we use the test by Bai and Perron (1998, 2003) to account for possible instabilities in the coefficients of Equation (11). The basic idea is to choose breakpoints such that the sum of squared residuals for all observations is minimized. The estimated breakpoints by definition represent the linear combination of these segments which achieve a minimum of the sum of squared residuals (Bai and Perron, 2003). Table 3 provides the estimated breakpoints as well as the subsample estimates of Equation (13) given this breakpoint. The break point is often located between 2008 and 2010. The significance of the rigidity coefficient varies across countries and is determined by the length of the subsample. For UK, Japan, Canada, Korea and Singapore the rigidity estimate is only significant in the second subsample and increased in absolute terms. A reversed picture is observed for Chile and India. However, their subsample ends in 2010, leaving a small number of observations for the second sample.

4.2 Information rigidities, rational expectations and random walk behavior

Assessing the significance of the vector z_t in the previous section is already equivalent to a test of rationality given the fact that all information on fundamentals should be included in the current forecast, implying a non-significant effect of fundamentals

⁶We have also excluded $(s_t - s_{t-1})$ when including $F_{t-2}(s_{t+h}) - F_{t-3}(s_t)$.

on forecast errors. This section aims at investigating the importance of information rigidities for more conventional tests of rationality. The literature on exchange rate expectations has adopted different tests for rational expectations. In particular, Chinn and Frankel (1984) were the first to use the predictive power of exchange rate expectations $s_{t+1} - s_t = a_1 + a_2(F_t s_{t+1} - s_t) + \xi_{t+1}$ as a measure of forecast rationality. A rejection of the null hypothesis that $a_1 = 0$ and $a_2 = 1$ have been taken as evidence of biased rather than rational expectations (Jongen et al., 2008). A second possibility is a test for error orthogonality. The idea is to regress the forecast error on its own lagged value which, under REH, should not contain any valuable information. Such a test can be conducted for both the forecast error and the estimation error of Equation (11) where we have accounted for the role of information rigidities as explanatory variables for the prediction error:

$$\xi_t = a_1 + a_2 \xi_{t-1} \tag{15}$$

$$u_{t+1,t} = a_1 + a_2 u_{t,t-1} \tag{16}$$

As outlined earlier, exchange rate expectations are formed at the beginning of each month t for the end of the next month $t+1$, implying that forecasters do not observe the end-of-month exchange rate in t when conducting forecasts for $t+1$. Quite surprisingly, the literature has not acknowledged the statistical fact that exchange rates are random walks in this context: The exchange rate in each period can be expressed as the sum of all previous shocks which do not die out implying a high degree of persistence and autocorrelation. In both Equation (15) and (16), significance of a_2 simply reflects this first-order autocorrelation which arises from the fact that s_{t-1} is embedded in both E_{t-1} and u_{t-1} . This pattern does neither imply irrational behaviour nor predictability in real time. It does, however, potentially violates the error term assumptions of OLS.

To address these issues, we re-estimate our main equation by including the end of month exchange rate change between t and $t - 1$ instead of the change between the date of the survey and the exchange rate at the end of the previous month.

$$s_{t+h} - F_t s_{t+h} = \alpha + \beta_0(F_t s_{t+h} - F_{t-1} s_{t+h}) + \phi(\Delta s_t) + \gamma z_{t-1} + u_{t+h,t}. \quad (17)$$

This equation now considers the last available information for exchange rate forecasts in t when forecasting for $t + 1$, including both the expected exchange rate and the final observation of the exchange rate. The full estimation results are available upon request but still display a significant β_0 coefficient for all countries, providing further robustness to our findings.

Table 4 provides the corresponding estimates and the p -value for the test $a_2 = 0$ for both the prediction error and Equation (17). While $a_2 = 0$ is always firmly rejected for Equation (16) at the 1% level, $a_2 = 0$ is not rejected at the 10% for 7 out of 10 cases based on Equation (17) with the rejection not significant at the 5% level for the British Pound. This suggests that significant prediction errors in conventional estimates reflect autocorrelation due to the frequency of survey updates. In fact, Equation (17) is equivalent to taking first-differences of the exchange rate which is well-known to remove predictability in random walks (Hamilton, 2017).

4.3 Disagreement among forecasters

As a starting point, we assess the stationarity of disagreement among exchange rate forecaster over 1 month, 3 month and 12 month. The unambiguous finding according to Table 5 is that disagreement is always stationary over all horizons since the null of a unit root is always rejected. This implies that the strongest and weakest forecast share the same stochastic trend and are therefore cointegrated. This finding is in line with the idea that disagreement among forecasters usually fluctuates around a steady state

level and is not driven by stochastic trends.

As a next step, we analyze potential drivers of exchange rate disagreement. Besides changes in relative interest rates, CPI and Industrial Production as fundamentals and lagged disagreement, we also consider exogenous oil price shocks according to the definition of Hamilton (1995) and domestic and US policy uncertainty and the VIX as potential drivers of uncertainty.⁷

The findings in Table 6 and 7 show that fundamentals hardly affect disagreement. Inflation, industrial production and interest rates are hardly significant. Exceptions are Japan, Brazil and Australia where changes in the industrial production differential reduce disagreement over one month. Another exceptions is the effect of interest rate changes in Brazil and Singapore. The unavailability of domestic policy uncertainty at the beginning of the sample reduces estimates for the four emerging economies. Estimating models with equivalent samples without domestic uncertainty does not change the underlying findings. This is in line with noisy information models and intuitive given the fact that exchange rates are easily observable.

Lagged disagreement is always significant, pointing to persistence in exchange rate uncertainty. A comparison of the estimates of τ in Equation (14) for disagreement over one month and one year according to Table 5 and Table 6 shows that the persistence is much higher for disagreement over one year with the estimates except for the euro always exceeding 0.5 and being close to 0.8 in many cases. This is plausible since disagreement over the exchange rate in the next month is by definition no longer materializes in the next period while the uncertainty regarding the exchange rate in $t + 12$ to a large extent remains relevant the $t + 1$.

An interesting question is whether exchange rate disagreement can be explained by alternative uncertainty measures. Newspaper based US economic policy uncertainty is

⁷We do not include the measure of Jurado et al. (2014) which is constructed out-of sample.

hardly relevant with only Japan and Canada over one month and one year positively affected while the effect on Brazil and India is even negative. Domestic policy uncertainty partly increases exchange rate disagreement in UK, Australia, Brazil and India over one month but is not relevant over one year.

The VIX also has a positive effect on exchange rate disagreement over one month for the euro area, Brazil, Chile, Singapore, India and Korea while the effect is slightly negative for Canada. The same patterns with slightly less significance is observed over a one year horizon. A positive impact is also found for Australia. Changing the underlying specification of price shocks according does not display any significant results.

4.4 Bayesian VAR estimates

Taking into account that the estimations of Equation (14) in the previous section assume that exchange rate uncertainty should be considered as the left-hand side variable, applying a vector autoregressive (VAR) framework is a natural extension since all variables are treated endogenously. We therefore adopt a Bayesian VAR approach for country-by-country models which are estimated via Gibbs sampling. Each model consists of the following set of variables for each model:

$$Z_t = [dis_t, Oil_t, d\pi_t, dy_t, di_t, Un_t, VIX_t]. \quad (18)$$

Similar to our Equation (14), we include interest rate differential, industrial production differential and inflation differential and incorporate US economic policy uncertainty, oil price shocks and the VIX to account uncertainty shocks. We neglect domestic policy uncertainty given the previous estimations and the lack of data for some countries.

We rely on a Minnesota prior specification and a burn-in period of 500 observations. The Bayesian framework enables us to include a prior specification which accounts for

the high degree of persistence and put more weight on the first two lags. This is in line with our previous empirical estimates.

For the sake of brevity, we only present findings for dispersion regarding the month exchange rate since the findings for twelve months essentially display equivalent findings. As a starting point of our analysis, we provide F -tests for the disagreement Equations in Equation (7). The findings are available upon request and show that disagreement is hardly explained by the considered regressors with the null hypothesis that the corresponding coefficients are equal to zero frequently not rejected.

Figure 1 to 8 provide the impulse response functions for the disagreement equation. In line with numerical estimates, no systematic significance is detected. It is also remarkable that all estimates despite own lags are small in absolute terms, suggesting that different confidence intervals would not change the overall conclusion. There are some small exceptions for VIX and US Policy Uncertainty with the former for example displaying a small but persistent shock for UK, Brazil, Canada and Korea, These findings are in line with a noisy information model which postulate that disagreement does not respond to shocks. The remaining impulse response functions available upon request show that disagreement hardly displays any significant effects.

5 Conclusion

This paper has analyzed the role of information frictions for exchange rates at an aggregated level. Our results illustrate a significant impact of forecast updates on expectation errors, providing evidence for information rigidities. This finding is robust against a variety of alternative specifications. Our results confirm the importance of unobserved fundamentals which reflect noisy signals for forecasters. The frequently observed insignificance of fundamentals can be potentially attributed to the fact that different

fundamentals are used as scapegoats for unobserved exchange rate changes at different points in time (Bacchetta and van Wincoop, 2004). We also argue that traditional tests for rationality are of little use since they do not account for the statistical implications of random walk behavior.

We detect little evidence for a systematic effect of fundamentals or uncertainty measures on exchange rate disagreement. This result is consistent with the findings obtained by Coibion and Gorodnichenko (2012) for inflation, implying that information rigidities in exchange rate expectations reflect imperfect information models characterized by noisy rather than sticky information. These findings do not rule out heterogeneous forecasting rules or beliefs at the individual level but suggest that the intuitive and general framework we adopt explains main patterns in exchange rate expectations.

Our analysis also offers interesting avenues for further research. While we have considered realized fundamentals, relying on expected fundamentals potentially delivers further insights on drivers of expectations and information rigidities. However, this task is currently complicated by the unavailability of survey data related to fundamentals over the same frequency. The analysis of aggregated exchange rate disagreement compared to exchange rate volatility measures also offers an interesting avenue for future research.

References

- Babus, A., and P. Kondor, 2013, Trading and Information Diffusion in Over-the-Counter Markets, mimeo.
- Andrade, P., Crump, R.K., Eusepi, S. and Moench, E. Fundamental disagreement, *Journal of Monetary Economics*, 8, 06-128.
- Andrade, P. and Le Bihan, H. 2013. "Inattentive professional forecasters," *Journal of Monetary Economics*, 60, 967-982.
- Bacchetta P. and E. van Wincoop 2004. A scapegoat model of exchange-rate fluctuations. *American Economic Review* 94: 1141-118.
- Bacchetta P., E. Mertens and E. van Wincoop. 2009. "Predictability in financial markets: What do survey expectations tell us?," *Journal of International Money and Finance* 28: 406-426.
- Baker, R., N. B. and S.J. Davis 2016. "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, 131: 1593-1636.
- Blake, D., Beenstock M., Brasse V. 1986. The performance of UK exchange rate forecasters. *Economic Journal* 96: 986-999.
- Cavusoglu, N., Neveu AR. 2015. The predictive power of survey-based exchange rate forecasts: Is there a role for dispersion? *Journal of Forecasting* 34: 337-353.
- Chinn M, Frankel J. 1994. Patterns in exchange rate forecasts for twenty-five currencies. *Journal of Money, Credit and Banking* 26: 759-770.
- Coibion O, Gorodnichenko Y. 2012. What can survey forecasts tell us about information rigidities? *Journal of Political Economy* 120: 1161-159.
- Coibion O, Gorodnichenko Y. 2015. Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review* 105: 2644-2678.
- Dominguez, Kathryn M., 1986. Are Foreign Exchange Forecasts Rational? New Evidence from Survey Data, *Economics Letters*, 21(3), 277- 281.
- Dovern J, Fritsche U, Slacalek J. 2012. Disagreement among forecasters in G7 countries. *Review of Economics and Statistics* 94: 1081-1096.
- Engel, Charles, 1996. The Forward Discount Anomaly and the Risk Premium: A Survey of Recent Evidence , *Journal of Empirical Finance* 3 (2), 1996, 123- 192.

- Fama, Eugene, 1984. Forward and spot exchange rates, *Journal of Monetary Economics* 14, p. 319.
- Frankel, Jeffrey, and Kenneth Froot, 1986. Understanding the US Dollar in the Eighties: The Expectations of Chartists and Fundamentalists. *The Economic Record*: 2438.
- Frankel, Jeffrey and Kenneth Froot, 1987. Using Survey Data to Test Standard Propositions Regarding Exchange Rate Expectations," *American Economic Review*, 77(1), Reprinted in Frankel, On Exchange Rates, MIT Press, 1993. 133 -153.
- Hamilton, James D., 2017. "Why You Should Never Use the Hodrick-Prescott Filter," *Review of Economics and Statistics*, forthcoming.
- Lewis, Karen, 1989. Changing Beliefs and Systematic Rational Forecast Errors with Evidence from Foreign Exchange, *American Economic Review* 79: 621- 636.
- Mankiw, N. Gregory, and Ricardo Reis, 2002. Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve. *Quarterly Journal of Economics* 117: 1295-1328.
- Rossi, B., 2013. Exchange rate predictability. *Journal of Economic Literature*, 51: 1063-1119.
- Sims, Christopher A. 2003. Implications of Rational Inattention. *Journal of Monetary Economics* 50: 665-90.
- Taylor, M., and H. Allen, 1992. The Use of Technical Analysis in the Foreign Exchange Market. *Journal of International Money and Finance* 11: 304-314.

A Appendix

A.1 Tables

Table 1: Full model with lagged changes and fundamentals as controls

Country	Constant	β_0	δ	IPDIFFDIFF	CPIDIFF	INTDIFF
UK	-0.0022 (-1.9666*)	0.1510 (2.6766***)	0.8624 (10.6557***)	0.0291 (1.6288)	0.5661 (1.8450*)	-0.0092 (-1.3613)
JP	-0.0040 (-0.0161)	0.1232 (2.2244**)	0.9373 (11.7190***)	3.1067 (1.1288)	-49.7236 (-0.8828)	-0.6503 (-0.7095)
CA	0.0013 (0.5798)	0.1332 (2.0824**)	0.7665 (9.5253***)	0.0226 (0.3710)	0.9733 (1.1272)	-0.0412 (-3.1713***)
EU	-0.0006 (-0.2911)	0.0886 (1.6100)	0.9952 (12.0108)	0.0368 (0.3719)	-0.4303 (-0.9076)	0.0046 (0.4348)
BR	0.0038 (0.3041)	0.1468 (2.0718**)	0.6979 (8.0924***)	0.2806 (0.5379)	0.6309 (1.5893)	0.0116 (1.0875)
CL	1.0988 (0.7463)	0.2198 (3.4094***)	1.0230 (13.3868***)	11.8414 (0.2727)	9.0269 (0.1875)	-1.8932 (-1.4116)
AU	0.0014 (0.3660)	0.1452 (2.7389***)	0.7644 (9.8275***)	-0.0917 (-0.4821)	0.2462 (2.0363**)	-0.0745 (-5.1059***)
IN	0.1258 (1.5123)	0.2041 (3.3096***)	0.9731 (12.7319***)	1.9997 (0.6397)	0.5239 (0.1909)	-0.3323 (-1.3441)
SG	0.0012 (0.6811)	0.1202 (1.9794**)	0.7644 (10.2269***)	0.0170 (1.0343)	0.1293 (2.2357**)	-0.0078 (-0.8415)
KR	2.7471 (0.9992)	0.1287 (2.1985**)	0.7434 (10.8268***)	-28.491 (-0.6789)	-61.2942 (-0.7020)	-10.3181 (-0.8608)

Note: The Table provides coefficient estimates for the full model according to Equation (11).

Table 2: Full model augmented by forecast smoothing

Country	Constant	β_0	β_1	δ	IPDIFF-DIFF	CPI-DIFF	INT-DIFF
UK	-0.0020 (-1.8070*)	0.1473 (2.7173***)	-0.0980 (-4.1726***)	0.8173 (10.4084***)	0.0300 (1.7455*)	0.6159 (2.0874*)	-0.0107 (-1.6508)
JP	-0.0034 (-0.0137)	0.1183 (2.1088**)	0.0137 (0.6006)	0.9342 (11.6373***)	3.0140 (1.0916)	-54.6572 (-0.9587)	-0.7537 (-0.8070)
CA	0.0014 (0.5952)	0.1375 (2.1423**)	-0.0244 (-0.9003)	0.7642 (9.4879***)	0.0206 (0.3366)	1.0317 (1.1909)	-0.0410 (-3.1547***)
EU	-0.0012 (-0.5445)	0.0875 (1.5186)	0.0047 (0.1711)	0.9874 (11.6381***)	0.0667 (0.6415)	-0.4727 (-0.9809)	0.0038 (0.3444)
BR	0.0042 (0.3344)	0.1517 (2.1169**)	-0.0162 (-0.5011)	0.6981 (8.0796***)	0.2679 (0.5120)	0.6521 (1.6304)	0.0111 (1.0343)
CL	1.1816 (0.8083)	0.2340 (3.6348***)	-0.0557 (-2.0041**)	1.0171 (13.4013***)	12.9587 (0.3007)	19.0329 (0.3963)	-2.2110 (-1.6493)
AU	0.0014 (0.3814)	0.1474 (2.7633***)	-0.0101 (-0.4465)	0.7630 (9.7825***)	-0.0914 (-0.4796)	0.2492 (2.0539**)	-0.0742 (-5.0666***)
IN	0.1369 (1.6101)	0.2094 (3.3615***)	-0.0146 (-0.6506)	0.9704 (12.6601***)	1.9005 (0.6064)	0.4604 (0.1674)	-0.3076 (-1.2284)
SG	0.0022 (1.2605)	0.1070 (1.8263*)	-0.0924 (-4.0767***)	0.7622 (10.5910***)	0.0163 (1.0321)	0.1286 (2.3108**)	-0.0071 (-0.7953)
KR	3.4799 (1.2620)	0.1338 (2.2982**)	-0.0462 (-1.9201**)	0.7482 (10.9630***)	-23.8175 (-0.5704)	-74.3740 (-0.8550)	-5.2152 (-0.4275)

Note: The Table provides coefficient estimates for the full model according to Equation (13). */**/** implies significance at the 1%/5%/10% level.

Table 3: Break Points and Rigidity Coefficients

Country	Break Point	β_0 First Period	β_0 Second Period
UK	2008:09	0.042 (0.611)	0.142 (2.031**)
JP	2003:10	0.0025 (0.026)	0.1708 (2.378**)
CA	2009:05	0.0918 (1.177)	0.2508 (2.125**)
EU	2003:05	-0.0621 (-0.632)	0.042 (0.633)
BR	2003:07	0.100 (1.34172)	-0.0947 (-0.592)
CL	2010:06	0.203 (2.822 **)	0.081 (0.575)
AU	2004:01	0.086 (0.430)	0.0545 (1.052)
IN	2010:10	0.1667 (2.424**)	0.098 (0,793)
SG	2003:05	-0.093 (-0.810)	0.116 (1.780*)
KR	2008:11	0.085 (1.106)	0.157 (1.731*)

Note: The Table provides estimates according to Equation (13) for two periods separated by periods separated by the break point with the common starting point in 1999:01 and the sample end in 2015:12. */**/** implies significance at the 1%/5%/10% level.

Table 4: Rational expectation test based on error orthogonality

Country	Forecast Error			Estimation Error		
	Constant	First lag	F-Test	Constant	First lag	F-Test
UK	-0.0007 (-0.6117)	0.6716 (12.7996***)	163.8301***	-0.0000 (-0.0099)	0.1331 (1.8887*)	3.5673*
JP	-0.0035 (-0.0156)	0.6568 (12.3486***)	152.4874***	0.0291 (0.0961)	0.1056 (1.1821)	1.3974
CA	0.0004 (0.1561)	0.6118 (10.8584***)	117.9054***	0.0005 (0.1604)	0.0294 (0.3342)	0.1117
EU	-0.0001 (-0.0413)	0.6206 (11.3132***)	127.9888***	-0.0000 (-0.0029)	0.1114 (1.5727)	2.4735
BR	-0.0010 (-0.0911)	0.5755 (10.5999***)	112.3573****	0.0007 (0.0616)	0.075 (1.0578)	1.1190
CL	0.6633 (0.4393)	0.6801 (13.1479***)	172.8673***	0.0630 (0.0325)	-0.0321 (-0.2661)	0.0708
AU	-0.0007 (-0.1737)	0.6293 (11.4128***)	130.2529***	0.0002 (0.0521)	0.2499 (3.6274***)	13.1580***
IN	0.0948 (1.1070)	0.6635 (12.5470***)	157.4281***	-0.0014 (-0.0170)	0.0513 (0.7188)	0.5166
SG	-0.0006 (-0.3427)	0.5838 (10.3075***)	106.2440***	0.0002 (0.0927)	0.1644 (2.3522**)	5.5330**
KR	1.5061 (0.5159)	0.5183 (8.5909***)	73.8028***	0.3319 (0.1262)	0.0915 (1.3017)	1.6943

Note: The Table provides estimates and tests statistics of the F test $a_1 = 0$ and $a_2 = 0$ according to according to Equation (14) (left panel) and Equation (15) (right pane). Equation */**/** implies significance at the 1%/5%/10% level.

Table 5: Unit Root Test of Disagreements

Country	DA-1M	DA-1Y
UK	-5.18051**	-3.64153**
JP	-5.39231**	-4.49869**
CA	-5.01615**	-3.73859**
EU	-3.95156**	-4.62003**
BR	-4.25024**	-3.62362**
CL	-4.03620**	-5.39886**
AU	-3.67960**	-2.22359
IN	-4.18828**	-4.04046**
SG	-4.68430**	-4.43903**
KR	-4.10070**	-2.99867*

Note: The Table provides test statistic results for the ADF unit root test results for 1 month and 1 year disagreement measures. */**/** implies that a unit root is rejected at the 1%/5%/10% level.

Table 6: Disagreement 1 Month

Country	Constant	IPDIFF-DIFF	CPI-DIFF	INT-DIFF	Domestic Policy Uncertainty	Lagged Disagreement	US POLICY UNCERTAINTY	VIX	OIL
UK	-1.9692*** (-6.5805)	0.1214 (0.3718)	10.2229 (1.6913)	0.1377 (1.1570)	0.1361** (2.9845)	0.3019*** (4.3927)	0.0747 (0.9648)	-0.0661 (-0.8150)	0.2030 (0.3433)
JP	0.7601** (3.1553)	-0.5851** (-2.7749)	-0.6509 (-0.1475)	0.0577 (0.7945)	-0.0544 (-1.3569)	0.5917*** (10.3631)	0.1316* (2.3709)	-0.0025 (-0.0392)	-0.0960 (-0.1964)
CA	-1.9033*** (-6.2271)	0.8842 (1.6358)	11.9267 (1.5054)	0.1463 (1.2983)	1.1040 (1.8456)	0.3741*** (5.6604)	0.1460 (1.7158)	-0.1922* (-2.2702)	-0.1406 (-0.2265)
EU	-1.8261*** (-5.5026)	0.3637 (0.4085)	4.6173 (0.9175)	0.0365 (0.3579)	-0.0301 (-0.4540)	0.4518*** (7.2024)	0.1052 (1.4117)	0.1588* (2.1516)	0.3768 (0.7050)
BR	-1.3222** (-2.9523)	-2.3100* (-2.1595)	3.4790 (0.6064)	0.0964*** (3.7223)	0.1658* (2.4867)	0.6296*** (12.4899)	-0.2158* (-2.4818)	0.3236** (3.0456)	-0.2998 (-0.3592)
CL	0.4804 (1.1598)	-0.7867 (-0.9656)	4.1724 (0.7108)	0.0437 (1.6560)	0.0656 (0.9876)	0.5829*** (10.2080)	-0.0248 (-0.2992)	0.2848** (2.6856)	-0.5750 (-0.7204)
AU	-1.6008*** (-4.8215)	-4.2455*** (-3.7944)	-11.2691* (-2.0180)	0.1033 (1.3573)	0.1818** (2.8511)	0.5941*** (10.2851)	0.0096 (0.1157)	-0.0792 (-0.9687)	0.2306 (0.3712)
IN	-0.3154 (-1.0110)	-1.6074 (-1.6648)	-1.3066 (-0.3537)	0.0813 (0.9175)	0.1881* (2.6006)	0.6742*** (11.4713)	-0.1801 (-1.8187)	0.2225 (2.1258)	0.0372 (0.0390)
SG	-1.9973*** (-4.7281)	-0.1503 (-0.6754)	1.4973 (0.3894)	0.0663 (0.7431)	0.0698 (0.6281)	0.5330*** (7.7366)	-0.1065 (-1.0617)	0.2973** (2.9176)	0.0381 (0.0436)
KR	0.5669 (1.8184)	-0.3073 (-0.8569)	-5.7505 (-1.3253)	0.0623 (0.7155)	0.0880 (1.2557)	0.5450*** (9.7020)	-0.0783 (-0.8946)	0.4677*** (4.7828)	-0.3724 (-0.5605)

The Table provides estimates for one month exchange rate disagreement based on Equation (14). */**/** denotes significance at the 1%/5%/10% level.

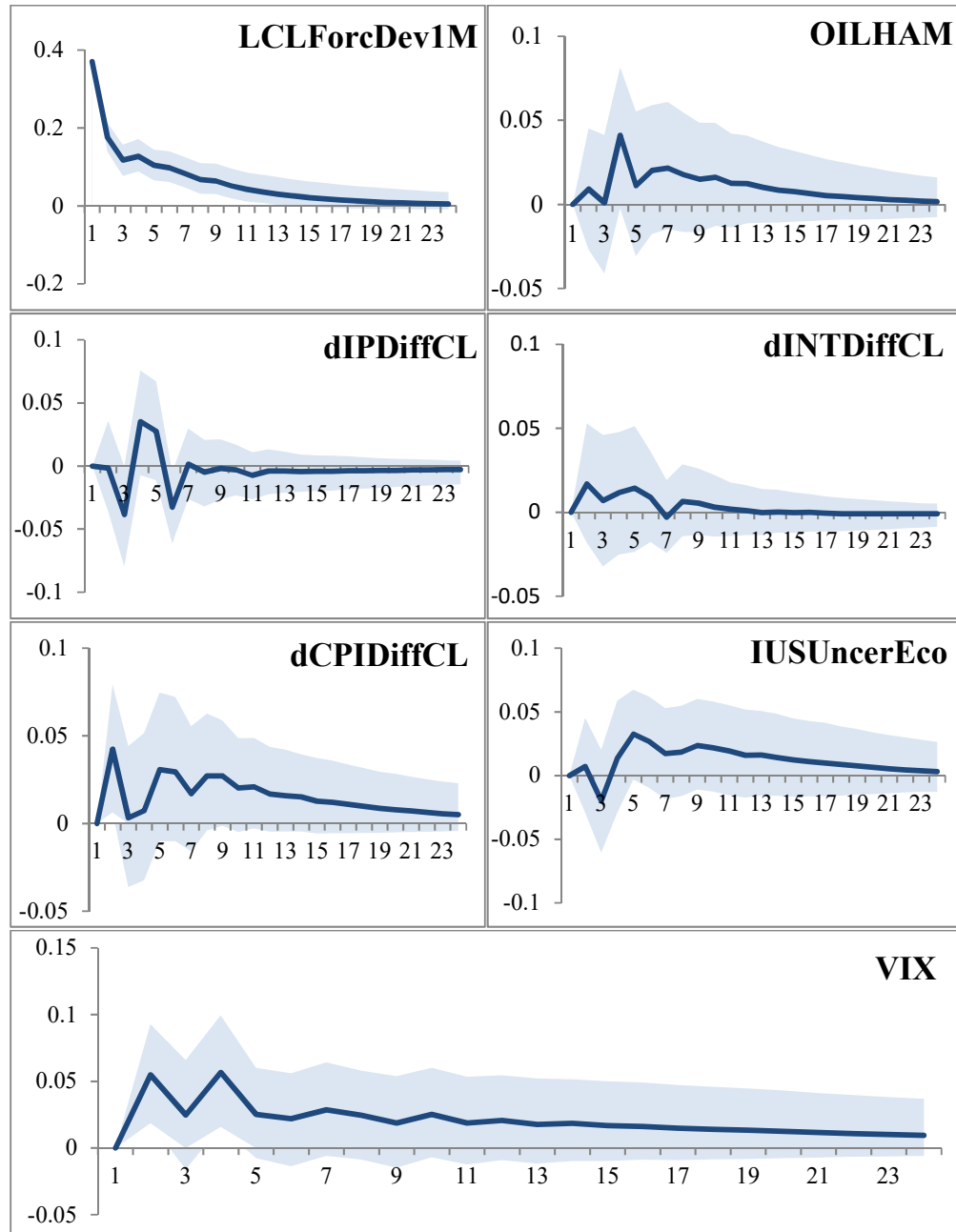
Table 7: Disagreement 1 Year

Country	Constant	IPDIFF-DIFF	CPI-DIFF	INT-DIFF	Domestic Policy Uncertainty	Lagged Disagreement	US POLICY UNCERTAINTY	VIX	OIL
UK	-0.4134*** (-3.0834)	-0.2901 (-1.4802)	4.6888 (1.3609)	-0.0668 (-0.9270)	-0.0002 (-1.1641)	0.7054*** (14.1818)	0.0005 (1.2838)	0.0293 (0.6743)	0.2321 (0.6118)
JP	0.6148** (3.1832)	-0.3382* (-2.4329)	-0.0507 (-0.0173)	0.0601 (1.2605)	-0.0340 (-1.2793)	0.7940*** (18.3176)	0.0144 (0.4039)	0.0636 (1.4746)	-0.0829 (-0.2556)
CA	-1.0677*** (-5.2541)	0.3101 (0.9225)	6.5056 (1.3132)	-0.0712 (-1.0122)	0.0242 (0.6970)	0.5714*** (9.8987)	0.1163* (2.1719)	-0.0710 (-1.4098)	0.3802 (0.9787)
EU	-1.0765*** (-4.7303)	0.5044 (0.7329)	-0.9220 (-0.2378)	0.1532 (1.8920)	-0.0878 (-1.6882)	0.3594*** (5.4126)	0.0675 (1.1599)	0.1541** (2.7104)	-0.4725 (-1.1426)
BR	-0.6485 (-1.9227)	-0.2721 (-0.3276)	4.9723 (1.1242)	0.0925*** (4.6085)	0.0232 (0.4520)	0.7249*** (16.2218)	-0.1313 (-1.9371)	0.2978*** (3.6004)	0.2789 (0.4283)
CL	0.7191* (2.1422)	0.3371 (0.5891)	1.5858 (0.3810)	-0.0234 (-1.2589)	0.0138 (0.2925)	0.6674*** (13.2866)	-0.0105 (-0.1791)	0.2297** (3.0088)	-0.0559 (-0.0989)
AU	-0.5303** (-3.0066)	0.9005 (1.5135)	0.1075 (0.0353)	-0.0070 (-0.1676)	0.0438 (1.2923)	0.8009*** (19.0915)	0.0191 (0.4148)	-0.0346 (-0.7639)	0.0999 (0.2941)
IN	0.0059 (0.0306)	-0.3421 (-0.5706)	-0.1108 (-0.0485)	-0.0612 (-1.1061)	-0.0219 (-0.5026)	0.7754*** (15.0919)	0.1199 (1.8996)	-0.0003 (-0.0046)	-0.1643 (-0.2770)
SG	-0.5467* (-2.0671)	0.0875 (0.5471)	3.4098 (1.2316)	-0.1466* (-2.2752)	-0.0022 (-0.0269)	0.7091*** (12.3014)	-0.0793 (-1.0975)	0.0959 (1.2524)	0.8309 (1.3140)
KR	0.8398** (3.1430)	0.0752 (0.3261)	-2.3771 (-0.8523)	0.0052 (0.0925)	0.0005 (1.1711)	0.7459*** (16.7284)	-0.0506 (-0.9007)	0.1187 (1.9450)	0.3427 (0.8109)

The Table provides estimates for one year exchange rate disagreement based on Equation (14). **/**/**/** denotes significance at the 1%/5%/10% level.

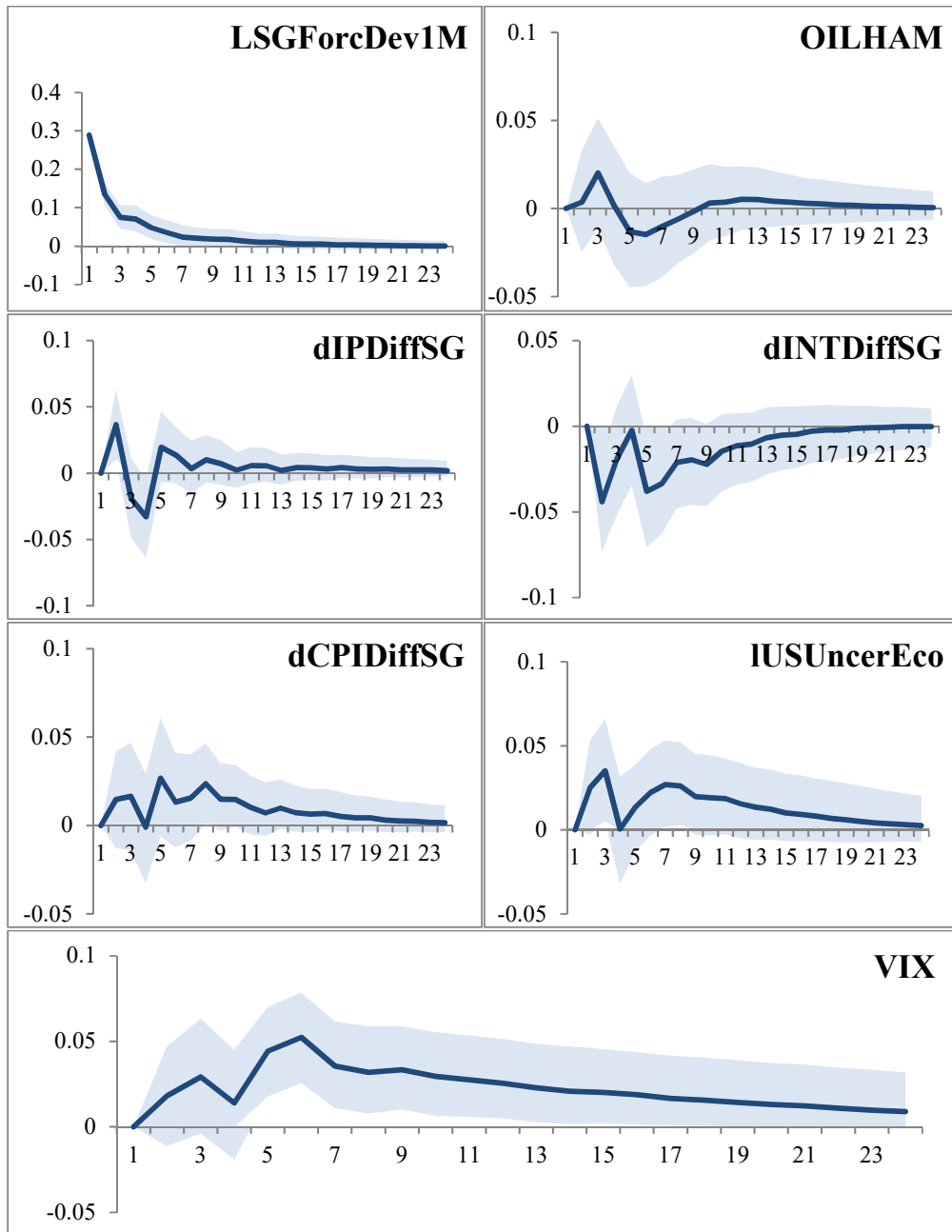
Figures

Figure 1: Exchange rate disagreement, Chile



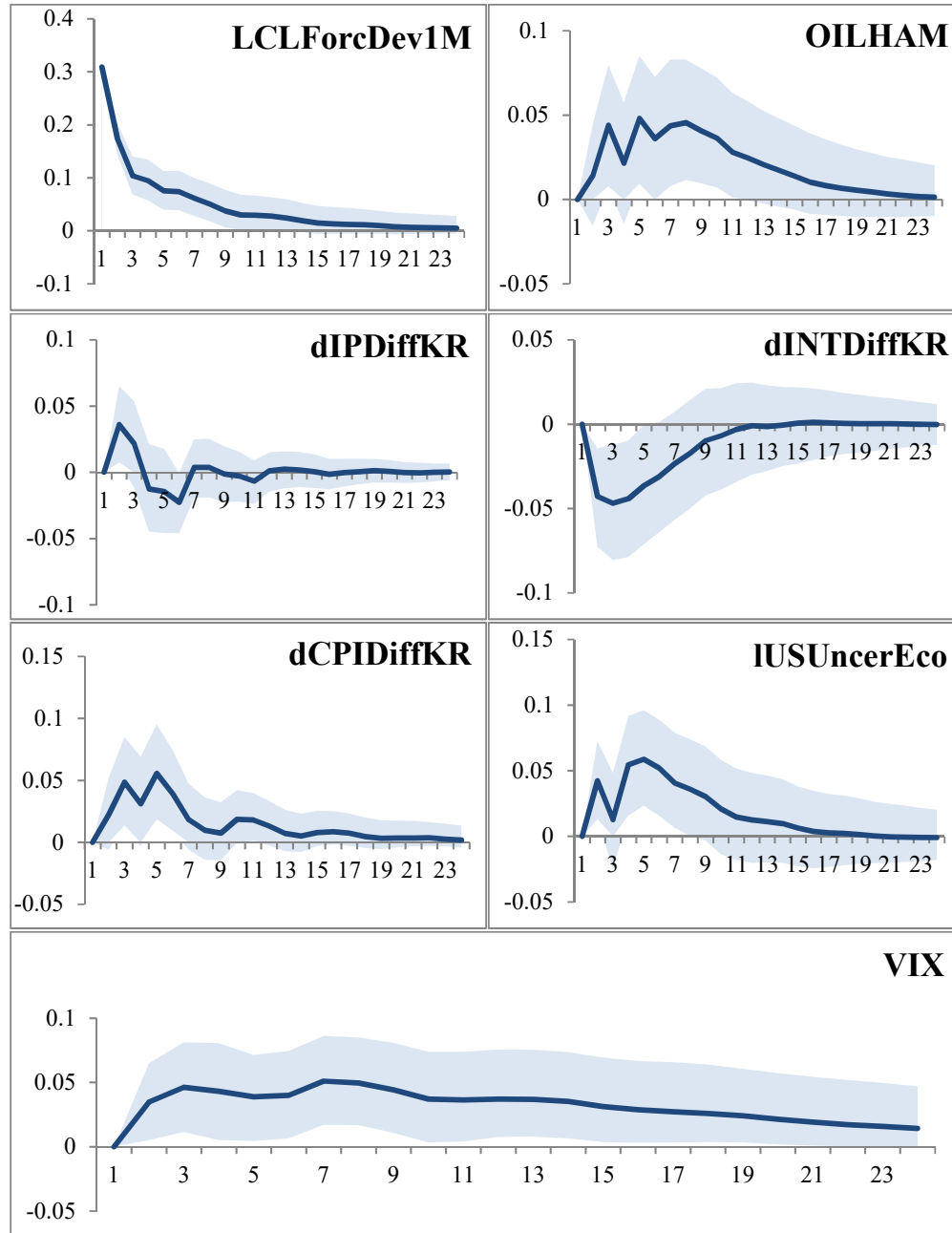
Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of Chile. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 2 : Exchange rate disagreement, Singapore



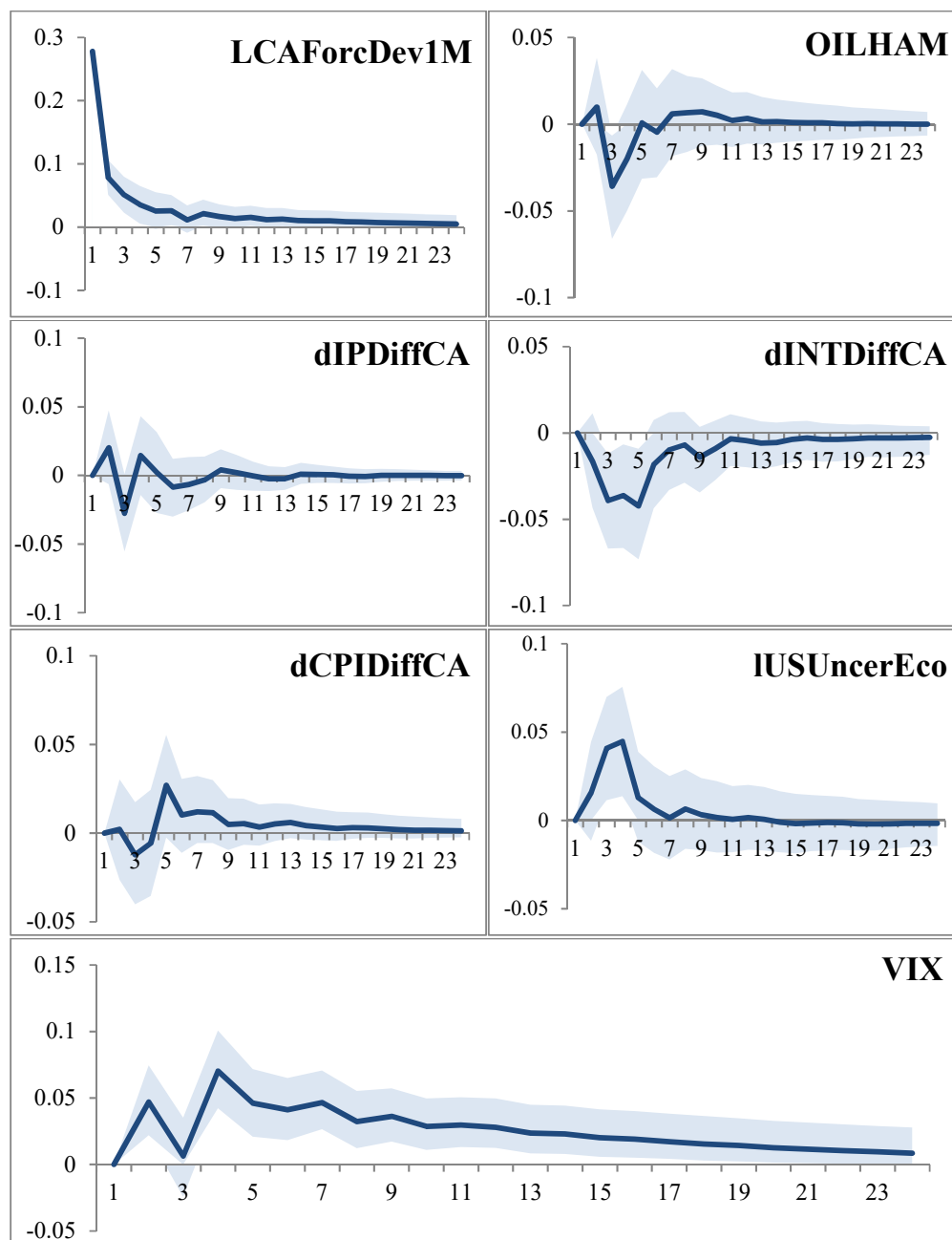
Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of Singapore. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 3: Exchange rate disagreement, Korea



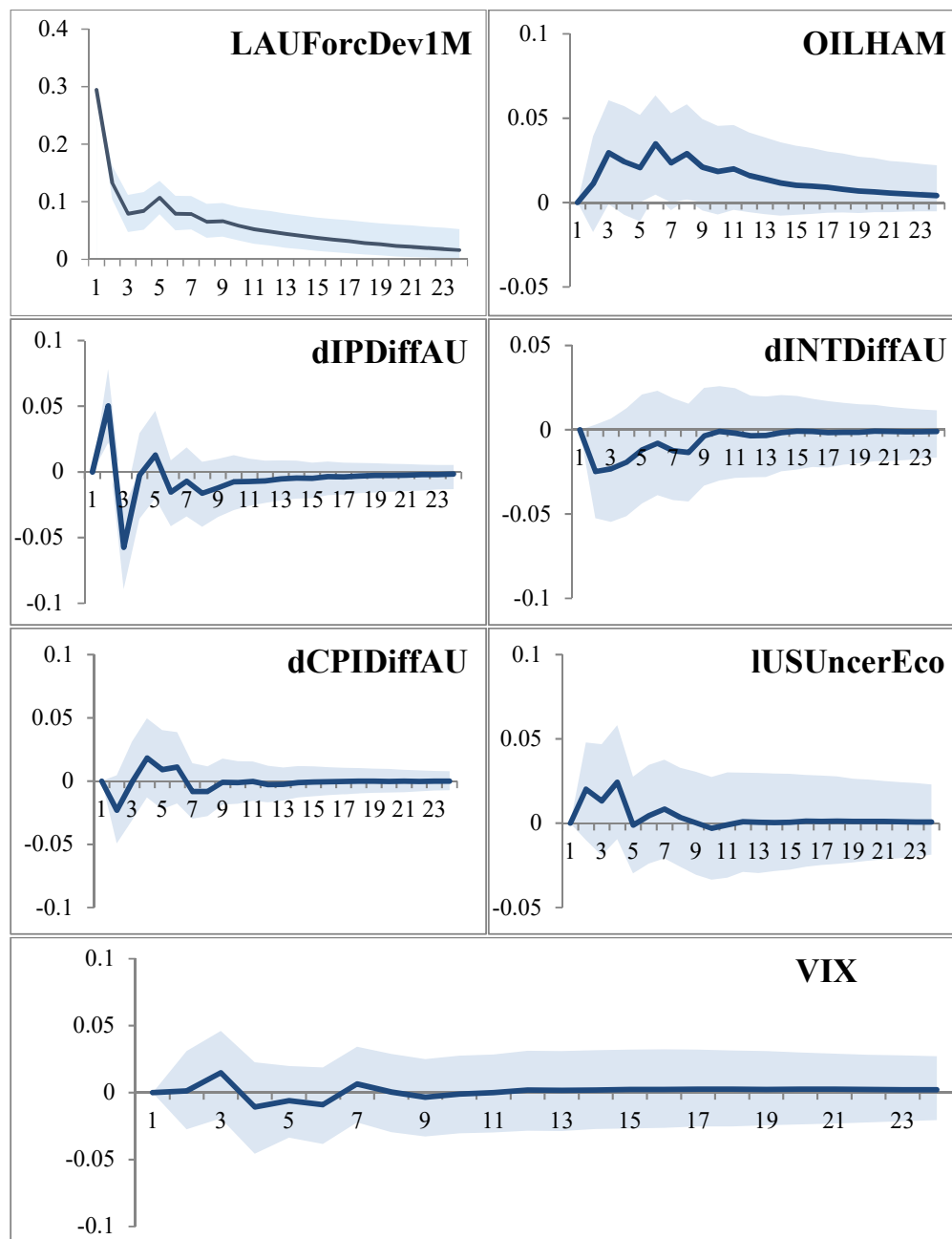
Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of Korea. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 4: Exchange rate disagreement, Canada



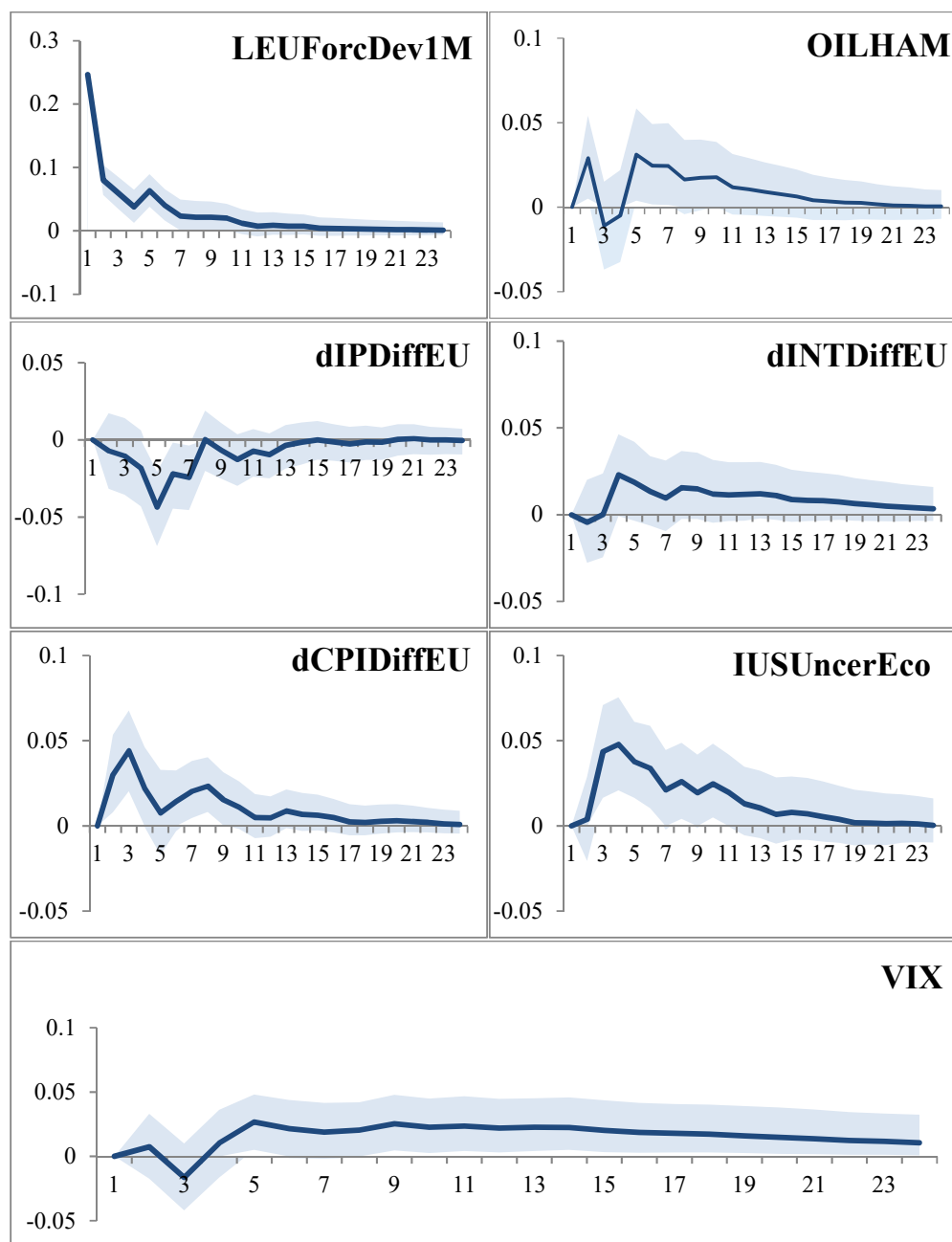
Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of Canada. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 5: Exchange rate disagreement, Australia



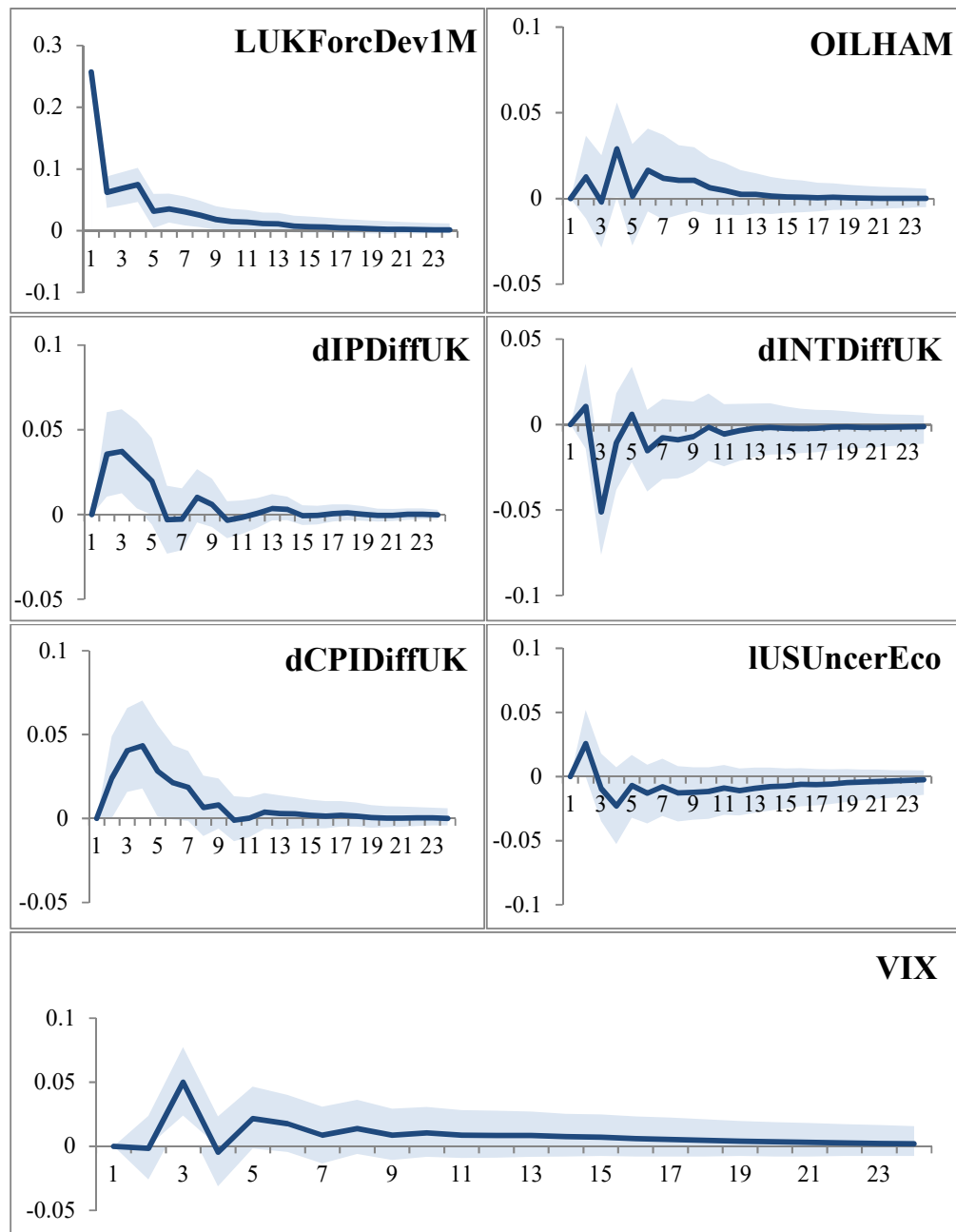
Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of Australia. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 6: Exchange rate disagreement, Euro



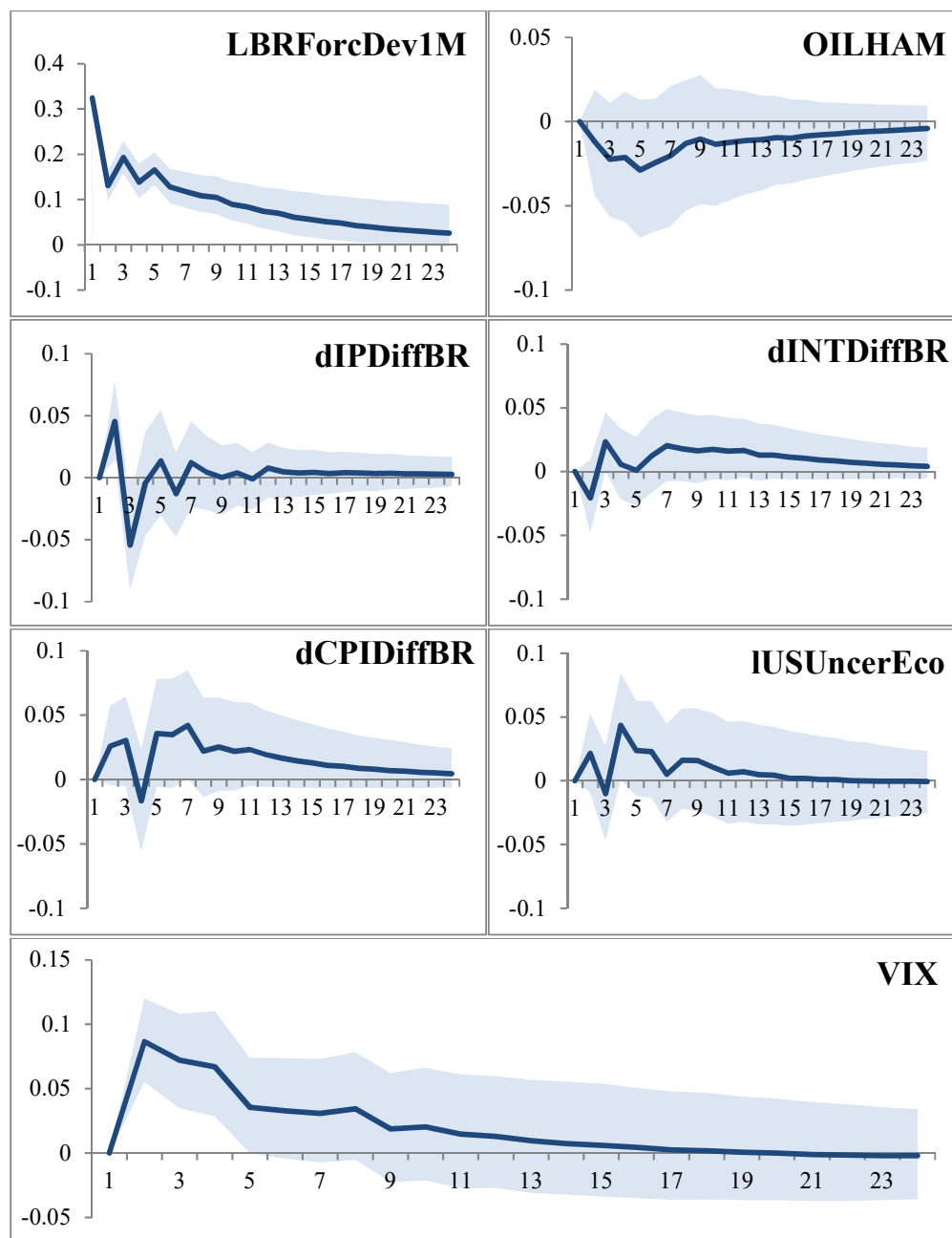
Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of the Eurozone. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 7: Exchange rate disagreement, UK



Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of UK. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).

Figure 8: Exchange rate disagreement, Brazil



Note: This Figure provides impulse response functions from the VAR model described in Equation (15) for one month exchange rate disagreement of Brazil. The results are provided with blue lines (impulse responses) and shadow areas (90% confidence bands).