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Model misspecification, learning and the exchange rate disconnect puzzle

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Model misspecification, learning and the exchange rate disconnect puzzle

by Vivien Lewis and Agnieszka Markiewicz

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Abstract

Rational expectations models fail to explain the disconnect between the exchange rate and macroeconomic fundamentals. In line with survey evidence on the behaviour of foreign exchange traders, we introduce model misspecification and learning into a standard monetary model. Agents use simple forecasting rules based on a restricted information set. They learn about the parameters and performance of different models and can switch between forecasting rules. We compute the implied post-Bretton Woods US dollar-pound sterling exchange rate and show that the excess volatility of the exchange rate return can be reproduced with low values of the learning gain. Both assumptions, misspecification and learning, are necessary to generate this result. However, the implied correlations with the fundamentals are higher than in the data. Including more lags in the model tends to tip the balance of our findings slightly towards rational expectations and away from the learning hypothesis.

Key Words:  exchange rate, disconnect, misspecification, learning
JEL Classification:  F31, E37, E44

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1 Introduction

The disconnect between the exchange rate and macroeconomic aggregates is a well-known fact of international macroeconomics. Obstfeld and Rogoff (2000) note that ‘...exchange rates are remarkably volatile relative to any model we have of underlying fundamentals such as interest rates, outputs and money supplies, and no model seems to be very good at explaining exchange rates even \textit{ex post}.’ Meese and Rogoff (1983) demonstrate that traditional exchange rate models produce forecasts which are no better than a random walk. Twenty years later, Cheung et al (2005) find that fundamental exchange rate models can explain the dynamics of only some currencies and during certain time periods.

Cheung et al (2005) study the out-of-sample forecasting performance of several fundamentals-based models for a set of exchange rates. They use several measures to compare those models to the random walk. For the British Pound/US Dollar, which is the exchange rate we focus on in this paper, they test thirty specifications for two sample periods. In all cases, the random walk does at least as well as any of the fundamentals-based models. Furthermore, the authors show that none of the fundamentals-based model forecasts can correctly predict the direction of the change in the British Pound/US Dollar rate. These results indicate that none of the available models is a better exchange rate predictor than the random walk.

The exchange rate is usually modelled as an asset price; it is expressed as a weighted average of a set of current fundamentals and its expected future value. Since the weight on expectations is high relative to the weight on the fundamentals, expectations formation is key in determining exchange rate dynamics. Rational expectations (RE) models fail to generate the exchange rate disconnect. We therefore assume two departures from the RE hypothesis: learning and model misspecification.

Our first departure from rational expectations is the introduction of statistical learning. Adam et al. (2008) show that learning improves the empirical performance of asset pricing models. Here, agents learn about the model parameters and about the relative performance of different forecasting rules; they are allowed to switch between rules.

Our second departure from rational expectations is the assumption of model underparameterisation. Agents do not use all available information to make forecasts. Experimental evidence in Adam (2007) suggests that agents base forecasts on simple rules using a restricted set of variables, even if information on other relevant variables is available to them. In a survey among foreign exchange traders, Cheung and Chinn (2001) find considerable variation
in the relative importance attached to different fundamentals both across time and market participants. They conclude that ‘a successful model should [...] allow for changes in the relative importance of macroeconomic fundamentals over time’. In Bacchetta and Van Wincoop’s (2004) scapegoat model, heterogeneous information in the foreign exchange market leads investors to attach excessive weight to an observed fundamental. Here, we allow for heterogeneity in beliefs as well as time-variation in the weight on a particular fundamental, following Branch and Evans (2007).

Experimental and survey studies find systematic forecast heterogeneity. Weale and Pesaran (2006) argue that expectations could differ considerably across individuals due to information disparity and differences in beliefs. These two sources of expectations heterogeneity are closely related and could be reinforcing. Information disparities could initiate and maintain disparities in beliefs, whilst differences in beliefs could lead to information disparities when information processing is costly.

Based on survey data, Frankel and Froot (1987a, 1987b, 1990a, 1990b), Taylor and Allen (1992) and Ito (1990) find evidence for the presence of heterogeneous beliefs in the foreign exchange market. This heterogeneity is dynamic such that foreign exchange market participants can change predictors over time. Bask (2007), De Grauwe and Grimaldi (2006a, 2006b), and De Grauwe and Markiewicz (2006) model this behaviour by introducing dynamic predictor selection. This approach is based on discrete choice theory and was initially applied to asset markets by Brock and Hommes (1997, 1998). In line with survey evidence, this mechanism assumes that agents evaluate forecasting rules by computing the past profits of these rules and increase (reduce) the weight of one rule if it is more (less) profitable than the alternative rule.

Heterogeneity in expectations has also been found in other markets. In particular, inflation forecasts display systematic heterogeneity. Branch (2004) tests for the ‘rationally heterogeneous’ expectations model using survey data on inflation expectations. He shows that agents select different predictors over time and their proportion varies inversely with the predictor’s past performance, in line with the mechanism proposed by Brock and Hommes (1997, 1998). Similarly, Branch (2007) demonstrates that models which allow the level of heterogeneity to change over time provide a better fit of the data. Finally, Pfajfar and Zakelj (2008) conduct an experimental study on the inflation expectations formation process. They find that agents form expectations in accordance with different theoretical models and they rather tend to switch between models than stick to one of them. Therefore, the authors provide important empirical support for models that postulate endogenous switching à la Brock and Hommes (1997, 1998).
We introduce misspecification and learning in the monetary model of Frenkel (1976) and Bilson (1978). Together with data on US-UK fundamentals over the post-Bretton-Woods period, we generate samples of artificial quarterly exchange rate data. We compute the exchange rate volatility and the correlation between the exchange rate and fundamentals. The model has two free parameters: the learning gain and the speed of switching between forecasting rules. We calibrate the learning gain so as to match the volatility of the exchange rate return with that in the data, for several values of the switching parameter. We then compare other exchange rate moments in the model to those in the data. We find reasonable values for the learning gain that reproduce the high volatility of the exchange rate return. However, the exchange rate under learning is too highly correlated with the fundamentals.

Chakraborty (2007a) also introduces learning into a monetary exchange rate model, but does not consider model misspecification. He investigates whether learning can reproduce the forward premium puzzle, while we focus on the volatility of the exchange rate and its correlation with the fundamentals. Another difference between his paper and ours is that we use actual data on fundamentals to construct the exchange rate under learning, while he simulates the fundamentals series.

2 Model

The monetary model by Frenkel (1976) and Bilson (1978) yields an asset pricing equation for the exchange rate.\footnote{Alternatively, one can derive such an equation from a microfounded general equilibrium model. See Engel and West (2005).} Money market equilibrium in the home country is

\[ m_t = p_t + c_1 y_t - c_2 i_t \]  

(1)

where \( m_t \) is the log money stock, \( p_t \) is the log price level, \( y_t \) is log output and \( i_t \) is the nominal interest rate. A similar relationship with identical parameters holds in the foreign country, with foreign variables indicated by a star. The log nominal exchange rate \( s_t \), the domestic price of a unit of foreign currency, is equal to its purchasing power parity (PPP) value.

\[ s_t = p_t - p_t^* \]  

(2)

We assume full price flexibility, such that PPP holds at all times. The uncovered interest parity condition is

\[ i_t = i_t^* + \tilde{E}_t s_{t+1} - s_t \]  

(3)
\( \bar{E}_{t+1} \) denotes the (not necessarily rational) market expectation of next period’s exchange rate. Combining (1) with its foreign counterpart, (2) and (3), we can write the exchange rate as

\[
s_t = (1 - \theta) \gamma' f_t + \theta \bar{E}_{t+1}
\]

(4)

where the observables are given by \( f_t = (f_{1t}, f_{2t})' \), \( f_{1t} = m_t - m_t^* \) and \( f_{2t} = y_t - y_t^* \). The parameters are \( \theta = c_2 / (1 + c_2) \) and \( \gamma = (1, -c_1)' \).

### 3 Disconnect Puzzle under Rational Expectations

We solve and calibrate the model under rational expectations (RE).\(^2\) Solving model (4) forward assuming RE, \( \bar{E}_t = E_t \), yields

\[
s_t = (1 - \theta) \gamma' \sum_{j=0}^{T} \theta^j E_t f_{t+j} + \theta^T E_t s_{t+T}
\]

Letting \( T \to \infty \) and imposing the no-bubbles condition \( \theta < 1 \) such that \( \lim_{T \to \infty} \theta^T E_t s_{t+T} = 0 \), we find the present value representation

\[
s_t = (1 - \theta) \gamma' \sum_{j=0}^{\infty} \theta^j E_t f_{t+j}
\]

Suppose that \( f_t \) follows a stationary first-order vector autoregressive process,

\[
f_t = A f_{t-1} + \varepsilon_t,
\]

where \( \varepsilon_t \sim N(0, \Sigma_\varepsilon) \). By forward substitution, we find \( E_t f_{t+j} = A^j f_t \). The term \( \sum_{j=0}^{\infty} \theta^j E_t f_{t+j} = \sum_{j=0}^{\infty} (\theta A)^j f_t \) is a geometric series equal to \( (I_2 - \theta A)^{-1} f_t \). Then the rational expectations solution to this model is

\[
s_t^{RE} = (1 - \theta) \gamma' (I_2 - \theta A)^{-1} f_t = [b_1^{RE}, b_2^{RE}] f_t.
\]

We assume the following parameter values for \( c_1 > 0 \), the income elasticity of money demand and \( c_2 > 0 \), the interest semi-elasticity of money demand.\(^3\) Setting \( c_2 \approx 40 \) implies a discount factor \( \theta = 0.97 \). The parameter \( c_1 \) is set to 1 such that \( \gamma = (1, -1)' \). In practice, we estimate a bivariate VAR(1) on the

---

\(^2\)All data and program files are available at http://sites.google.com/site/vivienjlewis.

\(^3\)See Engel and West (2005) for a discussion of plausible parameter values.
fundamentals with a constant and a trend. We use equation-by-equation ordinary least squares (OLS) to estimate \( f_t = B f_{t-1} + u_t \), where \( f_t = (f_{1t}, f_{2t}, c, t)' \) and \( u_t \sim N(0, \Sigma_u) \). The exchange rate under rational expectations is

\[
s^R_E = (1 - \theta) \gamma' (I_4 - \theta B)^{-1} f_t
\]

where \( \gamma' = [\gamma', 0_{1 \times 2}] \) and \( B \) is the OLS estimate of the coefficient matrix. The estimated VAR coefficients are

\[
B = \begin{pmatrix}
0.95 & -0.06 \\
-0.17 & 0.82
\end{pmatrix}
\]

\[
\Sigma_u = 10^{-3} \begin{pmatrix}
0.2802 & -0.0736 \\
-0.0736 & 0.2632
\end{pmatrix}
\]

\( B \) is the estimate of \( B \) and \( \Sigma_u \) is the estimate of \( \Sigma_u \) without the deterministic components.\(^4\) We calculate the exchange rate according to (5), using quarterly US-UK data\(^5\) on \( f_t \) over the post-Bretton-Woods period, 1974Q1-2006Q2.

Table 1: **Disconnect Puzzle under Rational Expectations (RE)**

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>RE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \sigma (s_t) )</td>
<td>14.69</td>
<td>38.04</td>
</tr>
<tr>
<td>( \sigma (\Delta s_t) )</td>
<td>5.16</td>
<td>2.81</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho (s_t, y_t) )</td>
<td>-0.29</td>
<td>-0.96</td>
</tr>
<tr>
<td>( \rho (s_t, m_t) )</td>
<td>-0.07</td>
<td>0.78</td>
</tr>
<tr>
<td>( \rho (\Delta s_t, \Delta y_t) )</td>
<td>-0.07</td>
<td>-0.73</td>
</tr>
<tr>
<td>( \rho (\Delta s_t, \Delta m_t) )</td>
<td>-0.03</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Note: \( \sigma (\cdot) \) denotes the standard deviation, \( \rho (\cdot, \cdot) \) denotes the correlation coefficient.

Table 1 presents descriptive statistics of the log exchange rate and its first difference in the data and in the RE monetary model.\(^6\) The volatility of the

\(^4\)The matrix \( B \) has one unstable root, indicating that the fundamentals-VAR is not stable over the post-Bretton-Woods sample period. We nevertheless maintain our assumption that the money supply and output differentials of two countries should not diverge indefinitely, such that stability holds at sufficiently long horizons.

\(^5\)Data are from the IMF’s International Financial Statistics. For the money supply we use seasonally adjusted M4, for real income we use seasonally adjusted GDP.

\(^6\)Because the variance is undefined for a unit root process, the statistic \( \sigma (s_t) \) is valid only under the assumption that the exchange rate is stationary. While economists agree that the exchange rate is highly persistent, it is a matter of debate whether it is exactly or nearly integrated.
observed exchange rate return is more than 80% higher than the model-based one. The level of the exchange rate under RE is over twice as high as in the data. In addition, the RE exchange rate is highly correlated with the two fundamentals series, while in the data, these correlations are weak.

4 Model Misspecification and Learning

We first assume that agents use a limited information set to forecast the exchange rate based on the monetary model of Section 2. There are two groups of agents, \(i = 1, 2\), each using a single explanatory variable to make the following forecasts

\[
\bar{E}_{i,t} (s_{t+1}) = b_{i,t-1} f_{i,t}
\]

where \(b_{i,t-1}\) is an estimate of the belief parameter \(\beta_{i,t-1}\) based on information up to time \(t - 1\). The market forecast \(\bar{E}_t s_{t+1}\) is a weighted average of the two forecasts, where \(n_{t-1}\) is the proportion of agents using the fundamental \(f_{1,t}\):

\[
\bar{E}_t s_{t+1} = n_{t-1} b_{1,t-1} f_{1,t} + (1 - n_{t-1}) b_{2,t-1} f_{2,t}
\]

The equilibrium stochastic process followed by the exchange rate is obtained by substituting the market forecast in (4).

\[
s_t = [(1 - \theta) \gamma_1 + \theta n_{t-1} b_{1,t-1}] f_{1,t} + [(1 - \theta) \gamma_2 + \theta (1 - n_{t-1}) b_{2,t-1}] f_{2,t}
\]

From (7), we see that using \(b_{i,t}\) instead of \(b_{i,t-1}\) to form \(\bar{E}_t s_{t+1}\) would result in a simultaneity problem, since \(b_{i,t}\) depends on \(s_t\).

Second, we introduce dual learning into the model: parameter learning and dynamic predictor selection. This allows the parameters and the model weights to vary over time. We assume constant gain learning, which weights recent data more heavily than observations further back in time. This algorithm is more appropriate than least squares learning, which in contrast weights all observations equally, if the relationship between variables is characterised by frequent structural breaks. Tests on the regression of the exchange rate on fundamentals reveal that structural breaks are indeed present, lending support to the constant gain assumption.\(^7\) Furthermore, Branch and Evans (2006) find that constant gain learning delivers good out-of-sample forecasts and provides a better fit to the Survey of Professional Forecasters for inflation and output.

\(^7\)See Chakraborty (2007a).
growth expectations than ordinary least squares learning. The learning process obeys

\begin{align*}
  b_{i,t} &= b_{i,t-1} + \kappa r_{i,t-1}^{-1} f_{i,t} (s_t - b_{i,t-1} f_{i,t}) \quad (8) \\
  r_{i,t} &= r_{i,t-1} + \kappa (f_{i,t}^2 - r_{i,t-1}) \quad (9)
\end{align*}

where \( r_{i,t} = \kappa \sum_{j=1}^{t} f_{i,j-1}^2 \) and \( \kappa \) is the learning gain.

Each period, agents evaluate the models’ forecasting performance by means of the mean square error (MSE) criterion. Following Branch and Evans (2007), agents update their MSE estimate according to a weighted least squares procedure with geometrically decreasing weights on past observations.

\[ MSE_{i,t} = MSE_{i,t-1} + \kappa \left[ (s_t - \tilde{E}_{i,t-1} s_t)^2 - MSE_{i,t-1} \right] \quad (10) \]

As in Brock and Hommes (1997), predictor proportions are determined according to the following discrete choice formula.

\[ n_t = \frac{\exp(-\alpha MSE_{1,t})}{\exp(-\alpha MSE_{1,t}) + \exp(-\alpha MSE_{2,t})} \quad (11) \]

The weight \( n_t \) on predictor 1 is higher when its mean square error is lower. The parameter \( \alpha \) measures the strength with which agents switch from one predictor to the other. A higher \( \alpha \) implies that agents react more strongly to the relative performance of the two forecasting rules. As \( \alpha \) approaches infinity, switching becomes instantaneous. If \( \alpha \) is equal to zero, agents are insensitive to the relative performance of the predictors and their weights are constant at 0.5.

The timing assumption of the model is as follows. Agents enter period \( t \) with a parameter estimate \( b_{i,t-1} \) and an exchange rate forecast \( \tilde{E}_{i,t-1} s_t \). They observe \( f_t \) and make a new forecast as in (6). The market expectation is formed as a weighted average of the forecasts 1 and 2, with predetermined weights \( n_{t-1} \) and \( (1 - n_{t-1}) \), respectively. The exchange rate materialises according to the actual law of motion (7). Agents observe \( s_t \) and update their belief parameters \( b_{i,t} \) (8), \( r_{i,t} \) (9) and their MSE estimate (10). Then they evaluate the relative performance of the forecasting rules, which determines the new predictor proportions \( n_t \) and \( (1 - n_t) \) as shown in (11). Thus, the dual learning algorithm is given by a loop over equations (6) to (11).

All variables with the time subscript \( t - 1 \) have to be initialised. Initial values are displayed in Table 2. For the parameters, we choose the rational expectations values \( b_{1,RE} \) and \( b_{2,RE} \). The \( r_{i,b} \)’s are set equal to 1. The mean
Table 2: **Initialisation of the Dual Learning Algorithm**

<table>
<thead>
<tr>
<th>( b_{1,0} )</th>
<th>( b_{2,0} )</th>
<th>( r_{i,0} )</th>
<th>( E_{i,0} s_1 )</th>
<th>( MSE_{i,0} )</th>
<th>( n_0 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( b_{1}^{RE} )</td>
<td>( b_{2}^{RE} )</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>( \sim U (0, 1) )</td>
</tr>
</tbody>
</table>

Square errors and the expected exchange rate are initialised at 0. The initial weight on model 1 is drawn from a standard uniform distribution.

The dual learning algorithm has two free parameters, \( \alpha \) and \( \kappa \). We compute the gain \( \kappa \) that is needed to produce a standard deviation of the exchange rate return under learning \( \Delta s_{i}^{\text{learn}} \) close to the one found in the data, for several assumptions on the switching parameter \( \alpha \). Branch and Evans (2007) argue that a low value for \( \alpha \) implies agents are not fully optimising. They consider equilibria with a large \( \alpha \). In line with this argument, we consider \( \alpha = 10,000 \), which produces model weights \( n_t \) close to either 0 or 1. The superior forecasting performance measured by a lower MSE results in an instantaneous shift of the whole population of forecasters towards the better model; the simulated exchange rate is then driven by one fundamental at a time. A high \( \alpha \) gives rise to faster switching than a lower value, given a value for \( \kappa \). Can a model with more inertial switching generate enough volatility with a reasonable gain? To answer this question, we also consider lower values for \( \alpha \).

We simulate the post-Bretton-Woods exchange rate under learning, given actual data for the fundamentals \( f_t \). To avoid dependence on the initial model weight \( n_0 \), we compute the exchange rate moments as an average over 1,000 realisations of \( n_0 \). We also remove the first three quarters from the generated exchange rate series as a sort of training period, so as to avoid that large swings at the start of the learning algorithm translate into high overall volatility.

Consider Table 3. The first two columns reproduce the disconnect puzzle under rational expectations as demonstrated in Table 1. Under the heading Dual Learning and below each value of the switching parameter \( \alpha \), we present the corresponding value for the learning gain \( \kappa \) that is needed to reproduce the exchange rate return volatility observed in the data. We evaluate the performance of the learning model in replicating the features of the disconnect puzzle. Since we have lost one degree of freedom for calibrating \( \kappa \), there are five dimensions left along which we can compare the summary statistics of the data with those of the learning model. In Table 3 we also report the mean proportion of agents that base their forecasts on model 1 using the money supply differential as an explanatory variable for the exchange rate. This mean weight on model 1, which we call \( \bar{n} \), is taken across time and across
Table 3: Disconnect Puzzle: RE vs Dual Learning

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>RE</th>
<th>Dual Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha ) (switching parameter)</td>
<td></td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>( \kappa ) (learning gain)</td>
<td></td>
<td>0.3354</td>
<td>0.3461</td>
</tr>
<tr>
<td>( \bar{n} ) (mean weight on model 1)</td>
<td></td>
<td>0.50</td>
<td>0.48</td>
</tr>
<tr>
<td>Volatility</td>
<td></td>
<td>14.69</td>
<td>38.04</td>
</tr>
<tr>
<td>( \sigma(s_t) )</td>
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<td>( \sigma(\Delta s_t) )</td>
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<td>5.16</td>
<td>5.16</td>
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<td>-0.73</td>
</tr>
<tr>
<td>( \rho(\Delta s_t, \Delta y_t) )</td>
<td></td>
<td>-0.03</td>
<td>0.78</td>
</tr>
<tr>
<td>( \rho(\Delta s_t, \Delta m_t) )</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: \( \sigma(\cdot) \) denotes the standard deviation, \( \rho(\cdot, \cdot) \) denotes the correlation coefficient. We consider several values for \( \alpha \) and search in the unit interval for the \( \kappa \) that minimises the squared distance between \( \sigma(\Delta s_{t, \text{learn}}) \) and \( \sigma(\Delta s_{t, \text{data}}) \). \( \bar{n} \) denotes the mean weight on model 1, where the mean is taken over time periods and realisations of \( n_0 \).
realisations of \( n_0 \).

With an appropriate value for \( \kappa \), we can match the excess return volatility for low and intermediate levels of switching \((\alpha = 0.1, \alpha = 1, \alpha = 10 \text{ and } \alpha = 50)\). To gauge whether our \( \kappa \)-values are plausible, we compare them to other values estimated and calibrated in the literature. Branch and Evans (2006) and Orphanides and Williams (2005) find that a value of 0.02 is appropriate to match forecasts of inflation and GDP growth. Kim (2009) and Chakraborty (2007a, 2007b) consider a monetary model of the exchange rate under constant gain learning. Kim (2009) sets the gain to 0.02; Chakraborty (2007a, 2007b) uses the values 0.01, 0.05 and 0.1. Both studies find that constant gain learning is superior to the RE benchmark. Notice that for intermediate switching, our gain values \((\kappa = 0.0182 \text{ and } \kappa = 0.0290)\) are of the same order of magnitude the values considered by those authors. We regard this finding as supportive of the dual learning model. It is well known that a higher gain increases the volatility of the updated parameter series. This, in turn, amplifies the volatility of the generated economic process, see Evans and Honkapohja (2001).

The correlations of the exchange rate with the fundamentals (in levels and in first differences) are higher than in the data, but lower than under rational expectations. Thus, the dual learning mechanism appears to weaken the link between exchange rates and fundamentals that is present under rational expectations. For \( \alpha = 10 \text{ and } \alpha = 50 \), the volatility of the exchange rate level is closer to the data than the corresponding volatility under RE. Turning to the average model weights, we observe that for low values of the switching parameter \( \alpha \), both models are equally important; \( \pi \) is close to one half. The money supply differential becomes less important as an explanatory variable of the exchange rate as \( \alpha \) is increased. When switching is instantaneous, however, the average weight on model 1 is 99%. Assuming intermediate values for \( \alpha \) would point to the output differential as the dominant fundamental driving exchange rate fluctuations.

Figure 1 plots the time series of \( n_t \) for different values of the switching parameter \( \alpha \).\(^8\) In line with Table 3, the figure shows that for our preferred values \( \alpha = 10 \text{ and } \alpha = 50 \), the exchange rate process is driven mainly by the output differential. This result can be interpreted in the context of UK monetary policy after Bretton-Woods. Nelson (2003) and Lubik and Schorfheide (2007) estimate a Taylor rule for the UK using post-Bretton-Woods data. They find that the Bank of England reacted to movements in both output growth and

\(^8\)The weight series depends on the realisation of \( n_0 \), which is drawn from a standard uniform distribution. Because the weight series for different \( n_0 \) do not differ substantially, we regard one single realisation as representative.
the exchange rate. Insofar as interest rate changes influence the exchange rate through uncovered interest parity, this suggests that output growth mattered for exchange rate determination. In contrast, the Bank of England abandoned monetary targeting in 1985 and encountered large misses in the money growth target already in the beginning of the 1980s. It is therefore conceivable that real output was seen as a better exchange rate predictor than the money stock differential over the sample period.

To conclude, the dual learning model generates sufficient volatility without relying on a high learning gain. The best results are achieved under intermediate degrees of switching. The findings summarised in Table 3 suggest that dynamic predictor selection and parameter learning interact with each other and with the data in a complex, non-linear way. To understand better which of the two features, model misspecification or parameter learning, is driving the dynamics of the exchange rate under dual learning, we study them separately in the next section.
5 Two Intermediate Cases

We disentangle the effects of dynamic predictor selection and parameter learning. First, we fix the model parameters at their RE values in order to isolate the effect of dynamic predictor selection alone. We run a loop over the following four equations with the same initial values as before.

\[
\bar{E}_{i,t}(s_{t+1}) = b_1^{RE} f_{i,t}
\]

\[
s_t = [(1 - \theta)\gamma_1 + \theta n_{t-1} b_1^{RE}] f_{1,t} + [(1 - \theta)\gamma_2 + \theta (1 - n_{t-1}) b_2^{RE}] f_{2,t}
\]

\[
MSE_{i,t} = MSE_{i,t-1} + \kappa \left[ (s_t - \bar{E}_{i,t-1} s_t)^2 - MSE_{i,t-1} \right]
\]

\[
n_t = \frac{\exp(-\alpha MSE_{1,t})}{\exp(-\alpha MSE_{1,t}) + \exp(-\alpha MSE_{2,t})}
\]

For the switching parameter \(\alpha\) we consider the same values as in the previous section. Table 4 presents the learning gain \(\kappa\), computed in the same way as before, the mean weight on model 1, \(\bar{n}\), as well as the relevant descriptive statistics of the exchange rate under dynamic predictor selection, for the various values of \(\alpha\).

The results of this exercise show that for very high values of \(\alpha\) (rapid switching), the dynamics of the exchange rate are insensitive to the size of the learning gain. The exchange rate is driven entirely by model 1, \(\bar{n} = 1\). Because there is no more switching between predictors, the speed of learning about the models’ relative performance becomes irrelevant. See also Figure 2. The model with dynamic predictor selection is not able to reproduce the volatility of the exchange rate return in the data for \(\alpha = 10,000\). For \(\alpha = 0.1\) (inertial switching), the model is equally unable to generate enough exchange rate return volatility; the calibrated learning gain is driven to 1. Only intermediate values for the switching speed \((\alpha = 1, \alpha = 10, \alpha = 50)\) can be combined with reasonable values for \(\kappa\) to deliver the "correct" volatility. In those cases, the volatility of the exchange rate level is far higher than in the data and model 1 has an average weight close to 1. Similarly to the dual learning model, this model generates too high correlations of the exchange rate with the fundamentals, both in levels and in first differences, although it performs better than rational expectations in this respect.

Second, we set the switching parameter \(\alpha\) equal to zero, which implies that the model weights are constant at 0.5. This shuts off the dynamic predictor selection mechanism. The model with parameter learning alone is given by a
<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>RE</th>
<th>Dynamic Predictor Selection</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>α (switching parameter)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>κ (learning gain)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>̅n (mean weight on model 1)</td>
</tr>
<tr>
<td>Volatility</td>
<td></td>
<td></td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>σ((s_t))</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>σ((\Delta s_t))</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td></td>
<td>ρ((s_t, y_t))</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ρ((s_t, m_t))</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ρ((\Delta s_t, \Delta y_t))</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>ρ((\Delta s_t, \Delta m_t))</td>
</tr>
</tbody>
</table>

Note: σ(\(\cdot\)) denotes the standard deviation, ρ(\(\cdot, \cdot\)) denotes the correlation coefficient. We consider several values for α and search in the unit interval for the κ that minimises the squared distance between \(σ(\Delta s_t^{learn})\) and \(σ(\Delta s_t^{data})\). ̅n denotes the mean weight on model 1, where the mean is taken over time periods and realisations of \(n_0\).
Figure 2: Weight on Model 1 under Dynamic Predictor Selection

\[
s_t = \left[ (1 - \theta)\gamma_1 + \frac{1}{2}\theta b_{1,t-1} \right] f_{1,t} + \left[ (1 - \theta)\gamma_2 + \frac{1}{2}\theta b_{2,t-1} \right] f_{2,t}
\]

\[
b_{i,t} = b_{i,t-1} + \kappa r_{i,t-1}^{-1} f_{i,t} (s_t - b_{i,t-1} f_{i,t})
\]

\[
r_{i,t} = r_{i,t-1} + \kappa \left( f_{i,t}^2 - r_{i,t-1} \right)
\]

We set \( \kappa \) to 0.01, 0.05 and 0.1 as in Chakraborty (2007a, 2007b). In addition, we compute the \( \kappa \) that delivers \( \sigma (\Delta s_t^{\text{learn}}) = \sigma (\Delta s_t^{\text{data}}) \). The initialisation of the model parameters \( b_{i,0} \) and \( r_{i,0} \) is as in Table 2.

From Table 5, we see that parameter learning alone is not enough to generate sufficient exchange rate return volatility. We need a learning gain as high as 0.35 to match this data moment. Following the discussion in Section 4, we do not regard such a value as plausible.

To summarise, we have studied separately the two features of the dual learning model considered in Section 4, dynamic predictor selection and parameter learning. On one hand, dynamic predictor selection alone succeeds in
Table 5: RE vs. Parameter Learning

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>RE</th>
<th>Parameter Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\kappa$ (learning gain)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>Volatility</td>
<td></td>
<td>14.69</td>
<td>38.04</td>
</tr>
<tr>
<td>$\sigma(s_t)$</td>
<td>5.16</td>
<td>2.81</td>
<td>1.40</td>
</tr>
<tr>
<td>Correlation</td>
<td></td>
<td>-0.29</td>
<td>-0.96</td>
</tr>
<tr>
<td>$\rho(s_t, y_t)$</td>
<td>-0.07</td>
<td>0.78</td>
<td>0.10</td>
</tr>
<tr>
<td>$\rho(s_t, m_t)$</td>
<td>-0.07</td>
<td>-0.73</td>
<td>-0.59</td>
</tr>
<tr>
<td>$\rho(\Delta s_t, \Delta y_t)$</td>
<td>-0.03</td>
<td>0.78</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Note: $\sigma(\cdot)$ denotes the standard deviation, $\rho(\cdot, \cdot)$ denotes the correlation coefficient. We search in the unit interval for the $\kappa$ that minimises the squared distance between $\sigma(\Delta s_t^{learn})$ and $\sigma(\Delta s_t^{data})$. 

reproducing the volatility of the exchange rate return with a reasonable learning gain parameter, at least for intermediate values of the switching parameter. On the other hand, the average weight on the money supply fundamental tends towards 1, which makes the switching mechanism redundant. Parameter learning on its own cannot account for the observed properties of the exchange rate: an implausibly high gain is needed to match the observed volatility of the exchange rate return. Considered jointly, the two mechanisms appear to reinforce one another, increasing the volatility of the generated series.

The reinforcement mechanism is as follows. Constant gain updating of the parameters introduces volatility into the exchange rate series, which carries over to the mean square errors ($MSEs$). More volatile MSEs in turn imply more volatile predictor proportions $n_t$. The parameter values $b_{i,t}$ also fluctuate between the equilibrium values corresponding to a fixed $n$. As a result, more volatile weights imply more volatile parameters. These again feed into the volatility of the exchange rate.

6 Robustness

We analyse the sensitivity of our results to two assumptions. First, we relax the assumption that the fundamentals follow a first-order vector autoregressive process. We instead consider a VAR with lag length equal to four, which is natural given that our data are quarterly. Second, we relax the assumption of constant gain learning and assume instead a decreasing gain algorithm.
6.1 AR(4) Fundamentals

A VAR(q) with constant term and trend can be written in companion form as

\[ F_t = AF_{t-1} + v_t, \quad v_t \sim N(0, \Sigma_v) \]

where the fundamentals series are stacked as \( F_t = [f_t, f_{t-1}, \ldots, f_{t-q+1}]' \) with lag length \( q \) and the residuals are defined as \( v_t = [v_t, 0, \ldots, 0]' \). \( F_t \) and \( v_t \) are of dimension \( mq \times 1 \), where \( m \) is the number of variables. The VAR coefficient matrix \( A \) is \( mq \times mq \). To find \( \sum_{j=0}^{\infty} \theta^j E_t f_{t+j} \), we compute the forecast \( E_t F_{t+j} = A^j F_t \).

The exchange rate under rational expectations becomes

\[ s_t^{RE} = (1 - \theta) \gamma' (I_m q - \theta A)^{-1} F_t \]

where \( \gamma' = [\gamma', 0_{1 \times mq - m}] \) and \( \gamma \) is \( m \times 1 \). In practice, we again estimate the VAR with a constant term and a trend. The descriptive statistics of the RE exchange rate under the assumption that the fundamentals follow an AR(4) process are given in Table 6.

<table>
<thead>
<tr>
<th>Table 6: Disconnect Puzzle under RE with VAR(4) fundamentals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility</td>
</tr>
<tr>
<td>( \sigma(s_t) )</td>
</tr>
<tr>
<td>( \sigma(\Delta s_t) )</td>
</tr>
<tr>
<td>Correlation</td>
</tr>
<tr>
<td>( \rho(s_t, y_t) )</td>
</tr>
<tr>
<td>( \rho(s_t, m_t) )</td>
</tr>
<tr>
<td>( \rho(\Delta s_t, \Delta y_t) )</td>
</tr>
<tr>
<td>( \rho(\Delta s_t, \Delta m_t) )</td>
</tr>
</tbody>
</table>

Note: \( \sigma(\cdot) \) denotes the standard deviation, \( \rho(\cdot, \cdot) \) denotes the correlation coefficient.

The exchange rate in the RE model with a VAR(4) process for the fundamentals has similar properties as the RE-VAR(1) model. The exchange rate return is less volatile than in the data. The standard deviation of the exchange rate level is twice that in the data. The correlations of the RE-VAR(4) exchange rate level with the fundamentals are again much higher than in the data. In first differences, however, the correlations are very low, which is more in line with the data. Including more lags in the fundamentals-VAR appears...
to break the tight link of the growth rates of the exchange rate and the fundamentals in the RE model. For this reason, we conclude that the RE-VAR(4) model performs somewhat better than the RE-VAR(1) model.

We also compute the exchange rate under dual learning for the case where the exchange rate depends on the first four lags of the respective fundamental. Define the variable

\[ z_{i,t} = (f_{i,t}, f_{i,t-1}, f_{i,t-2}, f_{i,t-3}) \]

The dual learning algorithm, which starts at date \( t = 4 \), becomes

\[
\tilde{E}_{i,t}(s_{t+1}) = b_{i,t-1}z'_{i,t}
\]

\[
\tilde{E}_t s_{t+1} = n_{t-1}b_{1,t-1}z'_{1,t} + (1 - n_{t-1})b_{2,t-1}z'_{2,t}
\]

\[
s_t = (1 - \theta)\gamma f_t + \theta \tilde{E}_t s_{t+1}
\]

\[
b_{i,t} = b_{i,t-1} + \kappa r_{i,t-1}^{-1}z_{t,i} \left( s_t - b_{i,t-1}z'_{i,t} \right)
\]

\[
r_{i,t} = r_{i,t-1} + \kappa \left( z_{i,t}z'_{i,t} - r_{i,t-1} \right)
\]

where \( r_{i,t} = \kappa \sum_{j=1}^{t} z_{i,j-1}z'_{i,j-1} \). The mean square error of each forecast and the model weights are determined by (10) and (11), respectively. We initialise \( b_i \) by estimating the following regressions by OLS

\[
f_{i,t} = b_{i,0}z'_{i,t-1} + \varepsilon_{i,t}
\]

for \( i = 1, 2 \).

The summary statistics of the Dual Learning-AR(4) model are given in Table 7. We find that we now need a higher gain to reproduce the observed exchange rate return volatility. In that sense, the Dual Learning-AR(4) model is less successful than the Dual-Learning-AR(1) model. The higher persistence in the relationship between exchange rates and fundamentals (the perceived law of motion) appears to reduce the volatility of the generated series.

The inclusion of additional lags into the model specification enriches the dynamics of the predictor weights. Figure 3 plots the weight on model 1 for different values of \( \alpha \). For low values of the switching parameter (\( \alpha = 0.1, \alpha = 1 \)), \( n_t \) hovers around 0.5. The weights are more volatile than in the previous calibrations for \( \alpha = 10 \) and \( \alpha = 50 \). Under instantaneous switching \( \alpha = 10,000 \), the model generates cycles between the two fundamentals where the weights switch between 0 and 1. As can be seen on Table 7, the average weight on model 1 is close to 0.5.
Table 7: Disconnect Puzzle: RE vs Dual Learning, AR(4) fundamentals

<table>
<thead>
<tr>
<th></th>
<th>Data</th>
<th>RE-VAR(4)</th>
<th>Dual Learning with $f_{i,t} \sim \text{AR}(4)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\alpha$ (switching parameter)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\kappa$ (learning gain)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$n$ (mean weight on model 1)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.50</td>
</tr>
<tr>
<td>Volatility</td>
<td></td>
<td></td>
<td>14.69</td>
</tr>
<tr>
<td>$\sigma(s_t)$</td>
<td>5.16</td>
<td>2.84</td>
<td>5.16</td>
</tr>
<tr>
<td>$\sigma(\Delta s_t)$</td>
<td>-0.29</td>
<td>-0.96</td>
<td>0.14</td>
</tr>
<tr>
<td>Correlation</td>
<td>-0.07</td>
<td>0.56</td>
<td>-0.71</td>
</tr>
<tr>
<td></td>
<td>-0.07</td>
<td>-0.01</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>-0.03</td>
<td>0.00</td>
<td>-0.21</td>
</tr>
</tbody>
</table>

Note: $\sigma(\cdot)$ denotes the standard deviation, $\rho(\cdot, \cdot)$ denotes the correlation coefficient. We consider several values for $\alpha$ and search in the unit interval for the $\kappa$ that minimises the squared distance between $\sigma(\Delta s^\text{learn}_t)$ and $\sigma(\Delta s^\text{data}_t)$. $\bar{n}$ denotes the mean weight on model 1, where the mean is taken over time periods and realisations of $n_0$. 

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Figure 3: Weight on Model 1 under Dual Learning and AR(4) fundamentals
6.2 Decreasing Gain Learning

We redo the dual learning exercise of Section 4 under the assumption of decreasing gain updating. The updating algorithm is as in Section 4 with equations (8), (9) and (10) replaced by

\[
\begin{align*}
b_{i,t} &= b_{i,t-1} + t^{-1}r_{i,t-1}^{-1}f_{i,t} (s_t - b_{i,t-1}f_{i,t}) \\
r_{i,t} &= r_{i,t-1} + t^{-1} (f_{i,t}^2 - r_{i,t-1}) \\
MSE_{i,t} &= MSE_{i,t-1} + t^{-1} \left[ (s_t - \hat{E}_{i,t-1}s_t)^2 - MSE_{i,t-1} \right]
\end{align*}
\]

respectively. We run a loop over these equations with the same alphas and the same initial values as before. Table 8 presents the mean weight on model 1, \(\bar{n}\), and the relevant descriptive statistics of the implied exchange rate, for the various values of \(\alpha\).

<table>
<thead>
<tr>
<th>(\alpha) (switching parameter)</th>
<th>0.1</th>
<th>1</th>
<th>10</th>
<th>50</th>
<th>10000</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\bar{n}) (mean weight on model 1)</td>
<td>0.44</td>
<td>0.23</td>
<td>0.06</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Table 8: Disconnect Puzzle: RE vs Dual learning with Decreasing Gain

<table>
<thead>
<tr>
<th>Data</th>
<th>RE</th>
<th>Dual Learning with (\kappa = t^{-1})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\sigma (s_t))</td>
<td>14.69</td>
<td>38.04</td>
</tr>
<tr>
<td>(\sigma (\Delta s_t))</td>
<td>5.16</td>
<td>2.81</td>
</tr>
<tr>
<td>Correlation</td>
<td>(-0.29)</td>
<td>(-0.96)</td>
</tr>
<tr>
<td>(\rho (s_t, y_t))</td>
<td>(-0.07)</td>
<td>0.78</td>
</tr>
<tr>
<td>(\rho (s_t, m_t))</td>
<td>(-0.07)</td>
<td>(-0.73)</td>
</tr>
<tr>
<td>(\rho (\Delta s_t, \Delta y_t))</td>
<td>(-0.03)</td>
<td>0.78</td>
</tr>
<tr>
<td>(\rho (\Delta s_t, \Delta m_t))</td>
<td>(-0.03)</td>
<td>0.78</td>
</tr>
</tbody>
</table>

Note: \(\sigma (\cdot)\) denotes the standard deviation, \(\rho (\cdot, \cdot)\) denotes the correlation coefficient. We consider several values for \(\alpha\). The mean weight on model 1 is denoted by \(\bar{n}\), where the mean is taken over time periods and realisations of \(n_0\).

Table 8 shows that under decreasing gain learning, the model is unable to generate sufficient volatility for any value of the switching speed parameter \(\alpha\). Despite the low weight on the money supply differential (see also Figure 4), we find that the correlation coefficients between the exchange rate and
both fundamentals are too high relative to the data. To conclude, we consider decreasing gain learning as inferior to constant gain learning. This is also in line with the findings in Kim (2009).

Figure 4: Weight on Model 1 under Dual Learning and Decreasing Gain

7 Conclusion

Asset pricing models have a self-referential structure with positive feedback; any expectational errors are magnified, such that the exchange rate may drift far away from its fundamental value. This paper introduces expectational errors due to model misspecification and learning into a monetary exchange rate model. These two departures from rational expectations seem appealing in the light of survey evidence of the foreign exchange market. While the excess volatility of exchange rate return can be reproduced with a remarkably low value for the learning gain, the exchange rate under learning is too highly correlated with the fundamentals. In this application, the learning model is not consistently superior to rational expectations.
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