A Consumption-Based Approach to Exchange Rate Predictability

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Abstract

This paper provides evidence of short run predictability for the real exchange rate by performing in-sample and out-of-sample tests using a predictability equation which is derived from a consumption-based asset pricing model. In this model, the real exchange rate is predictable as a result of the presence of habit formation and catching up with the Joneses in consumer's preferences. The empirical predictors are: domestic, US and World consumption growth. I find evidence of short-term predictability in 15 out of 17 countries vis-à-vis the US over the Post-Bretton Woods float. Estimated parameters reveal strong catching up with the Joneses effects in most countries.

Keywords: Real exchange rates, out-of-sample predictability, asset pricing, habits, catching up with the Joneses

JEL Classification: C5, F31, F47, G15

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1. Introduction

This paper provides a new framework to study real exchange rate predictability which is based on a consumption-based asset pricing model including habit formation and catching up with the Joneses[2]. The econometric methods follow recent literature on predictability in special the work by Rogoff and Stavrakeva (2008). A general equilibrium consumption-based asset pricing model is used to show that the presence of habits and catching up with the Joneses in consumer's preferences implies that the real exchange rate has a predictable component which depends on past consumption growth.

The econometric methods are applied to real exchange rate series for 17 industrialized economies over the Post-Bretton Woods float. It is found short-run out-of-sample predictability evidence in 15 countries. This evidence is obtained by computing tests which compare the forecasting power of the model with a random walk forecast. This predictability evidence can be compared with recent papers in the literature which study similar countries with similar tests and data span.

The empirical evidence is interpreted in the context of a consumption-based asset pricing model with N countries, complete markets, imperfect international risk sharing and representative consumers whose preferences include a benchmark consumption level. This benchmark is determined by habits and catching up with the Joneses. Therefore, the economic reason for real exchange rate predictability in this framework is the "benchmark" effect that current world consumption shocks exert in consumers' utility next period.

In the case of in-sample predictability tests, there is only predictability evidence for 5 countries. The reason for this result seems to be the presence of time-varying coefficients which are better estimated with rolling regressions in the context of out-of-sample estimation. However, the coefficients estimated with the full sample are still useful to understand the relative size of the habit and catching up with the Joneses effects across

[2] The concept of catching up with the Joneses in Abel (1990) is very similar to the concept of external habits which has been used in the literature since Campbell and Cochrane (1998).

countries. The results show that the most important factor behind the predictability evidence is the presence of catching up with the Joneses in investors' preferences.

The empirical methods described in this paper are therefore an alternative approach to real exchange rate forecasting in the short run. It is possible to compare the out-of-sample predictability evidence with recent approaches in the literature such as the monetary model, the Taylor rule model and Purchasing Power Parity (PPP). The results show that the approach in this paper has a satisfactory performance.

This paper is related to the empirical literature on exchange rate determination models. In particular, it addresses the puzzle originally described by Meese and Rogoff (1983) about the poor empirical out-of-sample forecasting power of the monetary approach to exchange rate determination[3]. Several, recent papers have shown that alternative specifications of the monetary model have out-of-sample predictability power at long run horizons (one year or more). Mark (1995), Mark and Sul (2001), Groen (2005) and Engel, Mark and West (2007), among others, find positive results for the standard monetary model on these kinds of horizons.

Additionally, several papers show out-of-sample predictability evidence with alternative exchange rate models. Gourinchas and Rey (2007) study an international financial adjustment model in which real exchange rate changes are the result of disequilibria in the country's external accounts. Molotdsova and Papell (2009) estimate a predictability equation which is derived from the Taylor rule for monetary policy in each country. Rogoff and Stavrakeva (2008) perform robustness exercises using these alternative models and conclude that the out-of sample predictability evidence is still weak on horizons shorter than one year.

This paper is organized in the following way. A consumption-based asset pricing framework and its implied predictability equation are described in section 2. The econometrics methods are presented in section 3. Country by country results and their comparison with recent literature are presented in Section 4. Finally, section 5 concludes.

[3] An early reference for the monetary model of exchange rates is Frenkel (1976). Frankel and Rose (1995) present a survey of the literature on empirical research on nominal exchange rates.

2. A Consumption-Based Asset Pricing Model

2.1 Basic Framework

Consider a consumption-based asset pricing framework which is based on Abel (1990, 2006) and extended to include N countries $(i = 1, 2, \ldots N)$. The representative consumer in each country *i* maximizes:

$$U_t = E_t\left[\sum_{j=0}^{\infty}\beta^j\left(\frac{1}{1-\alpha}\right)\left(\frac{C_{t+j}}{V_{t+j}^{\gamma}}\right)^{1-\alpha}\right] \tag{1}$$

In Equation (1), α denotes the risk aversion coefficient, β is the time discount factor, C_t is the level of consumption in each country and V_t^{γ} is the benchmark level of consumption where the parameter γ measures the importance of the benchmark in the preferences. Benchmark consumption includes past domestic consumption as well as past world consumption and it is defined by:

$$V_t = \left[\left(C_{t-1}\right)^D\left(C_{w,t-1}\right)^{1-D}\right] \tag{2}$$

In Equation (2), C_w denotes world consumption and D is a weight that measures the importance of domestic consumption relative to world consumption in the composition of the benchmark level of consumption. World consumption is defined as the geometric weighted average of consumption across countries. The weights ω_i in Equation (3) are determined by the relative size of country i.

$$C_w = \prod_{i=1}^{N} C_i^{\omega_i} \tag{3}$$

The utility framework in Equations (1) to (3) nests the standard CRRA case when $\gamma = 0$ because in this case the benchmark consumption does not have any influence in utility. When $\gamma > 0$, utility depends on the ratio between domestic and benchmark consumptions. The presence of V_t^{γ} in the utility function captures two effects: habit formation and catching up with the Joneses. In this paper, the latter effect is interpreted as the satisfaction from consuming as much as or more than the average world level of consumption.

From Equation (1), it is possible to compute the marginal utility of consumption in each country.

$$\frac{\partial U_t}{\partial C_t} = \frac{1}{C_t} E_t \left[\left(\frac{C_t}{V_t^\gamma} \right)^{1-\alpha} - \gamma D \beta \left(\frac{C_{t+1}}{V_{t+1}^\gamma} \right)^{1-\alpha} \right] \tag{4}$$

Note that marginal utility in (4) when $\gamma = 0$ is exactly equal to the case of a standard CRRA utility function ($C_t^{-\alpha}$). Therefore, it is possible to partition Equation (4) in three components: standard CRRA, benchmark consumption and habits. These three components are specified in Equation (5).

$$\frac{\partial U_t}{\partial C_t} = C_t^{-\alpha} V_t^{\gamma(\alpha-1)} H_t \tag{5}$$

The component $V_t^{\gamma(\alpha-1)}$ measures the effect of benchmark consumption on marginal utility. This effect has a negative as well as a positive component. The former component is the instantaneous drop in utility which occurs when V_t increases. The positive component is about the higher marginal utility which is possible to obtain with lower ratios C_t / V_t as a result of the concavity of the utility function. The parameter α determines the extent of this concavity; therefore when $\alpha > 1$, the positive effect dominates such that the net effect of V_t on marginal utility is positive. In Equation (5) it is also clear that in the log-utility case, $\alpha = 1$, both components cancel each other so that the effect is zero. Finally, when the utility function is less concave, $\alpha < 1$, the net effect of the benchmark consumption on marginal utility is negative.

The component H_t measures the effect of habits on marginal utility. It is a number between 0 and 1 which takes into account the fact that a higher consumption today has a negative effect on tomorrow's utility because it increases benchmark consumption.

$$H_t = 1 - D\gamma\beta E_t \left(X_{t+1}^{1-\alpha} \right) X_t^{D\gamma(\alpha-1)} X_{w,t}^{(1-D)\gamma(\alpha-1)} \tag{6}$$

In (6), X_t corresponds to the gross rate of consumption. Therefore, we define: $X_{t+1} \equiv C_{t+1}/C_t$ and $X_{w.t+1} \equiv C_{w,t+1}/C_{w,t}$.

Equation (5) and the definition of benchmark consumption allow computing easily the Stochastic Discount Factor (SDF) or pricing kernel as the product of the time discount factor and marginal utility growth.

$$M_{t+1} = \beta X_{t+1}^{-\alpha} X_t^{D\gamma(\alpha-1)} X_{w,t}^{(1-D)\gamma(\alpha-1)} \left(\frac{H_{t+1}}{H_t} \right) \tag{7}$$

2.2 Implications for the Real Exchange Rate

In order to analyze the real exchange rate, I consider the previous utility framework in the context of a two country endowment economy with complete markets. Assume that in each country the representative investor has access to a domestic bond that pays off one unit of domestic consumption next period in each state of the world. Additionally, these investors have access to a foreign bond that pays a stochastic return R_{t+1}^* .

Investors choose their optimal portfolios by solving a standard problem of dynamic optimization of utility. Therefore, the Euler equation for a foreign investor buying a foreign bond is :

$$E_t(M_{t+1}^* \mathrm{R}_{t+1}^*) = 1 \tag{8}$$

The Euler equation for a domestic investor buying the same foreign bond is:

$$E_t(M_{t+1} \mathrm{R}_{t+1}^* \, Q_{t+1}/Q_t) = 1 \tag{9}$$

The real exchange rate (Q_t) is denoted in terms of the number of domestic goods per unit of foreign good. Under complete markets SDFs are unique; therefore we must have from Equations (8) and (9):

$$M_{t+1}^* = M_{t+1} \, Q_{t+1}/Q_t \tag{10}$$

This result was shown originally by Backus and Smith (1993). Interpreting the domestic country as the US and the foreign country as country i and computing natural logarithms at both sides of Equation (10) we obtain:

$$q_{t+1} - q_t = m_{t+1}^i - m_{t+1}^{US} \tag{11}$$

Throughout this paper lower case letters are logs of the original variables. In (11), $m_{t+1}^{US}, m_{t+1}^{i}$ are the US and country i's log SDFs respectively. This equation says that the log variation in the real exchange rate is equal to the difference between the log SDF in country *i* and in the US. Computing logs at both sides of (7) and inserting it in (11) we obtain the following expression for the real exchange rate as a function of consumption growth and internal habit effects in both countries.

$$\Delta q_{t+1} = -\alpha(x_{t+1}^{i} - x_{t+1}^{us}) + D\gamma_i(\alpha-1)x_t^i - D\gamma_{us}(\alpha-1)x_t^{us} + (\gamma_i - \gamma_{us})x_t^w + \Delta h_{t+1} + \Delta h_{t+1}^{us} \qquad (12)$$

In Equation (12), the growth rates of the real exchange rate and the habit effect are denoted Δq_{t+1} and Δh_{t+1} respectively. Note that (12) can be interpreted as a predictability equation for real exchange rate changes which are determined by domestic, US and world consumption growth during the previous period.

In order to estimate the expected value of (12) using a linear regression framework, it is necessary to use a first order Taylor approximation to h_t and h_t^{us} because they are nonlinear functions of consumption growth. In order to perform this approximation it is necessary to define the following:

$$z_t \equiv D\gamma(\alpha-1)x_t + (1-D)\gamma(\alpha-1)x_t^w \qquad (13)$$

Therefore we can write h_t in the following simplified way:

$$h_t \equiv \log(H_t) = \log\left(1 - D\gamma\beta E(X_{t+1}^{1-\alpha})e^{z_t}\right) \qquad (14)$$

We want to find a linear approximation to h_t around $E(z_t) \equiv \bar{z}$. Therefore, once the derivative of (14) is computed, it is possible to express the first order Taylor approximation in the following way:

$$h_t \approx \log\left(1 - D\gamma\beta E(X_{t+1}^{1-\alpha})e^{\bar{z}}\right) - \frac{D\gamma\beta E(X_{t+1}^{1-\alpha})e^{\bar{z}}}{1 - D\gamma\beta E(X_{t+1}^{1-\alpha})e^{\bar{z}}}(z_t - \bar{z}) \qquad (15)$$

From (15), we can compute Δh_{t+1} which consists of a constant multiplied by Δz_{t+1}. Therefore, using (13) and (15), we can express the expected value conditional on information through *t* in the following way:

$$E_t(\Delta h_{t+1}) = -\theta\gamma(\alpha-1)g + \theta D\gamma(\alpha-1)x_t + \theta(1-D)\gamma(\alpha-1)x_t^w \qquad (16)$$

Where θ is a constant parameter defined in the following way:

$$\theta \equiv \frac{D\gamma\beta E(X^{1-\alpha})e^{\bar{\bar{z}}}}{1-D\gamma\beta E(X^{1-\alpha})e^{\bar{\bar{z}}}} \tag{17}$$

Equation (16) also assumes a log normal distribution for consumption growth in all countries such that in each period t:

$$\log(X_t) \equiv x_t \sim N\left(g,\sigma^2\right) \tag{18}$$

Taking conditional expectations at both sides of (12) and using (16) to insert the expressions for $E_t(\Delta h_{t+1})$ and $E_t(\Delta h^{us}_{t+1})$, it is possible to compute the following linear predictability equation for the expected real exchange rate appreciation as a function of past consumption growth.

$$E_t(\Delta q_{t+1}) = \psi_0 + \psi_1 \Delta c_t + \psi_2 \Delta c_t^{us} + \psi_3 \Delta c_t^{w} \tag{19}$$

The parameters to estimate in Equation (19) are defined in the following way:

$$\psi_0 = -\theta(\alpha-1)g(\gamma_i - \gamma_{us}) \tag{20}$$

$$\psi_1 = (1+\theta)D(\alpha-1)\gamma_i \tag{21}$$

$$\psi_2 = -(1+\theta)D(\alpha-1)\gamma_{us} \tag{22}$$

$$\psi_3 = (\gamma_i - \gamma_{us}) \tag{23}$$

Note that we need the benchmark consumption parameters, γ_i and γ_{us}, to be different across countries so that the parameters ψ_0 and ψ_3 be different from zero. Additionally, it is necessary that both countries have some internal habit effects ($D > 0$) so that the parameters ψ_1 and ψ_2 remain different from zero.

3. Econometric Methods

I estimate Equation (19) country by country using ordinary least squares with quarterly data for 17 OECD countries. This set of countries is the same one analyzed by Mark, Engel and West (2007) and by Rogoff and Stavrakeva (2008). First, in-sample predictability tests are calculated and the asset pricing model's estimated parameters are analyzed. Then, out-of-sample predictability tests are performed following the methods in Rogoff and Stavrakeva (2008).

3.1. In-Sample Predictability Test

The in-sample predictability analysis consists of evaluating the joint statistical significance of the estimated parameters from Equation (19) except the constant (ψ_0). These parameters are estimated with the full available sample for each country with quarterly data on the bilateral real exchange rate with respect to the US and consumption growth. For the computation of in-sample predictability tests, I use Newey-West heteroskedasticity-consistent standard errors with an optimal number of lags to estimate the spectral density matrix following Andrews (1991). This step is important because macroeconomic time series usually have some degree of serial dependence and heterokedasticity.

3.2. Out-of-Sample Predictability Tests

Following Rogoff and Stavrakeva (2008), I compute three alternative tests for out-of-sample predictability power: Theil's U (TU), Diebold-Mariano-West (DMW) and Clark-West (CW). In these tests, the criterion to identify a good forecast is that the mean-square forecasting error be significantly smaller than that of the random walk model. This criterion has been widely used in the exchange rate predictability literature since Meese and Rogoff (1983).

The first step on the out-of-sample predictability exercise consists of choosing a forecasting window. I initially use 40 observations to estimate Equation (19) with quarterly data. Since the total sample spans 1973 through 2007, the forecasting window has approximately 100 observations. The second step consists of using rolling regressions, with 40 observations each, to estimate the parameters in Equation (19). Then I use these estimations to perform one-quarter forecasts of exchange rate changes. The final step is about comparing the resulting 100 forecasts with actual real exchange rate data and to compute the predictability tests.

Assume that $y_t = q_t - q_{t-1}$, where q_t is the natural log of the exchange rate for period t[4]. Let X_t be the matrix of explanatory variables defined in Equation (19) and let ψ be the corresponding vector of parameters. We are interested in comparing the forecasting power of the model in Equation (19) with a driftless random walk model. Under the random walk model we have: $y_t = e_{1,t}$. We can rewrite the model in (19) as: $y_t = X_{t-1}\psi + e_{2,t}$. Innovations terms $e_{1.t}$ and $e_{2,t}$ are assumed to be unobservable.

The estimated forecasts for the random walk and the structural model are $\hat{y}_{1,t+1} = 0$ and $\hat{y}_{2,t+1} = X_t\hat{\psi}_t$ respectively, where $\hat{\psi}_t$ is the least squares estimator of ψ_t. The corresponding forecast errors are $\hat{e}_{1,t}$ and $\hat{e}_{2,t}$, respectively. The Mean Squared Forecast Error (MSFE) for either of the forecasting models is:

$$MSFE_i = P^{-1}\sum_{t=R+1}^{t=T} \hat{e}_{i,t+1}^2 \quad ,i = 1,2 \tag{24}$$

In Equation (24), P is the number of forecasts, T is the sample length and R is the number of observations used to estimate ψ_t on the first forecast. The TU test is defined as the ratio between the square root of the MSFE of the structural model and the square root of the MSFE of the random walk model. Therefore, $TU < 1$ implies that the structural model outperforms the random walk model.

$$TU = \sqrt{MSFE_2 / MSFE_1} \tag{25}$$

The DMW test measures the difference between the MSFE of the random walk model and that of the structural model. Therefore a significant and positive DMW test implies that the structural model outperforms the random walk. The formal definition of the DMW test follows assuming that the random walk model is $i = 1$.

$$DMW = MSFE_1 - MSFE_2 \tag{26}$$

The literature on forecasting has identified that the TU and DMW tests tend to reject the structural model when they are used to compare nested models like those in the current exercise[5]. In view of this problem, Clark and West (2006, 2007) propose a new test statistic

[4] In this part, I follow the notation in Rogoff and Stavrakeva's (2008) appendix.
[5] Note that if all the parameters in (19) are zero then a random walk model for the real exchange rate remains.

(CW) which builds on the DMW but takes in account that the two compared models are nested by assuming that, under the null hypothesis, the exchange rate follows a random walk. Therefore, the null hypothesis in the CW test assumes that the population parameter vector is $\psi = 0$, and that the forecast innovation terms are equal across models: $e_{1,t} = e_{2,t}$.

$$\hat{d} = 2P^{-1} \sum_{t=R+1}^{t=T} \left(y_{t+1} X_t \hat{\psi}_t \right) \tag{27}$$

Clark and West (2006) show that if $\hat{d}$, the quantity defined in (27), is significantly greater than zero then the structural model outperforms the random walk. Therefore, the CW is a significance test for $\hat{d}$ as in the following equation where $\Omega^{\hat{d}}$ is the estimated variance of $\hat{d}$.

$$CW = \frac{P^{0.5}\hat{d}}{\sqrt{\Omega^{\hat{d}}}} \tag{28}$$

Rogoff and Stavrakeva (2008) show that the CW test detects whether or not the actual model is a random walk but it does not always identify whether the structural model has lower MSFE than the random walk model. Therefore, they recommend computing all three tests, TU, DMW and CW, when performing an out-of-sample predictability exercise. Also, Rogoff and Stavrakeva (2008) recommend using bootstrapped critical values for TU and DMW in order to correct for the size distortion which results from working with nested models.

3.3. Bootstrap Procedure

I follow Rogoff and Stavrakeva (2008) and Mark and Sul (2001) on the bootstrap procedure used to calculate the p-values of the tests. Under the null hypothesis, the exchange rate follows a random walk model so that $y_t = \varepsilon_t^s$; where ε_t^s is an iid residual. For each right hand side variable in Equation (19) and for each country, we estimate the following OLS regression:

$$\Delta c_t^i = \delta_0 + \sum_{k=1}^{d} \delta_k y_{t-k} + \sum_{k=1}^{l} \zeta_k \Delta c_{t-k}^i + \varepsilon_t^i \tag{29}$$

In Equation (29), the number of lags, *d* and *l* as well as the appropriate trend (constant or linear) are selected by minimizing a Bayesian information criterion. The estimated residuals for all variables are resampled 1000 times; these resampled residuals are used to simulate recursively the exchange rate and the fundamentals. The first 100 simulated observations are discarded in order to attenuate potential bias related to choosing sample averages as the starting values of the recursion. Finally, the model is reestimated and the test statistics are calculated again for each resampling.

4. Country by Country Results

I present predictability results one quarter ahead for 17 countries. Their bilateral Real Exchange Rate (RER) with respect to the US is used to perform predictability tests. Quarterly data span the post Bretton-Woods period through 2007Q4; the starting date of the sample is determined by the availability of consumption data in each country. Most series were retrieved form International Financial Statistics (IFS). Consumption series correspond to nondurable goods and services purchased by households.

4.1. Summary of Results

Table 1: Summary of Exchange Rate Predictability Evidence
Quarterly Data

Country	Sample	Type of Predictability Test In-Sample	Out of Sample
UK	1973Q1-2007Q4	p	p
Austria	1973Q1-2007Q4	n	p
Belgium	1981Q1-2007Q4	n	n
Denmark	1978Q1-2007Q4	p	p
France	1973Q1-2007Q4	n	p
Germany	1973Q1-2007Q4	n	p
Netherlands	1977Q2-2007Q4	n	p
Canada	1973Q1-2007Q4	n	p
Japan	1973Q1-2007Q4	p	p
Finland	1973Q1-2007Q4	p	p
Spain	1973Q1-2007Q4	p	p
Australia	1973Q1-2007Q4	n	p
Italy	1973Q1-2007Q4	n	p
Switzerland	1973Q1-2007Q4	p	p
Korea	1973Q1-2007Q4	n	n
Norway	1973Q1-2007Q4	n	p
Sweden	1973Q1-2007Q4	n	p
Overall		6/17	15/17

p: positive predictability evidence; **n:** negative predictability evidence
This table summarizes the overall predictability results for the real exchange rate in 17 countries. The estimated equation (19) is derived from a consumption-based asset pricing model which includes habits and "catching up with the Joneses".

Table 1 presents a summary of the results from both in-sample and out-of-sample predictability tests in 17 developed countries. Although in-sample tests show predictability evidence in only 6 countries, it is found positive evidence in 15 countries with out-of-sample tests. A possible reason for this result is the presence of parameter instability when Equation (19) is estimated with the full sample of data. In contrast, out-of sample estimations which include 40-observation rolling samples allow capturing time-varying parameters thus performing more accurate forecasts.

4.2. In-Sample Tests

Positive in-sample predictability evidence holds if the parameters ψ_1, ψ_2 and ψ_3, estimated from Equation (19), are jointly significant. Although Table 1 shows that these parameters are significant in only 5 out of 17 countries, the estimations allow analyzing the value and sign of the underlying parameters according to the definitions in (20), (21), (22) and (23).

Table 2. Real Exchange Rate Predictability: In Sample Regressions
Quarterly Data

Country	A. Intercept	B. US Cons.	C. Domestic Cons.	D. World Cons.	R2	F-Test
UK	-0.77	-2.22*	0.57	2.29	8.0%	13.2***
Austria	-4.34	-1.45	0.09	4.04*	8.9%	4.24
Belgium	-7.01	-0.30	2.06	2.39	10.9%	1.91
Denmark	-6.7*	-1.60	1.22***	4.32	16.9%	14.7***
France	-3.52	-1.97	-0.70	4.43*	7.2%	4.34
Germany	-5.40	-0.99	0.55	3.48	10.6%	4.77
Netherlands	-2.30	-1.20	0.03	2.26	1.6%	1.67
Canada	-0.62	-0.45	0.20	0.44	1.3%	1.08
Japan	-7.52**	-0.67	-1.17*	5.89**	17.8%	11.9***
Finland	-4.99	-2.13*	0.60	3.93*	12.0%	7.02*
Spain	-12.25***	-4.48***	0.50	9.66***	42.6%	32.9***
Australia	-3.72	-1.66	0.15	3.31	6.8%	2.39
Italy	-2.91	-1.78*	-0.13	3.47*	4.8%	3.13
Switzerland	-4.35	-2.18	-0.91	5.22**	11.1%	20.2***
Korea	-4.27	-1.15	0.25	2.58	9.8%	3.85
Norway	-4.56	-2.00*	0.45	3.77*	10.6%	4.46
Sweden	-6.00	-2.35*	0.16	4.69**	10.5%	4.50

* denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.
This table presents country by country estimated parameters from Equation (19) using the total sample. The F-test corresponds to the in-sample predictability test for the joint significance of parameters B, C and D.

From equations 20-23 it is possible to interpret the sign and the value of the parameters estimated in Table 1 provided that $\alpha > 1$, which is a usual assumption in the literature. The sign of the estimated intercept (ψ_0) is negative in every country as shown in Table 1. Following Equation (20), this result implies that the benchmark consumption parameter is greater in each country than in the US ($\gamma_i > \gamma_{us}$). The estimated intercept is significant in the following cases: Spain, Japan and Denmark.

The parameter (ψ_1) which measures the effect of past domestic consumption on the real exchange rate should have a positive sign according to Equation (21). This implication is confirmed in Table 1 in 14 out of 17 countries. The exceptions are: Japan, Italy and Switzerland.

Equation (22) reveals that the parameter ψ_2, which measures the influence of past US consumption growth on the real exchange rate, should have a negative sign. This is confirmed in Table 1 for all countries. This estimated parameter is significant in the following six cases: Spain, UK, Finland, Italy, Norway and Sweden.

Interestingly, the value of the parameter ψ_3 has a clear-cut interpretation; according to (23), it corresponds to the difference between domestic and US benchmark consumption parameter ($\gamma_i - \gamma_{us}$). In this sense, the estimated values for ψ_3 are consistent with ψ_0 since they imply that $\gamma_i > \gamma_{us}$ for all countries. This parameter is significantly different from zero in 9 out of 17 countries. Significant values for this parameter are obtained in 9 cases: Austria, France, Japan, Finland, Spain, Italy, Switzerland, Norway and Sweden.

4.3. Out-of-Sample Tests

Table 3 shows the results from the estimation of the out-of-sample predictability tests described in section 3.2. The null hypothesis for the TU and DMW tests is that both the model in Equation (19) and a driftless random walk have the same Mean Squared Forecast Error (MSFE); the alternative hypothesis is that the model has lower MSFE than a random walk. In the case of the CW test the null hypothesis is that the real exchange rate follows a random and the alternative hypothesis is similar to the one in TU and DMW tests. All p-values in Table 3 are computed with the bootstrap procedure described in section 3.3 in which, for each series, i.i.d. innovations are estimated with Equation (29) and then 1000 resamplings are used to construct consumption series and reestimate (1000 times) all predictability tests.

Table 3. Out-of-Sample Exchange Rate Predictability Tests Based on forecasts one quarter ahead.						
Country	TU	P-value	DMW	P-value	CW	P-value
UK	0,95	0,00	10,16	0,00	3,15	0,01
Austria	0,98	0,01	4,96	0,01	2,71	0,01
Belgium	1,07	0,48	-14,87	0,18	1,10	0,12
Denmark	1,04	0,14	-7,81	0,08	3,02	0,00
France	1,01	0,01	-2,34	0,01	2,86	0,00
Germany	0,97	0,00	7,31	0,00	3,25	0,00
Netherlands	1,11	0,88	-23,27	0,49	2,42	0,01
Canada	1,02	0,01	-1,08	0,02	2,88	0,00
Japan	1,08	0,73	-24,77	0,66	1,75	0,06
Finland	0,95	0,00	15,83	0,00	3,62	0,00
Spain	0,80	0,00	55,37	0,00	6,52	0,00
Australia	1,02	0,05	-4,65	0,06	2,18	0,02
Italy	0,94	0,00	17,27	0,00	3,62	0,00
Switzerland	0,99	0,01	1,83	0,01	3,15	0,00
Korea	1,17	0,99	-43,89	0,99	1,25	0,13
Norway	0,98	0,00	3,78	0,00	2,79	0,01
Sweden	0,96	0,00	11,12	0,00	3,66	0,00

This table presents country by country out-of-sample predictability tests estimated from Equation (19) using rolling 40-observation samples. The tests TU , DMW and CW are described in equations (25), (26) and (28) respectively. P-values are computed with the bootstrap procedure described in Section 3.3.

Results from the TU and DMW tests are very similar in Table 3. There is out-of sample predictability evidence in 12 out of 17 countries according to the TU test. The DMW test shows positive evidence in one additional country (Denmark). The countries with no predictability evidence are: Belgium, Netherlands, Japan and Korea.

The positive evidence is even stronger when the CW test is examined. The no-predictability null hypothesis is only rejected for two countries: Belgium and Korea. Following Rogoff and Stavrakeva (2008), the meaning of this result is that for some countries, (Netherlands and Japan), the consumption-based model in Equation (19) should be pooled with a random walk in order to obtain good predictability results. For the remaining 13 countries, the model seems to be good enough to beat a random walk when forecasting real exchange rates variations one quarter ahead.

It is important to note that the results presented in Tables 2 and 3 are consistent with each other since all countries which show in-sample predictability evidence also show out-of-sample evidence. Additionally, those countries which do not have any out-of-sample evidence do not show any in-sample evidence either.

Table 4 compares the out-of-sample predictability results with those in recent papers in the literature which perform tests for short-run horizons. While the consumption-based model estimated in Table 3 makes forecasts for the real exchange rate, the alternative models in Table 4 compute predictions for the nominal exchange rate. The predictability results are still comparable since it is known that, in short-run horizons, real and nominal exchange rates are almost perfectly correlated; see Taylor and Taylor (2004). Therefore, it is not difficult to construct nominal exchange rate forecasts by using inflation forecasts along with real exchange rate predictions.

Engel, Mark and West (2007) perform similar tests based on panel data regressions, for the same set of 17 countries, using the monetary model of the exchange rate. Although their long horizon predictability results are positive for most countries, their short horizon results work well only in 4 countries as shown in Table 4. The failure of the monetary model of the exchange rate in this case can be explained by the lack of short-run empirical evidence of the model´s assumptions. Namely, Purchasing Power Parity (PPP) and Uncovered Interest Parity (UIP) fail to hold in the short run according to the literature on international finance[6].

Molodtsova and Papell (2008) construct a prediction regression by assuming that each country's Central Bank follows a Taylor rule for monetary policy which includes deviations of the real exchange rate from a PPP level. It is shown positive evidence of nominal exchange rate predictability with this framework using a one-month horizon for 10 out of 11 countries. Results are summarized in Table 4. It is important to observe that the consumption-based approach shows positive predictability results for all 11 countries analyzed in Molodtsova and Papell (2008).

Finally, the consumption-based approach is compared with the PPP approach by Rogoff and Stavrakeva (2008) who estimate a panel regression for 10 countries incorporating persistent common cross-country shocks in the forecast. They find positive predictability evidence in 7 out of 10 countries as described in Table 4. It is interesting to highlight that the

[6] See, for example, Rogoff (1996) on the failure of the PPP hypothesis and Fama (1984) on the UIP hypothesis.

consumption-based model allows obtaining good predictability evidence for those countries in which Rogoff and Stavrakeva (2008) did not obtain any evidence: UK, Switzerland and Norway.

Table 4: Comparison of Out of Sample Predictability with Recent Papers
p: positive predictability evidence; n: negative predictability evidence; na: not available

Country/Horizon	Consumption-Based One Quarter	Monetary Model One Quarter	Taylor Rule Model One Month	PPP Model One Quarter
UK	p	n	p	n
Austria	p	p	na	na
Belgium	n	n	na	na
Denmark	p	n	p	p
France	p	n	p	na
Germany	p	p	p	p
Netherlands	p	p	p	na
Canada	p	n	p	p
Japan	p	n	p	p
Finland	p	n	na	na
Spain	p	n	na	na
Australia	p	n	p	p
Italy	p	n	p	na
Switzerland	p	p	p	n
Korea	n	n	na	p
Norway	p	n	na	n
Sweden	p	n	n	p
Overall	15/17	4/17	10/11	7/10

This table compares the out-of-sample predictability results from the consumption-based model with the predictability results in recent papers in the literature at similar horizons. The results for the monetary model are retrieved from Engel, Mark and West (2007). The Taylor rule model was described and estimated by Molodtsova and Papell (2008). Finally, results from a model based on the Purchasing Power Parity (PPP) hypothesis are taken from Rogoff and Stavrakeva (2008).

5. Conclusions

Engel, Mark and West (2007) and Rogoff and Stavrakeva (2008), among others, describe that it is very difficult to obtain good out-of-sample predictability evidence for the exchange rate in short-run horizons with the existing models in the literature. Therefore, the puzzle described by Meese and Rogoff (1983) still seems to hold in the case of horizons shorter than one year. Recently, positive evidence in short run horizons has been found by Molodtsova and Papell (2008), using the Taylor-rule approach, and by Gourinchas and Rey (2007) using an external balance model.

This paper provides an alternative model to study short-run real exchange rate predictability using in-sample as well as out-of-sample tests. The framework is a consumption-based asset pricing model with two countries and complete markets such that real exchange rate variations are determined by fluctuations in the difference between Stochastic Discount Factors (SDF) across countries. When preferences include both internal and external habits, real exchange rate variations are predictable with past consumption growth. The functional form of the utility function allows computing linear specifications for real exchange rate variations with the following predictors: domestic consumption growth, US consumption growth and world consumption growth.

This framework, which is an open economy extension of the model studied by Abel (1991, 2006), is estimated and predictability tests, both in-sample and out-of sample, are calculated with data for 17 developed economies. Results show good out-of-sample predictability evidence in 15 countries. In-sample regressions allow studying the size and sign of the estimated coefficients. While signs are found to be consistent with those implied by the utility model, coefficient sizes are realistic in most countries. The estimated model predicts that, in average, positive shocks to US consumption depreciate all currencies with respect to the US Dollar. Furthermore, positive shocks to world consumption appreciate all currencies with respect to the US Dollar.

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