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Keywords: Exchange Rates, determination puzzle, non-linearities, cross-country asymmetries, automated model selection, indicator saturation

Non-Linear Exchange Rate Relationships: An Automated Model Selection Approach with Indicator Saturation

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Abstract: This paper examines whether the explanatory power of exchange rate models can be improved by allowing for cross-country asymmetries and non-linear effects of fundamentals. Both appear to be crucial. The data set looks at the USD versus pound and yen exchange rates from 1982:07-2013:10, and bias-corrected automated model selection is conducted with indicator saturation. Several non-linear effects are significant at the 1% level and reveal that larger changes in fundamentals typically generate changes in the exchange rate at an increasing rate, with the exception of variables eliciting countervailing central bank reactions (for example consumer prices) which exhibit diminishing effects.

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1 Introduction

The volume of trading in the foreign exchange market has increased dramatically in recent years from $3.3 trillion daily in April 2007 to $5.5 trillion in April 2013 (BIS 2013). Clearly understanding the driving forces behind exchange rate movements is more important now than ever given our increasingly globalized financial system and world economy. Despite this, connecting exchange rate movements to movements in fundamentals remains a daunting and contentious issue. Monetary models of the exchange rate have struggled to account for movements in the exchange rate even ex post (Rogoff 2001). This implies that the fundamentals which are supposed to drive the exchange rate in theory (namely relative money supplies, income, inflation, interest rates, trade etc.) have little explanatory power in reality. Certain sample periods have appeared well fitted (Mark 1995), but there has been little consistency as the samples have been extended (Cheung, Chinn and Pascual 2005). Some optimism has emerged regarding the longer-run ability of monetary models (MacDonald 1999, Engel, Mark, and West 2008), but the majority of short term and even longer term movements in exchange rates remain anomalous.

An important and promising strand of the literature has attempted to address this deficiency by allowing for non-linear effects of fundamentals on the exchange rate. Some of the empirical studies have allowed for recurrent shifts between two regimes in Markov switching models (Engel and Hamilton 1990, Frommel, MacDonald and Menkhoff 2005, De Grauwe and Vansteenkiste 2007), or smooth transition threshold models (Sarantis 1999, Taylor and Peel 2000, Killian and Taylor 2003). While these approaches have offered an improvement over linear models in many cases, few would argue that there is not much left to uncover. Others have allowed for stark and unpredictable changes in the relationship based on tests for parameter instability, though with linear relationships within regimes, and have offered notable improvement via these piece-wise linear models (Goldberg and Frydman 1996a, 2001; Beckman, Belke, and Kühl 2010). Questionnaire evidence from actual traders supports the notion that the effects of fundamentals change over time but also indicates that they differ across countries (Chueng, Chinn, and Marsh 2004).

This study investigates how much improvement can be garnered by allowing for cross country asymmetries and non-linear dynamic effects of the fundamentals; for example allowing the effect of a change in the interest rate

to depend on the country and magnitude of the change. Two exchange rates are examined at the often perplexing monthly frequency, the US dollar per Japanese yen (USD/JY) and US dollar per British pound (USD/BP), from July 1983 to October 2013. These currencies constitute three of the most heavily traded in the world (BIS 2013). The information set also includes data on money supplies, production, consumer prices, three-month T-bill rates, 10-year bond rates, current accounts, and unemployment, as well as squared, cubic, and exponential terms for each regressor.[1]

The model selection for both the linear and non-liner models is conducted using the Autometrics algorithm (Doornik 2009) with a model selection bias correction applied to the estimates which overcomes the usual detractions of step-wise regression (Hendry and Krolzig 2005). Autometrics allows for estimation even when the number of regressors exceeds the number of observations by conducting block searches with feasible subsets. This obviates the need to estimate models with fewer variables, for example assuming linearity and symmetric effects across countries, in order to conserve degrees of freedom.

Of course, there are still many potential omitted variables in this (or any) analysis. In this context, such omissions may include microstructure effects, impacts from technical trading, autonomous expectations related to imperfect knowledge, currency interventions, non-economic news, and other policy or institutional changes. Structural change external to the model is captured through the use of impulse and step indicator saturation procedures (Santos, Hendry and Johansen 2008; Doornik, Hendry and Pretis 2013). This provides a form of robust estimation, and the indicators prove highly significant and necessary to achieve the well behaved residuals required for valid inference.

The linear models account for less than 20% of the variation in the monthly exchange rate changes, whereas the non-linear models with asymmetries can account for over 60%. The latter is preferred according to several model selection criteria, including an index test for non-linearity (Castle and Hendry 2010), and both the asymmetries and non-linear effects appear to be vital under a variety of model specifications. Several of the non-linear effects are significant at the 1% if not 0.1% level, and significant lagged effects in-

[1] Unemployment is less commonly included in exchange rate models, though it is consistently reported by actual traders as among the most important they monitor (Cheung, Chinn, and Marsh 2004). This is perhaps attributable to the information it provides about future RGDP and the conduct of monetary policy.

dicate Granger causation. The results suggest that the market reaction to changes in fundamentals depends on the country of origin and the size of the shock. More specifically, the estimates indicate that larger changes in fundamentals tend to generate larger than proportional changes in the exchange rate, with the exception of those which may engender expectations of counter-cyclical central bank reactions (for example consumer prices in both samples and Japanese current account deterioration).[2] In the latter cases, the effect is diminishing and may even reverse sign for extreme changes.

Section two discusses the data and model specifications in more detail. Section three compares the performance of the general unrestricted models in terms of the fit, model selection criteria, and residual analyses. Section four compares the models after automated model selection and conducts an index test for non-linearity. Section five employs the indicator saturation procedures and discusses the estimated non-linearities. Lastly, section six concludes.

2 Data

The information set includes monthly data from the FRED database on the USD versus BP and JY spot exchange rates, consumer price indices, three month T-bill rates, M2 money supplies, 10 year government bond rates, civilian unemployment rates, and industrial production. Quarterly current account data is also included as a % of GDP and interpolated to monthly values to match the frequency of the other variables.[3] All of the variables are measured as log differences, with the exception of the variables in percentage terms including the unemployment rate, the current accounts (which cannot be logged due to their occasional negative values) and the interest rates though they have been divided by 1200 to correspond more closely to the units of the monthly changes in the log exchange rate (as is not uncommonly

[2] This latter result seems consistent with the spirit of the Taylor rule models of exchange rate determination (Engel and West 2006, Molodtsova and Papell 2009) and the emphasis by Engel, Mark, and West (2008) on the importance of the monetary policy rule, though with some new elaborations here.

[3] The Japanese current account data prior to 1985 is appended from the series excluding exceptional finance, which ends in 2008. The two series move very closely however until the mid-2000's. Industrial production is used as the denominator in this case, though again it mimics the movements in the shorter available sample of the current account as a % of GDP.

done, see for example Johansen et al. 2010).

Several of the variables undergo longer term trends, for example prices and industrial production. Consequently, the variables are measured in terms of their change minus their mean change, not dissimilar to detrending the data. This is designed to correspond to the notion that it is the "news" or unexpected change which drives the exchange rate. All variables are assumed to be I(0) after differencing and correcting for breaks. These two adjustments are capable of creating a stationary series even from variables which otherwise appear as approximately I(2).

The basic model is estimated in relative terms (domestic minus foreign variables), while the asymmetric models include each country's variables separately, and the non-linear models allow for squared, cubic, and exponential effects for each regressor following Castle and Hendry (2009). So for example, the squared, cubic and exponential values of the variable x_t are:

$$(\Delta x_t - \Delta \bar{x}_t)^2$$

$$(\Delta x_t - \Delta \bar{x}_t)^3$$

$$\exp(-abs(\Delta x_t - \Delta \bar{x}_t)) * (\Delta x_t - \Delta \bar{x}_t)$$

where Δ is the difference, $\Delta \bar{x}_t$ is the mean monthly change, exp is the exponential function, and abs is the absolute value. These effects combined are capable of approximating smooth transition threshold models with asymmetries (Castle and Hendry 2005) and higher order polynomial effects, since for example a quadratic function can resemble a quartic function and a cubic function can look quite similar to a 5th order polynomial, given suitably compensatory coefficients and a sufficiently limited range of values undertaken by the variable.

3 Comparisons of Model Fit

It is useful to begin with a simple overview comparing the models' performances based on various criteria including the R-squared, adjusted R-squared, information criteria, and residual analysis. This helps to avoid becoming too deluged initially in an over-abundance of coefficient estimates. We begin by examining the general unrestricted models (GUMs). Figures 3-6 in the appendix show the fit of the linear model in relative variables and the fit of the non-linear model with cross country asymmetries for both samples. Two lags are included as longer lags did not appear significant.

Below however we examine the models more completely including those with just the asymmetries or non-linear effects to distinguish the relative importance of each. The models are evaluated according to a larger number of model selection criteria, which more appropriately penalize for over-parameterization, including Akaike information criteria (AIC), Hannan-Quinn (HQ), and Schwarz or Bayesian criteria (SC). The AIC is asymptotically efficient while the latter two are consistent. The preferred model according to the information criteria exhibits the lowest value. The overall R-squared and adjusted R-squared are also reported where of course higher is better.

Due to spacing limitations, the linear relative model is labeled as Lin. Rel., the linear asymmetric model as Lin. Asym., the non-linear relative model as Nonlin. Rel., and the non-linear asymmetric model as Nonlin. Asym.

TABLE 1
Model Selection Criteria for the USD/BP GUMs

BP/USD	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AIC	-4.617	-4.711	-4.621	-4.700
HQ	-4.517	-4.523	-4.232	-3.961
SC	-4.365	-4.238	-3.643	-2.839
Adj. R^2	0.115	0.234	0.241	0.361
R^2	0.170	0.325	0.429	0.664

TABLE 2
Model Selection Criteria for the USD/JY GUMs

JY/USD	Lin. Rel.	Lin Asym.	Nonlin. Rel.	Nonlin. Asym.
AIC	-4.417	-4.434	-4.332	-4.374
HQ	-4.317	-4.246	-3.944	-3.635
SC	-4.165	-3.961	-3.355	-2.513
Adj. R^2	0.108	0.167	0.164	0.270
R^2	0.163	0.265	0.371	0.615

We can see that in the BP sample, the non-linear model with asymmetries is the preferred model according to both the AIC and adjusted-R squared. However, according to the criteria with harsher penalties for extra parameters (for example the HQ and SC), the linear models are preferred to the non-linear models and even the relative is preferred to the asymmetric in the case of the Schwarz criteria. In the JY sample, the non-linear model with asymmetries is only preferred according to the adjusted-R squared, while the asymmetries are preferred for the AIC, and linear relative model according to the HQ and SC.

A crucial diagnostic though is the residual analysis, which finds the most support for the non-linear model with asymmetries, in terms of providing a potentially reliable model for inference. One could argue that it would be reasonable to use the 1% significance level to reject the residual diagnostics (as Castle and Hendry 2009 do), since using a 5% level for each would lead to a type I error of rejecting an "adequate" model far more than 5% of the time based on one of the five tests.

TABLE 3
Residual Analysis for the USD/BP GUMs

USD/BP	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AR	0.053	0.104	0.729	0.613
ARCH	0.002	0.125	0.062	0.228
Normality	0.000	0.111	0.010	0.214
Hetero	0.000	0.000	0.144	0.906
Reset	0.082	0.006	0.008	0.000

TABLE 4
Residual Analysis for the USD/JY GUMs

USD/JY	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AR	0.134	0.065	0.027	0.766
ARCH	0.021	0.140	0.223	0.120
Normality	0.013	0.071	0.208	0.358
Hetero	0.001	0.005	0.789	0.985
Reset	0.180	0.862	0.076	0.107

Even with this less stringent threshold however, only the non-linear models are not rejected for the JY sample and all of the models in the BP sample are rejected prior to model reduction. Even after model reduction though, only the non-linear models cannot be rejected as shown in the next section (though the relative version is quite close to the rejection region in both samples).

While there is a natural bias variance trade-off in any model selection process, it is important to note that these violations of the OLS assumptions in the general models themselves create a bias, which then lessens the trade-off of model reduction. The bias from model reduction will be additionally mitigated through a correction procedure discussed in section five. Hendry and Krolzig (2005) demonstrate that the recently improved algorithms with correction are able to produce nearly unbiased R-squareds, standard errors, and coefficient estimates.

4 Automated Model Selection and Index Tests for Non-Linearities

With regard to the information criteria, it is important to note that the unrestricted non-linear models have maintained a very large number of (very strongly seeming) irrelevant variables. If however we conduct the model selection algorithm of Autometrics (Doornik 2009) to eliminate some of those highly insignificant variables, here using 5% and presenting the results at 10% in the appendix, we can see that the preference for the remaining polynomial model with asymmetries is much less ambiguous. For the sake of comparison, the relative model has seven variables with two lags each, and two lags for the dependent variable for a total of 23 regressors. Meanwhile, the asymmetric

model contains 7 variables for each country with two lags for each variable and the dependent variable, for a total of 44 regressors. The polynomial model with asymmetries includes all of those 44 variables, plus the squared, cubic, and exponential of each regressor for a total of 176 regressors. Clearly the model at that point is becoming quite heavily parameterized and could benefit tremendously from model reduction.

It is worth digressing momentarily to discuss some of the basic facets and previous literature on automated model selection, though what follows provides only a cursory introduction. Automated model selection has been dramatically improved over the last decade and a half, with much improved algorithms, beginning with for example the multi-path search of Hoover and Perez (1999). The excellent properties of the Autometrics procedure used here have been demonstrated in Doornik (2009), overcoming the previously documented biases of step-wise regression. These procedures rely on the general-to-specific methodology, where all potential variables are included from the outset. As Hendry and Krolzig (2004) note, the cost of not proceeding as such is either omitted variable bias, uncontrolled significance levels if adding variables later, or a potential confirmation bias where issues are "fixed" successively should results not conform with priors (see Campos, Ericsson and Hendry 2005 for a more comprehensive summary of the general-to-specific methodology).

These issues of course are why large scale model selection often encounters a degree of skepticism about "data mining". For example, some debate emerged regarding the astoundingly vast number of growth regressions which were being estimated, for example the "4 million" run by Sala-I-Martin (1997a). Automated model selection provides a "reality check on data snooping" as White (2000) put it, here by testing for congruency relative to the general model. The automated procedure then circumvents much of the subjectivity possible in the choice of presented results.[4] Hendry and Krolzig (2004) demonstrated, in their sardonically titled "We run one regression", that while the practice of large scale, manually selected growth regressions did not lead to biased inference, preferred and certainly much less time consuming results could be obtained simply by running essentially one model

[4]Of course, a researcher still needs to select the variables to include and significance levels at which to conduct the estimation. Herein though, sensitivity analyses are provided through the use of two exchange rate samples, GUMs in relative and asymmetric terms, and alternative significance levels in the appendix.

using the PcGets algorithm.[5]

Below are the information criteria based on the Autometrics procedure estimated at the 5% level for the four separate general unrestricted models (the linear relative model, linear model with asymmetries, non-linear relative model, and the non-linear model with asymmetries). The estimates using the 10% level are provided in the appendix as a sensitivity analysis, though the conclusions are not altered.

TABLE 5
Model Selection Criteria for the USD/BP Automated at 5%

USD/BP	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AIC	-4.666	-4.756	-4.782	-4.975
HQ	-4.645	-4.702	-4.694	-4.816
SC	-4.613	-4.620	-4.561	-4.575
Adj. R^2	0.115	0.234	0.244	0.402
R^2	0.125	0.208	0.285	0.462

TABLE 6
Model Selection Criteria for the USD/JY Automated at 5%

USD/JY	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AIC	-4.471	-4.520	-4.525	-4.660
HQ	-4.438	-4.491	-4.492	-4.560
SC	-4.387	-4.447	-4.441	-4.407
Adj. R^2	0.120	0.160	0.166	0.300
R^2	0.136	0.173	0.182	0.344

It is now clearer that the non-linear model with asymmetries is preferred in both samples. It obtains the lowest value for the AIC and HQ, and highest value for the adjusted and overall R squared in both samples. According to the SC however, the linear asymmetric model is preferred. Again though, we would also want to look at the residual analysis to determine whether the models are statistically well-specified and reliable for inference.

[5] PcGets is quite similar to Autometrics, it is a general to specific algorithm in Oxmetrics (see Doornik 1999) founded upon the theory of reduction as discussed in Hendry (1995, chp. 9).

TABLE 7
Residual Analysis for the USD/BP Automated at 5%

USD/BP	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AR	0.075	0.088	0.274	0.590
ARCH	0.001	0.011	0.020	0.640
Normality	0.001	0.025	0.052	0.839
Hetero	0.000	0.000	0.017	0.587
Reset	0.044	0.077	0.150	0.408

TABLE 8
Residual Analysis for the USD/JY Automated at 5%

USD/JY	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AR	0.136	0.190	0.187	0.137
ARCH	0.056	0.094	0.045	0.073
Normality	0.012	0.011	0.011	0.399
Hetero	0.022	0.013	0.091	0.101
Reset	0.157	0.679	0.903	0.426

The residual analysis is still not very favorable for the linear models, rejecting them outright at the 1% level in the BP sample. It does however tend to support the non-linear model with asymmetries particularly for the BP sample.

Again, the one conflicting result is that the SC preferred the linear asymmetric model in both samples. We can discriminate between these two choices (an asymmetric model with or without non-linearities) by using the index test for non-linearity of Castle and Hendry (2010) which has been found to outperform the RESET test and other linearity tests under a number of scenarios where the alternative form is uncertain, particularly when the number of possible regressors is large and they are highly correlated.[6] The test draws from White (1980) in that it includes squared and cubic terms for the regressors. However, the test uses the principal components of the regressors to overcome issues of high dimensionality and low power, and includes exponential effects as well. Two test statistics are yielded, one distributed as a Chi-squared approximation and an F-distribution (assuming fixed regressors). The p-values for the tests are presented below.

[6]The RESET test performs poorly when confronted with outliers, when the non-linearities enter without the linear terms, or when many variables enter with only linear terms. See Granger and Teräsvirta (1993) for a summary of other linearity tests.

TABLE 9
Index Test for Non-Linearity

	USD/BP	USD/JY
$\chi^2(132)$	0.001	0.030
F(132,196)	0.003	0.160

As can be seen, the test is rejected at below the 1% level in the BP sample, implying that the non-linear terms are significant. It is also rejected in the JY sample at the 5% level for the Chi squared statistic. The F test however does not quite reject at 10% in the USD/JY sample, though with a large GUM which is going to be reduced (lacking fixed regressors) this statistic may be less pertinent. In any event, the majority of the information criteria prefer the non-linear model and as will be seen in the next section, many of the non-linear terms are significant at the 1% level in both samples.

5 Indicator Saturation and Coefficient Estimates

The two potential pitfalls in model selection, or statistical inference more generally, are false inclusion and false exclusion (type I and type II errors in this context). In order to minimize the problems of false inclusion, we select a significance level α based on the number of regressors k to create an acceptable number of spuriously included variables, $k\alpha$. Of course what is deemed acceptable depends on the researcher's preferences in terms of the trade-off between obtaining spurious variables and excluding relevant ones. The previous literature on automatic model selection has in several instances used approximately one as an acceptable number of improper inclusions, for example Hendry and Krolzig (2004) and Castle and Hendry (2009).

Again, the non-linear model with asymmetries begins the GUM with 176 regressors. Using the 1% level, we have an expected false inclusion of 1.76 variables. The next lowest alternative of 0.1% would be a bit too conservative perhaps. To focus on the second potential mistake in inference, the possibility of excluding a relevant variable, the power to retain correctly is not much altered from using a very large GUM compared to even the extreme case when one knows exactly which variables are relevant and includes only those from the outset (Hendry and Krolzig 2004). This follows naturally from the elimination of almost all of the irrelevant variables. Further, given the critical

value chosen, the coefficient bias arising from only maintaining the variable when it is sampled as significant can be adjusted, which helps to mitigate the influence of falsely included variables (Hendry and Krolzig 2004). It is worth noting that Autometrics has been found to improve upon the common information criteria, so the results herein should be prioritized over those in sections four and five in determining whether the non-linearities are relevant, when compared to the asymmetric model without them (which is nested in the GUM).[7]

As mentioned previously, an important strand of the literature has developed which relates the exchange rate determination and other puzzles in international finance to the presence of structural breaks. Goldberg and Frydman (2001) for example show that the practice of estimating time invariant models has obscured the influence of fundamentals; within the partitioned structural breaks they obtain more significant results consistent with theory. An at least equally extensive econometric literature has developed on testing for structural breaks (see for example Bai and Perron 1998 and Hansen and Johansen 1999) and various alternatives abound.

In order to address structural breaks and ensure the reliability of the estimates, we use an impulse indicator saturation (IIS) and a step indicator saturation (SIS) procedure (see Santos, Hendry and Johansen 2008 for IIS, and Doornik, Hendry and Pretis 2013 for SIS). Shifts in the level of the exchange rate relationship would manifest as outliers in the differenced model, and shifts in the time varying trend would present as mean shifts. These indicators can control for omitted variables which impact the exchange rate aside from the included fundamentals and lagged changes in the exchange rate, for example policy changes, non-economic news, chartist or microstructure effects, or changes in forecasting due to learning or imperfect knowledge.[8]

These procedures include an impulse and step indicator for each observation, conducted in block searches, or sub-samples, to permit feasible estimation since the number of included variables automatically exceeds the number of observations. The indicators are included simultaneously with all potential fundamentals to prevent incorrect inclusion or exclusion of either.

[7] Of course, the relative and asymmetric models cannot be nested since it would create perfect multicollinearity. Given the previous results, we allow for asymmetries.

[8] Lyons (2003) and Dominguez and Panthaki (2006) discuss microstructure/non-economic news. Frankel and Froot (1990), De Grauwe and Grimaldi (2006), and Schulmeister (2006) discuss technical trading. Goldberg and Frydman (1996b) and Frydman and Phelps (2012) discuss learning/imperfect knowledge.

This is even more important when non-linearities are possible, given these can often mimic outliers when wrongly excluded (Castle and Hendry 2009). Castle and Hendry (2009) argue that if an economic variable truly has an effect, it should not be shrouded by the inclusion of indicators, and moreover the inclusion of indicators prevents correlations fabricated by chance coinciding of shifts in the variables. Following these previous papers, the indicators will be detected at the 0.1% level, meaning only one in 1,000 would be expected to be erroneously included. Thereafter, all of the fundamental regressors are re-included and model reduction is conducted at the 1% level.

5.1 USD/BP Estimates

Variables beginning with the capital letters SQ, CUB, and EXP represent the squared, cubic and exponentials of the variables. The change in the exchange rate is denoted by Δs, the change in the interest rate by Δi, the change in bond rates by Δb, and inflation by Δp. The foreign (non-US) countries are denoted by a superscript asterisk thereafter, while a number at the end following the underscore indicates whether the variable is a first or second lag.

TABLE 10
USD/BP Estimates at 1% with IIS and SIS at 0.1%

	Coeff.	t-value	Bias-adjusted
EXPΔs_1	0.249	5.17	0.248
SQΔi*	-8,036.24	-3.59	-7,128.1
SQΔi*_1	-12,088.7	-4.57	-11,918.0
EXPΔi*_1	19.781	5.44	19.756
CUBΔb*	-7.895e+7	-5.24	-7.877e+7
CUBΔp_1	-7,606.68	-2.71	-4,193.0
EXPΔp	1.963	4.43	1.924
I:1985(4)	0.115	5.47	0.114
I:1985(7)	0.071	3.45	0.047

In the BP sample, we see eight non-linear terms entering as significant at the 1% level. This is far more than the likely number of variables included by mere chance. Further, none of the linear terms enter in this sample. The UK interest rates and US prices enter with significant lags as well indicating Granger causation. It can be gleaned from the results that the bias correction pushes the marginally significant coefficients towards zero.[9]

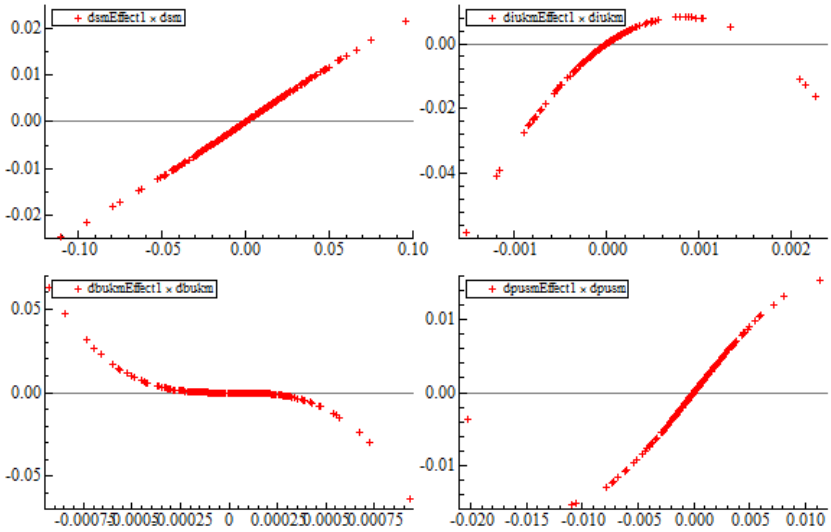
It is notable that the two indicators we observe correspond to a dollar appreciation outside of observed fundamental impacts during the mid-1980's. This corresponds to a time period which has often been invoked as a "bubble" in the USD (e.g. Frankel and Froot 1990), which may be what is being detected here. This bubble is occurring even outside of the average trend following behaviour captured in the model by the lagged change in the exchange rate.

The appendix presents the case where the indicators are also detected at 1%, corresponding to the case where one is more concerned about false exclusion of significant breaks. Under that specification, the number of indicators is much more prevalent, as would be expected. However, the increase is far more dramatic than simply the increase which would be expected from the change in significance level. Rather than the approximately seven additional indicators which would be expected purely from the increase in size, the added indicators exceed 15 in both samples. This suggests a genuine break roughly every two or three years on average over the sample.

The graphic below provides some clearer indication of the exact functional forms that have been estimated based on the domain of observed values the variables have undertaken over the sample. The graphs are created with a scatter plot of the effect of the variable after bias-adjustment against the values of the variable itself. The graphs obscure some of the time dynamics involved, for example the effects of US prices which occur with differing lags, though these will be discussed when applicable.

[9] The R-squared estimates have been omitted since some of the explanation is captured exogenously by the indicators, and the constant has no longer been imposed if insignificant (as is the case). The residual analysis is provided in the appendix however.

Figure 1: Estimates of the USD/BP Non-linearities



Caption: The effect of the variable plotted against the values of the variable. Clockwise from top right, the effect of changes in lagged UK interest rates, US inflation, changes in UK bond rates, and the lagged change in the exchange rate.

In this sample we see that decreases in the lagged UK interest rate (upper right panel) led to pound depreciation (as expected) and moderate increases led to pound appreciation, but very large increases (which may signal an over-heating economy) tend to bode less well or even poorly for the pound. This is not a mere by-product of capital flight causing both rising interest rates and simultaneous currency depreciation however, since the effect enters with a lag. The squared term also implies that larger decreases in the UK interest rate cause depreciation at an increasing rate.

We also observe a non-linearity for US prices (lower right), where an increase led to a dollar depreciation, due to inflationary effects as expected, but larger changes appear to have an increasingly muted effect. One could interpret this as inflationary effects giving way to expectations of central bank tightening and the commensurate expected interest rate effects. As seen in table 10, the positive exponential effect occurs contemporaneously and the negative cubic effect lags. This is consistent with the prior explanation

that the cubic effect results from possible central bank reaction, since such response would naturally occur with a lag.

We see a cubic effect of the UK bond rate (lower left). The sign is negative, so an increase in the UK bond rate led to pound depreciation. This is consistent with the typical exposition of monetary models of the exchange rate (for example Frankel's 1979 real interest rate differential model), where increases in the longer term bond rate, after controlling for the shorter term rate, are interpreted as being related to expected inflation. Larger changes however appear to have larger than proportional effects based on the observed functional form (similar to what was observed for decreases in the UK interest rate).

This phenomenon of larger changes having a larger than proportional effect occurs repeatedly (a positive second derivative), so it is worth taking an aside to contemplate the possible reasons for this behavior. The explanation for this non-linearity would of course require further research, but a few hypotheses seem immediately apparent. The first is that the market generally predicts the right direction of change, but larger changes tend to correspond with greater than proportional forecast errors and "news". Such behavior is potentially consistent with Gourinchas and Tornell (2004) who find, using interest rate survey forecasts, that individuals underestimate the persistence to interest rate shocks and that this distorted belief can account for the forward discount anomaly and delayed overshooting puzzle. A second possible explanation ventured here is that this may reflect market participants extracting a larger than proportional signal from larger shocks. In other words, they may view smaller shocks as more likely to be transitory and larger shocks as more likely to be permanent or consisting of a larger permanent proportion. This hypothesis could be similarly tested using interest rate forecast data. Third, this may result from the use of leverage, where larger changes require more individuals to unwind their positions or cause individuals to unwind them to a greater extent. This is potentially consistent with the work of Brunnermeier, Nagel, and Pedersen (2009).

Lastly for the USD/BP, we observe a slight exponential non-linearity in the effect of the past change in the exchange rate (upper left panel), with more interestingly a positive sign indicating trend following behavior as described in the work on chartism or extrapolative expectations (reminiscent of the old trader adage that "the trend is your friend"). The sign is also consistent with evidence that the exchange rate is actually more persistent than a simple random walk (Engel and Hamilton 1990, Johansen et al. 2010)

even outside of the effect of fundamentals (De Grauwe and Vansteekiste 2007 and Frommel, MacDonald, and Menkhoff 2005).

5.2 USD/JY Estimates

In addition to the variable name conventions already enumerated, Δm represents the change in money supply, Δca the change in the current account, and Δy the change in industrial production.

TABLE 11
USD/JY Estimates at 1% with IIS and SIS at 0.1%

USD/JY	Coeff.	t-value	Bias-adjusted
Δs_1	0.214	4.69	0.211
Δb	66,646.9	3.41	56,313.0
Δp	1.665	2.66	0.865
Δm*_2	-394.61	-3.26	-316.13
Δm_1	-0.854	-2.63	-0.427
Δca	1.278	3.63	1.143
SQΔb*_1	53,832.6	3.39	45,197.0
CUBΔb_2	-5.791e+7	-4.63	-5.721e+7
EXPΔb	-66,690.6	-3.41	-56,350.0
CUBΔy_2	2,387.11	4.08	2,284.20
EXPΔm*_2	397.15	3.27	319.43
CUBΔca	-1.642	-3.70	-1.491
EXPΔca	-1.431	-3.62	-1.278
CUBΔp	-33,345.4	-4.45	-32,718.0
I:1985(10)	0.084	3.68	0.062
S:1998(8)	-0.070	-4.30	-0.064
S:1998(10)	0.068	4.15	0.059

In the JY sample, we have an even larger number of significant regressors including non-linear regressors (eight non-linear terms compared to seven previously). Several linear terms enter as significant, but almost none enter only in a linear fashion, with the exception of the lagged change in the exchange rate and US money supply but the latter is only marginally significant and of the wrong sign (though consistent with findings that surprise money supply increases lead to appreciation, attributed to expected tightening, e.g. Engel and Frankel 1984). The two bond rates, US output, and the

money supplies all enter with significant lags demonstrating Granger causation from the fundamentals to the exchange rate. Further, the US current account, which enters contemporaneously, would be expected to possess the opposite sign if this were a case of reverse causation. In other words, dollar appreciation would tend to worsen the current account, but instead we see improvement in the current account coinciding with dollar appreciation (see figure 6 below). One could argue that this is occurring due to J-curve dynamics and reverse causation, but the sensitivity analysis in the appendix with differing significance levels finds significant and positive lagged effects for the current account as well.

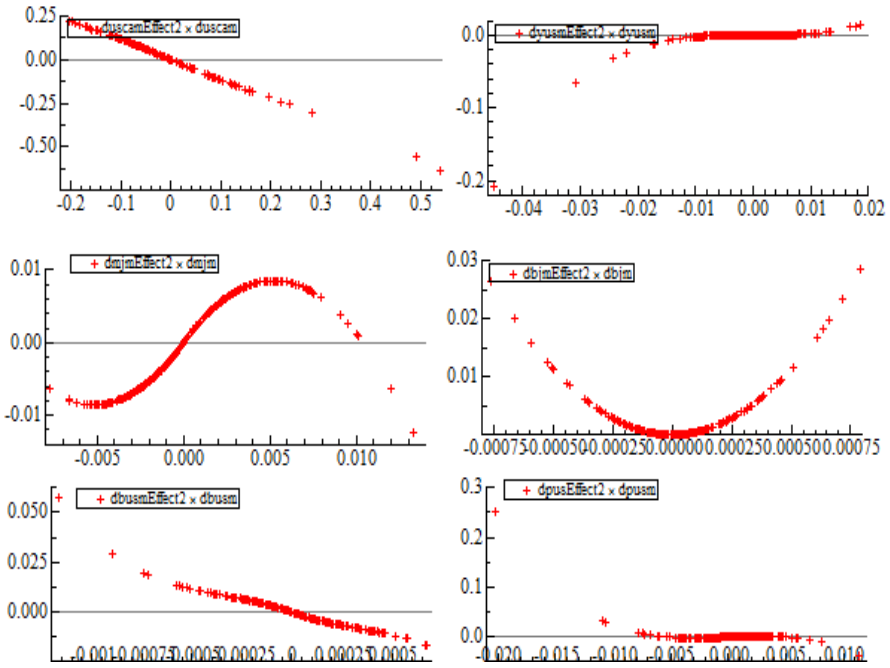
Again we can see a positive effect of the lagged exchange rate, consistent with trend-following behavior, though here it does not take on the slight non-linearity previously observed, or at least can be well-represented as linear over the magnitude of changes experienced.[10] Also again, we observe indicators that are significant at the 0.1% level, and with quite apparent historical interpretations. The impulse indicator in 1985(10) corresponds perfectly with the Plaza accord (which occurred on September 22, 1985). This indicator then is likely picking up the effect of the policy announcement on expectations, and the coordinated central bank intervention which prompted dollar depreciation external to the effects of private trading based on the observed changes in fundamentals and lagged change in the exchange rate.

The other two step indicators seem to indicate a two month trend that was largely reversed thereafter in late 1998, which coincided with the worsening of Japan's economy. This may be capturing some expectations about future fundamentals (for example predictions about the interest rate, money supply, and current accounts) and hence the exogenous trend reversed upon the realization of those expectations since the effect is then captured endogenously by the fundamentals.

Again, a clearer understanding of the non-linear effects can be obtained visually.

[10] It does however enter in a non-linear fashion for the JY/USD sample in the sensitivity analysis presented in the appendix which uses indicator saturation at 1%.

Figure 2: Estimates of the USD/JY Non-linearities



Caption: The effect of the variable plotted against the values of the variable. Clockwise from top right, the effect of changes in US production, Japanese bonds, US inflation, US bonds, Japanese money supply, and the US current account

The effect of changes in US industrial production (upper right) seems to be capturing trade effects, where increases led to dollar depreciation at an increasing rate, perhaps since the US interest rate effects are controlled for in the bond rates as discussed below. Similar to the cubic effect for UK bonds, this may be deriving from larger changes being associated with leverage, larger than proportional forecast errors, or their being interpreted as less transitory in character.

The quadratic relationship for Japanese bond rates (middle right) is perhaps the most difficult to interpret since it implies that both increases and decreases led to dollar depreciation. It would be too self-serving to presume that this effect is merely spuriously deduced (either because of mistaken inclusion or mistaken exclusion of the other terms relating to this variable) and

given it is significant at the 1% level it should be considered seriously. From the standard monetary models, and the previous results, we would expect that a rising bond rate would lead to yen depreciation due to inflationary concerns. Given Japan's unique and moribund economic environment however, where inflationary fears have given way to deflationary ones, a rise in the bond rates may signal a potential return to health, and hence the sign reversal for increases. Again, the non-linearity implies that the market reacts more than proportionately to larger changes in this fundamental.

For the effect of US prices (bottom right), we see an effect similar to the BP sample, where small increases led to dollar depreciation (though difficult to see at this scale), and larger increases have a more muted response. Here though the non-linear response is strong enough to actually reverse the sign of the effect for large enough changes. Again this may relate to an increasingly dominate effect of expected monetary tightening over inflationary considerations. This is consistent with the findings on Taylor rule models of the exchange rate, where "bad" news about inflation, where it exceeds expectations, leads to currency appreciation (Clarida and Waldman 2008). Some of the reverse effects over smaller ranges of changes then may arise from increases or decreases that fell short of expectations.

The effect of US bond rates (lower right) takes on a slight exponential and cubic form. The sign is the same as the UK bond rate in the last sample, which is contrary to what we might normally expect. In this sample the US bond rate seems to be capturing the interest rate effects rather than expected inflation effects posited in the monetary models of the exchange rate. This seems to occur because in the last sample we had UK interest rates and bond rates but no UK price levels. In this sample however we have the US bond rate and prices, but no short term interest rates. The two samples appear to have found alternative ways to parsimoniously proxy for the interest rate and inflation effects: one sample where short rates represent interest effects and bond rates depict inflation expectations, and the other where bond rates represent interest effects and the expected inflation effects occur directly through price changes. Again, from the cubic term for the US bond rate we can see that larger changes appear to cause changes in the exchange rate at an increasing rate.

The largest increases in the Japanese money supply (middle left) led to yen deprecation, as one would expect based on the monetary models, but moderate changes tend to reverse sign, which again may be a by-product of expected countervailing monetary policy, increases which fell short of ex-

pectations, or Japan's long experience with a liquidity trap/ balance sheet recession, whereby increases in the money supply signal improved economic vitality up to a point.[11]

Given the current account differentials and fluctuations were much greater between the US and Japan than with the UK, it seems quite sensible that it would arise in this sample but not the former. We observe a quite elaborate effect though. Decreases in the US current account led to depreciation, and small increases in the US current account led to dollar appreciation. Moderate increases however cause appreciations at a decreasing rate (perhaps because of the expectation of currency intervention by the Bank of Japan), but if the change is large enough the dampening effect is lessened (perhaps because the adjustment is now too large to be fully stemmed by standard interventions).

6 Conclusion

This work finds compelling evidence of cross country asymmetries and non-linear effects of fundamentals on the exchange rate. Allowing for such effects greatly improves the explanatory power of monetary models of the exchange rate. The non-linear effects are often significant at the 1% if not 0.1% level and in many cases the economic interpretation of the non-linearities are quite intuitive. The overriding theme seems to be that larger changes in fundamentals lead to larger than proportional exchange rate responses, with the exception of those variables where large changes may provoke central bank response. In the latter case, for example with consumer prices in both samples and Japanese current account deterioration, we observe a diminishing response which may even reverse sign in the extreme cases.

Of course it would be a bit hasty to presume we have fully identified the (or all) relevant functional forms, particularly since the analysis has erred on the side of avoiding spurious inclusion of variables at the expense of false exclusion. Additionally, the underlying reasons for the observed non-linearities have only been hypothesized; aside from some suggestive similarities to empirical results using survey forecast data. Further use of survey data on expected future fundamentals or interaction terms *between fundamentals* may

[11] See Krugman (2000) and Koo (2011) for discussion of these two related phenomena in Japan.

prove useful in investigating the conjectured mechanisms behind the non-linearities.

What can be more confidently deduced from this work however is that future research should (i) allow for non-linear effects of fundamentals and cross country asymmetries, and (ii) use indicator saturation to address the significant and prevalent shifts external to monetary models, which are liable to muddle inference otherwise. These insights can be used to supplement other proposed resolutions to the exchange rate determination puzzle including learning/imperfect knowledge, market microstructure, and chartist effects, which the indicators may be capturing. In particular, it may be beneficial to allow for structural change in (and not only external to) the non-linear effects; as the distinctions between the yen and pound samples suggest a degree of context dependence to the non-linearities, for example being dependent upon central bank proclivities towards intervention and experiences with prolonged deflation.

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8 Online Appendix

Figure 3: BP Linear Relative Model $R^2 = 0.170$; Adjusted $R^2 = 0.115$

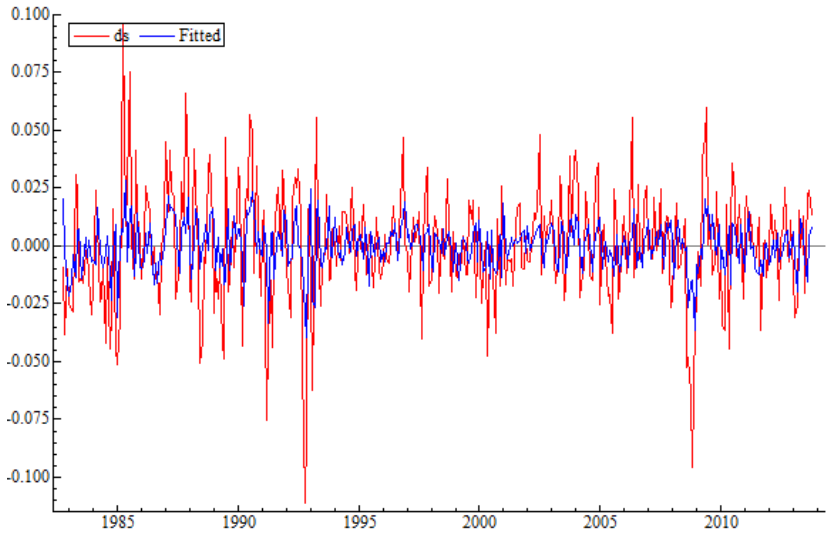

Figure 4: BP Non-Linear Model with Cross Country Asymmetries $R^2 = 0.664$; Adjusted $R^2 = 0.361$

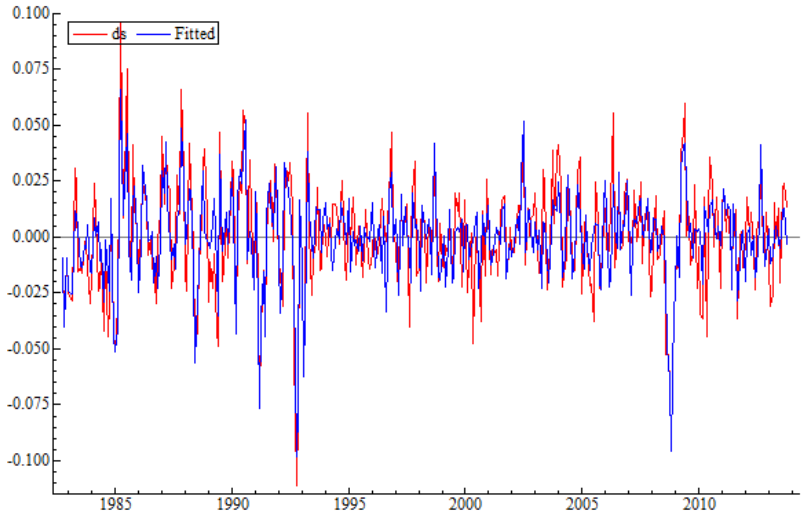

Figure 5: JY Linear Relative Model $R^2 = 0.163$; Adjusted $R^2 = 0.108$

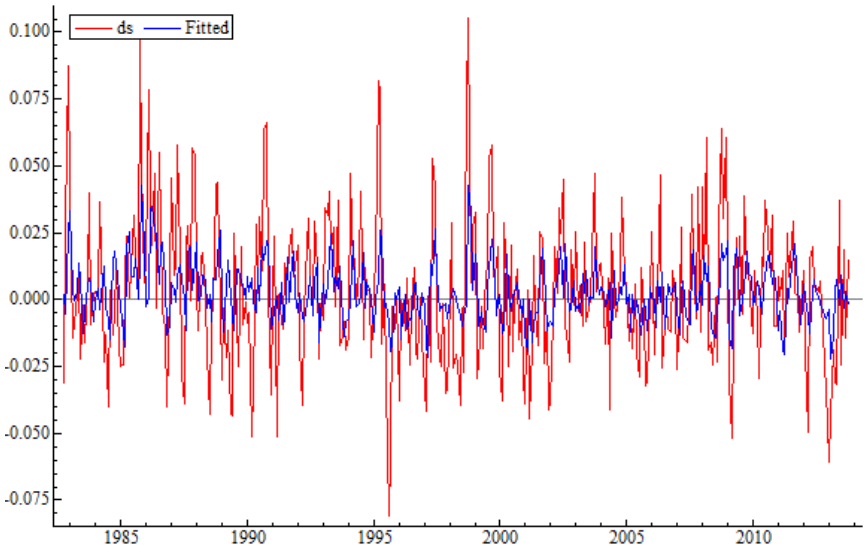

Figure 6: JY Non-Linear Model with Cross Country Asymmetries $R^2 = 0.615$; Adjusted $R^2 = 0.270$

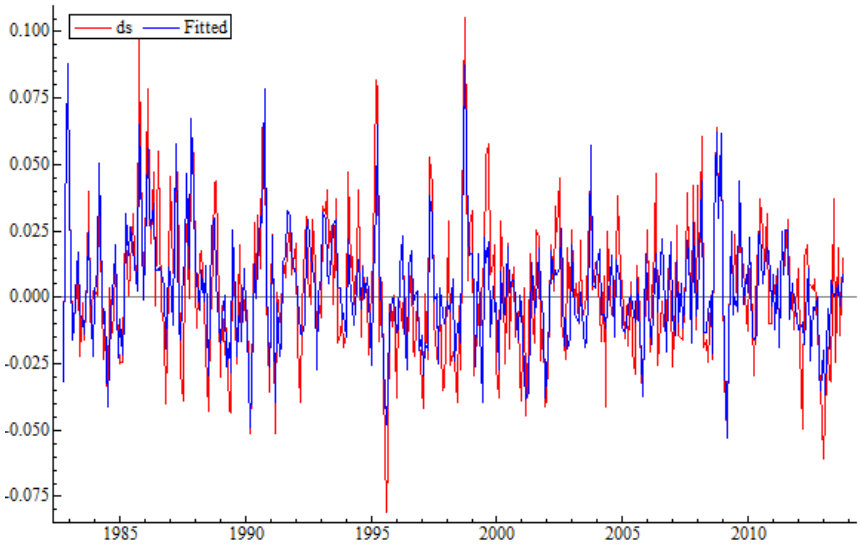

TABLE 12[12]

Model Selection Criteria for the USD/BP Automated at 10%

USD/BP	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AIC	-4.666	-4.772	-4.822	-4.859
HQ	-4.645	-4.693	-4.693	-4.733
SC	-4.613	-4.572	-4.496	-4.543
Adj. R^2	0.115	0.233	0.292	0.315
R^2	0.125	0.270	0.349	0.369

[12]It may be surprising to note that the R-squared is higher at 5% than at 10% for the non-linear model with asymmetries in the USD/BP sample. This can occur because the variables retained at 5% are not necessarily a subset of those retained at 10% given complications from multicollinearity, which is inherently prevalent in the non-linear models.

TABLE 13
Model Selection Criteria for the USD/JY Automated at 10%

USD/JY	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AIC	-4.476	-4.530	-4.558	-4.656
HQ	-4.438	-4.480	-4.492	-4.551
SC	-4.381	-4.404	-4.390	-4.393
Adj. R^2	0.126	0.179	0.210	0.299
R^2	0.145	0.203	0.242	0.344

TABLE 14
Residual Analysis for the USD/BP Automated at 10%

USD/BP	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AR	0.075	0.068	0.846	0.046
ARCH	0.001	0.011	0.015	0.061
Normality	0.001	0.012	0.023	0.105
Hetero	0.000	0.013	0.028	0.063
Reset	0.044	0.075	0.240	0.165

TABLE 15
Residual Analysis for the USD/JY Automated at 10%

USD/JY	Lin. Rel.	Lin. Asym.	Nonlin. Rel.	Nonlin. Asym.
AR	0.181	0.658	0.027	0.016
ARCH	0.039	0.154	0.042	0.010
Normality	0.011	0.010	0.104	0.405
Hetero	0.015	0.253	0.912	0.239
Reset	0.158	0.769	0.052	0.181

TABLE 16
Residual Analysis for IIS and SIS Models

	USD/BP	USD/JY
AR	0.178	0.539
ARCH	0.278	0.194
Normality	0.872	0.129
Hetero	0.094	0.473
Reset	0.245	0.437

TABLE 17
Fundamentals from the BP Model with IIS and SIS at 1%

USD/BP	Coeff.	t-value	Bias-adjusted
Δs_2	-0.215	-5.49	-0.215
Δi*_1	13.040	4.16	12.566
Δp_2	-1.991	-5.18	-1.985
Δy*_2	0.332	3.81	0.307
Δm_1	-1.206	-4.69	-1.194
SQΔi*	-6,950.99	-3.52	-6,060.60
SQΔi*_1	-9916.36	-4.41	-9711.30
CUBΔb*	-5.358e+7	-4.06	-5.117e+7
CUBΔp	5,475.05	2.61	2,665.8
CUBΔun*	-0.275	-2.15	0.000
CUBΔy_1	660.887	3.71	601.07
SQΔca*	-0.018	-2.71	-0.010
SQΔca*_1	0.023	3.44	0.020
EXPΔs_1	0.201	4.80	0.199

TABLE 18
Fundamentals from the JY Model with IIS and SIS at 1%

USD/JY	Coeff.	t-value	Bias-adjusted
Δb	56,960.1	3.28	45,993.000
CUBΔb_2	-5.524e+7	-5.10	-5.504e+7
EXPΔb	-57,005.9	-3.28	-46,030.000
EXPΔun	-0.021	-2.25	0.000
SQΔy_1	36.166	3.96	34.163
EXPΔy_2	0.512	2.66	0.266
SQΔm*_2	-201.368	-3.00	-141.460
EXPΔca*_1	0.022	3.46	0.018
SQΔca	0.173	3.35	0.143
SQΔca_1	-0.522	-4.21	-0.504
SQΔca_2	0.308	2.67	0.162
CUBΔca_1	0.900	3.94	0.848
CUBΔca_2	-0.903	-4.04	-0.861
EXPΔs_1	0.199	4.66	0.197

TABLE 19
Indicators for the BP Model with IIS and SIS at 1%

USD/BP	Coeff	t-value	Bias-adjusted
I:1985(4)	0.105	6.12	0.105
I:1985(7)	0.074	4.39	0.072
I:1985(10)	0.038	2.28	0.000
I:1987(3)	0.040	2.29	0.000
I:1987(11)	0.060	3.39	0.050
I:1988(3)	0.041	2.45	0.000
I:1989(7)	0.073	4.14	0.070
I:2005(7)	-0.044	-2.66	-0.023
I:2006(5)	0.052	3.15	0.040
I:2009(4)	0.055	3.26	0.044
I:2009(6)	0.051	3.02	0.037
I:2010(2)	-0.063	-3.67	-0.057
I:2010(5)	-0.069	-4.10	-0.066
S:1988(11)	0.019	3.39	0.016
S:1989(11)	-0.041	-6.09	-0.041
S:1991(2)	0.053	5.43	0.053
S:1991(6)	-0.038	-3.83	-0.035
S:1992(8)	0.046	5.27	0.046
S:1993(2)	-0.036	-4.80	-0.036

TABLE 20
Indicators from the JY Model with IIS and SIS at 1%

USD/JY	Coeff	t-value	Bias-adjusted
I:1985(10)	0.086	4.33	0.084
I:1986(2)	0.074	3.61	0.066
S:1987(7)	-0.035	-3.69	-0.032
S:1987(12)	0.032	3.09	0.023
S:1989(4)	0.052	3.44	0.044
S:1989(6)	-0.058	-3.76	-0.053
S:1990(8)	-0.058	-3.75	-0.053
S:1990(10)	0.141	6.00	0.141
S:1990(12)	-0.127	-4.93	-0.126
S:1991(2)	0.049	2.29	0.000
S:1995(2)	-0.062	-4.24	-0.060
S:1995(4)	0.104	6.21	0.104
S:1995(9)	-0.029	-2.91	-0.019
S:1997(4)	-0.043	-2.91	-0.029
S:1997(6)	0.055	3.63	0.049
S:1998(8)	-0.081	-5.32	-0.081
S:1998(10)	0.059	4.07	0.056
S:2013(1)	0.031	3.01	0.022
S:2013(5)	-0.087	-3.88	-0.081
S:2013(6)	0.059	2.96	0.040