USD EXCHANGE RATE CYCLES USING DEVELOPED AND DEVELOPING CURRENCIES AND RISK FACTORS

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Abstract - This paper predicts the exchange rates cyclical for US dollar [forecast two states for exchange rates; appreciation and depreciation] through using developing and developed currencies along with two risk factors (TED spreads and Inflation). Probity and logit models along with the principal component analysis and factor analysis are used to retain the most powerful components and factors. The empirical findings reveal that risk factors are not key factors in determining the exchange rates' cyclical behavior for the US dollar. Furthermore, the Sterling Pound is the only variable that has a consistent result that is more likely to cause appreciation for the US dollar exchange rate using all types of regressions. In addition, Renminbi shows inconsistent effects between different regressions; using OLS is less likely to cause appreciation for the US dollar exchange rate. By contrast, using Logit and Probit regressions is more likely to cause appreciation for the US dollar exchange rate. On the other hand, principal component analysis and factor analysis show that for all currencies we should retain two components and factors to be able to explain around 80% of the variation in exchange rate cyclical.

Keywords - Exchange Rates Cyclical; Risk Factors; Developing Currencies; Developed Currencies

I. INTRODUCTION

Jameel and Stefan (2015) define the exchange rate as "the relative price of one currency in terms of another".In addition, this tool can be considered an essential macroeconomic indicator for competitive power for countries. Cheung et al. (2018) compare the random walk benchmark performance with the performance of a bunch of models in predicting the exchange rates and conclude that co-integrated exists between predicted values and actual exchange rates value, and the elasticity of forecasted values is different than one.

This paper investigates using several developing and developed currencies besides two risk factors (TEDspreads and the inflation) in predicting the exchange rates cyclical behavior for US dollar [appreciation (bull), depreciation (bear)] using dynamic probit and logit models. In addition, I use the principal component analysis and factor analysis to know the components and factors that I should retain. The findings affirm that risk factors are not key factors in determining the exchange rates cyclical behavior for US dollar. Moreover, Sterling pound is the only currency that has a consistent result and is more likely to cause appreciation for US dollar exchange rate at all types of regressions. Furthermore, Renminbi shows inconsistent effects. In addition, On the other hand, principal component analysis and factor analysis show that for all currencies we should retain two components and factors to be able to explain around 80% of the variation in the data.

This study contributes to the existing finance literature, where this paper is the first paper that uses the principal component analysis and factor analysis techniques to predicts the exchange rates cyclical. Also, the sample of this paper uses vast number of currencies; includes both developed and developing currencies, while the past literature concentrates only on the developed countries.

II. LITERATURE REVIEW

Forbes et al. (2018) use a structural Vector Autoregression (SVAR) to examine the role of exchange rates movements in impacting the inflation rate in UK. Byrne et al. (2018) test the source of uncertainty in exchange rate forecasting models such as random variations in the data and estimation uncertainty, they find that those furcating model present more accurate results than the driftless random walk benchmark at all horizons. Moreover, using the benchmark allows to identify the set of related explanatory variables and the tine-varying weights for those explanatory variables. While Chen et al. (2018) find consistent mild RMB undervaluation as well as overvaluation across time, all Asian countries in their study have affected by RMB misalignments. Baghestani and Toledo (2017) show that there is a directional predictability for the US-Australia (US-UK) exchange rate between (1997–2007) but that does not work for the period (2008–2015) that makes difference between analysts' and random walk forecasts between them. On the other hand, Tsuchiya and Suehara (2015) show that for the short-term the exchange direction is not predictable as the long-term where the government keeps its foreign exchange policy over time. Beckmann et al. (2011).

III. HYPOTHESES

H1: The two risk factors with all currencies can predict the exchange rates cyclical behavior for US dollar to be bull (appreciation).

H2: The two risk factors with all currencies can predict the exchange rates cyclical behavior for US dollar to be bear (depreciation).
H3: We will retain all components from our PCA analysis.
H4: We will retain all factors from our factor analysis.

IV. METHODOLOGY, SAMPLE AND DATA

In this study, I examine the predictability of exchange rate cycles for ten exchange rate, Japanese yen (JPY), Indian rupee (INR), Brazilian real (BRL), South African rand (ZAR), Canadian dollar (CAD), new Turkish lira (TRY), Indonesian rupiah (IDR), Chinese yuan (renminbi) (CNY), Australian dollar (AUD), and the British pound (GBP) against the United States dollar (USD). These exchange rates represent a mix of reserve, funding and investment currencies and cover approximately 75% of average daily turnover (BIS, 2010). The monthly data span from January 2010 to December 2019. The explanatory risk factors, the TED spread, and the inflation. I employ 3-month money market rates for the calculation of TED spreads. The data obtains from DataStream, the FRED (FRB St. Louis) and the OECD. Because I study the behavior of bilateral exchange rates, the US dollar is treated as foreign currency. In a similar fashion I calculate the cross-country differentials by subtracting the US fundamentals (the foreign country) from the domestic fundamentals. For example, the term spread utilized in the model is actually the difference between the domestic term spread and the US term spread. The cycles, i.e., the bull and bear episodes, have been determined via the Bry and Boschan (1971) algorithm (BBA).

V. THE MODEL

I use asset price view of the exchange rate, and this currency price shows cyclical patterns, these series of patterns are basically binary events. So that, our model will start with binary modeling framework (binary event), with underlying unobserved process as follows:

$$S_t^* = \alpha + \sum_{h=0}^{q} \beta_h X_{t-h}^{\sim} + u_t \quad \text{Where } u_t \sim \text{i.i.d } (0,\sigma^2) \quad (1)$$

Where S_t^*: is the underlying unobserved process.
$X_{t-h}^{\sim}$: is the risk factors vector as cross-country differences (home minus foreign).
Because S_t^* is unobserved we will follow cycles via Bry and Boschan (1971)'s nonparametric algorithm[2] to create the binary variable as follows:

$$S_t = \begin{cases} 1, & if FXmarketinbearmoodatt, \\ 0, & otherwise \end{cases} \quad (2)$$

Setting u_t as i.i.d in the probit model we will have the followings:

$$\Pr(S_t = 1) = \Phi(\alpha + \sum_{h=0}^{q} \beta_h X_{t-h}^{\sim}) \quad (3)$$

where $S_t$represents the exchange rate cycles.

To account for persistence of asset price cycles we add the lagged dummy as exogenous variable, so the dynamic model will be as follows:

$$\Pr(S_t = 1) = \Phi(\alpha + \sum_{h=0}^{q} \beta_h X_{t-h}^{\sim} + \gamma S_{t-1}) \quad (4)$$

Following the literature as Kauppi and Saikkonen (2008) the lag h should match the forecast horizon. All parameters (α, β_h, γ) are estimating using the means of the method of the likelihood. After that we will estimate in-sample as Estrella (1998) using Pseudo-R^2. It compares the unconstrained and the constrained models based on the likelihood values, its formula will be as follows:

$$\text{Pseudo-}R^2 = 1 - \left[\left(\frac{\log(L_u)}{Log(lc)}\right)\right]^{-\frac{2Log(lc)}{T}} \quad (5)$$

To estimate $L_c$we restrict model (4) by assuming β_h= $\gamma = 0$as Kauppi and Saikkonen, (2008). However, as (Dueker, 1997) we should start with zero pseudo-R2 value by assuming $\beta_h = 0$ in equation (4)in order to assess the explanatory power and the relevance of the included variable $X^{\sim}$, the resulting statistic can be seen as an incremental pseudo-R2. On the other hand, For out-of-sample forecasts. We will use again Kauppi and Saikkonen (2008) and use iterated forecasting procedures. Specifically, h periods ahead forecasts can be calculated iteratively as follows:

$$\mathrm{P}_{t-h}(S_t = 1) = E_{t-h}[\Phi(\alpha + X_{t-h}^{\sim}\beta + \gamma S_{t-1})$$
$$= \sum_{y_{t-1}\in\{0,1\}} \mathrm{P}_{t-h}(y_{t-1})\Phi\,(\alpha + X_{t-h}^{\sim}\beta + \gamma S_{t-1}) \quad (6)$$

Where $\mathrm{P}_{t-h}(y_{t-1})$ are the probabilities of (y_{t-1}) to be either zero or one, conditional on information known in the forecast period $t-h$. In addition, to evaluate the out-of-sample forecasts. I assigned the value 1 for appreciation in the us dollar (bull), and the value 0 for depreciation in the us dollar (bear) for the logit and probit models.

Variables Definitions:

US: is the dependent variable and it is a binary variable takes the value 1 for appreciation in the us dollar, and the value 0 for depreciation in the us dollar.
Japan: the cross Japan differentials by subtracting the US fundamentals from the Japanese yen fundamentals.
China: the cross-China differentials by subtracting the US fundamentals from the Renminbi fundamentals.
India: the cross India differentials by subtracting the US fundamentals from the Indian rupee fundamentals.
Brazil: the cross-Brazil differentials by subtracting the US fundamentals from Brazilian real fundamentals.
UK: the cross British differentials by subtracting the US fundamentals from sterling pound fundamentals.
SouthAfrica: the cross-South Africa differentials by subtracting the US fundamentals from South African rand fundamentals.

Canada: the cross Canada differentials by subtracting the US fundamentals from the Canadian dollar fundamentals.
Turkey: the cross-Turkey differentials by subtracting the US fundamentals from new Turkish Lira fundamentals.
Indonesia:the cross Indonesia differentials by subtracting the US fundamentals from Indonesian rupiah fundamentals.
Australia:the cross Australia differentials by subtracting the US fundamentals from Australian dollar fundamentals.
TEDspreads: 3-month money market rates.
Inflation: the US inflation rate.

VI. ANALYSIS AND EMPIRICAL RESULTS

Part A: Logit and Probit Models:

Variable	Mean	Std. Dev.	Min	Max
US	0.8	.4016772	0	1
Japan	99.312	13.99505	75.98999	123.955
China	6.500289	.2714907	6.0488	6.9496
India	57.64123	8.448439	44.18	73.3675
Brazil	2.538103	.7515454	1.5328	4.08025
UK	0.6698428	.0610084	.58803	.81719
South Africa	10.49793	2.692045	6.6745	16.38914
Canada	1.149463	.1336954	.94355	1.4093
Turkey	2.433962	1.0114351	8505	15216.5
Indonesia	11391.48	1985.65	0	1.09405
Australia	0.8369769	. 1978366	0	1.09405
TEDspreads	0.3181667	.5039407	.01	2.75
Inflation	229.4201	10.4215	211.398	247.91

Table1: Descriptive statistics for all variables.

From the previous table we can notice that for 10-years monthly data we have 120 observations, Japan and Inflation have the highest standard deviation of 13.99505 and 10.4215 respectively. Furthermore, the only binary variable is the dependent variable (US) which tells if the US dollar is in appreciation (bull) or depreciation (bear), we can notice that from the maximum and minimum values of this variable from the previous table.

Country	OLS Coefficients	Probit Coefficient	Logit Coefficient
Japan	.003	-.071	-.115
China	$-.657^{*}$	9.494^{*}	15.02^{*}
India	.0114	.216	.381
Brazil	$.466^{*}$	-.160	-.026
UK	6.809^{*}	85.7^{*}	145.4^{*}
South Africa	-.0209	.498	.537
Canada	-2.028	-36.2^{*}	-59.1
Turkey	-.118	7.7	12.2
Indonesia	.00003	.0004	.0009
Australia	-.031	1.27	2.07^{*}
TEDspreads	$-.066^{*}$	2.43	4.21
Inflation	.0222	-.164	-.286

* Indicates significance at the 10% level.

Table 2: OLS, Probit, and Logit Regressions

From the OLS regression the R-squared = 0.4305 which means the independent variables explain about 43% of the variation in the US exchange rate appreciation and depreciation, while the Adj R-squared = 0.3661.On the other hand, we just have four significant independent variables at 10% level, three currencies (Renminbi, Brazilian real, Sterling pound) and one risk factor (Inflation). The negative coefficient for Renminbi means that Renminbi exchange rate is less likely to cause appreciation for US dollar exchange rate. A positive coefficient signs for both Brazilian real and Sterling pound mean that both of these currencies' exchange rates are more likely to cause appreciation for US dollar exchange rate. Finally, for the only significant risk factor (Inflation) a positive coefficient means that inflation is more likely to cause appreciation for US dollar exchange rate. From Probit regression, we have that observations are 119, the Pseudo R2 = 0.6330, while here we have different results than OLS regression where we do not have any significant risk factor, but we have three significant currencies at 10% level (Renminbi, Sterling pound, Canadian dollar), for both Renminbi and Sterling pound they have positive coefficients mean that both of these currencies' exchange rates are more likely to cause appreciation for US dollar exchange rate. While the opposite is true for Canadian dollar which is less likely to cause appreciation for US dollar exchange rate. From Logit regression, we have those observations are 119, Pseudo R2 = 0.6279 and it is close to Probit Pseudo R square, for the independent variables we can interpret them as the Probit table without any difference.

Country	OLS marginal effects	OLS average marginal effect	Logit marginal effects at the mean	Logit average marginal effect	Probit marginal effects at the mean	Probit average marginal effect
Japan	.003	.003	-2.31	-.006	-4.51	-.007
China	-.657	-.657	3.06	.867	6.05	.953
India	.011	.011	7.78	.022	1.38	.021
Brazil	.466	.466	-5.33	-.001	-1.02	-.016
UK	6.8	6.8	.0297	8.393	5.47	8.61
South Africa	-.0209	-.021	1.10	.031	3.17	.0499
Canada	-2.01	-2.02	-.001	-3.41	-2.31	-3.63
Turkey	-.118	-.118	2.50	.708	4.91	.772

Indonesia	.003	.003	1.97	.005	3.13	.004
Australia	-.030	-.030	4.22	.119	8.13	.128
TEDspreads	-.0655	-.065	8.60	.243	1.55	.244
Inflation	.0222	.0222	-5.83	-.0164	-1.05	-.0165

Table 3: Marginal effects (at the mean and average marginal effect)

Table 3 shows that the marginal effects at the mean and the average marginal effects for all types of regression (OLS, Logit, and Probit) for all independent variables, as we mentioned for OLS regression, the significant variables at 10% level are Renminbi, Brazilian real, Sterling pound and risk factor (Inflation). In addition, here we can interpret the magnitude of the coefficient and not just the sign, for Renminbi is about 65% less likely to cause appreciation for US dollar exchange rate, for both Brazilian real and Sterling pound are about 46.5% and 6 are more likely to cause appreciation for US dollar exchange rate respectively. Inflation just about 2% is more likely to cause appreciation for US dollar exchange rate. Regarding Probit and Logit regressions we also can interpret the magnitude as well as the sign of the coefficients.

Variable	Obs	Mean	Std. Dev.	Min	Max
US	120	0.8	.4016772	0	1
Plogit	119	0.7983193	.3227403	.0007844	1
PProbit	119	0.7970599	.3253431	6.57e-06	1
POLS	119	0.7983193	.2643987	.1546851	1.302336

Table4: Predicted probabilities

We can see from table4 that the probability of mean of being US dollar in appreciation is .8 in the sample, while the probability of the logit mean is .7983193, and .7970599 is the probability of Probit. Finally, the probability of OLS is .7983193. In conclusion, the probabilities are very close in all regressions.

Classified	D	D	Total
+	90	6	96
-	5	18	23
Total	95	24	119
Correctly Classified		90.76%	

Table 5: Percent correctly predicted values for Logit Model

From table 5 we can notice the true and false predictions, and the most important thing is the correctly classified is 90.76% which is perfect.

Part B: Principal Component Analysis and Factor Analysis:

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	7.91767	6.17927	0.6598	0.6598
Comp2	1.7384	.877678	0.1449	0.8047
Comp3	.860723	.129392	0.0717	0.8764
Comp4	.731331	.390659	0.0609	0.9373
Comp5	.340672	.19732	0.0284	0.9657
Comp6	.143351	.0288546	0.0119	0.9777
Comp7	.114497	.0520773	0.0095	0.9872
Comp8	.0624194	.0304385	0.0052	0.9924
Comp9	.0319809	.000460679	0.0027	0.9951
Comp10	.0315203	.0158203	0.0026	0.9977
Comp11	.0156999	.00396686	0.0013	0.9990
Comp12	.0117331	.	0.0010	1.0000

Table 6: Principal Component Analysis (PCA)

In table 6 we have 12 components in the first column, the first component has a very high Eigenvalue of about 7.92, this component by itself explains about 66% of the variation in data, from the third column we can see the differences between the Eigenvalue of one component to the other. Additionally, the second component explains about 14.5% of the variation in data, from the last column in the table we can see that first 2 components explain more than 80% of the variation in data. We will retain the first 2 components because the best rule is to retain components that have Eigenvalue exceeds one.

Variable	Comp1	Comp2	Unexplained
Japan	0.3061	-0.1759	.2046
China	0.0553	0.6806	.1706
India	0.3236	-0.2552	.05764
Brazil	0.3467	-0.0488	.04428
UK	0.2754	0.2795	.2635
South Africa	0.3412	-0.1271	.05037
Canada	0.3349	0.1092	.09118
Turkey	0.3187	0.0679	.1878
Indonesia	0.3453	-0.0636	.04868
Australia	-0.1931	-0.2161	.6236
TEDspreads	0.1199	0.4965	.4576
Inflation	-0.3185	0.1741	.1441

Table 7: Principal components (eigenvectors)

Table7 retain just the first 2 components, they can explain together about 80% of the variation in Japan, while about 83% of the variation in China, about 43% of the variation in India, for Brazil about 56%, about 74% for UK, half of the variation in South Africa data can be explained by the retain 2 components, about 91% of the variation in Canada, about 92% of the variation in Turkey, more than 51% of the variation in Indonesia, just about 38% of the variation in Australia data can be explained by the retained components, about 55% of the variation in TED spreads, and about 86% of the variation in Inflation

can be explained by the retained components as well. In the first column of the table, we can see the original variables, from the last column we can notice the percentage of the unexplained variations. In conclusion, the retain 2 components have a strong power of explaining the variation in the data of the original variables, the rule is to retain just the components that have higher than one eigenvalue.

Country	KMO
Japan	0.9225
China	0.4842
India	0.8668
Brazil	0.8786
UK	0.8417
South Africa	0.8685
Canada	0.8496
Turkey	0.7691
Indonesia	0.8655
Australia	0.9451
TEDspreads	0.4927
Inflation	0.8272
Overall	0.8373

Table8: KMO Measure of Sampling Adequacy

Notice in table 8 that the KMO values are really very high, the rule says for more than 0.50 KMO means we are justified in using principal component analysis. We are justified with 10 variables except China and TEDspreads, but they still very close to 0.50 KMO which means we have high correlations between variables and that is very good indicator for estimating the principal component analysis. Furthermore, the overall KMO is about 84% which is perfect.

Component	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.84784	6.29552	0.7441	0.7441
Factor2	1.55232	0.96804	0.1472	0.8913
Factor3	0.58427	0.02164	0.0554	0.9467
Factor4	0.56264	0.47791	0.0533	1.0001
Factor5	0.08473	0.04297	0.0080	1.0081
Factor6	0.04177	0.03499	0.0040	1.0121
Factor7	0.00678	0.01184	0.0006	1.0127
Factor8	-0.00506	0.01279	-0.0005	1.0122
Factor9	-0.01785	0.00778	-0.0017	1.0105
Factor10	-0.02562	0.00892	-0.0024	1.0081
Factor11	-0.03454	0.01638	-0.0033	1.0048
Factor12	-0.05092	.	-0.0048	1.0000

Table 9: Factor Analysis

Intable 9we have 12 factors in the first column, the first factor has a very high Eigenvalue of about 7.85, this factor by itself explains about 74% of the variation in data, from the third column we can see the differences between the Eigenvalue of one factor to the other. Additionally, the second component explains about 14.72% of the variation in data, from the last column in the table we can see that first 2 factors explain more than 89% of the variation in data. We will retain the first 2 factors because the best rule is to retain factors that have Eigenvalue exceeds one.

Variable	Factor1	Factor2	Uniqueness
Japan	0.8517	-0.2221	0.2252
China	0.1499	0.8371	0.2768
India	0.9109	-0.3333	0.0591
Brazil	0.9762	-0.0551	0.0439
UK	0.7649	0.3774	0.2725
South Africa	0.9613	-0.1644	0.0489
Canada	0.9421	0.1577	0.0875
Turkey	0.8970	0.1140	0.1823
Indonesia	0.9735	-0.0756	0.0466
Australia	-0.5063	-0.2031	0.7024
TEDspreads	0.3292	0.6219	0.5049
Inflation	-0.8962	0.2169	0.1497

Table 10: Factor Loadings Matrix

We can observe in table 10 that we again retain just two factors, because they have the best explanation power for variation in data. In addition, the last column is the uniqueness of these factors versus the commonality in explaining variation, the uniqueness is reversely related to commonality which can be calculated as commonality = 1- uniqueness value. Uniqueness is the error term of variable that is not explained by the variable and the commonality is the opposite which is explained by the variable.

VII. CONCLUSION

This paper investigates using several developing and developed currencies besides two risk factors (TEDspreads and the inflation) to predict the exchange rates cyclical behavior for US dollar [appreciation (bull), depreciation (bear)] using dynamic probit and logit models. In addition, I use the principal component analysis and factor analysis to know the components and factors that I should retain. The empirical findings reveal that risk factors are not key factors in determining the exchange rates cyclical behavior for US dollar. In addition, Sterling pound is the only variable which has a consistent result which is more likely to cause appreciation for US dollar exchange rate using all types of regressions. These finding are important for the federal bank to decide which currencies and factors can appreciate or depreciate the USD exchange rate cycles. It could be helpful for other researchers who are interested in exchange rate forecasting.

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