UNIVERSITY OF CAPE TOWN

FACTORS OF THE TERM STRUCTURE OF SOVEREIGN YIELD SPREADS AND THE EFFECT ON THE UNCOVERED INTEREST RATE PARITY MODEL FOR EXCHANGE RATE PREDICTION

By

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Abstract

Using a Principal Component Analysis (PCA) approach, we investigate the sovereign yield spread term structure of the BRICS economies against the U.S. We show that the term structure for these markets are primarily driven by three latent factors which can be classified as the spread level, slope and curvature factors. We further postulate that a country's yield curve contains valuable information about its future economic state and as such the PCA derived spread factors, which are based on the differences between sovereign yield curves, encapsulates material macro-economic information between the countries. In light of this, we show that augmenting the traditional Uncovered Interest Rate Parity model (UIRP) with these factors improves the models predictive accuracy of exchange rate movements.

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Table of Contents

List of Tables

List of Figures

1. Introduction

The Uncovered Interest Rate Parity (UIRP) is a well-known economic theorem which states that the expected change in the exchange rate between two countries should be equal to the difference in interest rates between the countries (Alexius, 2001). It thus follows that the country with the higher interest rate should expect to see their currency depreciate by this interest differential. As such sovereign yield spreads, which represent the difference between two governments yields of equivalent maturity, are an important factor in exchange rate forecasting models. In addition, yield spreads are also often used by market participants as an indicator as to the relative economic strength (or position) between two countries.

Practitioners also pay close attention to a country's sovereign yield curve due to its strong link to macroeconomic variables (Coroneo, Giannone and Modugno, 2015). It thus follows that expectations relating to changes in these economic factors play a key role in determining the future path of interest rates (Ang, Piazzesi and Wei, 2006; De Pooter, Ravazzolo and van Dijk, 2007). Evidently, central banks often respond to changes in a countries economic condition (most notably to changes in domestic growth and inflation) by using monetary policy to adjust the short end of the yield curve (Taylor, 1993; Fuhrer, 1996; Evans and Marshall, 1998; Jotikasthira, Le Lundblad, 2015). In addition, it is also widely accepted that the general level of longer-term rates, are established using risk-adjusted averages of the expected future short term interest rates (Woodford, 2003; Diebold, Piazzesi and Rudebusch, 2005) as well as a market price or time-varying premium (Jotikasthira, Le and Lundblad, 2015).

In light of the relationship between the short and long term rates as well as their link to the macro-economy, we incorporate the entire yield spread term structure into an exchange rate forecasting model. We accomplish this by using a Principal Component Analysis (PCA) approach to identify the key driving factors of the term structure of sovereign spreads.

At this point, we would like to highlight that the application of the PCA procedure, as well as the use of the derived latent factors, replicates the work previously done by Truck and Wellman (2016). Following their study, we apply PCA directly to the sovereign yield spreads and thereafter we examine the predictive power of the derived factors on exchange rate movements for 13, 26, 52 and 104 weeks ahead, i.e. 3, 6 ,12 and 24 months equivalently[1].

[1] The 3 months (13 weeks), 6 months (26 weeks), 12 months (52 weeks) and 24 months (104 weeks) forecasting horizons were chosen to be in line, and hence comparable, with research by Trück and Wellmann (2016). In

Unlike the Truck and Wellman (2016) study however, which only focused on developed countries, (namely: UK, Japan, Canada and Switzerland), our study analyses the FX and yield spreads of the BRICS economies, namely: Brazil, Russia, India, China and South Africa. These specific countries were chosen due to their strong economic relations and trade alliances with each other as well as their emerging market status (GovInn[2], 2013).

We would also like to highlight at this early stage, that due to the People's Bank of China (PBOC) pegging its currency, the yuan (CNY), to the U.S. dollar (USD), as well as the large amount of U.S. debt owned by the Chinese government, the inclusion of China in our analysis would not have been appropriate[3]. However, in an effort to be complete, it was decided to retain China in our study, given that the country forms part of the BRICS economies. Next, we considered the government bonds issued in the relevant country's currency and as such, the bonds were taken to be free of credit/default risk[4]. Following this, weekly FX and zero coupon bond yields were obtained from Bloomberg for the period 15/06/2007 to 17/06/2016[5].

Similar to prior research (Dungey et al., 2000; Boudoukh et al., 2005; Menkhoff et al., 2012, Truck and Wellman, 2016), the yield spread term structure for all the economies were calculated against the U.S. yields and were constructed across 12 maturities, ranging from 3 months, 6 months, 12 months and 24 months up to 120 months. Our analysis shows that the level, slope and curvature factors[6] estimated through PCA can explain up to 99% of the variation in the term structure of spreads for the BRICS economies. In addition to this and in line with earlier work, it was also found that the derived latent factors could be classified as the spread level, spread slope and spread curvature factors (Litterman and Scheinkman, 1991; Dai and Singleton, 2000, Afonso and Matins, 2012; Truck and Wellman, 2016).

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addition, the forecasting horizons was chosen to be weekly as this matched the frequency of the FX and yield data retrieved from Bloomberg. The reason for using weekly data, as opposed to monthly data, was to increase the number of data points in our analysis, given that we were only able to retrieve at most 10 years' worth of bond data for many of the BRICS countries.

[2] GovInn refers to the Centre for the Study of Governance Innovation.

[3] Please see appendix for more details on the trade and economic relations between China and the United States.

[4] Again, this follows from the Truck and Wellman (2016) study whereby the authors used the yields from locally issued government bonds which they considered to be risk-free.

[5] It is noted that due to the infancy of many of these markets (with South Africa being the exception), we were only able to retrieve just over 10 years' worth of bond data for many of the considered economies. As a result, it was decided that for comparability purposes the sample period would be restricted to the last 10 years.

[6] Incidentally, these are the first three factors and will be referred to as such later on in the study.

Given that an economy's yield curve is postulated to contain valuable information about a country's future macro-economic state (Rudebusch and Wu, 2008), which includes output, inflation and monetary policy, differences between the yield curves of two countries and hence between the same fundamentals of these economies are regularly used in exchange rate prediction models (Rossi, 2013). As such, we argue that including these latent factors, which encompass the cross-country differentials between bond yields and hence fundamentals, provides a promising approach to improving the forecasting accuracy of exchange rate models.

We support this view by showing that the forecasting precision of the traditional Uncovered Interest Rate Parity model (UIRP) is improved by including these latent spread factors. Using four model selection criteria's, namely: the Adjusted R-Squared, the Root Mean Square Error (RMSE), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), we show that the extended UIRP model (UIRP-Ext), which includes the PCA derived spread factors is superior to the traditional UIRP model. In addition, we use the Likelihood Ratio Test (LR-Test) to formally test and confirm the supremacy of the extended UIRP model. As such, our findings advocate for the inclusion of these latent spread factors in exchange rate forecasting models, and in particular, in the traditional UIRP model.

With this in mind, we contribute to previous macro-economic literature in the following ways: Firstly, our work builds on the Truck and Wellman (2016) study for advanced nations by investigating the yield spread dynamics of the BRICS economies (which is construed as representative of emerging market countries). In addition, we also argue for the relative value and importance of the PCA derived latent factors and not only do we link these factors to macro-economic variables, but we also show that incorporating these spread factors into exchange rate prediction models, and specifically into the traditional UIRP model, enhances the models forecasting accuracy.

The remainder of this study is organized as follows: We begin with a literature review on previous studies describing the relationship between yield spreads, macro-economic fundamentals and exchange rates in section 2. We then go on to describe how the data was obtained and enriched in section 3. Thereafter we outline the Principal Component Analysis procedure that was used to estimate and interpret the latent spread factors in section 4. Following this, we then setup the regression model, and provide the results of the tests used in our analysis in section 5, and lastly in section 6, we provide the conclusions from our investigation.

2. Literature Review

The term structure of interest rates or the yield curve essentially describes the relationship between bond yields and their term to maturity. Usually, the yield curve is used to describe the term structure of government bonds, which are commonly used as the benchmark or risk-free level of interest rates for a country. Accordingly, sovereign yield spreads, which represent the interest rate differential between two countries, may be calculated for various maturities, and as such, also exhibit a yield spread curve of their own.

Although the specific mandate for central banks varies from country to country, in general the banks are tasked with maintaining a nation's monetary and financial stability. Primarily, this requires that they keep prices stable, which they accomplish by means of inflation targeting (Taylor, 1993).

Accordingly, by controlling the level of short-term rates[7], central banks are able to manage a countries inflationary pressures. The adjustment of the short term interest rate however, also has implications and knock-on effects on other economic indicators such as domestic growth, consumer spending, unemployment and Gross Domestic Product (Favero, Niu and Sala, 2012 and Ludvigson and NG, 2009). It thus follows that there is a strong link and co-movement between the short end of the yield curve and macro-economic variables (Dewachter and Lyrio, 2006).

In light of this and in accounting for earlier work advocating that bond yields may be decomposed into investors' expectations about the future path of short term interest rates as well as a time-varying term premium (Campbell and Shiller, 1991; Crump, Eusepi and Moench, 2017), it follows that the yield curve of an economy may also contain valuable information relating to the expected future economic outlook of a country with respect to growth, GDP and inflation (Evans and Marshall, 2001; Rudebusch and Wu, 2008; Erdogen et al, 2015). As such, the shape and movements of a countries yield curve have become important indicators for both central banks in monetary policy decision making and market practitioners alike (Truck and Wellman 2016).

[7] Through monetary policy decision making.

With this in mind, we argue that the factors derived from the PCA decomposition of the yield spread term structure, encompass valuable information with respect to the cross-country economic differentials between the countries, and consequently may be key inputs for market practitioners in both carry trade strategies[8] and exchange rate prediction models.

This naturally leads us to the Uncovered Interest Rate Parity (UIRP) which postulates that the future exchange rate between two countries should adjust to the interest differential between those countries. The parity implies that regressing the exchange rate returns against the interest differential should produce a slope coefficient of one and an intercept of zero. That is:

$$\Delta S_{t+h} = i_t^h - i_t^{h*} + \rho_t \tag{1}$$

where ΔS_{t+h} is the logarithmic change in the nominal spot exchange rate (domestic currency per unit of foreign currency) between time t and $t+h$, with i_t^h and i_t^{h*} representing the respective domestic and foreign interest rates at maturity h and ρ_t being the risk premium for holding foreign currency investments at time t (Truck and Wellman, 2016). It is evident that the relationship builds on sovereign spreads of a certain maturity with the h - month spread encompassing information up to the maturity of the underlying interest rate instrument.

However, earlier studies have since rejected this model and have found that most often the estimated slope coefficient is negative, implying that the currency with the higher interest rate tends to appreciate (Chaboud and Wright, 2002)[9]. The failure of the UIRP condition was first highlighted by Fama (1984) whereby the author referred to the disconnect as the "Forward Premium Puzzle." More recently similar deviations between the UIRP and interest rates have been emphasized by Engel (2016) and Valchev (2016)[10]. This violation is also observed in

[8] In essence, a carry trade in its simplest form is an investment strategy that involves borrowing currency from a country with a low interest rate (funding currency), converting it to the currency of a country with a high interest rate (target currency) and investing the proceeds in the higher yielding assets of that country. According to the Covered Interest Rate Parity, any gains from the interest differential between the funding country and target country should be offset by the expected depreciation of the target currency - thus eliminating any arbitrage opportunities.

[9] Further to this, it is also mentioned in the Chaboud and Wright (2002) study that the carry trade was found to be profitable on average.

[10] We also note however that when running the UIRP regression over longer horizons, the rejection of the UIRP hypothesis become less distinct (Meredith and Chinn, 1998; Fujii and Chinn, 2001).

other more prominent economic exchange rate forecasting models as well. One of which is the Monetary Model.

The Monetary Model is an established and theoretically grounded model first introduced by Frenkel and Mussa (1985). The model asserts that exchange rates are the relative prices of assets and as such, are determined in organized markets whereby prices adjust instantaneously[11]. In addition to assuming that prices are flexible, the model also assumes that the Purchasing Power Parity (PPP)[12] always holds, which implies that the real exchange rate is constant over time (Diamandis, Georgoutsos and Kouretas, 1998; Boyko, 2002).

Although the assumptions of the Monetary Model appear to be unrealistic, especially in the short run, the model nonetheless illustrates the theoretical and economic relationship between exchange rates, money, real incomes and interest rates (Holod, 2000; Boyko, 2002).

Previous Studies testing the relevance of the Monetary Model have in general produced mixed and inconclusive results (Afat, Gomez-Puig and Sosvilla-Rivero; 2015). Cheung et al. (2005) concludes that the model is a poor predictor in out of sample tests and performs no better than a naïve random walk model, even when realized explanatory variables are used in the post sample period. In contrast however, Macdonald and Taylor (1992) contend that the Monetary Model outperforms the random walk model and other economic models in an out of sample forecasting contest. In a more recent study using panel data of co-integration estimates, Cerra and Saxena (2010) find further support for the validity of the Monetary Model.

Another commonly used model in exchange rate determination makes use of the Taylor Rule. In essence, the Taylor Rule is a popular model used by central banks in monetary policy decision making and postulates that the monetary authorities adjust the short-term nominal interest rate in response to changes in inflation and the output gap.

Building on this framework, Engel and West (2005) argue that in addition to the current fundamentals, exchange rates are also driven by expectations of future fundamentals. Accordingly, the authors show that exchange rate models can also be written as the present

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[11] Similarly, Dornbusch (1976) developed the monetary model using a sticky price variant whereby the author assumed that the prices of goods are sticky in the short run, and that PPP only holds in the long run.

[12] Using a “market basket of goods” approach, the Purchasing Power Parity (PPP) states that two countries’ currencies are in equilibrium if the market price of those goods, when adjusted for the exchange rate between those two countries, are the same.

value of both current and expected economic fundamentals. Similarly, by adopting the pricing model presented by Engel and West (2005), Chen and Tsang (2011) were able to show that the information contained between two countries yield curves were valuable inputs in forecasting exchange rates.

In related work involving the U.S. dollar and the Deutsche mark, Engel and West (2006) find a positive relationship between the model-based exchange rate[13] and the real exchange rate of the two countries.

Similarly, using Taylor Rule fundamentals, Molodtsova and Papell (2008) test the predictability of exchange rates over the post Bretton Woods period. The authors find significant results for 11 out of 12 currencies against the U.S. dollar.

Likewise, Mark (2009) uses the Taylor Rule fundamentals along with least squares learning rules to construct a model for exchange rate determination. The author finds that from 1973 to 2005, his progressive model captures six prominent reflections of the Deutsche mark/U.S. dollar real exchange rate.

In contrast, there have been numerous studies that, in general, have rejected the standard models relating exchange rates to economic variables (Sarno and Taylor, 2002; Bachetta and van Wincoop, 2013). In addition, Meese and Rogoff (1983) as well as subsequent research by Flood and Taylor (1997) and Rossi (2013) have found that a theoretical random walk model is a better predictor of exchange rates than traditional macro-economic models in the short run.

Given these findings, and in accounting for the fundamental information contained by the PCA derived spread factors, we contend that a possible way to advance these macro-economic models is to incorporate the derived latent factors into traditional forecasting models.

Our proposal is also supported by earlier work in which the PCA derived factors between two countries yield curves were found to be significant inputs in exchange rate prediction models (Ang and Chen, 2010; Chen and Tsang, 2013; Truck and Wellman, 2016).

[13] In their study, the authors used the present value of the difference between home and foreign output gaps and inflation rates to construct the model-based real exchange rate.

3. FX and Spread Data

3.1. Exchange Rate Data

Weekly FX rates for each of the BRICS economies (relative to the U.S. dollar) were obtained from Bloomberg. For our analysis, we considered the U.S. dollar as the home currency, with the respective BRICS currency being considered as the foreign currency. Furthermore, the exchange rates retrieved were obtained as the foreign currency (BRICS) per unit of the home currency (USD)[14].

Figure 1 below plots the time series of the log exchange rates of the considered countries for the period 15/06/2007 to 17/06/2016. All currencies, with the exception of the Chinese CNY depreciated against the dollar over the chosen period. In addition, the currencies for India and China appear to be relatively stable[15], with South Africa (ZAR) and Brazil (BRL) displaying a gradual weakening in their currencies. In addition, it is also noted that both of these countries (i.e. South Africa and Brazil) displayed a sudden and extraordinary depreciation in their currencies in 2015.

For Brazil, this was primarily due to the political turmoil and subsequent anti-corruption marches against then president Dilma Rousseff.

In South Africa, the infamous, "Nenegate" debacle, which saw the unexpected removal of then Finance Minister Nhlanhla Nene triggered a sell-off in South African assets and with that a notable depreciation in the rand. The Minister was replaced with the relatively unknown Desmond Van Rooyen. This caused the markets to panic and lead to a sell-off in the rand. Van Rooyen was then replaced a few days later by the more familiar Pravin Gordhan (who had held the position of Finance Minister before). This saw the markets settle and regain some confidence in the country again, which resulted in the rand strengthening and return to levels similar to pre "Nenegate".

Although being fairly stable for most of the sample period, there was a drastic depreciation in Russian RUB currency towards the end of 2014. It is noted that since the Russian economy

[14] Thus a rise in the exchange rate meant an appreciation of the USD currency with a decrease representing a depreciation.

[15] As highlighted previously, we note that the intervention by the PBOC in the FX market, may explain the observed stability of the USDCNY currency pair over the considered sample period. For more on this, please see the appendix for more details on the trade and economic relations between China and the United States.

depends heavily on crude oil exports, the sudden drop in oil prices in December 2014 largely contributed to the depreciation of the Russian Ruble during this period. This was followed by a prolonged period of increased volatility for the USDRUB currency pair.

Figure 1 - Log Exchange Rates

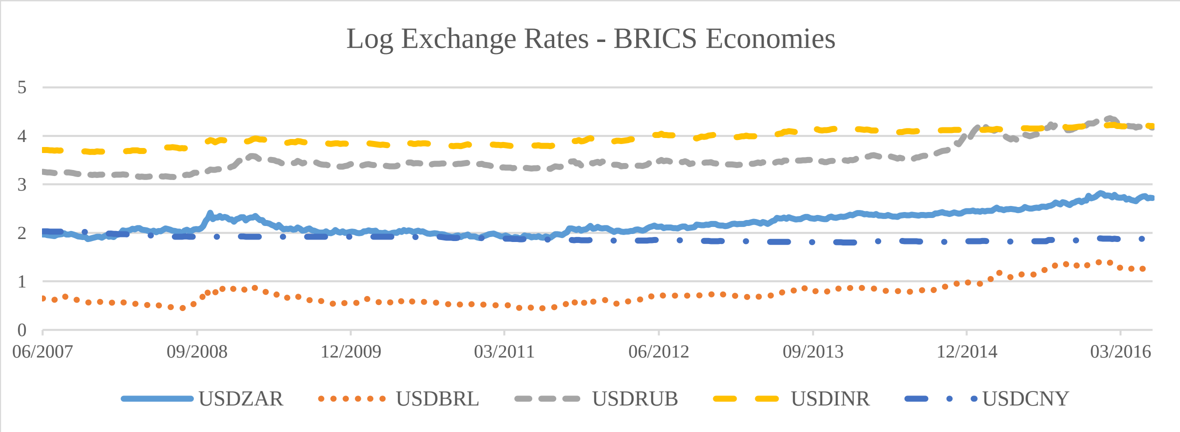


Figure 1. Log Exchange Rates: Time Series of the log exchange rates for USD against the BRICS currencies, namely: Brazil (BRL), Russia (RUB), India (INR), China (CNY) and South Africa (ZAR) for the sample period 15/06/2007 - 17/06/2016. The exchange rate is measured as the foreign currency (BRICS) per unit of the home currency (USD). Thus an increase in the exchange rate represents a depreciation in the foreign currency (BRICS) and an appreciation of the home currency (USD).

3.2. Spread Data

Again for our analysis, we looked at the sovereign yields for each of the BRICS countries as well as the United States. It should be noted that the considered yields were obtained from bonds issued in the respective country's currency and as such would have little to no credit or default risk.

Accordingly, the zero yields for these economies were obtained directly from Bloomberg for the period 15/06/2007 to 17/06/2016. The frequency of the yields retrieved was weekly and the term structure was constructed using 12 maturities ranging from 3 months, 6 months, 12 months, 24 months up to 120 months. Following this, we then calculated the weekly sovereign yield spreads $\Delta S\, y_t^h$ as the difference between the sovereign yields of two countries $Sy_t^h - Sy_t^{h*}$ of equal maturity h. Since the U.S. economy is widely viewed as an advanced market, we used the sovereign yields of the U.S. as the benchmark yield from which we calculated the term structure of yield spreads for each of the BRICS economies. That is, we considered the yield curves of the BRICS economies as the foreign curve (Sy_t^h) and the yield curve of the U.S. as the home curve (Sy_t^{h*})[16]. As such we obtain five datasets of sovereign spreads; namely: Brazil – U.S. (BR-US), Russia – U.S. (RU-US), India – U.S. (IN-US), China – U.S. (CH-US) and South Africa – U.S. (SA-US).

3.3. Spread Statistics

Table 1 below provides a summary of the statistical analysis implemented on the relevant sovereign yield spreads (for the selected maturities: 3 months, 12 months, 60 months and 120 months)[17]. As could be expected, the mean spreads for all the BRICS economies are positive. This is due to these countries being labelled as emerging markets, compared to the benchmark U.S. economy which is considered to be an advanced market. As such the growth prospects, as well as the risks to growth, are anticipated to be higher for the BRICS countries, resulting in higher term premiums and consequently higher yield curves.

Using the mean spreads as an indicator, it is interesting to note that the shape of the term structure of yield spreads for two economies (namely: Brazil and Russia) is humped with the remaining three (i.e. India, China and South Africa) being downward sloping. This is in contrast to previous research on sovereign yield spreads performed on developed countries, in which it was found that the term structure of spreads, which were also measured against the U.S., were upward sloping (Trück and Wellmann, 2016). Further to this, our analysis also revealed that for all the considered countries, the average 3 months spread was higher than the average 10 years spread for the period under review. This observation does not seem unreasonable when we consider that during the Global Financial Crises (GFC) of 2007-2009, the Federal Funds Target Rate (short-term interest rate) in the U.S. was cut to almost zero percent by the Federal Open Market Committee (FOMC), where it remained for the better part of 7 years[18]. In addition, longer term rates in the U.S. also dropped during this period but the impact was not as drastic and did not last as long. These observations help explain our finding of a lower average long term spread when compared to the short term average (i.e. average 10 years spread vs. 3 months spread).

[16] This is also consistent with the way the FX data was retrieved from Bloomberg.

[17] The selected maturities were chosen to be consistent with previous research by Trück and Wellmann (2016).

[18] The FOMC began to increase the Federal Funds Target Rate again in December 2015.

We also find that for all five of the BRICS economies, the yield spreads for the shorter maturities (3 months) appears to be more volatile than the longer maturities (120 months). For example, we obtain a standard deviation of 2.214 and 1.815 for the 3 months yield spreads of Brazil and South Africa respectively. In contrast, we compute the 120 month standard deviation for Brazil as 1.702 and South Africa as 0.832. This is in line with previous findings on developed economies (Trück and Wellman, 2016).

Lastly we show the correlation coefficients for each yield spread at different maturities. As can be expected, the spreads are highly correlated for adjacent maturities. The correlation between the 3 months and 120 months spreads range from 0.062 to 0.876 with the correlation between the 60 months and 120 months spreads ranging from 0.879 to 0.951.

Overall, we deduce the following from the yield spread statistics:

- The long end (120 months) of the yield spread curve appears to be less volatile than the short end (3 months).
- The term structure of yield spreads, as depicted by the average yield spreads, may be humped (Brazil and Russia) or downward sloping (India, China and South Africa).
- The yield spreads for adjacent maturities are highly correlated.

Table 1 - Sovereign Yield Spreads: Descriptive Statistics

Selected Sovereign Yield Spreads - Descriptive Statistics										
BR-US Spread										
Maturity (Months)	**Mean**	**Median**	**Std. Dev**	**Range**	**Min**	**Max**	**Corr(3)**	**Corr(12)**	**Corr(60)**	**Corr(120)**
3	10.48	10.575	2.214	8.299	6.306	14.605	1			
12	10.735	10.961	2.18	9.515	5.712	15.227	0.96	1		
60	10.897	10.867	1.744	11.687	5.416	17.103	0.834	0.863	1	
120	10.066	9.794	1.702	10.738	5.19	15.927	0.805	0.803	0.967	1
RU-US Spread										
Maturity (Months)	**Mean**	**Median**	**Std. Dev**	**Range**	**Min**	**Max**	**Corr(3)**	**Corr(12)**	**Corr(60)**	**Corr(120)**
3	6.154	5.718	2.837	14.72	0.269	14.989	1			
12	6.695	6.059	2.749	14.983	0.518	15.501	0.981	1		
60	6.763	6.577	2.539	13.304	1.006	14.31	0.851	0.914	1	
120	6.102	5.982	2.584	12.404	1.055	13.459	0.765	0.82	0.936	1

IN-US Spread										
Maturity (Months)	Mean	Median	Std. Dev	Range	Min	Max	Corr(3)	Corr(12)	Corr(60)	Corr(120)
3	6.799	7.404	1.975	10.96	-0.454	10.506	1			
12	6.805	7.389	1.743	7.862	2.172	10.034	0.985	1		
60	6.237	6.481	1.25	5.509	2.683	8.192	0.921	0.928	1	
120	5.339	5.79	1.194	4.585	2.608	7.193	0.876	0.884	0.951	1

CH-US Spread										
Maturity (Months)	Mean	Median	Std. Dev	Range	Min	Max	Corr(3)	Corr(12)	Corr(60)	Corr(120)
3	2.18	2.367	1.249	7.497	-2.573	4.924	1			
12	2.07	2.17	1.232	6.614	-2.465	4.149	0.981	1		
60	1.506	1.603	0.955	4.686	-1.504	3.182	0.867	0.909	1	
120	0.876	1.048	0.764	3.236	-1.074	2.162	0.718	0.76	0.928	1

SA-US Spread										
Maturity (Months)	Mean	Median	Std. Dev	Range	Min	Max	Corr(3)	Corr(12)	Corr(60)	Corr(120)
3	7	6.69	1.815	8.028	4.544	12.572	1			
12	6.591	6.53	1.177	5.871	4.494	10.365	0.881	1		
60	6.104	6.148	0.737	5.197	3.504	8.701	0.41	0.604	1	
120	5.702	5.714	0.832	5.796	2.839	8.635	0.062	0.261	0.879	1

Table 1: Descriptive statistics of the weekly sovereign yield spreads, of the BRICS countries, for the time period from 15/06/2007 to 17/06/2016. For each spread and selected maturities (3 months, 12 months, 60 months and 120 months) we report the mean, median, standard deviation, range, min, max and correlations between the reported maturities.

We note that some of these observations are in line with earlier work found on yield curve datasets (Poorter, 2010; Koopman and van der Wel, 2013), namely: the short end of the spread curve is more volatile than the long end and that yield spreads at adjacent maturities are highly correlated . It is also noted however, that unlike conventional yield curves that usually display an upward sloping and more concave shape, the yield spread curves, for the considered BRICS economies, were found to be either humped or downward sloping.

3.4. Yield Spread Behavior

We next consider the evolution of yield spreads for the short (3 months), medium (36 months) and long (120 months) tenors[19] over the considered sample period – see figures 2-4 below.

[19] Again, the tenors were chosen to be comparable with research by Trück and Wellmann (2016) in which the authors used the 3 months, 36 months and 120 months maturities as proxies for the short, medium and long term periods respectively.

We note that for all the considered maturities, Brazil has the highest spreads amongst the BRICS economies, with China having the lowest.

Further to this, we also observe that spreads for each of the BRICS countries, have in general, increased over the sample period, with all spreads exhibiting a characteristic spike during the GFC in 2007-2009. As mentioned earlier, this is when the U.S. cut their short-term interest rates to nearly zero percent. This in an effort to stimulate economic growth and maintain stability in the country. Subsequent to this, the central banks for all of the BRICS economies, also followed the U.S. and reduced their short-term lending rates, which resulted in a narrowing of their sovereign yield spreads.

Thereafter, yield spreads for the BRICS countries remained fairly flat with the exception of Brazil, Russia and South Africa, which experienced a sudden and sharp increase in their spreads in 2014-2015. The surge in these countries yields can be explained as follows:

- In Brazil, a series of anti-corruption marches, in which protesters denounced the government and then President Dilma Rousseff lead to a sell-off in Brazilian bonds and consequently an increase in bond yields.

- For Russia, the increase in spreads can be attributed to two reasons. The first being the rapid fall in oil prices towards the end of 2014 and the second the result of economic sanctions imposed on Russia following their capture of Crimea and their military intervention in Ukraine in 2015.

- In South Africa, the unexpected removal of then Finance Minister Nhlanhla Nene ("NeneGate") triggered a sudden sell-off in South African assets and contributed to a significant increase in bond yields. This was particularly the case for the longer dated (10 years) South African bonds. With the appointment of the well-known Pravin Gordhan as Finance Minister a few days later, bonds yields dropped again to levels slightly above pre "NeneGate".

Further to this, the difference between the short-term and long-term spread volatility, mentioned earlier, is also visually evident from figures 2-4 below. As can be seen, the short-term spreads are notably more volatile than long-term spreads (which have remained fairly stable throughout the sample period), and can be taken as an indication that the underlying long-term differences between two countries economic position do not vary as quickly as changes in their short-term fundamentals.

Figure 2 - 3 Months Sovereign Yield Spreads

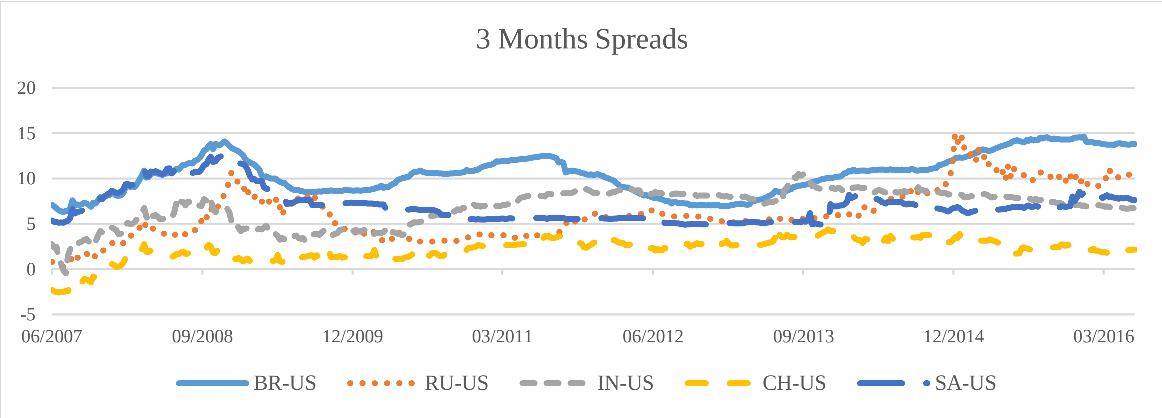


Figure 3 - 36 Months Sovereign Yield Spreads

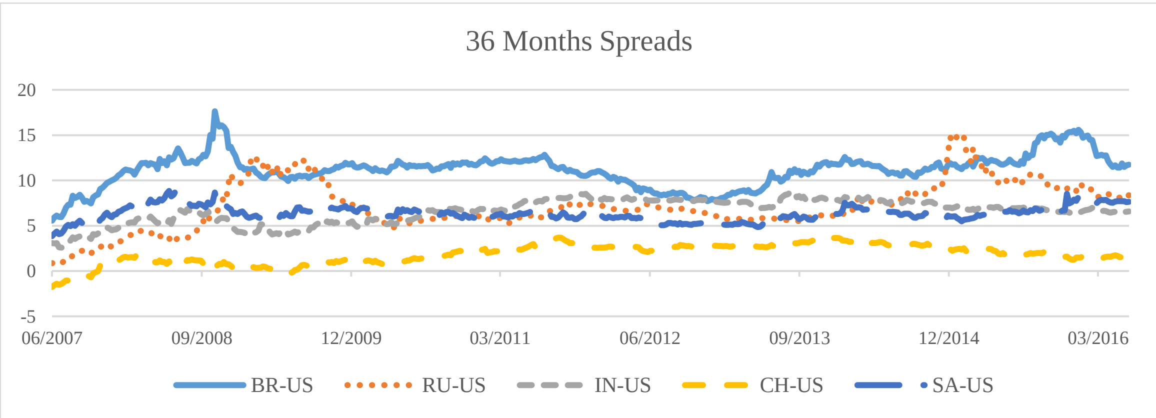
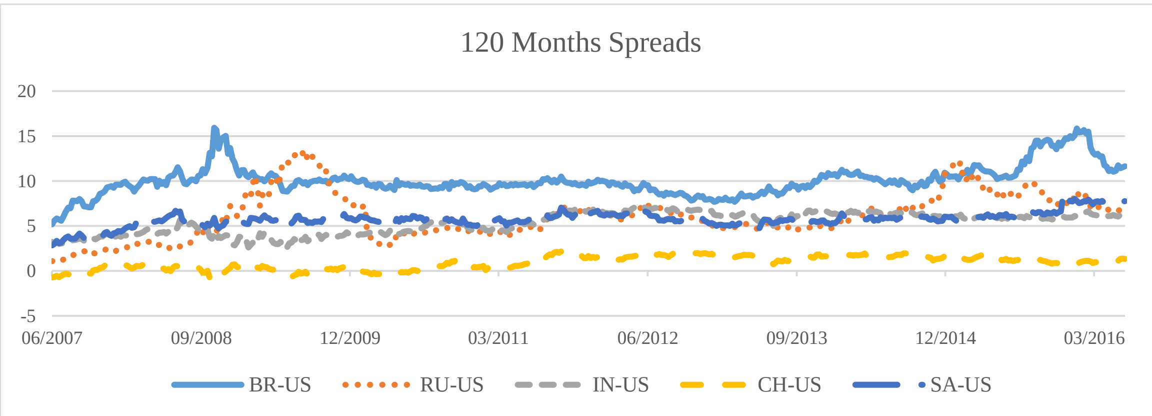


Figure 4 - 120 Month Sovereign Yield Spreads



Figures 2-4. Sovereign Yield Spreads: Time series of the BRICS countries sovereign yield spreads for the selected short term (3 months), medium term (36 months) and long term (120 months) maturities. We plot the BR-US, RU-US, IN-US, CH-US and SA-US sovereign yield spreads for the sample period 15/06/2007 to 17/06/2016.

4. Principal Component Analysis (PCA)

4.1. PCA of the Spread Term Structure

The primary goal of this section is to identify and investigate the underlying factors driving the term structure of sovereign spreads. These factors are derived using Principal Component Analysis (PCA). The procedure makes use of a basic method that is commonly used to reduce the number of correlated variables (i.e. the dimensionality) of a data set into a smaller number of uncorrelated factors called principal components. As such, the method allows us to encapsulate the information, contained in the sovereign spread term structure, in a more parsimonious form.

Accordingly, using this approach we were able to deconstruct the yield spread curves for the BRICS economies by computing the eigenvalues and corresponding eigenvectors from the correlation matrix of the underlying datasets. This is in line with earlier studies using PCA to investigate the term structure of interest rates (Duffee, 2011; Barber and Copper 2012; Truck and Wellman, 2016). Overall, we found the PCA calculations to be fairly straight forward and a convenient choice for our analysis.

4.2. PCA Procedure

The concept behind Principal Component Analysis is to find a linear combination of variables (Y_t) that can explain the highest amount of variance in a system. The coefficients of this linear combination are called loadings (α_i) with the combination itself called the "component" or "factor", (i.e. $X_{i,t} = \alpha_i' Y_t$)[20].

From this, we are able to obtain the first principal component or factor by maximizing the following equation[21] and solving for α_1. That is:

[20] Note that we will use the term component or factor interchangeably throughout our study.

[21] It is noted that in order to get a unique solution, it is common practice to arbitrarily fix the Euclidian norm of the loadings to one.

$$Var(X_1) = Var(\alpha_1^{'}Y) = \alpha_1^{'}YY^{'}\alpha_1 = \alpha_1^{'}\sum\alpha_1$$

$$\| \alpha_1 \| = \alpha_1^{'}\alpha_1 = 1$$

With $\sum$ being the covariance matrix (or correlation matrix) of the underlying data $Y = [Y(\tau_1), Y(\tau_2), ..., Y(\tau_m)]$ and α_1 being the loading of the first factor.

The variance of the linear combination is maximized by solving for the following Lagrange equation:

$$\mathrm{L} = \alpha_1^{'}\sum\alpha_1 - \lambda_1(\alpha_1^{'}\alpha_1 - 1) \tag{2}$$

A solution is then found by differentiating (2) with respect to α_1 and λ_1:

$$\alpha_1^{'}\alpha_1 - 1 = 0$$

$$(\Sigma - \lambda_1 I_m)\alpha_1 = 0$$

It thus follows, from these equations, that the first factor (X_1) has the coefficients of the eigenvector ($\alpha_1 = B_{1PC}$) and corresponds to the highest eigenvalue (λ_1).

Now, after identifying the first factor X_1 (from the first eigenvalue and corresponding eigenvector decomposition), the next step would be to determine a second factor X_2 which has unit length and is orthogonal to the first factor (i.e. $Cov(\alpha_2^{'}Y_t, \alpha_1^{'}Y_t) = 0$). Similarly to before, we obtain the following Lagrange system:

$$L = \alpha_2^{'}\Sigma\alpha_2 - \lambda_2(\alpha_2^{'}\alpha_2 - 1) - \phi\lambda_1\alpha_2^{'}\alpha_1 \tag{3}$$

$$0 = \Sigma\alpha_2 - \lambda_2\alpha_2 - \phi\lambda_1\alpha_1 \tag{4}$$

By multiplying (4) by $\alpha_2^{'}$ we obtain:

$$\alpha_2^{'}\Sigma\alpha_2 - \lambda_2\alpha_2^{'}\alpha_2 - \phi\lambda_1\alpha_2^{'}\alpha_1 = 0$$

$$(\Sigma - \lambda_2 I_m)\alpha_2 = 0$$

Which is nothing more than the familiar eigenvalue equation. This time though, the coefficients of the second eigenvector ($\alpha_2 = B_{2PC}$) relate to the loadings of the second factor (X_2) and corresponds to the second highest eigenvalue (λ_2).

Following this process, we can identify the eigenvalues and corresponding eigenvectors up to the rank of the data covariance/correlation matrix. Eigenvalues are zero beyond the rank, and as such we can assign eigenvectors arbitrarily[22].

To summarize, by following an eigenvalue and corresponding eigenvector decomposition of the covariance or correlation matrix, we are able to perform a Principal Component Analysis on the underlying data as follows:

$$\Sigma = YY' = B_{PC}' \Lambda B_{PC}$$

$$X_t = (\alpha_1, \alpha_2, ..., \alpha_m)' Y_t = B_{PC}' Y_t \tag{5}$$

With B_{PC} representing the eigenvector matrix of the covariance/correlation matrix Σ and $X_t = [x_{1t}, x_{2t}, ..., x_{mt}]$ being the factor matrix.

As mentioned previously, these Principal Components (PC's) are orthogonal, independent and are extracted from the data in a natural and simplistic way. In addition, it is also noted that X_t has the same dimensions as the underlying data Y_t.

For the analysis that follows, we would like to highlight that the PCA procedure was applied directly to the standardized sovereign spreads (i.e. spreads with zero mean and unit variance)[23].

4.3. Dimension Reduction

Due to the eigenvectors being orthogonal, it can be shown that equation (5) can be expanded into the following regression equation:

$$\mathrm{Y}_t = B_{1PC} x_{1t} + B_{2PC} x_{2t} + ... + B_{mPC} x_{mt} \tag{6}$$

[22] It is noted though, that with real data, eigenvalues are seldom zero due to noise.

[23] Please see Appendix for an outline of the Principal Component modification procedure.

From which it can be deduced that it is possible to reduce the number of variables from this equation, given that the Principal Components are orthogonal. Consequently, omitting a variable from this regression will not cause bias to any of the other coefficients as each factor independently contributes a specific portion to the co-efficient of determination (or R^2 measure)[24]. That is:

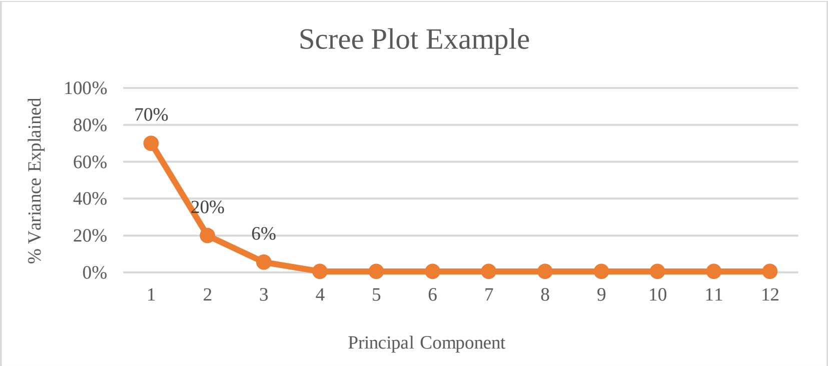
$$Var(b_{ijPC} X_j) = b_{ijPC} X_j X_j^{'} b_{ijPC} = \lambda_j b_{ijPC}^2$$

$$Var(Y_i) = \sum Var(b_{ijPC} X_j) = \sum_{j=1:m} \lambda_j b_{ijPC}^2$$

$$\sum_{i=i:m} Var(Y_i) = \sum_{j=1:m} \lambda_j$$

with $Y_i = [\mathrm{y}_{i1}, \mathrm{y}_{i2}, ..., \mathrm{y}_{it}]$ and $X_j = [x_{j1}, x_{j2,}, ..., x_{jt}]$. Consequently, it can be seen that Principal Components corresponding to a relatively low eigenvalue (λ_j) can be omitted from the equation with little loss of accuracy. Accordingly, the process simplifies and makes it straightforward to identify and remove those PC's that make a trivial contribution to the model.

A common approach used to determine the number of PC's, is to make use of a scree plot. Essentially, a scree plot is a graph that plots the total percentage of variance explained on the y-axis with the corresponding Principal Component on the x-axis. Given that the first PC explains the most variation, with the second PC the second most variation, and so on, scree plots are typically arranged to show the PC's in ascending order[25], similarly to the graph below:



[24] The co-efficient of determination or R-Squared measure, indicates the proportion of the variation that can be explained by the regression model and is obtained by dividing the regression sum of squares by the total sum of squares.

[25] Consequently the percentage of variation explained is shown in descending order.

The above example illustrates visually that the first three Principal Components are able to explain most of the variance in the underlying data. The remaining PC's which are associated with smaller eigenvalues have minimal explanatory power, and as such can be omitted.

Interestingly, the term "scree" is taken from the word for rubble at the bottom of a mountain and stems from the fact that the plot looks like the side of a mountain. The test is visual and postulates to stop including PC's at the point where the mountain ends. In this regard, it can be seen that this approach involves a certain amount of subjective judgement.

Another widely used approach is called the Kaiser-Guttman criterion[26]. According to this rule, only those Principal Components that are able to explain more variance than an original variable should be retained. As such the criteria suggests keeping PC's with eigenvalues that are greater than one.

4.4. Factor Dynamics

Following the PCA procedure outlined above, we are able to identify and extract the latent factors from the correlation matrix of the underlying data. Table 2 below shows the variance explained by the first three Principal Components extracted from the yield spreads of the BRICS countries.

Table 2 - Variance Explained by the First Three Principal Components

Factor	Brazil	China	India	Russia	South Africa
F_1	91.80%	91.87%	95.61%	91.20%	70.81%
F_2	6.07%	6.95%	3.12%	6.99%	25.38%
F_3	1.77%	0.78%	0.80%	1.23%	2.50%
Total	***99.65%***	***99.60%***	***99.53%***	***99.42%***	***98.68%***

Table 2: Variance explained by the first three Principal Components (F_1, F_2, F_3) in percent. The PC's were extracted using Principal Component Analysis (PCA) on Brazil's, Russia's, India's, China's and South Africa's sovereign yield spread curves over the time period 15/06/2007 to 17/06/2016.

Our results show that the first three factors are able to explain between 98.68% - 99.65% of the variance in the underlying spread term structure. Interestingly, we find that the first component

[26] The method requires standardised variables with unit variance.

accounts for more than 90% of the variance in all countries except South Africa, which only explains around 70.81%. The remaining factors explain a further 3.12% to 25.38% and 0.78% to 2.5% for the second and third factors respectively. Using the scree plot method[27], we find that the first three factors should naturally be retained for the considered countries, and accordingly allows our research to be comparable with factor interpretations from previous studies (Trück and Wellmann, 2016).

Following this, we plot the time series of the latent factors in figures 5-7 below, from which we see that the three estimated factors have behaved rather differently. It is noted however, that all factors exhibited increased volatility during the GFC. Thereafter we find that, in general, for each factor, the time series of the different spread pairs move together rather closely, aside from idiosyncratic shocks resulting from social and political unrest (namely: protests in Brazil, Russia's capture of Crimea, Nenegate, etc…).

Figure 5 - PCA Factor 1

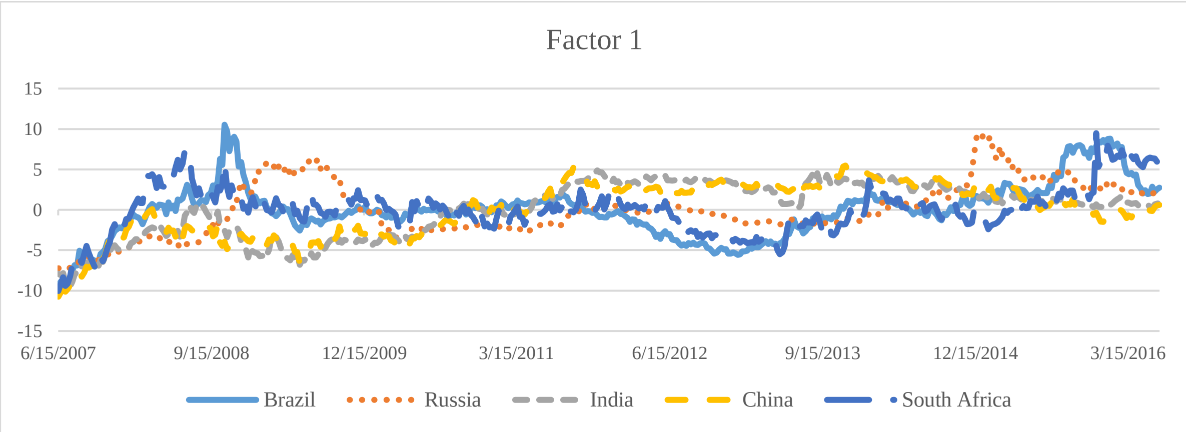
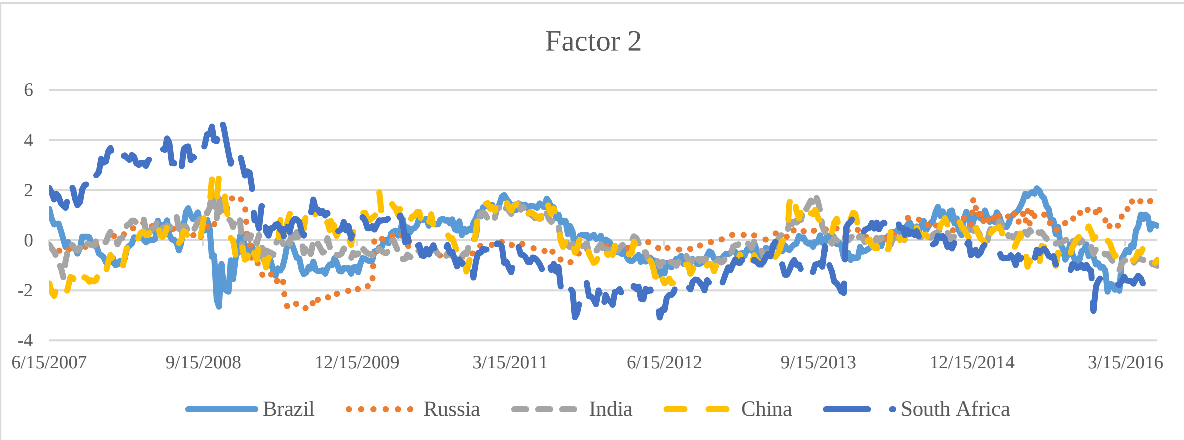
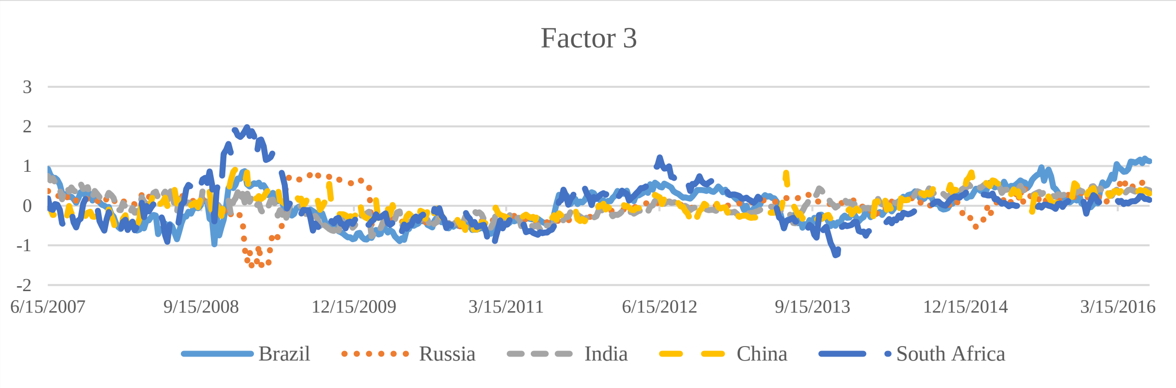


Figure 6 - PCA Factor 2



[27] Please see Appendix for scree plots.

Figure 7 - PCA Factor 3



Figures 5-7. PCA Factors: Time series of the first three factors (F_1, F_2, F_3) estimated by Principal Component Analysis (PCA) for the BR-US, RU-US, IN-US, CH-US and SA-US sovereign yield spread curves for the sample period 15/06/2007 to 17/06/2016.

4.5. Interpreting the factors – Level, Slope and Curvature

After determining the number of factors to retain, we further analyze the estimated latent factors (F_1, F_2 and F_3) by plotting their loadings as a function of maturity, see figures 8-10 below. Examination of the graphs show that the first factor is positive (constant) across all maturities with the second factor displaying positive loadings at the front-end and negative loadings at the back-end of the yield curve. The third component was found to have positive loadings at both the short and long ends of the curve and a negative loading around the belly of the curve.

Accordingly and in line with previous studies (Dai and Singleton, 2000; Bikbov and Chernov 2010; Afonso and Martins, 2012; Truck and Wellman, 2016), we interpret the first component to be the level factor with the second and third components taken as the spread and curvature factors respectively.

Figure 8 - PCA Factor 1 Loading

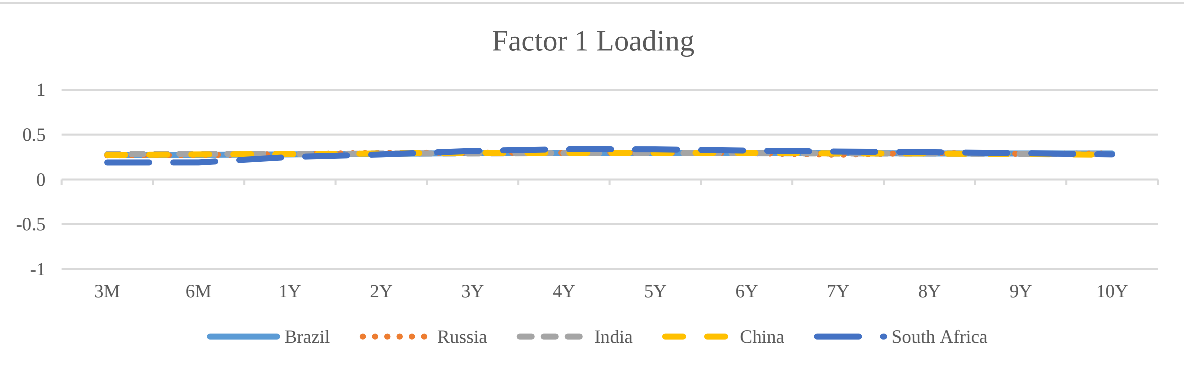


Figure 9 – PCA Factor 2 Loading

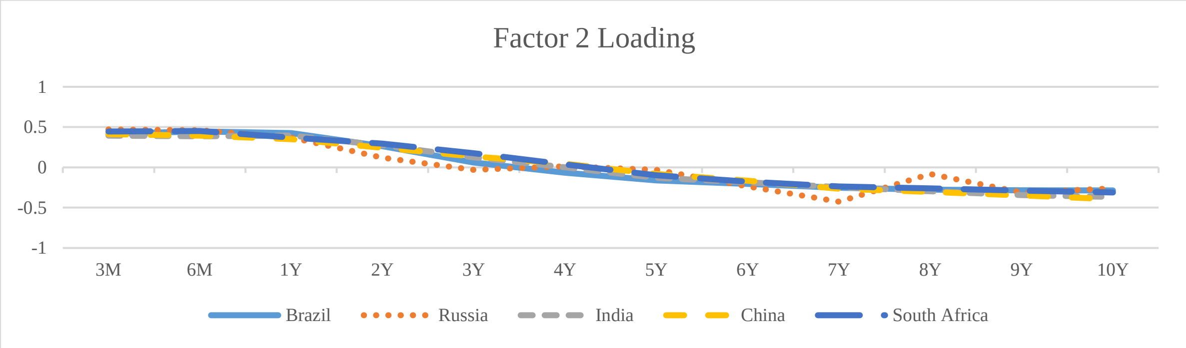
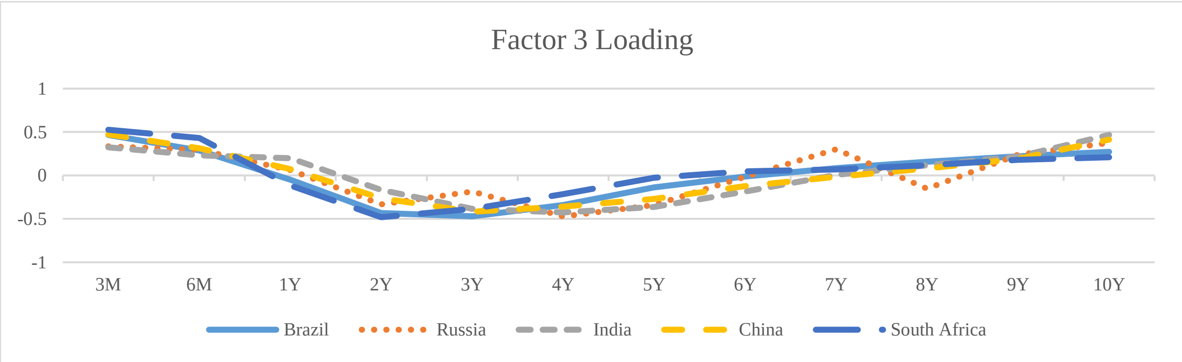


Figure 10 - PCA Factor 3 Loading



Figures 8-10. PCA Factor Loadings: We plot the factor loadings, as a function of maturity, for the first three factors of Brazil's, Russia's, India's, China's and South Africa's sovereign yield spreads. We note that Principal Components are not unique up to sign, i.e. multiplying a Principal Component by (-1) has no effect on the explanatory power of the component.

Next, following research by Truck and Wellman (2016), we show further support for our readings of the principal components by looking at the time series between the PCA derived latent factors and the empirical factors. As mentioned earlier, we consider the 3 months spread to characterize the short-end of the spread curve with the 36 months spread and 120 months spread depicting the medium-term and long-end of the spread curve respectively. Using these selected spreads, we then compute the empirical spread, slope and curvature factors as follows[28]:

- Empirical Level = average of the three spreads (i.e. average of the 3 months, 36 months and 120 months spreads)
- Empirical Slope = 120 months spread – 3 months spread
- Empirical Curvature = 2 x (36 months spread) – (3 months spread + 120 months spread)

[28] The empirical factor calculations follows from earlier work by Afonso and Martins (2012) and Truck and Wellman (2016).

Following this, we then examine the correlation of the time series between the estimated and empirical factors. We present our findings in the table 3, as well as a graphical representation of the relationship for South Africa in figures 11-13 below. In general, we find the correlations to be notably high, and particularly so for the first factor which ranges from 0.882 to 0.996. We also observe relatively high correlations for the second and third factors which ranges from 0.678 to 0.985 and 0.746 to 0.986 respectively. Given these results, we find further support to interpret the estimated latent components as the spread level, slope and curvature factors.

Table 3 – Correlation: Estimated vs. Empirical Factors

Factor	Brazil	Russia	India	China	South Africa
F_1-Level	0.994	0.995	0.996	0.992	0.882
F_2-Slope	0.913	0.985	0.678	0.849	0.954
F_3-Curvature	0.986	0.746	0.845	0.860	0.877

Table 3: Correlation between the time series of the first three estimated factors (F_1, F_2, F_3) and the empirical level, slope and curvature estimates, for BR-US, RU-US, IN-US, CH-US and SA-US sovereign spreads over the time period 15/06/2007 - 17/06/2016.

Figure 11 - SA: Empirical Level vs. Estimated Factor 1

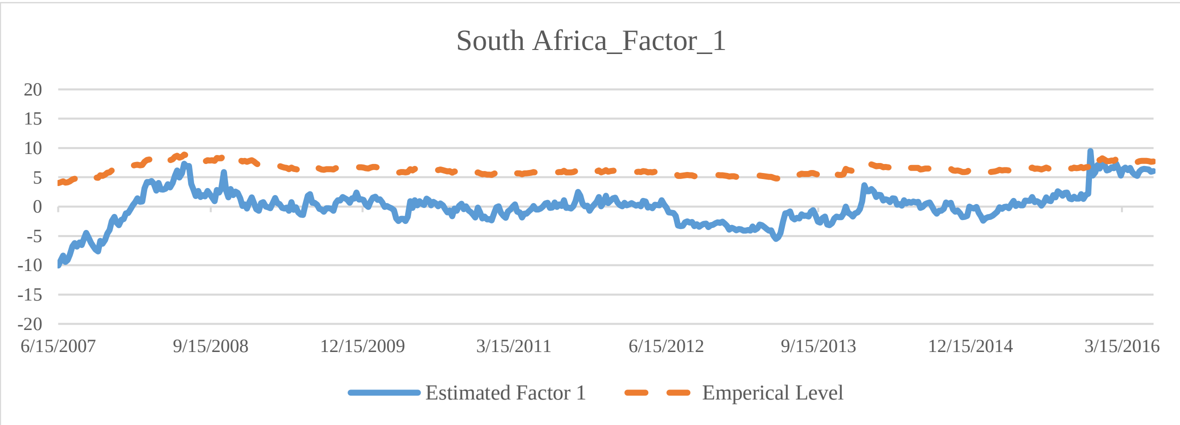


Figure 12 – SA: Empirical Slope vs. Estimated Factor 2

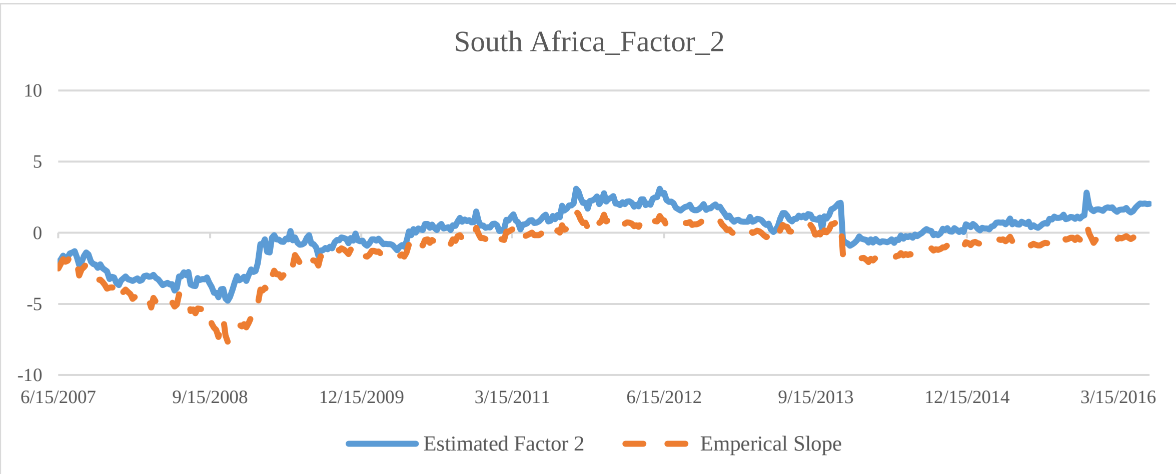
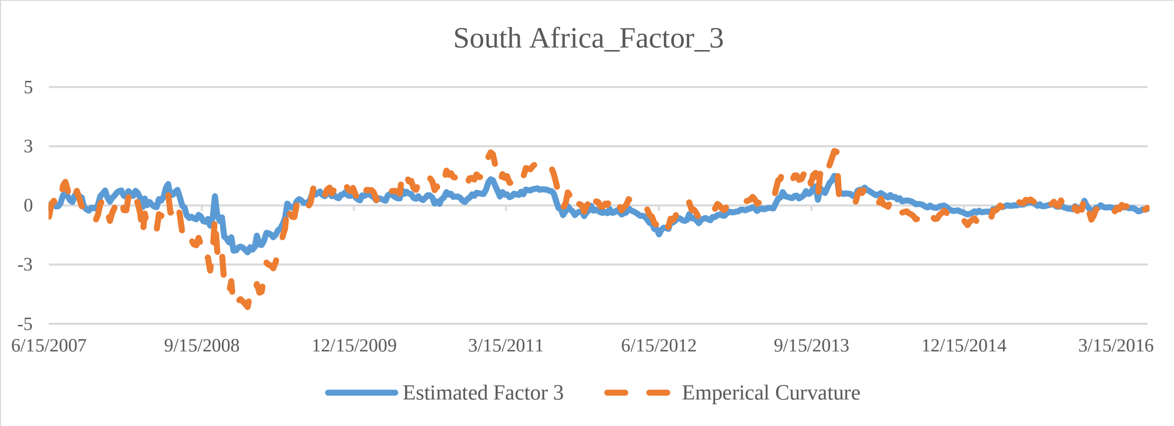


Figure 13 - SA: Empirical Curvature vs. Estimated Factor 3



Figures 11-13. Empirical vs. Estimated level, slope and curvature Factors: Time series of the first three latent factors (F_1, F_2, F_3) against the empirical level, slope and curvature estimates for the SA-US sovereign spreads. In line with existing literature, we calculate the empirical level as the average of the longest (120 months), the shortest (3 months) and a medium term maturity (36 months); the empirical slope as the difference between the longest and shortest maturity and the curvature as twice the medium term maturity minus the sum of the shortest and longest maturity.

In summary, we find that for the investigated BRICS economies, the sovereign spread curve can be broken down and predominantly explained by the first three estimated latent spread factors, derived using PCA. In addition, it was found that the first three factors could appropriately be labelled as the spread level (F_L), spread slope (F_S) and spread curvature (F_C) factors. Our findings are also consistent with previous literature conducted on advanced economies (Trück and Wellmann, 2016).

5. Exchange Rate Predictability

We have earlier argued that the Principal Components derived from a PCA decomposition of the yield spread term structure may contain valuable information relating to the differences in cross-country economic fundamentals. In view of this, we postulate that the estimated latent factors summarize information over the entire spread curve and as such may serve as a natural measure and a key input in exchange rate forecasting models.

Accordingly, our study further tests this theory for the BRICS economies, and investigates whether or not the estimated latent factors are able to provide additional information, and in doing so, improve on the traditional UIRP model (UIRP) for exchange rate prediction. In motivation of this hypothesis, we note that while both the UIRP and spread factors link differences in interest rates to changes in exchange rates, the UIRP model only uses information up to a certain maturity whereas the PCA derived latent spread factors summarize information encompassed over the entire spread term structure.

In view of this and following the work of Truck and Wellman (2016), we setup the following regression model, which we will call the extended UIRP model (UIRP-Ext):

$$\Delta S_{t+h} = \alpha_{h,UIRP}^{\Delta S} UIRP_{h,t} + \beta_{h,\mathrm{L}}^{\Delta S} F_{\mathrm{L},t} + \beta_{h,\mathrm{S}}^{\Delta S} F_{\mathrm{S},t} + \beta_{h,\mathrm{C}}^{\Delta S} F_{\mathrm{C},t} + \mu_{t+h} \tag{7}$$

The model naturally builds on the UIRP relation by including the interest rate differential between two economies, i.e. the UIRP factor: $UIRP_{h.t} = i_t^h - i_t^{h*}$ with i_t^h and i_t^{h*} representing the respective domestic and foreign interest rates at maturity h. We then enhance the model by including the three latent spread factors, i.e. the level factor ($F_{L,t}$), the slope factor ($F_{\mathrm{S},t}$), as well as the curvature factor ($F_{\mathrm{C},t}$) and lastly, we have the intercept term μ_{t+h}.

To begin with, it is common knowledge that the credit crises of 2007–2009 caused major disruptions in the financial markets, including the bond and foreign exchange markets. Research following the collapse found that during the crises, the standard yield curve no-arbitrage relation did not hold (Bianchetti, 2010). It was also found that, at the time, the sudden movements in the exchange rate markets were the result of the global financial crises (Fratzcher, 2009). To this end, we run two regressions - the first regression is conducted on the complete dataset (i.e. over the entire sample period 15/06/2007 to 17/06/2016) with the second regression being run for the period following the GFC (i.e. for the post crises period: 05/06/2009 to 17/06/2016)[29].

Following this, we evaluate the PCA derived latent factors by estimating $\beta^{\Delta S}_{h,[L,S,C]}$ over both sample periods, and thereafter test for the significance of these factors in the UIRP-Ext regression model.

5.1. Breusch-Pagan Test

Firstly, it is noted that due to the forecast horizon h over-lapping the frequency of observations (one week in this case), the error term μ_{t+h} in the UIRP-Ext regression model will be a moving average process. As such, the regression model would need to account for the bias due to the over-lapping data (Harri and Brorsen, 2009). We confirm this by testing for the presence of heteroskedasticity[30] using the Breusch-Pagan test.

Results of the test are shown in tables 4-5 below and as expected confirms the presence of heteroskedasticity in the extended UIRP model for the BRICS economies.

Table 4 - Breusch Pagan Test Statistic (Complete Period)

Breusch-Pagan Test Statistic (Complete)				
Spread	**h = 13**	**h = 26**	**h = 52**	**h = 104**
BR – US	***18.503****	***40.715****	***25.944****	***45.163****
p-value	0.0009836	3.089E-08	0.00003	3.677E-09
CH – US	***12.693**	***11.388**	***40.946****	***93.024****
p-value	0.01288	0.02253	2.76E-08	2.20E-16
IN - US	***36.668****	***36.944****	***36.276****	***42.326****
p-value	2.11E-07	1.85E-07	2.54E-07	1.43E-08
RU - US	***84.895****	***40.941****	***44.723****	***164.79****
p-value	2.20E-16	2.77E-08	4.54E-09	2.20E-16
SA - US	***55.842****	***133.99****	***78.717****	***16.275****
p-value	2.16E-11	2.20E-16	3.26E-16	0.002672

[29] Guidolin and Tam (2013) provide an overview of the crises dating literature in which they conclude that the conservative consensus date for the crises centered around August 2007 – May 2009.

[30] Heteroskedasticity refers to the non-constant variance of the error terms in a regression model, with the variance itself dependent on the values of the predictor variables.

Table 5 - Breusch Pagan Test Statistic (Post Crises Period)

Breusch-Pagan Test Statistic (Post Crises)				
Spread	**h = 13**	**h = 26**	**h = 52**	**h = 104**
BR - US	5.2408	***38.455****	***99.329****	***60.062****
p-value	0.2636	9.03E-08	2.20E-16	2.82E-12
CH - US	***25.167****	***13.621***	***50.383****	***73.188****
p-value	4.66E-05	0.00861	3.00E-10	4.82E-15
IN - US	***41.454****	***51.976****	***101.11****	***27.668****
p-value	2.16E-08	1.40E-10	2.20E-16	1.46E-05
RU - US	***58.25****	***63.306****	***43.586****	***31.219****
p-value	6.76E-12	5.85E-13	7.82E-09	2.76E-06
SA - US	***26.413****	***24.232****	***17.446***	***51.723****
p-value	2.61E-05	7.18E-05	0.001583	1.58E-10

Tables 4 and 5: Breusch-Pagan test statistics and corresponding p-values of the UIRP-Ext model for the BRICS economies over the time period 15/06/2007 - 17/06/2016. *, **, *** indicate significance of the test statistic at the 5%, 1% and 0.1% level respectively.

5.2. Test for Significance of the Latent Spread Factors

Given the presence of heteroskedasticity, it thus follows that simple ordinary least squares (OLS) parameter estimates would not be appropriate and would lead to biased hypothesis test results (Hansen and Hodrick, 1980). One way to overcome this problem would be to only use non-overlapping observations as this would take care of the autocorrelation of the error terms. However this process is clearly inefficient, since it drastically reduces the sample of data points used in the regression and potentially overlooks valuable information.

We therefore use an alternate and more practical approach, (to estimate the parameter coefficients), developed by Newey and West (1987) in our study. The Newey-West derived estimators allows us to improve on the standard error estimates of the ordinary least squares regression by using an estimate of the covariance matrix of the parameters from the regression, (when the residuals are heteroskedastic and/or auto-correlated). Accordingly, the procedure uses heteroskedastic and auto-covariance consistent (HAC) estimators in the OLS regression, and suitably accounts for the bias in the error terms. Using this approach, we test for the significance of the estimated latent factors $\beta^{\Delta S}_{h,[L,S,C]}$ in the UIRP-Ext regression model over both the complete and post crises periods for each of the BRICS economies. Results of the tests are shown in the tables 6-15 below:

Table 6 – Brazil: UIRP-Ext Regression Results (Complete Period)

	FX - Brazil - U.S. (Complete)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	-440.821 (-1.7102)	502.494 (0.9552)	293.5239 (1.7521)	128.5250 (0.5159)
$\alpha_{h,UIRP}$	-41.359 (-1.6713)	48.153 (0.9791)	28.2684 (1.8168)	12.2297 (0.5487)
$B_{h,L}^{\Delta S}$	-25.878 (-1.7656)	28.872 (0.9534)	16.8612 (1.7391)	7.4336 (0.6094)
$B_{h,S}^{\Delta S}$	***-55.558**** (-2.249)	31.470 (0.6453)	18.1212 (1.3525)	1.6832 (0.1659)
$B_{h,C}^{\Delta S}$	-50.796 (-1.6461)	26.514 (1.0014)	-8.4036 (-0.8520)	-8.1433 (-0.3606)
no. obs	***458***	***445***	***419***	***367***
Adj. R-Squared	***0.2071***	***0.2498***	***0.2137***	***0.1568***

Table 7 - Brazil: UIRP-Ext Regression Results (Post Crises Period)

	FX - Brazil - U.S. (Post Crises)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	-233.252 (-0.6465)	238.3755 (0.4901)	24.712 (0.0544)	***-289.3919**** (-1.9818)
$\alpha_{h,UIRP}$	-21.468 (-0.6191)	23.4395 (0.5156)	3.6303 (0.0781)	-24.9034 (-1.8763)
$B_{h,L}^{\Delta S}$	-11.060 (-0.5465)	15.4689 (0.5585)	0.77012 (0.0564)	***-14.5787**** (-2.1420)
$B_{h,S}^{\Delta S}$	-35.542) (-0.9891)	10.7447 (0.2671)	-2.18339 (-0.1611)	***-15.5256***** (-2.6050)
$B_{h,C}^{\Delta S}$	-45.897 (-1.1841)	-9.9837 (-0.4299)	-21.7949 (-0.1903)	14.6799 (0.8892)
no. obs	***354***	***341***	***315***	***263***
Adj. R-Squared	***0.3027***	***0.4831***	***0.4231***	***0.2112***

Tables 6 and 7: Results of the regression coefficients for the BRL/USD UIRP-Ext model over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). Newey-West t-statistics are reported in parenthesis. *, **, *** indicate significance of the coefficients at the 5%, 1% and 0.1% level respectively. No. obs denotes the number of observations for the corresponding forecasting horizon h in weeks.

Table 8 - Russia: UIRP-Ext Regression Results (Complete Period)

	FX - Russia - U.S. (Complete)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	102.8462 (0.3514)	***-655.110**** (-2.0477)	-24.5083 (0.3219)	-71.7913 (-1.4992)
$\alpha_{h,UIRP}$	18.6421 (0.4111)	***-100.678**** (-2.0351)	-1.4462 (-0.1303)	-8.0510 (-1.2760)
$B_{h,L}^{\Delta S}$	14.3052 (0.3660)	***-80.591**** (-2.0283)	-1.7398 (-0.2059)	-7.0532 (-1.2715)
$B_{h,S}^{\Delta S}$	7.3855 (0.1013)	***-150.033**** (-2.1085)	-13.4002 (-1.0980)	-13.1288 (-1.7530)
$B_{h,C}^{\Delta S}$	-2.0488 (-0.0420)	***-105.797**** (-2.2034)	***-17.7640****** (-3.5721)	-6.6580 (-0.9496)
no. obs	***458***	***445***	***419***	***367***
Adj. R-Squared	***0.1452***	***0.3759***	***0.3754***	***0.451***

Table 9 - Russia: UIRP-Ext Regression Results (Post Crises Period)

	FX - Russia - U.S. (Post Crises)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	-19.5309 (-0.0346)	-940.855 (-1.6083)	-7.49957 (-0.0440)	-21.2886 (-0.1683)
$\alpha_{h,UIRP}$	-0.96679 (-0.0108)	-145.396 (-1.6019)	1.28051 (0.0521)	-0.188897 (-0.0104)
$B_{h,L}^{\Delta S}$	2.29134 (0.0320)	-115.276 (-1.5958)	0.74463 (0.0399)	0.073464 (0.0056)
$B_{h,S}^{\Delta S}$	-19.90065 (-0.1430)	-214.529 (-1.6345)	-13.1555 (-0.5080)	***-17.6738**** (-2.2487)
$B_{h,C}^{\Delta S}$	-37.01226 (-0.3041)	-155.959 (-1.6905)	***-21.91214**** (-2.2799)	***-28.666***** (-2.7601)
no. obs	***354***	***341***	***315***	***263***
Adj. R-Squared	***0.1175***	***0.4212***	***0.3812***	***0.7193***

Tables 8 and 9: Results of the regression coefficients for the RUB/USD UIRP-Ext model over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). Newey-West t-statistics are reported in parenthesis. *, **, *** indicate significance of the coefficients at the 5%, 1% and 0.1% level respectively. No. obs denotes the number of observations for the corresponding forecasting horizon h in weeks.

Table 10 - India UIRP-Ext Regression Results (Complete Period)

	FX - India - U.S. (Complete)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	-24.157 (-0.4153)	-208.998 (-1.5939)	***113.6848***** (2.8249)	***81.003***** (3.1005)
$\alpha_{h,UIRP}$	-2.752 (-0.3152)	-29.473 (1.5517)	***17.6121***** (3.029)	***12.8862***** (3.3117)
$B_{h,L}^{\Delta S}$	-2.533 (-0.5277)	-16.984 (-1.666)	***8.2837***** (2.8135)	***5.0185***** (3.1327)
$B_{h,S}^{\Delta S}$	-9.091 (-0.9455)	-27.906 (-1.9502)	9.8126 (1.8878)	***5.7465***** (2.98)
$B_{h,C}^{\Delta S}$	-0.077 (-0.0078)	-12.395 (-1.0373)	4.3181 (0.788)	-0.6971 (-0.2468)
no. obs	***458***	***445***	***419***	***367***
Adj. R-Squared	***0.08698***	***0.1763***	***0.1509***	***0.2572***

Table 11 - India: UIRP-Ext Regression Results (Post Crises Period)

	FX - India - U.S. (Post Crises)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	1.572 (0.0113)	-50.1509 (-0.2939)	45.3437 (0.6486)	-41.4095 (-1.5363)
$\alpha_{h,UIRP}$	0.635 (0.0306)	-6.8567 (-0.2755)	7.1704 (0.7066)	-5.7174 (-1.4156)
$B_{h,L}^{\Delta S}$	-1.1917 (-0.1121)	-5.3241 (-0.3949)	2.2153 (0.4041)	-3.3042 (-1.8351)
$B_{h,S}^{\Delta S}$	-2.9468 (-0.2099)	-9.3564 (-0.5625)	2.721 (0.2556)	-2.9071 (-1.1942)
$B_{h,C}^{\Delta S}$	6.0642 (0.2705)	4.4725 (0.3035)	8.5522 (1.5822)	***14.1535****** (5.7161)
no. obs	***354***	***341***	***315***	***263***
Adj. R-Squared	***0.05918***	***0.1745***	***0.2956***	***0.4568***

Tables 10 and 11: Results of the regression coefficients for the INR/USD UIRP-Ext model over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). Newey-West t-statistics are reported in parenthesis. *, **, *** indicate significance of the coefficients at the 5%, 1% and 0.1% level respectively. No. obs denotes the number of observations for the corresponding forecasting horizon h in weeks.

Table 12 - China: UIRP-Ext Regression Results (Complete Period)

	FX - China - U.S. (Complete)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	***21.6237***** (2.7241)	7.14571 (0.7888)	-6.02011 (-0.8135)	***10.7283***** (3.1972)
$\alpha_{h,UIRP}$	***9.1598***** (2.6260)	2.64883 (0.5973)	-3.5929 (-1.0559)	***4.7951***** (2.6164)
$B_{h,L}^{\Delta S}$	***2.7207**** (2.2495)	0.40897 (0.2691)	-1.7896 (-1.4739)	***1.1661**** (2.1284)
$B_{h,S}^{\Delta S}$	***3.9656**** (2.1207)	0.30218 (0.1291)	***-2.5155**** (-2.1518)	***1.1333**** (2.4767)
$B_{h,C}^{\Delta S}$	-1.6267 (-0.567)	***-5.93527****** (-3.3732)	***-6.4452****** (7.7816)	***-4.10625****** (-5.4910)
no. obs	***458***	***445***	***419***	***367***
Adj. R-Squared	***0.25***	***0.43***	***0.6918***	***0.6134***

Table 13 - China: UIRP-Ext Regression Results (Post Crises Period)

	FX - China - U.S. (Post Crises)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	22.9118 (1.9187)	-4.1175 (-0.5587)	-2.399 (-0.0616)	***8.32668**** (2.4718)
$\alpha_{h,UIRP}$	10.2087 (1.8989)	-2.3043 (-0.6179)	-1.8794 (-0.1112)	3.34945 (1.9249)
$B_{h,L}^{\Delta S}$	3.3824 (1.9113)	-1.0167 (-0.7126)	-1.1976 (-0.2273)	0.5152 (0.8512)
$B_{h,S}^{\Delta S}$	5.0191 (1.9364)	-1.1686 (-0.3892)	-1.6454 (-0.4997)	0.5166 (0.8204)
$B_{h,C}^{\Delta S}$	-0.5993 (-0.1346)	***-6.9517***** (-2.8329)	***-6.4064**** (-2.1493)	***-3.3152****** (-3.3907)
no. obs	***354***	***341***	***315***	***263***
Adj. R-Squared	***0.1365***	***0.2297***	***0.561***	***0.6149***

Tables 12 and 13: Results of the regression coefficients for the CNY/USD UIRP-Ext model over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). Newey-West t-statistics are reported in parenthesis. *, **, *** indicate significance of the coefficients at the 5%, 1% and 0.1% level respectively. No. obs denotes the number of observations for the corresponding forecasting horizon h in weeks.

Table 14 - South Africa: UIRP-Ext Regression Results (Complete Period)

	FX - South Africa - U.S. (Complete)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	-118.3038 (-0.6722)	170.4374 (1.3135)	84.7224 (1.541)	***178.1924***** (3.1258)
$\alpha_{h,UIRP}$	-15.7199 (-0.6179)	25.7991 (1.3712)	14.009 (1.6789)	***28.9169***** (3.2577)
$B_{h,L}^{\Delta S}$	-4.672 (-0.5427)	8.9299 (1.4544)	***6.1426***** (2.6067)	***8.4459****** (3.4821)
$B_{h,S}^{\Delta S}$	-13.5139) (-0.6203)	20.7155 (13.8695)	7.6492 (1.5896)	***11.7949****** (4.6545)
$B_{h,C}^{\Delta S}$	-6.5215 (-0.3344)	31.541 (1.6232)	6.0187 (1.144)	-6.0956 (-1.4631)
no. obs	***458***	***445***	***419***	***367***
Adj. R-Squared	***0.02577***	***0.1324***	***0.2749***	***0.7194***

Table 15 - UIRP-Ext Regression Results (Post Crises Period)

	FX - South Africa - U.S. (Post Crises)			
Factor	**h = 13**	**h = 26**	**h = 52**	**h = 104**
μ_{t+h}	218.480 (1.5245)	-99.9739 (-1.1219)	***214.3168***** (2.5991)	***232..344**** (2.0913)
$\alpha_{h,UIRP}$	32.4975 (1.5543)	-13.1564 (-1.0185)	***32.829***** (2.8050)	***37.4263**** (2.1367)
$B_{h,L}^{\Delta S}$	***14.1389**** (2.1113)	-3.171 (-0.6773)	***11.9573***** (2.5992)	***10.9856**** (2.3628)
$B_{h,S}^{\Delta S}$	***27.8384**** (2.1734)	-7.1619 (-0.65)	***22.3962***** (2.7924)	***14.4913***** (3.0324)
$B_{h,C}^{\Delta S}$	***20.1475**** (2.1110)	-15.010 (-0.8278)	2.4842 (0.4338)	-13.4823 (-1.5063)
no. obs	***354***	***341***	***315***	***263***
Adj. R-Squared	***0.1287***	***0.1015***	***0.3759***	***0.435***

Tables 14 and 15: Results of the regression coefficients for the ZAR/USD UIRP-Ext model over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). Newey-West t-statistics are reported in parenthesis. *, **, *** indicate significance of the coefficients at the 5%, 1% and 0.1% level respectively. No. obs denotes the number of observations for the corresponding forecasting horizon h in weeks.

Readings from the tests are inconclusive and in general we obtain mixed results with regards to the significance of the coefficients for the estimated latent factors. Overall we find that tests for the longer forecasting periods (i.e. h = 104 weeks and h = 52 weeks) produced more significant test results than the shorter forecasting horizons (i.e. h = 26 weeks and h = 13 weeks). This observation is true for all the considered economies and over both the complete and post crises periods.

We supplement these findings by next investigating the joint significance of the spread factors in the UIRP-Ext model using the Wald Test.

5.3. Wald Test

The Wald test is based on the parameter estimates and their covariance. The estimates, as well as the test statistic, are derived using maximum likelihood estimation. Essentially, the Wald test evaluates whether imposing a set of restrictions on the parameter estimates significantly reduces the fit of the model. For example, the test may be used to test whether several regression coefficients in a larger model are all simultaneously equal to zero. For our analysis, we apply the Wald test to test the null hypothesis that the coefficients of the latent spread factors, i.e. $\beta^{\Delta S}_{h,[L,S,C]}$ are jointly equal to zero against the alternative that at least one of the coefficients is not equal to zero, i.e.

Null - H$_0$: $\beta^{\Delta S}_{L} = \beta^{\Delta S}_{S} = \beta^{\Delta S}_{C} = 0$

Alternative - H$_A$: At least one $\beta^{\Delta S}_{j} \neq 0$ j = L, S, C

The basic Wald statistic on multiple parameters is given by:

$$W = (Rb - q)'[RVar(b)R']^{-1}(Rb - q) \qquad (8)$$

where R and q implement a set of linear restrictions representing the null hypothesis, such that $(Rb - q) = 0$. For the restrictions currently tested, q is a (3x1) vector of zeros, and R is a k x m matrix, with k representing the number of restrictions and m denoting the number of parameters in b . Given that we have 3 parameters being tested with 3 restrictions, R in our case, represents a 3x3 matrix with each column of R containing zeros and a single 1 in the column corresponding to one of the parameters being test.

Since the maximum likelihood estimator has a multivariate normal distribution with mean vector 0 and variance-covariance matrix $Var(b)$, it follows that when σ^2 is known, the quadratic form of W is exactly chi-squared with k degrees of freedom (k = 3 in our case and represents the three latent spread factors being tested).

However, in the more general case where σ^2 is estimated based on $n - p$ degrees of freedom then we would have the distribution of $\frac{W}{k}$ being an F distribution with $n - p$ degrees of freedom (where n represents the number of data points in the regression and p the number of parameter estimates, which is five in our case and includes the intercept, the interest differential or UIRP factor as well as the three latent spread components).

It thus follows that as the number of data points n approaches infinity (i.e. as the sample size gets large) and for a fixed set of parameters p, so too does the degrees of freedom $n-p$ approach infinity, and as such the F distribution (multiplied by k) approaches a chi-squared distribution with k degrees of freedom.

Consequently we can deduce, that for large samples, the distribution of $\frac{W}{k}$ as an F statistic is equivalent to W as a chi-squared statistic - that is, the two distributions are effectively the same for large samples.

In this regard and in an effort to be conservative, we have chosen to use the finite sample F Statistic to conduct the Wald test. In addition, given the presence of heteroskedasticity in the error terms, we again use the Newey-West estimate of the covariance matrix of the parameters. Results of the Wald-test are shown in the tables 16 and 17 below:

Table 16 - Wald Test (Complete Period)

Wald Test - F Statistic (Complete)				
Country	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	2.1451	***3.8945*****	2.155	***2.8043****
China	***5.665******	***10.763******	***37.818******	***19.39******
India	0.4091	1.7548	***2.9144****	***4.6993*****
Russia	***2.6942****	2.3053	***7.4253******	1.1895
South Africa	0.1545	0.8896	2.5589	***27.96******

Table 17 - Wald Test (Post Crises Period)

Wald Test - F Statistic (Post Crises)				
Country	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	2.0232	***3.8367****	0.0201	***8.7836******
China	2.488	***3.8155****	***19.275******	***6.9066******
India	0.1587	0.7195	0.8524	***11.168******
Russia	***4.0033*****	1.2916	2.2493	***3.8642*****
South Africa	2.1143	0.2802	***4.0198*****	***4.8272*****

Tables 16 and 17: Wald test statistics on the UIRP-Ext model for the BRICS economies over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). *, **, *** indicate significance of the test statistic at the 5%, 1% and 0.1% level respectively.

We note that readings from the Wald Test are again inconclusive and also produces varied results with regards to the joint significance of the spread factors. This concurs with our earlier findings for the significance of the individual factor coefficients. In addition, we find that more factors are jointly significant for the longer forecasting period (i.e. h = 104 weeks) than for the shorter forecasting horizon, which is also in line with our earlier results.

Since the primary focus of our investigation is to determine if the extended UIRP model (which includes the PCA derived latent spread factors) improves the predictive power of the traditional UIRP model, we next consider four common model selection measures. In particular, we examine the Adjusted R-Squared, the Root Mean Squared Error (RMSE), the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) measures. It is proposed that should the extended UIRP model be the superior model then we should see this come through in our evaluation of these four model selection criteria's. Finally, we conclude our investigation by formally testing our theory by performing a Likelihood Ratio Test (LR-Test) between the extended UIRP model and the traditional UIRP model.

We begin though by first comparing the Adjusted R-Squared values between the two models.

5.4. Adjusted R-Squared

Usually researchers consider the R-Squared measure (also called the co-efficient of determination) when evaluating the fit of a linear regression model. Unfortunately, this R-Squared estimate is biased, with the magnitude of the bias depending on the number of observations used to fit the model as well as the number of independent variables there are relative to the sample size. Essentially, whenever an independent variable is added to the model, the value of R-Squared always increases, it never decreases, and as a result, a model with many predictor variables may appear to have a better fit than it actually does.

The adjusted R-Squared measure accommodates for this bias, and is thus a more appropriate measure to use, when comparing the explanatory power of regression models that contain different numbers of predictor variables. This measure adjusts the R-Squared calculation by using $n-1$ instead of n as the divisor for the total sum of squares estimate and similarly the measure uses $n-p-1$ as the divisor in the model, or regression, sum of squares estimate, that is:

$$R^2_{adj} = 1 - \frac{\frac{1}{n-p-1}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\frac{1}{n-1}\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{9}$$

where n denotes the sample size, $\hat{Y}_i$ denotes the predicted value of Y_i, $\bar{Y}$ denotes the sample mean of Y_i and p denotes the number of parameters in the regression model. The formula can be rearranged to show that:

$$R^2_{adj} = R^2 - (1 - R^2)\frac{p}{n-p-1} \tag{10}$$

Adjusted R-Squared values for the traditional (UIRP) and extended (UIRP-Ext) models over both the complete and post crises periods, for forecasting horizons 13, 26, 52 and 104 weeks are shown in tables 18-19 below:

Table 18 - Adjusted R-Squared Measures (Complete Period)

Adjusted R-Squared (Complete)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	0.042	0.066	0.030	0.003
	UIRP-Ext	***0.207***	***0.250***	***0.214***	***0.157***
Russia	UIRP	0.020	0.046	0.030	0.071
	UIRP-Ext	***0.145***	***0.376***	***0.375***	***0.451***
India	UIRP	0.054	0.075	0.061	0.123
	UIRP-Ext	***0.087***	***0.176***	***0.151***	***0.257***
China	UIRP	0.120	0.248	0.383	0.483
	UIRP-Ext	***0.250***	***0.430***	***0.692***	***0.613***
South Africa	UIRP	0.000	0.008	0.096	0.157
	UIRP-Ext	***0.026***	***0.132***	***0.275***	***0.719***

Table 19 - Adjusted R-Squared Measures (Post Crises Period)

Adjusted R-Squared (Post Crises)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	0.013	0.045	0.088	0.005
	UIRP-Ext	***0.303***	***0.483***	***0.423***	***0.211***
Russia	UIRP	0.008	0.076	0.122	0.024
	UIRP-Ext	***0.118***	***0.421***	***0.381***	***0.719***
India	UIRP	0.049	0.114	0.221	0.124
	UIRP-Ext	***0.059***	***0.175***	***0.296***	***0.457***
China	UIRP	0.007	0.036	0.243	0.549
	UIRP-Ext	***0.137***	***0.230***	***0.561***	***0.615***
South Africa	UIRP	0.065	0.062	0.143	0.063
	UIRP-Ext	***0.129***	***0.102***	***0.376***	***0.435***

Tables 18 and 19: Adjusted R-Squared measure (UIRP vs. UIRP-Ext model) for the BRICS economies over the time period 15/06/2007 - 17/01/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises).

Our results indicate that when considering the adjusted R-Squared measure, the extended UIRP model has the higher value for all the considered BRICS economies and thus appears to be the superior model. This across all forecasting horizons and for both the complete and post crises periods.

We supplement our findings from the adjusted R-Squared measure by next looking at the Root Mean Square Error (RMSE) measure.

5.5. Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) is another measure that is commonly used to evaluate the fit of a model. This measure is similar to the adjusted R-Squared metric discussed earlier, and also serves to provide a single measure of a model's fit, by looking at the square root of the mean squared errors. More formally, the RMSE with respect to the estimated variable $\hat{Y}_i$ is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}} \qquad (11)$$

where Y_i represents the observed value and $\hat{Y}_i$ the modelled or estimated value at time i.

The RMSE is also related to the standard deviation of the observed values Y_i as well as the coefficient of determination (R^2) as follows:

$$RMSE = \sqrt{1 - R^2}.\mathrm{SD}_Y \qquad (12)$$

Given that R^2 ranges from 0 to 1, it follows that the RMSE is measured on the same scale with the same units as Y_i. The RMSE for the traditional and extended UIRP models, for both the complete and post crises periods are presented in tables 20 and 21 below:

Table 20 - Root Mean Square Error Measures (Complete Period)

RMSE (Complete)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	36.469	26.476	17.782	11.471
	UIRP-Ext	***33.067***	***23.647***	***15.952***	***10.475***
Russia	UIRP	42.757	27.600	18.195	12.703
	UIRP-Ext	***39.800***	***22.250***	***14.547***	***9.724***
India	UIRP	17.184	11.648	8.268	4.558
	UIRP-Ext	***16.830***	***10.954***	***7.836***	***4.177***
China	UIRP	5.179	3.914	2.673	1.511
	UIRP-Ext	***4.766***	***3.396***	***1.882***	***1.302***
South Africa	UIRP	32.167	22.254	14.674	9.446
	UIRP-Ext	***31.648***	***20.745***	***13.091***	***5.429***

Table 21 - Root Mean Square Error Measures (Post Crises Period)

RMSE (Post Crises)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	29.899	20.174	14.615	9.205
	UIRP-Ext	***25.026***	***14.775***	***11.568***	***8.147***
Russia	UIRP	44.239	26.760	17.530	14.220
	UIRP-Ext	***41.555***	***21.080***	***14.646***	***7.583***
India	UIRP	16.196	10.116	6.191	3.772
	UIRP-Ext	***16.031***	***9.721***	***5.860***	***2.954***
China	UIRP	5.036	3.714	2.588	1.474
	UIRP-Ext	***4.677***	***3.306***	***1.961***	***1.353***
South Africa	UIRP	23.296	15.009	10.306	6.413
	UIRP-Ext	***22.391***	***14.628***	***8.754***	***4.950***

Tables 20 and 21: RMSE measure (UIRP vs. UIRP-Ext model) for the BRICS economies over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises).

We obtain a lower RMSE value for the extended UIRP model for all the BRICS economies. This over all forecasting horizons and for both the complete and post crisis periods. These results supplement our earlier findings from the adjusted R-Squared measure and provides further evidence to suggest that the extended UIRP model is the better model between the two. We also note that in general, the RMSE value decreases as the forecasting horizon increases. This is true for both models and over both the complete and post crises periods.

Further to this, we also find that the volatility of the extended UIRP model appears to be much closer to the volatility of the logarithmic change in the nominal spot exchange rate ΔS_{t+h} [31], and consequently provides further support for the superiority of the extended UIRP model.[32]

Following our assessment of both the Adjusted R-Squared and RMSE measures, we next examine the Akaike Information Criterion (AIC) for model selection.

5.6. Akaike Information Criterion (AIC)

The Akaike Information Criterion (AIC) is used to select the best model from a set of models. The measure basically evaluates, the relative quality of the models for a given set of data. In other words, given a collection of models and for a set data, the AIC measure estimates the comparative quality of each model. According to the criterion, the best model is the one that minimizes the Kullback-Leibler distance between the regression model and "reality" (Burnham and Anderson, 2003). As such the model with the smallest AIC value is chosen as the superior model. The measure is defined as:

$$AIC = -2.\ln(likelihood) + 2P \tag{13}$$

where *likelihood* is the probability of the data given a model and P is the number of parameters in the model.

It is noted that when using the conventional Ordinary Least Squares regression, the AIC score can easily be computed using the following formula (omitting arbitrary constants):

$$AIC = n.\ln(\tilde{\sigma}^2) + 2P \tag{14}$$

where $\tilde{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$ and n is the sample size. Importantly, we also note that because the variance is estimated, it must also be included in the count of the parameters P.

It also follows from equation 17, that the AIC score is penalized for the unnecessary addition of parameters, and consequently, the measure will look to select or choose the model that not only fits well but also has the minimum number of predictor variables.

[31] This is particularly the case for the longer forecasting horizons.

[32] Please see Appendix for volatility calculation results.

AIC scores for the traditional (UIRP) and extended (UIRP-Ext) models over both the complete and post crises periods, for forecasting horizons 13, 26, 52 and 104 weeks are shown in tables 22-23 below:

Table 22 - Akaike Information Criterion Scores (Complete Period)

AIC Scores (Complete)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	4,600	4,185	3,607	2,838
	UIRP-Ext	***4,516***	***4,090***	***3,522***	***2,778***
Russia	UIRP	4,746	4,222	3,626	2,913
	UIRP-Ext	***4,686***	***4,036***	***3,445***	***2,723***
India	UIRP	3,911	3,454	2,965	2,161
	UIRP-Ext	***3,898***	***3,405***	***2,926***	***2,103***
China	UIRP	2,812	2,483	2,019	1,351
	UIRP-Ext	***2,742***	***2,363***	***1,731***	***1,247***
South Africa	UIRP	4,485	4,030	3,446	2,696
	UIRP-Ext	***4,476***	***3,974***	***3,356***	***2,295***

Table 23 - Akaike Information Criterion Scores (Post Crises Period)

AIC Scores (Post Crises)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	3,416	3,023	2,590	1,920
	UIRP-Ext	***3,296***	***2,816***	***2,448***	***1,862***
Russia	UIRP	3,694	3,215	2,704	2,149
	UIRP-Ext	***3,655***	***3,059***	***2,597***	***1,824***
India	UIRP	2,982	2,552	2,049	1,451
	UIRP-Ext	***2,981***	***2,531***	***2,020***	***1,328***
China	UIRP	2,155	1,869	1,499	956
	UIRP-Ext	***2,109***	***1,795***	***1,330***	***918***
South Africa	UIRP	3,240	2,821	2,370	1,730
	UIRP-Ext	***3,218***	***2,809***	***2,273***	***1,600***

Tables 22 and 23: Akaike Information Criterion statistics (UIRP vs. UIRP-Ext model) for the BRICS economies over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises).

Our findings show that in all cases the extended UIRP model has the smaller AIC scores, which suggests that this model (i.e. the UIRP-Ext model) is superior and hence should be chosen over the traditional UIRP model. In addition, it is also noted that for both models, the AIC scores decrease as the forecasting horizon increases. This suggests that the power of the prediction models gets stronger over longer forecasting periods.

We complement our findings from the AIC scores by looking at the Bayesian Information Criterion (BIC) measure next.

5.7. Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) or Schwarz criterion is closely related to the AIC measure and is also used to select the best model among a finite set of models. Similarly to the AIC score, the BIC measure is also based on a likelihood function and is formally defined as:

$$BIC = -2.\ln(likelihood) + \ln(n)P \tag{15}$$

where P denotes the number of parameters (including the intercept) and n is the sample size (Burnham and Anderson, 2003).

Again, using Ordinary Least Squares regression, it can be shown that the BIC scores can be computed as follows:

$$BIC = n.\ln(\tilde{\sigma}^2) + \ln(n)P \tag{16}$$

where $\tilde{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$.

Like the AIC measure, the model with the smallest BIC score is preferred. It is also noted (from equation 19 above) that the BIC measure penalizes models more for free parameters and as such is a stricter model selection measure than the Akaike Information Criterion.

BIC scores for the traditional (UIRP) and extended (UIRP-Ext) models over both the complete and post crises periods, for forecasting horizons 13, 26, 52 and 104 weeks are shown in tables 24-25 below:

Table 24 - Bayesian Information Criterion Scores (Complete Period)

BIC Scores (Complete)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	4,612	4,197	3,619	2,850
	UIRP-Ext	***4,541***	***4,115***	***3,546***	***2,801***
Russia	UIRP	4,758	4,234	3,638	2,925
	UIRP-Ext	***4,711***	***4,061***	***3,469***	***2,746***
India	UIRP	3,923	3,466	2,977	2,173
	UIRP-Ext	***3,923***	***3,430***	***2,950***	***2,126***
China	UIRP	2,825	2,496	2,031	1,362
	UIRP-Ext	***2,767***	***2,387***	***1,755***	***1,270***
South Africa	UIRP	4,498	4,042	3,458	2,708
	UIRP-Ext	***4,501***	***3,998***	***3,381***	***2,319***

Table 25 - Bayesian Information Criterion Scores (Post Crises Period)

BIC Scores (Post Crises)					
Country	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	UIRP	3,428	3,034	2,601	1,931
	UIRP-Ext	***3,320***	***2,839***	***2,471***	***1,883***
Russia	UIRP	3,705	3,227	2,715	2,159
	UIRP-Ext	***3,679***	***3,082***	***2,619***	***1,845***
India	UIRP	2,994	2,563	2,060	1,461
	UIRP-Ext	***3,004***	***2,554***	***2,042***	***1,350***
China	UIRP	2,167	1,880	1,510	967
	UIRP-Ext	***2,132***	***1,818***	***1,353***	***939***
South Africa	UIRP	3,251	2,833	2,381	1,741
	UIRP-Ext	***3,241***	***2,832***	***2,295***	***1,621***

Tables 24 and 25: Bayesian Information Criterion statistics (UIRP vs. UIRP-Ext model) for the BRICS economies over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises).

Overall, the computed BIC scores (over both sample periods and across all forecasting horizons) are also smaller for the UIRP-Ext model and again indicates that the extended UIRP model should be chosen over the traditional model. This concurs with our AIC results from earlier. Furthermore, we also observe that the BIC scores for both models, decreases for longer forecasting horizons and, similarly to the AIC measure, also suggests that the power of the prediction models increases for longer forecasting periods.

We provide further support of our findings from both the AIC and BIC model selection measures by formally showing the superiority of the extended UIRP model using the Likelihood-Ratio Test (LR-Test).

5.8. Likelihood Ratio Test (LR-Test)

The Likelihood Ratio Test is a common test used to evaluate the goodness of fit between two nested models, when one of the models (the simpler model) is a special case and is encompassed in the other more complex model. The test is based on the likelihood ratio and compares the maximum likelihood between the two models[33].

[33] We note that adding additional estimators to a model will always result in a higher likelihood score for that model. However the LR-Test is able to account for the loss in degrees of freedom (for the more complex model) and is able to provide an objective measure on whether or not the difference in likelihood scores between the two models is statistically significant.

For the purpose of our analysis, if L_{UIRP} represents the likelihood of the traditional UIRP model (i.e. the likelihood of the simpler model) and $L_{UIRP-Ext}$ is the likelihood of the extended UIRP model (i.e. the complex model) then the LR-Test statistic (LRT) is computed as:

$$LRT = -2\ln\left(\frac{L_{UIRP}}{L_{UIRP-Ext}}\right) \tag{17}$$

with the test statistic asymptotically following a chi-squared distribution and the degrees of freedom equal to the difference in the number of independent variables between the two models (Casella and Berger, 2001). Results of the LR-Test are presented in the tables 26-27 below.

Table 26 - Likelihood Ratio Test Statistic (Complete Period)

LR Test Statistic (Complete)				
Country	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	***89.68****	***100.59****	***91.007****	***66.63****
China	***76.121****	***126.49****	***249.1****	***109.61****
India	***19.058****	***54.699****	***45.065****	***64.132****
Russia	***65.649***	***191.77****	***187.53****	***196.19****
South Africa	***14.881***	***62.496****	***95.653****	***406.58****

Table 27 - Likelihood Ratio Test Statistic (Post Crises Period)

LR Test Statistic (Post Crises)				
Spread	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	**125.96***	**212.39***	**147.31***	**64.201***
China	**52.397***	**79.358***	**174.68***	**44.733***
India	7.2657	***27.127****	***34.709****	***128.61****
Russia	***44.329****	***162.71****	***113.24****	***330.72****
South Africa	***28.048****	***17.572****	***102.83****	***136.14****

Tables 26 and 27: LR Test statistics for the BRICS economies over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises). *, **, *** indicate significance of the LR-Test statistic at the 5%, 1% and 0.1% level respectively.

We note that almost all of the LR-Test statistics are significant, many of which at the 0.1% level of significance[34]. These results indicate that the UIRP-Ext model is the better fitting model and formally supports the superiority of the extended UIRP model over the traditional model. Our readings from the LR-Test complements our earlier results from both the AIC and BIC model selection measures.

In light of these findings, we conclude that the latent spread factors, which has been argued to contain valuable information over the entire yield spread term structure, provides additional explanatory power, and as such improves on the traditional UIRP models forecasting accuracy.

Our findings can be explained by considering the exchange rate as an asset price, the value of which is determined, to a large degree, by the expected long term values of future fundamentals. We argue that for the traditional UIRP model, information embodied in the yield curve is only used up to a certain maturity[35], and as such appears to be an inferior model to that of the extended UIRP model, which makes use of yield spread factors that encompass information over the entire yield spread term structure. Accordingly, our results strongly motivate for the inclusion of these extracted latent factors in future empirical exchange rate forecasting models.

[34] The only instance in which the statistic was found not to be significant was for India in the post crises period over the h = 13 weeks forecasting horizon.

[35] That is, until the underlying interest rate asset matures.

6. Conclusion

In accounting for the macro-economic and fundamental information that is postulated to be embedded in a country's yield curve, we have argued throughout this study for the relevance of the sovereign spread curve (i.e. the difference between the sovereign yields of two countries). Accordingly we have also motivated for the importance of the latent factors driving the spread term structure and in addition, have also look to investigate the predictive power of these factors, when augmented with the traditional UIRP model for exchange rate forecasting.

Our analysis considered the yield curves of the BRICS economies (namely: Brazil, Russia, India, China[36] and South Africa) for bonds issued in the respective country's currency[37]. Using weekly zero bond yields, retrieved from Bloomberg, we investigate the term structure of yield spreads[38], for the period 15/06/2007 to 17/06/2016. In addition, weekly FX data for each BRICS currency (foreign currency) against the U.S. dollar (home currency) was also obtained from Bloomberg and used in our study.

By applying a Principal Component Analysis (PCA) decomposition to each of the sovereign spread data sets, we were able to derive and examine the latent spread factors driving the term structure of yield spreads. Our analysis shows that the spread term structure is primarily driven by the first three factors (namely: the level, slope and curvature factors), which together can explain more than 99% of the variation in the underlying spread curve. We also find that the identified factors have a similar shape to those reported in earlier studies on the term structure of interest rates (Dai and Singleton, 2000; Bikbov and Chernov 2010, Afonso and Martins 2012, Truck and Wellman, 2016).

Although we obtained mixed results with regards to the significance of the individual latent spread factors in the extended UIRP model, we also obtained overwhelming results, from all four model selection measures, advocating for the superiority of the UIRP-Ext model over the traditional UIRP model. This over both the complete and post crises periods. We also note, from both the AIC and BIC criteria's, that the power of both exchange rate prediction models

[36] Due to the Chinese government's intervention in the FX market as well as their high holding of U.S. treasuries, it would not have been appropriate to include China in our investigation. However, in an effort to be complete, we have decided to retain China in our study, given that the country forms part of the BRICS economies.

[37] As such the bonds are considered to have no credit/default risk.

[38] Yield spreads were calculated as the difference between the yields for each BRICS country and the benchmark U.S. yield curve. As such, we obtained five data sets of sovereign spreads.

increased over longer forecasting horizons. In addition, our findings were further supported by the results obtained from the LR-Test, which we used to formally test and confirm the supremacy of the extended UIRP model.

In light of these results, our findings have important implications for this area of research, and not only build on the work by Truck and Wellman (2016), but also provides a good foundation for future work on this topic.

Firstly, studies relating to the term structure of yield spreads have been widely neglected so far, and our study aims to not only provide a platform for researchers to build on but to also stimulate and encourage more research in this field as well. In particular, our work may be useful to researchers that wish to build on the concept that the latent spread factors may contain valuable macro-economic information with respect to the cross-country differentials that is encompassed in the term structure of sovereign spreads.

In view of this, we have also argued that the PCA derived latent spread factors, may also serve as a natural proxy for the unobservable fundamentals input in more orthodox and economic exchange rate forecasting models. This follows from research by Balke et al (2013), in which the authors contend that is it difficult to account for the relative contribution of fundamentals in exchange rate models, using only observable fundamentals data.

With this in mind, we have motivated in our study that including these latent factors may be a promising approach to improving the forecasting accuracy of conventional exchange rate models, and in particular the traditional UIRP model. In support of this view, we have provided additional evidence, linking interest rates, macro-economic fundamentals and exchange rates, and have further substantiated the view that the exchange rate can be modelled as an asset price.

We believe that more research is required to fully understand and appreciate the fundamental information that these factors contain. We also believe, having strongly advocated for the inclusion of these latent factors in future exchange rate forecasting models, that the proposed models can be further enhanced by using non-linear spread factors, (e.g. quadratic factors) and we encourage the development of these models in future studies.

7. References

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8. Appendix

8.1. Trade and Economic Relations between China and the United States

It is common knowledge that China is predominately an export driven economy. The country is able to produce and export consumer goods at lower costs than most countries, including the United States. As a result, American companies that are unable to compete with these low costs, import their products from China. In addition, and also because of the lower costs, many U.S. manufacturers choose to send their raw materials to China for assembly. Once assembled and shipped back to the U.S., these products as considered as imports (Amadeo, 2017). This has resulted in the United States being a net importer of goods and services, and particularly so from China.

As of May 2017, the goods and services deficit for the United States stood at $46.5 billion (United States Balance of Trade, 2017) with China reflecting a trade surplus of $40.79 billion (China Balance of Trade, 2017) for the same period. The Chinese exporters that receive dollars for their goods sold to the U.S., sell these for yuan. This naturally increases the supply of U.S. dollars in the market and at the same time creates demand for the Chinese yuan. Basic economic theory would suggest that given these supply and demand conditions, one would expect the USD to trade weaker relative to the CNY. However, China's central bank (the PBOC) actively intervenes and looks to prevent such supply and demand imbalances between the two currencies by buying the available U.S. dollars from the Chinese exporters in exchange for the required yuan. In essence, this intervention by the PBOC creates a shortage of U.S. dollars in the market, which helps keep the U.S. dollar high, relative to the yuan. The PBOC does this, in an effort to keep their exchange rate competitive, and as such maintain its cost advantage with regards to exports to the United States.

In addition, the USD reserves accumulated by China is then used to buy U.S. Treasury notes[39]. This demand for U.S. treasuries assists in keeping the U.S. interest rates low and helps support consumer consumption in the U.S., which further sustains the demand for, and import of Chinese goods.

[39] Interestingly, China is the second largest owner of U.S. debt, behind Japan, and as of May 2017 held around $1.1 trillion of U.S. treasuries (Amadeo, 2017).

8.2. Modifying the Principal Components

Preceding the original PCA setup, we apply two modifications to the underlying spread data:

1. First, we subtract the mean spread from each of the maturities of the BRICS economies spread curve. That is, we first compute the mean sovereign spread for each of the maturities making up the yield spread term structure of the BRICS economies (over the complete sample period) and then subtract this mean spread from the corresponding maturity of the respective country. We call this the centered data. It is also noted that subtracting the mean spread from the data does not change the covariance of the data and consequently does not change the Principal Component, however it does change the resulting factor and gives it a mean of zero.

2. Next we divide the centered data by the standard deviation. That is, we calculate the standard deviation for each of the maturities making up the BRICS economies spread curve (again over the complete sample period), and thereafter we divide the centered data by the computed standard deviation for the corresponding maturity of the respective country. By doing this, we are able to apply the Principal Component Analysis to the correlation matrix of the underlying data (as opposed to the covariance matrix), and ensures that the component has a variance of one.

8.3. Scree Plots

Figure 14 - Brazil Factor Contribution (Scree Plot)

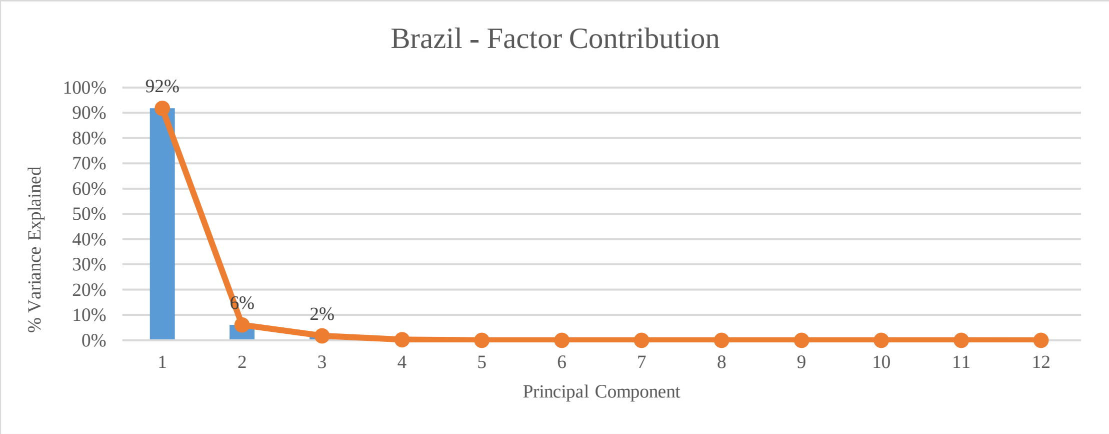


Figure 15 - Russia Factor Contribution (Scree Plot)

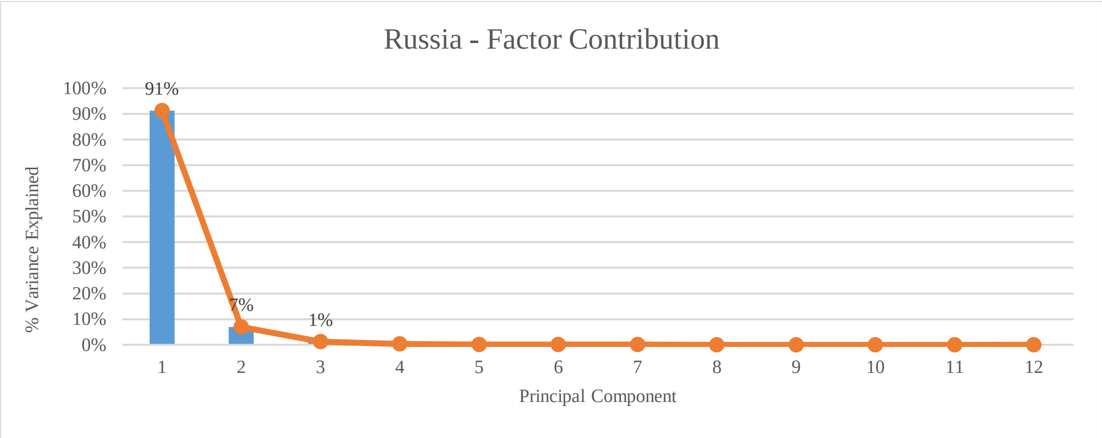


Figure 16 - Russia Factor Contribution (Scree Plot)

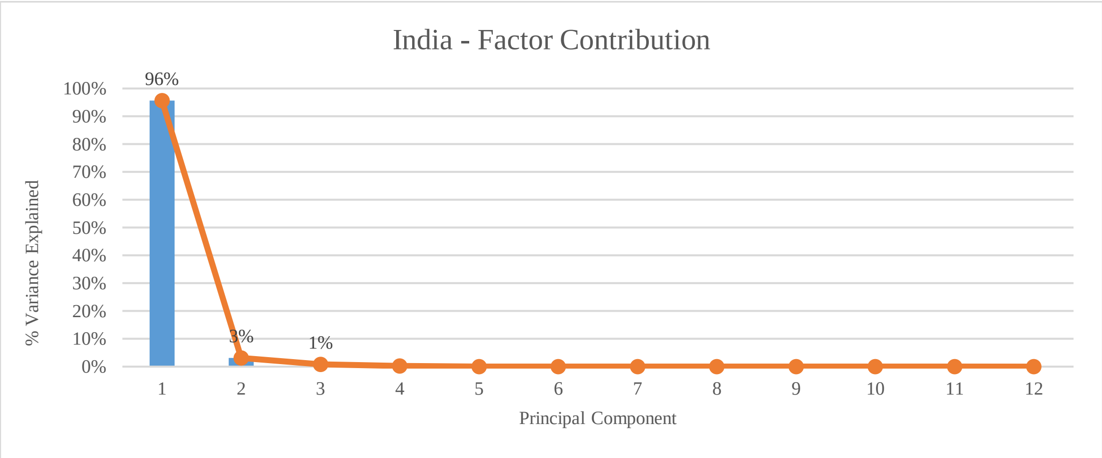


Figure 17 - China Factor Contribution (Scree Plot)

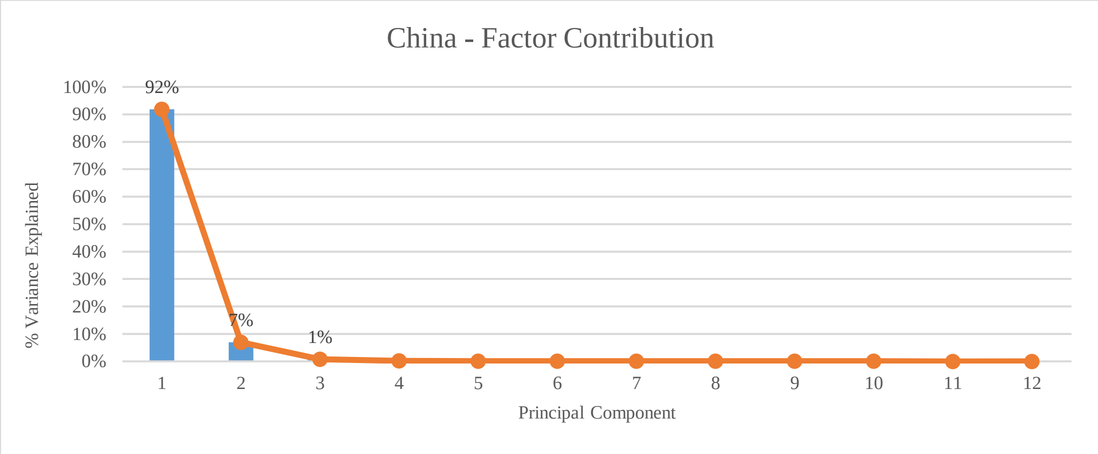
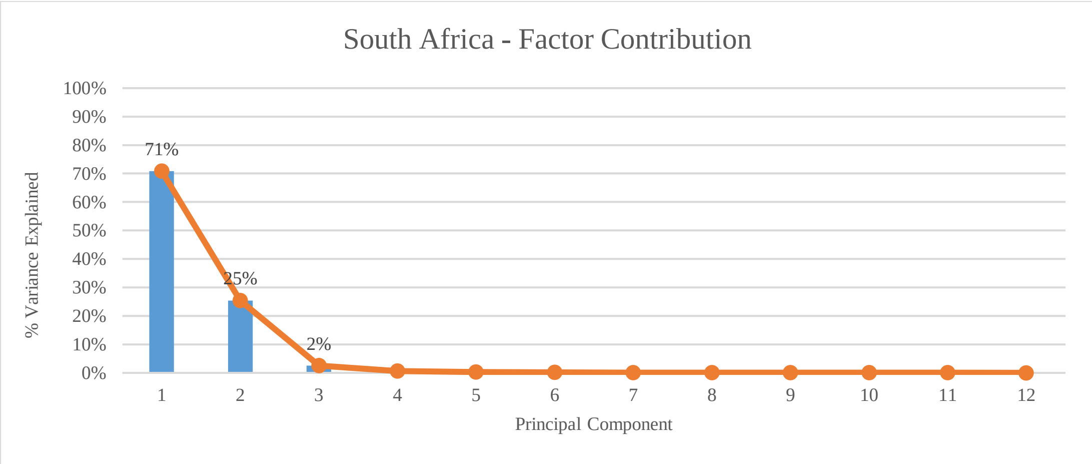


Figure 18 - South Africa Factor Contribution (Scree Plot)



Figures 14-18. Factor Contributions (Scree Plots): Scree Plots, representing the % of variation explained by the respective Principal Components for the BRICS economies.

8.4. Model Volatility - ΔS_{t+h} vs. UIRP vs. UIRP-Ext

Table 28 - Model Volatility: ΔSt+h vs. UIRP vs. UIRP-Ext (Complete Period)

Model Volatility (Complete)					
Statistic	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	ΔS_{t+h}	37.34	27.46	18.10	11.49
	UIRP	7.84	7.16	3.25	0.07
	UIRP-Ext	***17.28***	***13.91***	***8.51***	***4.68***
Russia	ΔS_{t+h}	43.28	28.32	18.52	13.21
	UIRP	6.43	6.22	3.32	3.58
	UIRP-Ext	***16.91***	***17.49***	***11.43***	***8.93***
India	ΔS_{t+h}	17.71	12.14	8.55	4.88
	UIRP	4.21	3.37	2.16	1.73
	UIRP-Ext	***5.46***	***5.20***	***3.41***	***2.51***
China	ΔS_{t+h}	5.53	4.52	3.41	2.11
	UIRP	1.93	2.26	2.11	1.47
	UIRP-Ext	***2.80***	***2.98***	***2.84***	***1.66***
South Africa	ΔS_{t+h}	32.24	22.40	15.47	10.32
	UIRP	1.58	2.31	4.83	4.12
	UIRP-Ext	***5.97***	***8.39***	***8.21***	***8.77***

Table 29 - Model Volatility: ΔSt+h vs. UIRP vs. UIRP-Ext (Post Crises Period)

Model Volatility (Post Crises)					
Statistic	**Model**	**h = 13**	**h = 26**	**h = 52**	**h = 104**
Brazil	ΔS_{t+h}	30.18	20.70	15.35	9.26
	UIRP	3.82	4.53	4.63	0.85
	UIRP-Ext	***16.82***	***14.48***	***10.07***	***4.38***
Russia	ΔS_{t+h}	44.55	27.91	18.77	14.45
	UIRP	4.70	7.81	6.63	2.42
	UIRP-Ext	***15.91***	***18.26***	***11.71***	***12.29***
India	ΔS_{t+h}	16.65	10.78	7.04	4.05
	UIRP	3.74	3.68	3.33	1.45
	UIRP-Ext	***4.40***	***4.63***	***3.88***	***2.76***
China	ΔS_{t+h}	5.07	3.80	2.98	2.20
	UIRP	0.51	0.75	1.48	1.63
	UIRP-Ext	***1.94***	***1.85***	***2.25***	***1.74***
South Africa	ΔS_{t+h}	24.16	15.55	11.17	6.65
	UIRP	6.28	3.97	4.27	1.71
	UIRP-Ext	***8.99***	***5.20***	***6.92***	***4.43***

Tables 28 and 29: Model Volatility (ΔS_{t+h} vs. UIRP and UIRP-Ext) for the BRICS economies over the time period 15/06/2007 - 17/06/2016 (Complete) and 05/06/2009 to 17/06/2016 (Post Crises).

9. Index