Essays in international finance

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This dissertation is submitted for the degree of

Doctor of Philosophy

May 2015

To Waard and Yara ...

Acknowledgements

I would like to express my sincere gratitude to my advisors Professor Jerry Coakley and Dr Stuart Snaith, you have been tremendous mentors for me. Your advice on both research as well as on my career have been invaluable.

Writing this thesis would not have been possible without the help and continuous support from the people around me during this wonderful journey, to only some of whom it is possible to give particular mention here. I would like to thank my parents, Atta and Mouna, brother, Bayan, and sisters, Afak and Zelal, for their love and support, and for believing in me and my goals.

My heartfelt regard goes to my father in law, Muhammad, mother in law, Hanan, sister in law, Mais and brothers in law, Ayman and Osama, for their love and continuous support.

To my friend, Woroud, thank you for listening, offering me advice, and supporting me through this entire process.

Above all I would like to thank my wife Yara for her love and constant support, for all the late nights and early mornings, and for keeping me sane over the past few months. Thank you for being my muse, editor, proofreader, and sounding board. But most of all, thank you for being my best friend. I owe you everything.

The last word goes for Waard, my baby boy, who has been the light of my life for the last two years and who has given me the extra strength and motivation to get things done.

Abstract

This thesis contributes to the extant research on international finance by presenting a collection of three separate essays. The first essay tests the validity of long-run Purchasing Power Parity (PPP) in two panels of real exchange rates for 13 OECD countries (1989:07-2012:11, 1989:07-2006:12). Three panel unit root tests are applied, one that assumes cross-sectional independence, one that accounts for cross-sectional dependence using a single factor approach, and one that controls for cross-sectional dependence through a multi-factor approach. The main difference in the results is attributed to ignoring or allowing for cross-sectional dependence.

The second essay also examines long-run PPP, but uses a panel cointegration test which allows for (i) heterogeneous and multiple structural breaks and (ii) cross-sectional dependence. Based on a panel of 53 economies (1992:01-2014:05) no evidence of PPP can be found using two types of models that can be equipped/ill-equipped to handle the potential presence of structural breaks in the data.

The third essay employs a factor approach to analyse exchange rate prediction at multiple horizons, from 1 month to two years for a panel of 10 OECD economies spanning the period 1999:01-2013:04. Two new models are proposed, that are based on the separate use of forward rates and interest rate differentials to be added in conjunction with the extracted factors. Factor-based exchange rate models were found to beat the random walk model for long horizons over the latter parts of our forecasting sample.

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Chapter1

Introduction

Purchasing Power Parity (PPP) is based on the premise that national price levels in different countries should be identical once expressed in the same currency. In the more recent empirical literature on exchange rates a substantial effort has been devoted to investigating the validity of PPP, as well as forecasting nominal foreign exchange rates. The reasons for such intense research interest are probably the importance of the theoretical foundations underlying PPP for exchange rate determination, and the advantages of accurate exchange rate predictability for global market investors.

Despite the voluminous amount of liquidity in foreign exchange markets, it is notoriously difficult to improve on the random walk model in predicting floating exchange rates.[1] In an influential study, Meese and Rogoff (1983) noted that exchange rate models based on macro fundamentals were not able to outperform the random walk model at short or medium horizons. This apparent exchange rate disconnect from the underlying fundamentals remains one of the long standing puzzles in international finance (see, inter alia, Obstfeld and Rogoff (2001)).

The PPP theory has a long history in economics. Today there is a massive and ever growing empirical literature addressing a wide range of different PPP applications such as determining the appropriate initial exchange rate for a newly independent country, forecasting long-term movements of real exchange rates, and adjusting for price differentials in cross-border income comparisons.[2] However, the empirical evidence supporting PPP remains inconclusive and the vast literature on PPP is indicative of this ambiguity, a situation that makes the research on PPP more interesting and attractive.

In the research on PPP, recent econometric tests were based on two alternative approaches. The first approach tests for a unit root in panels of real exchange rates, and a rejection of the unit root hypothesis is interpreted as potential evidence in favour of PPP. The second approach tests for a cointegrating relationship between

[1] A report by the London Foreign Exchange Joint Standing Committee estimated that in April 2013 the daily average turnover recorded in the UK was approximately \$2.547 billion.

[2] Deutsche Bank published its annual snapshot of prices around the world for some of the goods and services using PPP based index

panels of nominal exchange rates and relative price ratios. A rejection of the null hypothesis of no-cointegration in the latter approach implies favourable evidence supporting PPP. Early panel unit root and panel cointegration tests of PPP have been ill-equipped to handle the potential presence of cross-sectional dependence and structural breaks in exchange rates, hence adversely affecting the statistical power of the corresponding panel test statistics and leading to invalid conclusions about PPP.

As a form of tackiling the above mentioned issues, this thesis comprises three separate essays, two of them address long-run PPP and the other forecasting exchange rates. The latter essay analyses exchange rate predictions by utilising the factor approach, proposed by Engel et al. (2015), which has been shown to produce promising results in the field of exchange rate forecasting. The first of the two essays addressing the validity of long-run PPP uses the novel panel unit root test, proposed by Pesaran et al. (2013), which allows for the presence of cross-sectional dependence among real exchange rates by using a multi-factor error structure approach. The second of these two essays evaluates the evidence on PPP by using the novel panel cointegration test, suggested by Banerjee and Carrion-I-Silvestre (2013), which allows for the presence of both heterogeneous and multiple structural breaks and of cross-sectional dependence.

Prior to presenting the main contributions of the present thesis, we review earlier work achieved by related papers in the literature.

1.1 Literature

Early work by Meese and Rogoff (1983) demonstrated that exchange rate models (time series and structural models) based on macro fundamentals (such as the money supply, trade balance and national income) were not able to outperform the random walk model in providing a better forecast at short or medium horizons. Succeeding work by Chin and Meese (1995) and Berben and Dijk (1998), who focused on similar models, also reported no evidence in favour of long-horizon exchange rate predictability.[3]

In defence of the fundamental-based exchange rate models, several studies proposed using various combinations of econometric techniques and economic variables aiming to overturn Meese and Rogoff's finding. For instance, MacDonald and Taylor (1994), Mark (1995), and Lothian and Taylor (1996), among others, all reported significant evidence in favour of exchange rate predictability at long horizons. Similar results were also obtained by Kilian and Taylor (2003) who argued that models that incorporate nonlinear exchange rate dynamics can improve the forecasting accuracy of fundamental models at long horizons (2 to 3 years).

In the context of panel data estimation, Mark and Sul (2001), Groen (2005), and Engel et al. (2007) found relatively good success of exchange rate predictability using models based on monetary fundamentals. However, different results were obtained by Sarno and Taylor (2002), Cheung et al. (2005), and Alquist and Chinn (2008), among others, who argued that standard macroeconomic models of exchange rates (conventional forecasting models) cannot predict nominal exchange rates with significantly higher accuracy than the random walk model. This apparent weak relationship between the exchange rates and the macroeconomic aggregates remains to be one of the long standing puzzles in international finance. This has continued until recent models based on a factor approach introduced promising results in the field of exchange rate prediction. This is shown in the work of Engel et al. (2015) who established that factor models tend to provide a successful forecast of nominal exchange rates at long horizons.

Concerning PPP, early econometric methods were based on examining the time-series properties of real exchange rates, with early work tending to apply univariate unit root tests. These studies tended to provide evidence against long-run PPP. A selection of such studies includes, inter alia, Roll (1979), Darby (1980), Frenkel (1981), Adler and Lehmann (1983), Mishkin (1984), and Pigott and Sweeney (1985)

[3] Chin and Meese (1995) found no evidence in favour of long horizon prediction for the Sterling-Dollar exchange rate in an analysis mainly based on error correction terms specifications. However, the authors noted that models with other exchange rates, such as the German Mark and the Japanese Yen vis-à-vis the US dollar, beat the random walk in providing a better forecast at long horizons.

who all found no evidence in favour of long-run PPP using various techniques of univariate unit root tests.

It is widely recognised by researchers that one of the main limitations of standard univariate unit root tests is their poor statistical power against the stationary alternative, a problem that has been partially attributed to the small size of samples under consideration. One way the literature attempts to tackle this problem is to increase statistical power by using panel unit root tests. Example works of early adoption of the panel approach in testing PPP are those of Abuaf and Jorion (1990), Oh (1996), MacDonald (1996), Jorion and Sweeney (1996), Papell and Theodoridis (1998), and Flores et al. (1999), among others, who all provided favourable evidence supporting PPP. This evidence of PPP was later overturned by O'Connell (1998) who asserted that failing to control for cross-sectional dependence when testing for a unit root in panels of real exchange rates could result in overvaluation of PPP. Consistent with the latter finding, recent studies that attempt to control for cross-sectional dependence, such as Harris et al. (2003), Moon and Perron (2004), Smith et al. (2004), Pesaran (2007), Choi and Chue (2007), and Snaith (2012) contradicted the earlier literature and failed to provide favourable evidence supporting PPP.

A second approach for assessing the evidence of PPP is based on testing for a cointegrating relationship between nominal exchange rates and relative price ratios. Early studies, which applied univariate cointegration techniques, such as Corbae and Ouliaris (1988), Enders (1988), Taylor (1988), and Patel (1990), among others, showed that PPP does not hold in the long-run. Succeeding work on PPP focused on using panel cointegration methods in the aim of avoiding criticism linked to the apparent poor statistical power associated with univariate cointegration tests. Studies such as Taylor (1996), Chinn (1997), Obstfeld and Taylor (1997), Canzoneri et al. (1999), Pedroni (2001), Azali et al. (2001), and Nagayasu (2002), inter alia, all employed panel cointegration techniques and consequently reported supporting evidence in favour of PPP. One problem with these studies was that they used panel cointegration tests which have been ill-equipped to consider the presence of cross-sectional dependence and structural breaks, a situation that is very likely in the case of testing PPP in panels.

Recent development in panel cointegration tests of PPP shows that several studies employed various techniques which partially addressed the problems arising from relaxing the assumptions of structural breaks and cross-sectional dependence. For example, Gengenbach et al. (2005) and Westerlund and Edgerton (2008) employed panel cointegration tests that allow for cross-sectional dependence and structural breaks, respectively, and reported no evidence supporting PPP.

1.2 Contributions

This thesis contributes to the extant literature on forecasting exchange rates (Chapter 4). It builds on the factor approach, proposed by Engel et al. (2015), by comparing the predictions from two new proposed models with those from the random walk model on the basis of their performance in an out-of-sample predictive accuracy test. We propose the separate use of forward rates and interest rate differentials as the two new sets of fundamentals to be used in conjunction with the extracted factors. The leading Engel et al. model uses factors only (with no additional fundamentals). Their remaining three models utilise factors together with different measures of observable fundamentals based on the (1) Taylor rule (2) purchasing power parity (PPP) and (3) monetary models.

The thesis also contributes to the literature with respect to panel unit root tests on real exchange rates (Chapter 2). It is the first study to examine PPP by using the new panel unit root test of Pesaran et al. (2013) (CIPSM) that accounts for cross-sectional dependence through a multi-factor error structure approach. In contrast to other existing panel unit root tests with cross-sectional dependence such as Bai and Ng (2007) and Moon and Perron (2004), the CIPSM test has desirable size properties and is easy to apply. Pesaran's test is essentially an extension of the cross-sectionally augmented panel unit root test (CIPS) proposed by Pesaran (2007) to a more general setting where cross-sectional dependence is generated by a multi-factor error structure. The CIPS test also accounts for cross-sectional dependence but through a single unobserved common factor approach. Critical values for the CIPS and CIPSM tests are obtained via simulation and reported by Pesaran (2007) and Pesaran et al. (2013) , respectively.

Finally, the thesis contributes to the literature regarding panel cointegration tests of PPP (Chapter 3). To the best of our knowledge, our study introduces the first use of the novel panel cointegration test of Banerjee and Carrion-I-Silvestre (2013) in examining PPP. Early panel cointegration tests were ill-equipped to handle the potential presence of cross-sectional dependence and structural breaks (e.g.: Azali et al. (2001), Nagayasu (2002), Basher and Mohsin (2004), and Jenkins and Snaith (2005)), a situation that can adversely affect the empirical size of the corresponding panel test statistics (Westerlund and Edgerton (2008)). Unlike these studies, we examine the cointegrating relationship between nominal exchange rates and relative price ratios using Banerjee and Carrion-I-Silvestre's panel cointegration test that allows for both heterogeneous and multiple structural breaks and cross-sectional dependence.

1.3 Chapters preview

Chapter 2 examines long-run PPP by testing for a unit root in two panels of real exchange rates for 13 OECD countries (1989:07-2012:11, 1989:07-2006:12). Three panel unit root tests are applied; the IPS test of Im et al. (2003) under the assumption of cross-sectional independence; the CIPS test of Pesaran (2007) which accounts for cross-sectional dependence via a single unobserved common factor approach; and finally the novel panel unit root test CIPSM of Pesaran et al. (2013) that allows for cross-sectional dependence through a multifactor error structure approach. Cross-sectional dependece is evaluated using the CD test of Pesaran (2004).

The first stage is to assess the evidence on cross-sectional dependence among real exchange rates, and the second stage is to test the null that the real exchange rates are non-mean reverting, using the above three panel unit root tests. The results show that by using the IPS test there is a clear support for long-run PPP. Conversely, there is clear evidence against PPP using the CIPS and CIPSM panel unit root tests. The overall conclusion from the results discussed above is that cross-sectional dependence is a key determinant of (non) rejection of the null unit root hypothesis. Further, this verdict on the validity of long-run PPP is consistent across the two panels under consideration. A careful assessment of this result reveals that an influence by the financial crisis (2007-2008) on long-run PPP is unlikely.

Chapter 3 applies the new panel cointegration test, proposed by Banerjee and Carrion-I-Silvestre (2013), that allows for (i) heterogeneous and multiple structural breaks and (ii) cross-sectional dependence. This chapter examines long-run PPP by testing the null hypothesis of no-cointegration in a large cross-section of nominal exchange rates and of relative price ratios (53 countries) 1992:01-2014:05. Prior to checking for the above cointegrating relationship, the chapter tests non-stationarity of the variables under consideration using the unit root testing approach of Bai and Ng (2004).

The results of these two tests (mentioned above) show that the variables of nominal exchange rates and price ratios are non-stationary but not cointegrated, thus the implication is that PPP does not hold. This evidence against PPP is obtained by two types of models that can be equipped/ill-equipped to handle the potential presence of structural breaks in the data, a situation that could lead to the conclusion that structural breaks are not key determinants of (non) rejection of the no-cointegration null hypothesis.

Chapter 4 focuses on the task of forecasting a large panel of exchange rates, employing the factor approach proposed by Engel et al. (2015). Factors are constructed from a panel of exchange rates only, and not from other observable fundamentals added to the forecasting process subsequently. The chapter proposes the separate use of forward rates and interest rate differentials as the two new sets of fundamentals to be used in conjunction with the extracted factors. The chapter also adopts a more comprehensive forecasting exercise that addresses the performance of each competing model in order to determine which model is best able to forecast spot exchange rates in each economy tested.

Employing monthly data from 10 OECD economies spanning the period 1999:01-2013:04, the estimation results show that exchange rate models based on a factor approach can beat the random walk model over long horizons (18 and 24 months) when used over the latter parts (out of sample periods are 2008:01-2013:04 and 2009:01-2013:04) of our forecasting sample. However, when used over the first part (2004:01-2007:12) of our forecasting sample, none of our candidate models outperforms the random walk model in predicting exchange rates at long horizons. This situation is in a stark contrast to Engel et al. (2015) who found all their fundamental models' predictions have lower (though not significantly so) mean squared prediction error than the random walk model for long (2 and 3 year) horizon predictions over the later part (1999-2007) of their forecasting sample.

Despite the fact that our candidate models produce better forecasts for the spot exchange rates than the random walk model does (for samples (2) and (3) where forecasting samples are 2008:01-2013:04 and 2009:01-2013:04, respectively), it remains difficult to identify the best model among our candidate models that is able to consistently outperform the random walk model. The implication is a high level of heterogeneity in model performance across (varying) prediction accuracy measurements, currencies, factors, and horizons.

Finally, Chapter 5 ends the thesis with concluding remarks and points to potential areas for future research.

Chapter2

Long-run purchasing power parity: Evidence from new panel unit root test

2.1 Introduction

Purchasing Power Parity (PPP) has appeared in the economic literature, specifically, in the discussion of appropriate nominal exchange rates during and after the First World War following a significant rise in inflation rates of many industrial countries. The concept is based on the law of one price which posits that in a perfect capital market homogeneous goods in two economies should have the same price when expressed in the same currency. Put simply, PPP is an aggregation of the law of one price considering a basket of goods rather than an individual good.

A much of the recent empirical literature investigating the validity of PPP has focused on examining the time-series properties of the real exchange rate, with early work tending to apply univariate unit root tests.[1] One main shortcoming of these studies is that standard univariate unit root tests could suffer from poor statistical power against the stationary alternative, a problem that has been partially attributed to the small size of samples under consideration. One way the literature attempts to address this issue is to gain statistical power by adopting multivariate unit root tests. However, this approach has been shown to potentially overvalue PPP by failing to account for cross-sectional dependence among the individual series of real exchange rates in the panel O'Connell (1998). Therefore, in this chapter we aim to circumvent falling into the trap often encountered in the literature by employing a novel panel unit root test that is robust to the cross-sectional dependence.

In this chapter we contribute to the extant literature by examining the validity of long-run PPP through the novel panel unit root test suggested by Pesaran et al. (2013) (henceforth CIPSM). This extends the cross-sectionally augmented panel unit root test (CIPS) proposed by Pesaran (2007) to a more general setting where cross-section dependence is generated by a multifactor error structure (multiple common factors). The CIPSM test makes use of additional regressors that are supposed to share the same common factors with the essential variables under consideration.

[1] A selection would include, inter alia, Roll (1979), Dickey and Fuller (1979), and Adler and Lehmann (1983).

Pesaran et al. (2013) further showed that their proposed CIPSM test has the correct size for all combinations of N and T, regardless of whether the idiosyncratic errors were serially correlated or not.[2]

As a benchmark test for our chapter, we apply the IPS test of Im et al. (2003) which is based on the assumption of cross-sectional independence. This is followed by applying the CIPS test of Pesaran (2007) which simultaneously takes into account the potential presence of residual serial correlation and cross-section dependence, where the latter is modelled through a single unobserved common factor approach.

The dataset in this chapter is quoted on a monthly basis and it comprises two panels of real dollar exchange rates from 13 OECD countries for the periods 1989:07-2012:11 and 1989:07-2006:12. The initial motivation for including two panels in our dataset was to assess the potential influence of the financial crisis in 2007-2008 on the validity of long-run PPP using our testing criteria.

Our analysis yields a number of important results. On the one hand, it is established that by accounting for cross-sectional dependence, using the CIPS and CIPSM tests, there is significant evidence against long-run PPP. The evidence against long-run PPP arrived at this chapter is interesting in the sense that it is obtained by a novel testing technique that accounts for cross-sectional dependence through a multi-factor error structure approach. On the other hand, using the IPS test, which ignores the cross-sectional dependence, we clearly find supporting evidence in favour of long-run PPP. This suggests that cross-sectional dependence is a key determinant of (non) rejection of the null unit root hypothesis. Another important outcome of our study, based on the fact that our testing results are consistent across the two panels under consideration, indicates that the financial crisis in 2007-2008 played no significant role in determining long-run PPP.

Our results are consistent with those of Harris et al. (2003), Smith et al. (2004), Moon and Perron (2005), Pesaran (2007), Choi and Chue (2007), Chang and Song (2009), and Snaith (2012) who employed various techniques of panel unit root tests under the assumption of cross-sectional dependence and all failed to provide favourable

[2] N and T are the cross-section dimension and time series dimension, respectively.

evidence supporting PPP.

The plan of this chapter is as follows. Section 2 introduces the PPP theory. Section 3 includes the literature review. Section 4 discusses the data. Section 5 introduces the econometric methodology and outlines the panel unit root tests. Section 6 holds the empirical analysis and provides the results, and Section 7 concludes the chapter.

2.2 Theory of PPP

PPP investigates the relationship between a country's exchange rate and the level of its national price. Absolute PPP states that the price of a basket of goods in one country should equal that of another country, once expressed in a similar currency. More formally it implies that the nominal exchange rate between two economies is equal to the ratio of the relevant national price levels between the two countries concerned.

$$s_t = p_t - p_t^* \tag{2.1}$$

where s_t is the log nominal exchange rate expressed as the domestic price of foreign currency, p is the price index in the domestic country in a logarithmic form, p^* is the price index in the foreign country in a logarithmic form.

Relative PPP, on the other hand, can be presented by taking the differentials of the logged nominal exchange rates and price indices in (2.1). Relative PPP implies that inflation differentials between two countries are offset by exchange rate depreciation between the same economies over the same period.

$$\Delta s_t = \Delta p_t - \Delta p_t^* \tag{2.2}$$

where $(\Delta s_t, \Delta p_t$, and $\Delta p_t^*)$ are the first differences of the logged nominal exchange rate and the other variables in (2.1).[3]

One important method in the literature for examining the validity of long-run PPP is based on testing for a unit root in the real exchange rates which are the nominal exchange rates adjusted by price changes at home and abroad. This testing technique is based on the notion that when real exchange rates are constant PPP is said to hold, whereas movements in real exchange rates can be viewed as deviations from long-run PPP.

[3] See Taylor (2006) for early tests of the absolute and relative forms of PPP.

Equation (1.3) represents the real exchange rates expressed in logarithmic form

$$q_t = s_t - p_t + p_t^* \tag{2.3}$$

where (q_t) is the logarithm of the calculated real exchange rate, (s_t) is the logarithm of the nominal exchange rate, (p_t) is the logarithm of the price index in the domestic country, (p_t^*) is the logarithm of the price index in the foreign country.[4]

A second approach for assessing the evidence of PPP is based on testing for a cointegrating relationship between nominal exchange rates and relative price ratios (see chapter 3).

[4]Nominal exchange rates are expressed as domestic price of foreign currencies.

2.3 Literature review

A large body of literature examined the validity of long-run PPP by testing for a unit root in the real exchange rate. The following literature review documents the progression from simple univariate testing to the application of the latest panel unit root models that account for cross-sectional dependence. This literature review eschews a treatment of the very early testing of PPP that has been covered in a number of extensive literature reviews.[5]

2.3.1 Univariate unit root tests

In early tests of long-run PPP univariate unit root tests were applied to single series of real exchange rates aiming to test the null hypothesis of a unit root. If the null hypothesis is rejected then PPP is said to hold, otherwise, PPP is considered to be invalid. Early studies of PPP tended to use models that span short or medium-length time series of real exchange rates, and were typically unable to reject the null hypothesis that real exchange rates have a unit root. For instance, Roll (1979), Darby (1980), Frenkel (1981), Adler and Lehmann (1983), Mishkin (1984), and Pigott and Sweeney (1985), among others, all found no evidence in favour of long-run PPP using various univariate unit root tests.

A possible explanation of why the above studies have failed to provide evidence on PPP is the lack of statistical power of unit root tests in small samples. One approach to overcome the small sample problem is to use more powerful univariate unit root tests. Cheung and Lai (1998), using the DF-WS and DF-GLS univariate unit root tests of Park and Fuller (1995) and Elliott et al. (1996), respectively, reported supporting evidence in favour of PPP for five real exchange rates over the period 1973:4-1994:12 but mostly at the %10 significance level. However, Lopez (2009) stated that the DF-GLS test could suffer from limited performance when applied to economic time series data that have limited length .

[5]See Sarno and Taylor (2002) for extensive literature review on the early testing for PPP.

2.3.2 Solutions to the poor power problem

One major problem with the early literature on PPP is the issue of low power associated with the univariate unit root tests. A possible explanation for this problem is probably the small size of samples under consideration. This is what concluded by Frankel (1986) who noted that using 15 years of real exchange rates data is insufficient to reject the null hypothesis of a unit root.

As a response, to alleviate the poor power problem, it has been suggested by many researchers to increase the number of observations included in the samples under consideration by using longer time series of data, a situation that would give real exchange rates higher chance to return to their mean levels. For instance, Frankel (1986) found some evidence of PPP using annual data covering 117 years from 1869 to 1984. Similar results were also obtained by Lothian and Taylor (1996) after using very long time series, as long as two hundred years of data series. However, Sarno and Taylor (2002) concluded that, based on Monte Carlo experiments using statistics from several empirical real exchange rate studies, the chance of rejecting the null unit root hypothesis in real exchange rates is less than 50 percent even with 100 years of data.

Studies based on long-span data have attracted lots of criticism in the literature. One major criticism is linked to the fact that, using long time periods of data, it is possible to encounter problems resulting from datasets spanning multiple exchange rate regimes. Also, because of the very long data spans involved, it is more likely that real shocks may have generated structural changes in the long-run equilibrium real exchange rate.[6] One way to overcome the problem of structural changes is by using non-linear models. This is clearly demonstrated in the work of Chortareas and Kapetanios (2004) and Sarno et al. (2006), who provided supporting evidence for PPP for two groups of (i) ten Yen real exchange rates against the other G7 and Asian currencies and (ii) for five developed countries, respectively.

[6] The term "real shock" is used by Corbae and Ouliaris (1991) to describe situations such as changes in consumption preferences, tariffs, and shocks to the terms of trade.

Some researchers advocate an alternative approach wherein instead of increasing the length of the dataset or using non-linear models, the new technique is based on expanding the number of cross-section dimensions by using panels of data. The basic idea for this approach is to exploit cross-section information and consequently increase the power of the test.

2.3.3 Panel unit root tests

The main motivation for adopting panel unit-root tests is to gain important statistical power by considering information combined across individual units and thereby improve upon the poor performance of univariate unit root tests. Panel unit root tests have been extensively used in a variety of applications in finance and economics. One of the most common implementations was to examine the validity of PPP in real exchange rates. An example of early adoption of the panel approach is Abuaf and Jorion (1990) using Seemingly Unrelated Regression (SUR) approach on a panel of ten real exchange rates. This study found evidence in favour of PPP in the long-run and claimed a significant increase in the power of the deployed test.

Similarly, Flores et al. (1999) developed a panel unit root test based on a heterogeneous Seemingly Unrelated Regression. This was applied to a panel of eleven real exchange rates and provided favourable evidence supporting long-run PPP. Similar results were also obtained by, among others, Jorion and Sweeney (1996), Oh (1996), and Papell and Theodoridis (1998).

In a related manner, MacDonald (1996) reported supporting evidence in favour of PPP for two panels of real exchange rates using the panel unit root test of Levin and Lin (1992). The test implemented used pooled cross-section data set and allowed for individual and time specific effects across groups. One major limitation of the Levin and Lin designed tests (LL) is that they test a very restrictive hypothesis that is rarely practical in economic studies. They require, under the alternative hypothesis, the autoregressive parameters to be common to all individual units in the panel.[7]

Relaxing the assumption of homogenous autoregressive coefficients under the alternative hypothesis, Im et al. (2003) developed a panel unit root test (IPS) based on combining the t-statistics from individual augmented Dickey and Fuller (1979) regressions.[8] Using these tests (the LL and IPS), Banerjee et al. (2005) were unable

[7]The LL tests are based on homogeneity of the autoregressive coefficients. The tests allow for heterogeneity in the error variances and the serial correlation structure of the errors Maddala and Wu (1999).

[8]The null hypothesis in the two tests (the LL and IPS) is the same (each individual series has a unit root).

to find evidence supporting PPP for a panel of 18 OECD countries over the period 1975:1-2002:4.

While the panel data approach was seen as the initial solution to the poor power problem, it was later realised that panel tests of PPP are subject to cross-sectional dependence which has been largely ignored in the above literature. Cross-section dependence is likely to be evident when testing for PPP in panels of bilateral exchange rates that share the same numeraire currency and price index.

2.3.4 Panel unit root with cross-section dependence

Early panel unit root tests, which were typically ill-equipped to handle the problem of cross-sectional dependence, tended to provide evidence in favour of long-run PPP. A selection would include, inter alia, MacDonald (1996), Oh (1996), Wu (1996) and Coakley and Fuertes (1997). This was later overturned by O'Connell (1998) who argued that failing to control for cross-sectional dependence could lead to spuriously favouring the PPP hypothesis.

In response to this concern, researchers have developed various panel unit root tests for cross-sectionally correlated panels. For instance, Taylor and Sarno (1998) used multivariate augmented Dickey-Fuller test statistics in building their panel unit root test. Maddala and Wu (1999), Chang (2004), and Smith et al. (2004) developed panel unit root tests based on bootstrap methods. Choi (2002) used a two way error-component model to account for cross-sectional correlations in panel unit root testing. Bai and Ng (2004), Moon and Perron (2004), Phillips and Sul (2003) proposed several panel unit root tests in which cross-section correlations are modelled via dynamic factor methods.

In the context of PPP, early studies based on panel unit root tests with cross-sectional dependence failed to provide supporting evidence for PPP. See for example Harris et al. (2003), Moon and Perron (2004), and Smith et al. (2004).

Pesaran (2007) also found no evidence in favour of long-run PPP using a new panel unit root test that controls for cross-section dependence through a single unobserved common factor approach. The new test (CIPS) is based on augmenting the standard augmented Dickey-Fuller regressions (ADF) with the cross-section averages of lagged levels and first-differences of the individual series. The author found that the support for PPP obtained from using panel unit root test that assume the individual time series in the panel to be cross-sectionally independent (namely the IPS test) is overturned when using panel unit root test that allows for cross-sectional dependence. Pesaran's findings were based on the analysis of two panels of quarterly real exchange rates constructed from 17 OCED countries for the periods

1974:1-1998:4 and 1988:1-1998:4.

In search for evidence of PPP, Choi and Chue (2007) used panel unit root testing framework with subsampling procedure to tackle cross-section dependence. The authors found no evidence in favour of PPP for two panels (7 industrial and 26 OECD economies) of quarterly real exchange rates spanning the same period 1973:2-2000:4. In a different study, Chang and Song (2009) investigated the validity of PPP using a modified panel unit root test with the cross-section dependence being accommodated through an orthogonal instrument generating approach. They did not find any evidence in favour of PPP for two panels of monthly (17 industrialised countries) and quarterly (20 industrialised countries) real exchange rates over the period 1973-1998.

One major weakness of the above panel unit root tests is that the joint nature of the non-stationarity hypothesis. As a result, the rejection of the null unit root hypothesis may be driven by a small number of real exchange rates, that share particular features, in a given panel. Put differently, the gauge on whether PPP holds or not is sensitive to the inclusion of particular series of real exchange rates in the panel. This is what pointed out by Chortareas and Kapetanios (2009) who proposed a testing procedure that when applied to a set of panel unit root tests allows the identification of the stationary real exchange rates within a panel. The latter authors applied the above-mentioned procedure to a panel of 25 OECD economies and were able to identify the cross-sectional units on which PPP was found to be valid.

Further analysis has been conducted by Snaith (2012) who found no evidence in favour of PPP when simultaneously accounting for structural breaks and cross-sectional dependence. Snaith's analysis was based on the application of several panel unit root tests that allow for heterogenous structural breaks and cross-sectional dependence to a panel of 15 OECD countries for the period 1973:03-1998:12.

Hanck (2013), on the other hand, found supporting evidence for long-run PPP using a panel unit root test based on the classical intersection technique. Hank's approach was based on testing the global hypothesis that all series have a unit root, while controlling for the probability of falsely rejecting at least one individual true null hypothesis at some chosen significance level α. The author employed a panel of 19 real exchange rates and found that PPP holds for all countries except for the following three economies (Denmark, Switzerland and Japan).[9]

[9] In this chapter, we do not discuss the issue of half-live PPP deviation but we turn our focus on studying the impact of allowing/ ignoring for cross-sectional dependence in PPP results.

2.4 Summary of the data

The present chapter employs a panel of monthly real exchange rates for 13 OECD countries (1989:07-2012:11). There are indeed good reasons to believe in common long-run relationship (PPP) between OECD countries since these economies have common floating exchange rate regimes and intensive intra-trade. The choice of time period and OECD economies included in this chapter is based on data availability. For robustness we also consider a second panel covering the period (1989:07-2006:12). The second panel avoids a period that has been identified to have substantial volatility of exchange rates induced by the financial crisis in 2007-2008. The initial motivation for including two panels in our dataset was to assess the potential influence of the financial crisis in 2007-2008 on the validity of long-run PPP using our testing criteria

The 13 countries considered are: Canada, Denmark, Japan, Mexico, Iceland, Norway, Turkey, Sweden, Switzerland, Chile, South Korea, Israel and the UK. The nominal exchange rates are the WM/Reuters closing spot rates vis-à-vis the US dollar expressed as domestic price of foreign currencies. The U.S. dollar is designated as the numeraire currency, reflecting the global importance of the U.S. economy and the U.S. dollar along with the availability of the U.S. dollar-based exchange rate data. The price indexes are the consumer price indexes expressed in local currency and not seasonally adjusted.

We construct our two panels of data using real exchange rates calculated for the 13 OECD countries under consideration. The real exchange rates are computed as in equation (2.4) in logarithmic form

$$q_t = s_t - p_t + p_t^* \tag{2.4}$$

where q_t is the logarithm of the calculated real exchange rate, s_t is the logarithm of the nominal exchange rate, p_t is the logarithm of price index in the domestic country,

p_t^* is the logarithm of the price index in the foreign country.

The present chapter also employs two samples of real equity indexes and short-term real interest rates for the following 8 OECD economies: Canada, Japan, Mexico, Switzerland, Sweden, Israel, South-Korea, and the UK. The composition of these two samples was determined by data availability.

The real equity prices, eq_{it}, are quoted on monthly basis and are calculated as in (2.5) in logarithmic form

$$eq_{it} = ln[\frac{(EQ_{it})}{(CPI_{it})}] \tag{2.5}$$

where EQ_{it} and CPI_{it} are the nominal equity price index and the consumer price index, respectively for country i at times t.

The real interest rates are also quoted on a monthly basis and are calculated as follows

$$r_{it} = r_{it}^S - \pi_{it} \tag{2.6}$$

$$r_{it}^S = \frac{1}{12} * ln(\frac{1 + R_{it}^S}{100}) \tag{2.7}$$

$$\pi_{it} = p_{it} - p_{i,t-1} \tag{2.8}$$

where R_{it}^S is the short-term annual interest rates (three months), and $p_{it} = ln(CPI_{it})$.

2.5 Methodology

In this chapter we empirically assess the evidence on PPP by testing for a unit root in two panels of real exchange rates from 13 OECD countries. This is achieved via the application of three different panel unit root tests, namely the IPS test of Im et al. (2003) under the assumption of cross-sectional independence, the CIPS test of Pesaran (2007) where cross-sectional dependence is accommodated through a single unobserved common factor approach, and finally the novel panel unit root test CIPSM of Pesaran et al. (2013) that allows for cross-sectional dependence through a multifactor error structure technique.

In the first stage of the analysis we provide evidence on the degree of cross-sectional dependence among the real exchange rates in the panels. In doing so, we ensure that our choice of the panel unit root test is consistent with the uncovered level of cross-section dependence in the dataset. This argument is supported by O'Connell (1998) who suggested that using panel unit root tests that do not allow for cross-sectional dependence can lead to spurious results once it is established that the panel under consideration is subject to a significant degree of cross-section dependence. In case, where cross-sectional dependence is not sufficiently high, a potential loss of statistical power could result if panel unit root tests that accommodate cross-sectional dependence are employed.

To check for the potential presence of cross-section dependence we implement Pesaran (2004) CD (Cross-section Dependence) test defined in (2.9), which is based on the simple average of all pair-wise correlation coefficients of the OLS residuals from the individual regressions in the panels. The CD test is distributed as $N(0,1)$ under the null hypothesis of cross-sectional independence. At the 5% significance level, the null hypothesis of cross-sectionaly independent errors is rejected if $|CD| \geq 1.96$.[10]

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{2.9}$$

[10]The CD test is a 2−sided test distributed as $N(0,1)$ under the null hypothesis of cross-sectional independence.

where $\hat{\rho}_{ij}$ is the pair-wise simple correlation coefficient between e_{it} and e_{jt} for all i and $i \neq j$.

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \sum_{t=1}^{T} e_{it}e_{jt}/[(\sum_{t=1}^{T} e_{it}^2)^{\frac{1}{2}}(\sum_{t=1}^{T} e_{jt}^2)^{\frac{1}{2}}] \tag{2.10}$$

where e_{it} is the Ordinary Least Squares (OLS) estimate of μ_{it}, and is defined as follows

$$e_{it} = y_{it} - \hat{\alpha}_i - \hat{\beta}_i' x_{it}, \tag{2.11}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i'$ are the estimates of α_i and β_i using the OLS regression of y_{it} on an intercept and x_{it} for each i for the case of intercept only, and on a time trend, intercept and x_{it} for each i for the case of intercept and trend.

Moran (1948) and Breusch and Pagan (1980) suggested different testing procedures for measuring cross-sectional dependence in panels; their techniques were based on the spatial correlation method and the Lagrange multiplier approach, respectively. In this chapter, we adopt neither of these two procedures because we consider the more recent CD test to be superior to both of them for two reasons; (i) it does not require an earlier identification of spatial weight matrix, which is mandatory in the method of Moran (1948); (ii) it is valid even when (N) is large and (T) is small unlike the Lagrange Methodology which suffers from substantial size distortions.

In the second stage of the analysis we report statistics based on the implementation of three panel unit root tests, namely the IPS test, the CIPS test, and the CIPSM tests. The initial motive for using these tests is to assess the impact of cross-sectional dependence on PPP validity. Specifically, using our three panel unit root tests makes it possible to compare our PPP testing results, where cross-sectional dependence is (i) ignored (ii) modelled using a single factor approach (iii) modelled using a multi-factor approach.

The IPS t-bar panel unit root test is based on the t-ratio (t_{iT_i}) of the least squares estimate of β_i in the augmented Dickey-Fuller regression in (2.14). The IPS standardised test statistics are given in (2.12) below. We use the resulting IPS statistics to test the null unit root hypothesis (i.e. no evidence in favour of long-run PPP) against the heterogenous alternative stationary hypothesis (i.e. PPP holds for a significant portion of the countries in the panel).[11]

$$IPS(N,T) = \frac{\sqrt{N}\{tbar_{NT} - N^{-1}\sum_{i=1}^{N} E(t_{iT_i}|\beta_i = 0)\}}{\sqrt{N^{-1}\sum_{i=1}^{N} Var(t_{iT_i}|\beta_i = 0)\}}} \overset{T,N}{\Longrightarrow} N(0,1) \tag{2.12}$$

where $E(t_{iT})$ and $Var(t_{iT})$, respectively, are simulated values provided by Im et al. (2003) for the mean and the variance of the standard Dickey-Fuller test statistics based on T_i observations, and $tbar_{NT}$ is the average of the augmented Dickey-Fuller statistics defined as follows

$$tbar_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT_i} \tag{2.13}$$

where t_{iT_i} is the standard Dickey-Fuller estimate of β_i in the following augmented Dickey-fuller (ADF) regression for each country

$$\Delta q_{it} = \alpha_i + \beta_i q_{i,t-1} + \sum_{j=1}^{p} \rho_{ij}\Delta q_{i,t-j} + e_{it}, \tag{2.14}$$

where $\Delta q_{it} = q_{it} - q_{i,t-1}$ is the first difference of logarithm of the real exchange rates, β_i is the autoregressive coefficient, p is the number of lagged first differences, and e_{it} is the error term.

The main drawback of using the IPS in testing for PPP is its assumption of no cross-sectional dependence among the individual units in the panel. Indeed, cross-

[11] See Pesaran (2012) for an interpretation of the rejection of the panel unit root hypothesis.

section independence is unlikely, given that it comprises bilateral exchange rates that are defined vis-à-vis one common numeraire currency and price index.[12] The existence of these two components, mainly originated by the numeraire country, induces a high level of cross-sectional correlation across the individual real exchange rate series, a situation that casts doubt on the credibility of the IPS compared with the other used tests of PPP.

For this reason, we proceed in our analsysis of PPP using panel unit root tests that are equipped to handle the problem of cross-sectional dependence. The first test accounting for cross-sectional dependence is the CIPS test of Pesaran (2007), which accommodates cross-sectional dependence through a single unobserved common factor. To be more precise, the author proposed as a strategy to tackle the problem of cross-sectional dependence augmenting the ADF regressions with the cross-section averages of lagged levels and first-differences of the individual series. These cross-section averages are then presented as a proxy of the assumed single unobserved common factor.

The CIPS test statistic, defined by (2.15), is based on the t-ratio of the coefficient of $q_{i,t-1}$ in the Cross-sectionally ADF (CADF) regression in (2.16) for each country.[13]

$$CIPS(N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T) \tag{2.15}$$

where $t_i(N,T)$, known as the individual cross-sectionally augmented Dickey-Fuller (CADF) statistics, is the OLS t-ratio of the coefficient of $q_{i,t-1}$ in the following CADF regression for each country

$$\Delta q_{it} = \alpha_i + \beta_i q_{i,t-1} + c_i \bar{q}_{t-1} + \sum_{j=0}^{p} d_{ij}\Delta\bar{q}_{t-j} + \sum_{j=1}^{p} \rho_{ij}\Delta q_{i,t-j} + e_{it}, \tag{2.16}$$

[12] Hakkio (1984) and O'Connell (1998), among others, argued that real exchange rates are naturally correlated due to the fact that they are defined vis-à-vis one common numeraire currency and price index

[13] Critical values can be found in Pesaran (2007).

where $\Delta q_{it} = q_{it} - q_{i,t-1}$ is the first difference of logarithm of the real exchange rates, $\bar{q}_t = N^{-1} \sum_{i=1}^{N} q_{it}$, (p) is the number of lagged first differences, and e_{it} is the error term.

In this chapter, we use the CIPS test outcomes to test the null unit root hypothesis (H_0: no evidence in favour of long-run PPP) against the heterogenous alternative stationary hypothesis (H_1: PPP holds for a significant portion of the countries in the panel).

The third panel unit root test we implement is the CIPSM test of Pesaran et al. (2013), which is an extension of the CIPS test to the case where cross-sectional dependence is captured by multiple common factors. The basic idea in the CIPSM test is to utilise additional variables, $\mathbf{x}_{it}$, that are likely to simultaneously share the same common factors with the original series of interest q_{it}. Cross-sectional dependence is then accommodated by augmenting the individual ADF regressions for q_{it} with the cross-section averages of the dependent variable as well as a number of k additional regressors.

There are distinctive advantages of the CIPSM test making it appropriate to our study. First, in contrast to other existing panel unit root tests with cross-sectional dependence such as Bai and Ng (2007) and Moon and Perron (2004), the CIPSM has the correct size for all combinations of (N) and (T), regardless of whether the idiosyncratic errors were serially correlated or not. Second, the CIPSM testing procedure only requires a specification of the maximum number of factors, whereas in other panel unit root tests that are based on principal component methods, such as Bai and Ng (2004), it is required to estimate the number of factors as well as the factors themselves.[14]

The CIPSM test, defined by (2.17), is based on the t-ratio of the OLS estimate

[14] Pesaran et al. (2013) found, based on Monte Carlo experiments, that the CIPS test could suffer from potential size distortions in the case where the number of common factors exceeds unity.

of β_i in the cross-sectionally augmented ADF regression in (1.18)[15]

$$CIPSM_{NT} = N^{-1}\sum_{i=1}^{N} t_i(N,T), \tag{2.17}$$

where $t_i(N,T)$ is the t-ratio of the OLS estimate of β_i in the following cross-sectionally augmented ADF regression

$$\Delta q_{it} = \beta_i q_{i,t-1} + c_i^{'}\bar{z}_{t-1} + h_i^{'}\Delta\bar{z}_t + g_i^{'}d_t + \epsilon_{it}, \tag{2.18}$$

where $z_{it} = (q_{it}, x_{it}^{'})^{'}$, $x_{it} = (x_{i1t}, x_{i2t}, ..., x_{ikt})^{'}$ is $k \times 1$ vector of additional regressors, and d_t is 2×1 vector consisting of an intercept and a linear trend so that $d_t = (1,t)^{'}$.[16] Similar to the two aforementioned panel unit root tests (the IPS and the CIPS tests), the CIPSM test statistics are interpreted as evidence in favour PPP for the cases where the null unit root hypothesis can be rejected.

In this chapter, we augment the individual ADF regressions of q_{it} in the CIPSM test with the cross-section averages of the dependent variables (current and lagged levels, $\Delta\bar{q}_t$, $\bar{q}_{t-1}$) and of the two additional regressors, namely real equity indexes eq_{it} and short-term real interest rates r_{it}. Our choice of these two additional regressors is based on them being driven by at least the same set of common trends that drive the real exchange rates in our dataset. Put differently, we argue that the unobserved factors that correlate nominal exchange rates across the countries in our panels could also affect short-term interest rates and equity prices across the same markets in the panels.

Pesaran et al. (2013) suggested that real exchange rates are most likely to simultaneously share common factors with several variables such as real interest rates, real equity indexes, prices of Brent Crude oil, nominal Gross Domestic Products, and long-term real interest rates. However, due to data unavilability, in this chapter,

[15]Critical values can be found in Pesaran et al. (2013).

[16]Pesaran (2013) assumed that $d_0 = 0$ and $\Delta d_1 = (0,1)^{'}$.

only short-term real interest rates and real equity indexes were used in the present implementation of the CIPSM test.

Throughout the analysis in this chapter, we present results based on the application of our three panel unit root tests using heterogenous autoregressive lags i.e we allow the number of lags used in computing our panel unit root tests statistics to vary per country. We employ the modified Akaike information criterion (MAIC) method to select the appropriate lag length with $p_{max} = int(12(T/100)^{1/4})$, where p is the lag autoregressive order.[17]

[17] In the cases of homogenous autoregressive , and for the sake of comparison and consistency we provide results based on the application of the IPS, the CIPS and the CD tests using a maximum of 8 autoregressive lags for each of the above mentioned tests. Note that means and variances of the t-statistics used in the IPS test are only available for values up to 8 autoregressive lags. For the CIPSM tests (with multi-factor error structure) we provide results based on the use of a maximum 4 autoregressive lags, and this is because critical values are reported in Pesaran et al. (2013) for 4 lags only

2.6 Empirical analysis

To begin the analysis with, we start by examining cross-sectional dependence among the series of real exchange rates in our panels. This is achieved via the application of Pesaran (2004) CD test, defined in (2.9), which is distributed as $N(0, 1)$ under the null hypothesis of cross-sectional independence. The CD test statistics, presented in Tables 2.1 and 2.2 for the cases of CD regressions with and without a time trend, respectively, show that the null hypothesis of no cross-sectional dependence is clearly rejected for our panels at the 5% significance level, irrespective of the values of autoregressive lags (p).

This result is consistent with the recent panel studies of PPP (see for instance the work of O'Connell (1998) and Pesaran (2007)). These studies emphasised that real exchange rates, which are defined vis-à-vis one common numeraire currency and price index, are cross-sectionally correlated.

Tables 2.3 and 2.4 report our panel unit root testing results with and without a time trend, respectively.[18] On the basis of the IPS test statistics, the null unit root hypothesis is clearly rejected in the majority of cases at the 5% significance level both with and without a time trend (Tables 2.3 and 2.4), and thus the implication is that long-run PPP holds in our panels.[19] However, due to the presence of cross-sectional dependence uncovered in our dataset (see Tables 2.1 and 2.2), this conclusion is open to question, therefore, we proceed in our analysis of PPP using panel unit root tests that control for cross-sectional dependence; the CIPS and the CIPSM panel unit root tests.

On the basis of the CIPS test statistics in Tables 2.3 and 2.4, the unit root null hypothesis can not be rejected at the 5% significance level for both panels under consideration. This implies that PPP does not seem to hold in our panels, and highlights the importance of accounting for cross-sectional dependence when compared with the IPS test results.

[18]Results based on homogenous autoregressive lags can be found in the appendix.
[19]The null unit root hypothesis can not be rejected in the pre-crisis sub-sample (Table 2.3).

This result is consistent with the findings of Harris et al. (2003) who report no evidence in favour of PPP using a procedure that tests the null hypothesis of stationarity against the unit root alternative in real exchange rates. A similar conclusion is also reached by Pesaran (2007) who reported, using the CIPS test, no supporting evidence of PPP for two panels of real exchange rates from 17 OECD countries.

Finally, we report results based of the CIPSM panel unit root test of Pesaran et al. (2013), where cross-sectional dependence is accounted for using a multifactor error structure approach. As a preliminary step, we choose the number of additional regressors that are supposed to collectively share the same unobserved common factors with the real exchange rates under consideration. Pesaran et al. (2013) suggested two possible ways to deal with the uncertainty surrounding the number of additional variables. One method is to estimate the true number of common factors m^0 in the real exchange rates using the Bai and Ng (2002) information criteria IC_1, and then proceed to find the number of additional regressors as follows[20]

$$k = \hat{m}^0 - 1 \tag{2.19}$$

where k is the number of additional regressors, and $\hat{m}^0$ is the estimated value of the true number of common factors.

However, our empirical application of the information criteria of Bai and Ng (2002) shows that the estimated number of unobserved factors always turn out to be the maximum set. Hence, we avoid estimating the true number of common factors m^0, and instead we follow Pesaran et al. (2013) second approach where the true number of common factors can be any integer between zero and m_{max}, where m_{max} is an assumed maximum number of common factors

$$k = m_{max} - 1 \tag{2.20}$$

[20] Bai and Ng (2004) reported that the information criteria IC_1 performs well in Monte Carlo simulation.

where k is the number of additional regressors.

In the present analysis we set the maximum number of common factors to be 3. Therefore, for $m_{max} = 3$, the $CIPSM$ test requires two additional regressors $k = (m_{max} - 1) = 2$. namely the real equity indexes eq_{it} and the short-term real interest rates r_{it}.

The CIPSM tests statistics are reported in Tables 2.3 and 2.4 with and without a time trend, respectively, for all the combinations of candidate regressors. Examining these statistics also help check the robustness of our testing results to the choice of additional variables used in the test augmentation process. As can be seen in these tables, the CIPSM tests statistics show that the null hypothesis of a panel unit root can not be rejected at the 5% or 10% significance level across different choices of additional regressors. Thus the implication is that long-run PPP does not hold in our two panels of real exchange rates when the CIPSM unit root test procedures are used.

The evidence against long-run PPP arrived at this chapter is interesting in the sense that it is obtained by panel unit root tests that are equipped to deal with the high level cross-sectional dependence in our dataset. However, ignoring cross-sectional dependence by using the IPS test, we clearly find supporting evidence in favour of long-run PPP. This yields clear evidence that accounting for cross-sectional dependence is vital in PPP testing. Having found no robust evidence supporting PPP in this chapter, further research is required to solve the conundrum of why PPP does not hold using our testing criteria. Possible reasons could be, for example, the presence of transaction costs, non-traded goods, taxes, tariffs and duties and non-tariff barriers. This failure of PPP casts serious doubt on the usefulness of various adjusted PPP-based measurements for price differentials, which are central to policy makers and practitioners in cross-border income comparisons.

The above results confirm the point reached by O'Connell (1998) who argued that failing to control for cross-sectional dependence could lead to an overvaluation of PPP. Our results are also in line with those of Harris et al. (2003), Smith et al.

(2004), Moon and Perron (2005), Pesaran (2007), Choi and Chue (2007), Chang and Song (2009), and Snaith (2012) who employed various panel unit root tests with cross-sectional dependence and all failed to provide favourable evidence supporting PPP.

Finally, it is worth noting that the results from the three panel unit root tests we applied are consistent across the two panels of real exchange rates under consideration. This consistency diminishes the possibility of the influence of the financial crisis in 2007-2008 on long-run PPP. Having found no robust evidence for an impact of the financial crisis on our PPP results, further research is required to solve the conundrum of why PPP does not hold using our testing criteria.

2.7 Conclusion

The aim of this chapter is to empirically examine the evidence of long-run PPP employing two panels of real exchange rates from 13 OECD countries. This is achieved by using the novel panel unit root test CIPSM of Pesaran et al. (2013), extending the CIPS test of Pesaran (2007) to the case where cross-sectional dependence is generated by multifactor error structure. The CIPSM test utilises the information contained in a number of (k) additional variables that are assumed to simultaneously share the same common factors with the essential variables under consideration. Our analysis of PPP is also carried out using the panel unit root test of Pesaran (2007) (CIPS) that controls for cross-sectional dependence through one single unobserved common factor, and the benchmark IPS test under the assumption of cross-sectional independence.

A number of important results emerge from our analysis. First, ignoring cross-sectional dependence, it is established that there is signifiant evidence of long-run PPP in our panels. This result is overturned when using panel unit root tests that are equipped to handle the problem of cross-sectional dependence in the panel leading to the implication that PPP does not hold. This situation probably indicates that accounting for cross-sectional dependence is a key determinant of (non) rejection of the null unit root hypothesis. Finally, the fact that the results from our tests are consistent across the two panels under consideration does not support the potential influence of the financial crisis in 2007-2008 on the validity of long-run PPP.

Table 2.1 Pesaran's CD statistics to test the null hypothesis of cross-section independence among the real exchange rates. (Case I: intercept and trend)

The table reports statistics based on the CD test proposed by Pesaran (2004) for testing the null hypothesis of cross-section independence among the real exchange rates for the case of intercept and trend. The CD test is a 2−sided test distributed as $N(0,1)$ under the null hypothesis of cross-sectional independence. At the 1% significance level, the null hypothesis of cross-sectional independent errors is rejected if $|CD| \geq 2.55$.
(***) indicates rejection of the null hypothesis of cross-section independence at the 1% significance level.

Lag order	CD test	
	Full sample (1989:07-2012:11)	Sub-sample (1989:07-2006:12)
p=0	48.38***	31.30***
p=1	48.31***	31.90***
p=2	48.19***	30.84***
p=3	47.89***	30.87***
p=4	47.57***	30.46***
p=5	47.16***	30.20***
p=6	47.43***	29.99***
p=7	47.00***	30.03***
p=8	47.08***	29.55***

Table 2.2 Pesaran's CD statistics to test the null hypothesis of cross-section independence among the real exchange rates. (Case II: intercept only)

The table reports statistics based on the CD test proposed by Pesaran (2004) for testing the null hypothesis of cross-section independence among the real exchange rates for the case of intercept only. The CD test is a 2−sided test distributed as $N(0, 1)$ under the null hypothesis of cross-sectional independence. At the 1% significance level, the null hypothesis of cross-sectional independent errors is rejected if $|CD| \geq 2.55$.
(***) indicates rejection of the null hypothesis of cross-section independence at the 1% significance level.

Lag order	CD test	
	Full sample (1989:07-2012:11)	Sub-sample (1989:07-2006:12)
p=0	48.13***	31.60***
p=1	48.04***	31.16***
p=2	47.89***	31.05***
p=3	47.59***	31.06***
p=4	47.29***	30.69***
p=5	46.89***	30.44***
p=6	47.13***	30.25***
p=7	46.71***	30.28***
p=8	46.78***	29.72***

Table 2.3 Panel unit root tests statistics to test the null unit root hypothesis using heterogenous autoregressive lags (Case I: intercept and trend)

This table reports statistics based on the application of various panel unit root tests for investigating the validity of PPP using heterogenous number of autoregressive lags (p) across the individual series of real exchange rates in the panel. The appropriate lag length is selected using the modified Akaike information criterion (MAIC) method with $p_{max} = int(12(T/100)^{1/4})$, where p is the lag autoregressive order. The IPS statistic is the standardised $t-$bar test of Im et al. (2003), defined by (2.11), under the assumption of cross-section independence. The CIPS test is the cross-sectionally augmented IPS test proposed by Pesaran (2007), defined by (2.14), where cross-section dependence is accommodated through a single unobserved common factor approach. The CIPSM(q), CIPSM(r) and CIPSM are the panel unit root tests suggested by Pesaran et al. (2013), defined by (2.16), where cross-section dependence is accommodated through multifactor error structure approach. The latter three tests are established using, in addition to the real exchange rates, additional regressors of real equity prices eq_{it}, real interest rates r_{it}, and both eq_{it} and r_{it}, respectively.
(***), (**) and (*) indicate rejection of the null unit root hypothesis at the 1%, 5% and 10% significance level, respectively.

	IPS	$CIPS$	$CIPSM(q)$	$CIPSM(r)$	$CIPSM$
Panel A: full sample (1989:07-2012:11)					
Test statistic	-2.53**	-2.73*	-2.41	-2.66	-2.48
Average number of lags	2	2	4	4	4
Panel B: sub-sample (1989:07-2006:12)					
Test statistic	-2.27	-2.54	-2.26	-2.44	-2.29
Average number of lags	3.6	3.6	4	4	4

Table 2.4 Panel unit root tests statistics to test the null unit root hypothesis using heterogenous autoregressive lags (Case II: intercept only)

This table reports statistics based on the application of various panel unit root tests for investigating the validity of PPP using heterogenous number of autoregressive lags (p) across the individual series of real exchange rates in the panel. The appropriate lag length is selected using the modified Akaike information criterion (MAIC) method with $p_{max} = int(12(T/100)^{1/4})$, where p is the lag autoregressive order. The IPS statistic is the standardised $t-$bar test of Im et al. (2003), defined by (2.11), under the assumption of cross-section independence. The CIPS test is the cross-sectionally augmented IPS test proposed by Pesaran (2007), defined by (2.14), where cross-section dependence is accommodated through a single unobserved common factor approach. The CIPSM(q), CIPSM(r) and CIPSM are the panel unit root tests suggested by Pesaran et al. (2013), defined by (2.16), where cross-section dependence is accommodated through multifactor error structure approach. The latter three tests are established using, in addition to the real exchange rates, additional regressors of real equity prices eq_{it}, real interest rates r_{it}, and both eq_{it} and r_{it}, respectively.
(***), (**) and (*) indicate rejection of the null unit root hypothesis at the 1%, 5% and 10% significance level, respectively.

	IPS	$CIPS$	$CIPSM(q)$	$CIPSM(r)$	$CIPSM$
Panel A: full sample (1989:07-2012:11)					
Test statistic	-2.13***	-2.18*	-2.14	-2.22	-2.22
Average number of lags	3.6	3	4	4	4
Panel B: sub-sample (1989:07-2006:12)					
Test statistic	-2.08***	-2.22*	-1.96	-2.15	-2.00
Average number of lags	3.6	3.6	4	4	4

Chapter3

Long-run Purchasing Power Parity: Evidence from a new panel cointegration test

3.1 Introduction

Long-run Purchasing Power Parity (PPP), which is based on the premise that prices of similar goods in different countries should be identical once expressed in the same currency, has been tested through two alternative approaches. The first method tests for unit root in real exchange rates, where a rejection of the unit root hypothesis is interpreted as evidence in favour of PPP.[1] The second approach tests for a cointegrating relationship between nominal exchange rates and relative price ratios. The underlying rationale is in the spirit of Engle and Granger (1987) who suggested that one way of defining the long-run equilibrium between integrated variables is by a cointegrating relationship. PPP is said to hold when the null of no-cointegration is rejected.

Early panel cointegration tests provided mixed evidence on the empirical validity of long-run PPP.[2] The main characteristic that is shared by these panel cointegration tests is that they fail to account for the potential presence of structural breaks and cross-sectional dependence, and these can adversely affect the empirical size of the corresponding panel test statistics (Westerlund and Edgerton (2008)). In particular, structural changes might be present when analysing exchange rates that span long periods of time. Cross-section dependence could also be evident when testing for PPP in panels of bilateral exchange rates that share the same numeraire currency. Therefore, the main goal of this chapter is to fill a gap in the literature that previous research has so far failed to tackle. This task will be achieved by employing a novel panel cointegration test that considers the presence of structural breaks and cross-section dependence.

Our analysis contributes to the extant literature by evaluating the evidence on PPP through the novel panel cointegration test suggested by Banerjee and Carrion-I-Silvestre (2013). This tests for cointegration in individual units and then uses

[1] Rejection of the null unit root hypothesis implies that deviations of the real exchange rates from their mean values are temporary, and thus the real exchange rates tend to converge to their long-run mean values.

[2] See, inter alia, Azali et al. (2001), Nagayasu (2002), Basher and Mohsin (2004), and Jenkins and Snaith (2005).

the idiosyncratic statistics to construct their panel cointegration test. They show that their cointegration statistics, which allow for (i) heterogeneous and multiple structural breaks and (ii) cross-sectional dependence, achieve good performance when the testing procedure accounts for structural breaks.

The dataset in this chapter is quoted on a monthly basis and it comprises nominal dollar exchange rates and relative price ratios for 53 countries over the period 1992:01-2014:05. Two important results emerge for our analysis in this chapter. On the one hand, using the unit root testing approach of Bai and Ng (2004), it is found that the variables of nominal exchange rates and relative price ratios are non-stationary. On the other hand, using the panel cointegration testing approach of Banerjee and Carrion-I-Silvestre (2013), there is no evidence of a cointegrating relationship between the two above mentioned variables; thus the implication is that PPP does not hold. This evidence against PPP is interesting in the sense that it is obtained by two types of models that can be equipped/ill-equipped to handle the potential presence of structural breaks in the data, a situation that could lead to the following conclusion that structural breaks are not key determinants of (non) rejection of the no-cointegration null hypothesis. The evidence against long-run PPP arrived at this chapter casts doubt on the findings by early panel cointegration testing approaches that largely ignored the potential existence of structural breaks and cross-sectional dependence, and consequently found evidence in favour of PPP. For instance, studies by Canzoneri et al. (1999), Chinn (1997), Obstfeld and Taylor (1997), Pedroni (1995), and Taylor (1996) all found support for PPP via using the panel cointegration test of Pedroni (1995) which allows for heterogeneous slope coefficients.

Our results are in line with those of Westerlund and Edgerton (2008).[3] The latter found no evidence in favour of PPP using a panel cointegration test that also allows

[3] Banerjee and Carrion-I-Silvestre (2013) highlight three specifications which distinguish their testing procedures from the cointegration testing framework that is proposed by Westerlund and Edgerton (2008). First, the former restricted the level term to appear in the deterministic part of the stochastic process only (without trend). Second, they allowed the factors that generate the cross-section dependence to be integrated. Finally, they allowed for possible breaks in the trends generating the process.

for structural breaks and cross-sectional dependence. Their analysis was based on a panel of 17 developed countries over the period 1973:1 to 1988:1.

The rest of this chapter is organised as follows. Section 2 presents the details of our database. Section 3 introduces the econometric methodology by specifying the model and the panel cointegration testing framework. Section 4 holds the empirical application to PPP and presents the results, and Section 5 provides some concluding remarks.

3.2 Literature review

Early cointegration tests, which were typically based on the augmented Dickey-Fuller (ADF) regression and Johansen maximum likelihood procedure, tended to provide evidence against the long-run PPP. For instance, among others, Corbae and Ouliaris (1988), Enders (1988), Taylor (1988), and Patel (1990) employed various univariate techniques of cointegration to show that PPP does not hold in the long-run.

The main concern of these cointegration tests is that they could suffer from potential low power against stationary alternatives. Such results have been partially attributed to the small size of samples under consideration. To circumvent this problem, researchers have attempted to gain statistical power by pooling information across units, and thereby improve upon the poor performance of the univariate cointegration techniques. A selection of the first wave of panel cointegration tests would include, inter alia, Pedroni (1999), Kao (1999), Kao and Chiang (2001), Larsson and Lyhagen (1999), Pedroni (2001), and Larsson et al. (2001). In the early stages, researchers proposed panel cointegartion estimators assuming homogeneity across units in the panel. This restriction was later abandoned by subsequent research allowing the slope coefficients vary among the individual members of the panel.

In this context, special attention should be drawn to the work of Pedroni (1995) who proposed a residual-based test for cointegration in heterogenous panels. The author investigated the validity of PPP and reported evidence in favour of a long-run relationship between exchange areas and price indices. Equation (3.1) represents the cointegration estimation model suggested by Pedroni (1995) where the United States is considered as the benchmark country.

$$e_{it} = \alpha_i + \beta_i(p_{it} - p^*_{it}) + \epsilon_{it} \tag{3.1}$$

where e_{it} is the log nominal exchange rate for country i vis-à-vis the US dollar at time t, p_{it} is the log aggregate price index for country i, p^*_{it} is the log aggregate price index for the United States at time t, $\beta_{i,t}$ is the cointegrating vector, and ϵ_{it} is the error term.

The literature indicates that Pedroni's (1995) panel cointegration test has been extensively employed for testing the weak version of the long-run PPP in panels. Weak PPP implies that changes in exchange rates between two economies over a given period adapt to account for (offset) differences in the countries inflation rates over the same period. Studies such as Taylor (1996), Chinn (1997), Obstfeld and Taylor (1997), and Canzoneri et al. (1999) all used the panel cointegration method that is developed by Pedroni (1995) and consequently reported supporting evidence in favour of the weak version of PPP.

Those results do not contradict the findings obtained for the stronger version of PPP which are documented by Pedroni (2001). The latter investigated the validity of PPP using pooled and group mean dynamic OLS methods proposed by Kao and Chiang (1997), Pedroni (1999), and Pedroni (2001), respectively and consequently reported strong evidence in favour of the strong version of PPP.

Similar evidence has been obtained by Nagayasu (2002) who empirically examined the validity of PPP for a panel of 17 African countries. The author utilised Pedroni's (1995) panel cointegration test and reported evidence in favour of a cointegrating relationship between parallel market exchange rates and relative prices.

Azali et al. (2001) also assessed the evidence on PPP using the panel cointegration test of Pedroni (1999). They reported strong evidence of PPP for a panel of seven Asian countries over the period 1977:4-1998:3. Basher and Mohsin (2004), on the other hand, found no evidence in support of a cointegrating relationship between nominal exchange rates and relative prices for a panel of ten Asian countries spanning the period 1980:1-1999:12.

Jenkins and Snaith (2005) examined the PPP hypothesis for a panel of 11 OECD countries over the period 1981:1-1995:6. They used Pedroni's (1999) panel cointegration test and found supporting evidence in favour of the weak version of PPP only for those goods that could be characterised as highly traded commodities.

One of the problems of the above literature is that most of the panel cointegration tests used are ill-equipped to handle the potential presence of cross-sectional dependence and structural breaks. From a PPP perspective, a high level of cross-sectional correlation among the individual series of bilateral exchange rates is expected. This is because, by construction, bilateral exchange rates are defined using one common numeraire currency, for instance the US dollar in most of the studies.[4] Structural changes in the cointegrating relation are also likely to be evident especially when analysing long time series of exchange rates that span long periods of time.
As a response, recent studies employed techniques that partially addressed the problems arising from relaxing the assumptions of structural breaks and cross-sectional dependence. For in- stance, Narayan (2010) empirically examined the validity of PPP employing the panel cointegration test of Westerlund (2006) which accounts for multiple structural breaks. The author documented strong evidence in favour of PPP using a sample that includes annual nominal exchange rates and relative price ratios for six Asian countries over the period from 1967 to 2002.

Gengenbach et al. (2005) also investigated the PPP hypothesis using a panel cointegration testing framework, where the cross-sectional dependence is modelled following the common factor approach of Bai and Ng (2004). The authors were unable to find significant evidence in support of PPP for a sample that contained quarterly data for 18 countries spanning the period 1974:1-1998:3. Equation (3.2) represents the empirical model adopted by Gengenbach et al. (2005) where the rejection of the no-cointegration null hypothesis is considered as evidence in favour of the weak version of PPP.

$$s_{i,t} = \alpha_i + \beta_i p_{i,t} + \epsilon_{i,t}, \tag{3.2}$$

where $s_{i,t}$ is the log nominal exchange rate for country i vis-à-vis the US dollar at time t, p_{it} is the log price differential between country i and the United States at

[4]See O'Connell (1998).

time t, and $\epsilon_{i,t}$ is the error term.

Finally, Westerlund and Edgerton (2008) found no evidence in favour of PPP using a panel cointegration test that accounts for structural breaks and cross-sectional dependence. Their analysis was based on a panel of 17 developed countries over the period 1973:1 to 1988:1.

3.3 Data

The present chapter employs monthly data on nominal exchange rates and price indexes obtained from DataStream and cover the period 1992:01-2014:05. The nominal exchange rates are the WM/Reuters closing spot rates vis-à-vis the US dollar and the price indexes are the consumer price indexes expressed in local currency and not seasonally adjusted.[5]

We construct our panels of data using the maximum panel dimensions in testing the existence of a cointegrating relationship between the exchange rates and the aggregate price ratios. In this chapter, PPP is examined for its applicability to the currencies of a large group of developed and developing economies. The designation of the U.S. dollar as the numeraire currency reflects the global importance of the U.S. economy and the U.S. dollar, and is motivated by the availability of the U.S. dollar-based exchange rate data. The choice of time period is based on data availability. For the cross-section dimension, we combine the 53 individual series of nominal exchange rates and the 53 individual series of price ratios to construct the panels of exchange rates and price ratios, respectively ($N = 53$). Price ratios were individually calculated by taking the ratio of the domestic to the foreign price level ($\frac{p}{p^*}$), where p is the log aggregate price index for country i and p^* is the log aggregate price index for the USA.
Further, we use the longest possible panel dataset that is available to the countries in our panel ($T = 269$). In doing so, we comfortably satisfy the condition that requires the time dimension of the panel datasets to be larger than the panel's cross-section dimension.[6] All the variables are expressed in logs.

[5]See Appendix A for details regarding the data.
[6]See Banerjee and Carrion-I-Silvestre (2013).

3.4 Methodology

In this chapter we formally assess the evidence on PPP by examining the long-run relationship between nominal exchange rates and aggregate price ratios. This is achieved via the application of a novel panel cointegration test proposed by Banerjee and Carrion-I-Silvestre (2013) which simultaneously allows for structural breaks and cross-sectional dependence. Cross-section dependence is accommodated through a factor framework specification as in Bai and Ng (2004).

Using this testing procedure in investigating the PPP hypothesis is motivated by the fact that the nominal exchange rates for most of the countries included in our panel are characterised by dramatic changes. To be more precise, extraordinary events such as the severe currency crisis in 1994 known as "the Tequila crisis" and the two international financial crises in 1997 and 2008 may have constituted breaks in the nominal exchange rates, and thus had a significant impact on the cointegrating relationship between exchange rates and price ratios.

A good example of the above situation is presented by Kamin (1999) who suggested that the financial crisis in 1994 may have triggered sharp movements in the nominal exchange rates for several countries such as Mexico, Brazil, Argentina, Colombia, and Venezuela. The author also showed that the Asian financial crisis in 1997 may have had a significant impact on currency movements especially for the ones belonging to the following markets: Hong Kong, Indonesia, Malaysia, Korea, Philippines, Singapore, Taiwan, Thailand, Russia, South Africa, Argentina, Brazil, Chile, Colombia, Mexico, Peru, Venezuela. In a similar manner, Melvin and Taylor (2009) studied the impact of the global financial crisis in 2007-2008 on foreign exchange markets, and reported a substantial shift in exchange rate behaviour across the major currencies, in particular the Japanese Yen, the Euro, and the British Pound.

The analysis of PPP is carried out assuming heterogeneous structural breaks across the individual units. Put differently, structural breaks are allowed to be located at different dates for different countries in the panel. Allowing the break dates to be country specific is required in our analysis given the fact that our dataset contains information from 53 countries around the globe, where the assumption of common break dates in exchange rates seems to be rather restrictive and unrealistic.

In addition to its capability to account for heterogeneous and multiple structural breaks, the cointegration test used is designed to handle the potential presence of cross-sectional dependence among the units in the panel. From a PPP perspective, we expect the level of cross-sectional dependence to be significantly high due to the fact that our bilateral exchange rates are defined vis-à-vis the US dollar. Hakkio (1984) and O'Connell (1998), among others, established that using bilateral exchange rates that share the same numeraire currency could lead to significant level of cross-sectional dependence among the units in the panel.

For testing the cointegrating link between the nominal exchange rates and the relative price ratios, we consider the model specification that is represented by equation (3.3) following the cointegration testing framework proposed by Banerjee and Carrion-I-Silvestre (2013)

$$s_{it} = \alpha_{i,t} + \beta_{i,t} p_{i,t} + \mu_{it} \tag{3.3}$$

where s_{it} is the log nominal exchange rate for country i vis-à-vis the US dollar at time t, p_{it} is the log aggregate price differential in terms of the CPI between country i and the United States at time t. $\beta_{i,t}$ is the cointegrating vector specified as a function of time and $\alpha_{i,t}$ is a deterministic term.[7] μ_{it} the disturbance term, is decomposed as in equation (3.4)

$$\mu_{it} = F_t' \pi_i + e_{it} \tag{3.4}$$

[7] Banerjee and Carrion-I-Silvestre (2013) proposed six models based on the combination of different specifications in the number and position of the structural breaks. See Banerjee and Carrion-I-Silvestre (2013) for more details about the establishment of their proposed six models

where F_t is an $(r \times 1)$ vector contains the common factors, π_i is the vector of factor loadings, and e_{it} is the idiosyncratic disturbance term.

The estimation of the common factors and factor loadings is carried out using the principle component approach as in Bai and Ng (2004). The idiosyncratic disturbance terms are recovered from the preceding estimation of the common factors and factor loadings through cumulation as follows:

$$\hat{e}^*_{i,t} = \sum_{j=2}^{t} \hat{z}_{i,j}, \tag{3.5}$$

where $z_{i,j}$ are the estimated residuals resulting from the estimation of common factors and factor loadings.[8]

These recovered idiosyncratic disturbance terms are then employed in the estimation of the following augmented Dickey-Fuller type regression equation so that the null hypothesis of a unit root (i.e. $\alpha_{i,0} = 0$ in equation (3.6)) can be tested using the pseudo t-ratio $t^j_{\widetilde{e}^*_i}(\lambda_i)$ for $j = c, \tau, \gamma$

$$\Delta\widetilde{e}^*_{i,t} = \alpha_{i,0}\widetilde{e}^*_{i,t-1} + \sum\nolimits_{j=1}^{ki} \alpha_{i,0}\Delta\widetilde{e}^*_{i,t-1} + \epsilon_{i,t} \tag{3.6}$$

where $j = c$ refers to the model that includes a constant only, $j = \tau$ refers to the model that includes a linear time trend with a stable trend, and $j = \gamma$ refers to the model with a time trend with changing trend. λ_i represents a break fraction vector for each unit in the panel. $\lambda_i = (\lambda^b_{i,1}, ..., \lambda^b_{i,mi}, \lambda^c_{i,1}, ..., \lambda^c_{i,ni})$ where m_i and n_i refer to the number of structural breaks affecting the deterministic component of the model and the cointegrating vector, respectively. (b) and (c) implies the break dates are not required to be located on the same date.

The panel cointegration test that is used in the current PPP analysis is then based on the sum of the individual statistics for the idiosyncratic disturbance terms and is

[8] See Banerjee and Carrion-I-Silvestre (2013) for detailed information on how to obtain the estimated residuals $z_{i,j}$.

defined as follows

$$z_j(\lambda) = \frac{N^{-\frac{1}{2}} \sum_{i=1}^{n} t^{j}_{\underset{e_i}{\sim *}}(\lambda_i) - \Theta^e_j(\lambda)\sqrt{N}}{\sqrt{\psi^e_j(\lambda)}} \tag{3.7}$$

where $\Theta^e_j(\lambda) = \Theta^e_j$ and $\psi^e_j(\lambda) = \psi^e_j$ for $j = c, \tau$ are the mean and the variance, respectively of the relevant function of Brownian motion. Banerjee and Carrion-I-Silvestre (2013) approximated the moments of the limiting distribution of the statistics by means of Monte Carlo simulation and produced the following results $(\Theta^e_c, \Theta^e_\tau) = (-0.424, -1.535)$ and $(\psi^e_c, \psi^e_\tau) = (0.964, 0.341)$.[9]

[9]For $j = \gamma$, see Banerjee and Carrion-I-Silvestre (2013) for a table of simulated values for the mean and the variance.

3.5 Empirical analysis

Banerjee and Carrion-I-Silvestre (2013) defined the structure of their proposed six models as follows Model 1: no linear trend and a stable cointegrating vector; Model 2: stable trend and stable cointegrating vector; Model 3: changes in level and trend and a stable cointegrating vector; Model 4: no linear trend and multiple structural breaks in the level and the cointegrating vector of the model; Model 5: stable trend, multiple structural breaks in the level and the cointegrating vector of the model; and Model 6: changes in the level, trend and in the cointegrating vector.

In this chapter, the panel cointegration test statistics $z_j(\lambda)$ are calculated for only four of the six potential specifications that are allowed by the test and described above, particularly for Model 1, Model 2, Model 4, and Model 5. The two remaining models (Model 3 and Model 6) are excluded because they are excessively restrictive. They require the break dates to be (i) known a priori and (ii) homogeneous to all units in the panel.

Before testing for cointegration, we must provide evidence on the non-stationarity of the data employed in the analysis. To do this, we consider the unit root testing approach that is proposed by Bai and Ng (2004). Their testing framework was based on checking for unit roots in the estimated common factors or the idiosyncratic disturbance terms or in both. In particular, the null hypothesis of non-stationary time series is rejected if either the tests of the common factors or the idiosyncratic terms failed to reject the null hypothesis of non-stationary components.[10]

We proceed in assessing the order of integration of our data by testing for a unit root in the common component. Our choice is motivated by the fact that it is

[10] Pesaran (2007), Phillips and Sul (2003), and Moon and Perron (2007) proposed different statistics for testing non-stationarity in panel data. At the same time, they extract common factors to generate the cross-section dependence between the units in the panels. However, Bai and Ng (2004) tests for non-stationarity in the estimated common factors rather than the observations in the panel. Additionally, Pesaran (2007) and Phillips and Sul (2003) based their tests on one common factor, whereas Bai and Ng (2004) allowed the potential existence of multiple common factors. Bai and Ng (2004) proposed using the principle component method to estimate the unobserved common factors and idiosyncratic disturbance terms. Once the common factors and the idiosyncratic disturbance terms had been estimated, they proceeded to assess their order of integration using unit root testing procedures.

possible to consistently estimate non-stationary common factors from large dimensional panels (Bai and Ng (2004) and Breitung and Pesaran (2008)).[11] To do this check, we employ the two tests suggested by Bai and Ng (2004), denoted MQ_f and MQ_c, which can determine the number of non-stationary common factors (common stochastic trends).[12]

Table 3.1 indicates that the testing procedure of Banerjee and Carrion-I-Silvestre (2013) produces 12 non-stationary common stochastic trends, and thus the implication is that our panel variables are non-stationary. The presence of 12 global stochastic trends indicate that the source of this non-stationarity is common for all units in the panel i.e. not country specific.

For the number of structural breaks, we consider the following three possibilities; (i) no structural breaks,(ii) one structural break, and (iii) two structural breaks. The maximum number of structural breaks is set to be 2. Banerjee and Carrion-I-Silvestre (2013) suggested that using two structural breaks is enough due to restrictions imposed by the length of the time series and in order to avoid criticism relating to data mining.

We proceed to test for structural breaks for each unit in our panel assuming heterogeneity in break dates across the units. This is achieved by minimising the sum of square residuals following the approach in Bai and Perron (2003), Bai and Carrion-I-Silvestre (2009), and Banerjee and Carrion-I-Silvestre (2013).

Tables 3.2 and 3.3 report the estimated break dates for the 53 countries for the cases of one and two structural breaks, respectively. For the two cases, the tables reveal a significant level of heterogeneity in the estimated break dates. This confirms our prior assumption that homogenous breaks dates would be inappropriate for our panel data. We proceed by utilising models that allow for heterogeneous structural breaks only.

Figure 2.1, for the case of one structural break, shows that the estimated break

[11] Our panel is relatively a large panel ($N = 53, T = 269$).

[12] The number of common factors is estimated using the panel BIC information criteria as in Bai and Ng (2004). The order of the autoregressive corrections used in the computation of the augmented Dickey-Fuller type regression equation (equation (3.6)) is selected using the t-sig criterion in Ng and Perron (1995) with a maximum $k_{max} = 12ceil[T/100]^{1/4}$ lags.

dates are mostly positioned around 2006 to reflect the financial crisis that started in 2007, and to a lesser extent around 1994-1996 to reflect the two financial crises in 1994 and 1997.[13] For the two structural break model specifications Figure 2.2 shows similar results. The estimated break dates were mostly placed around 1996 for the first estimated structural break, and around 2006 for the second estimated structural break.

Since the limiting distribution of the present testing procedure requires the individual statistics $e_{i,t}$ to be cross-sectionally independent, we proceed to check for cross-sectional independence among $e_{i,t}$ using the CD test proposed by Pesaran (2004).[14] This is to ensure the possibility of pooling the individual statistics that are based on $e_{i,t}$ and thus obtain valid panel cointegration test statistics. The CD of Pesaran (2004) is distributed as $N(0,1)$ under the null hypothesis of cross-sectional independence. At the 5% significance level, the null hypothesis of cross-sectional independent errors is rejected if $|CD| \geq 1.96$.[15]

$$CD = \sqrt{\frac{2T}{N(N-1)}}(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}) \tag{3.8}$$

where $\hat{\rho}_{ij}$ is the pair-wise simple correlation coefficient between e_{it} and e_{jt} for all i and $i \neq j$.

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \sum_{t=1}^{T} e_{it}e_{jt}/[(\sum_{t=1}^{T} e_{it}^2)^{\frac{1}{2}}(\sum_{t=1}^{T} e_{jt}^2)^{\frac{1}{2}}] \tag{3.9}$$

where e_{it} is the Ordinary Least Squares (OLS) estimate of μ_{it} defined by $e_{it} = y_{it} - \hat{\alpha}_i - \hat{\beta}_i' x_{it}$, where $\hat{\alpha}_i$ and $\hat{\beta}_i'$ are the estimates of α_i and β_i using the OLS regression of y_{it} on an intercept, time trend, and x_{it} for each i.

[13] Banerjee and Carrion-I-Silvestre (2013) suggested that their estimation procedures do not necessarily lead to consistent estimates of the break dates. See Banerjee and Carrion-I-Silvestre (2013) for further details about estimating break dates.

[14] The limiting distribution of the present panel ccointegration test statistics is given by Banerjee and Carrion-I-Silvestre (2013)

[15] The CD test is a $2-$sided test distributed as $N(0,1)$ under the null hypothesis of cross-sectional independence.

Table 3.4 shows that the null hypothesis of cross-sectional independence of the idiosyncratic disturbance terms is clearly rejected at the 1% significance level for the two structural breaks model specifications (Model 1, Model 2, Model 4, and Model 5), and for the one structural break model specification (Model 1, Model 4, and Model 5), regardless of the values of autoregressive corrections (k). Hence, in these cases, inference based on the applied panel cointegration test cannot be considered, and thus the values of the corresponding panel test statistics are not reported.

The results of the cointegration test are reported in Table 3.5. The table shows that the null hypothesis of no cointegration cannot be rejected for any of the models under consideration. Consequently, there is no evidence for long-term relationship (cointegration) between the nominal exchange rates and the price ratios, and thus the implication is that PPP does not hold. This evidence against PPP raises the question of whether exchange rates adjust toward a level established by purchasing power parity can help to explain how the international macroeconomic system is equilibrating. The results also imply that several factors, including transaction costs, existence of hyperinflation, discrepancies and/or interruptions in statistical releases, and differences in price indices across countries may cause the cointegration-based test of PPP to fail. In fact, many developing economies are likely to suffer from the above problems. Consequently, finding support for PPP despite such obstacles should be regarded as very strong evidence confirming the long-run validity of this concept.

This evidence against PPP arrived at this chapter is interesting in the sense that it is obtained by two types of models that can be equipped/ill-equipped to handle the potential presence of structural breaks in the data. Hence, it is concluded that accounting for structural breaks in our current examination of PPP is not a key determinant of (non) rejection of the null no-cointegration hypothesis. Further, since the null hypothesis of no-cointegration implies that there is no cointegration in all units in the panel and taking into account the cointegration results in Table 3.5, we can conclude that PPP does not hold for all countries in our sample.[16]

[16] Banerjee and Carrion-I-Silvestre (2013) stated that the null hypothesis of no cointegration could

Our results are consistent with those of Westerlund and Edgerton (2008). They found no evidence in favour of PPP despite the fact that their testing procedures were based on a panel cointegration test that simultaneously accounted for structural breaks and cross-sectional dependence. The results are also in line with those of Harris et al. (2005). The latter reported no evidence in support of PPP using a sample of 17 countries over the period 1973:01-1998:12. Their testing procedure was based on the application of a panel unit root test that accommodates structural breaks and cross-sectional dependence. Snaith (2012) also reported no evidence in favour of PPP when simultaneously accounting for structural breaks and cross-sectional dependence. The author also concluded that the additional consideration of cross-sectional dependence can reverse the findings of structural break tests alone.

Our evidence against PPP casts doubt on the findings by early panel cointegration testing approaches that largely ignored the potential existence of structural breaks and cross-sectional dependence, and consequently found evidence in favour of PPP. For instance, studies by Canzoneri et al. (1999), Chinn (1997), Obstfeld and Taylor (1997), Pedroni (1995), and Taylor (1996) all found support for PPP via using the panel cointegration test of Pedroni (1995) which allows for heterogeneous slope coefficients.

be rejected if some of the units in the panel were cointegrated.

3.6 Conclusion

The goal of this chapter is to provide evidence on the empirical validity of PPP using a panel of 53 countries spanning the period 1992:01-2014:05. Our testing approach is based on examining the cointegration relationship between nominal exchange rates vis-à-vis the US dollar and relative prices. This is achieved via the application of a novel panel cointegration test that is proposed by Banerjee and Carrion-I-Silvestre (2013). One advantage of using this test is that it allows for the possibility of simultaneously accommodating the potential presence of multiple (heterogeneous) structural breaks and cross-sectional dependence.

Two important results emerge from our analysis. First, the tests statistics show that the variables are non-stationary but not cointegrated. This apparent lack of evidence of cointegration between the nominal exchange rates and relative prices implies that the PPP does not hold for all countries in our dataset. Second, the evidence against PPP is obtained by two types of models that can be equipped/ill-equipped to accommodate the potential presence of structural beaks in the data. This situation implies that accounting for structural breaks played no significant role in determining the (non) rejection of the null no-cointegration hypothesis.

Table 3.1 Testing for unit root using the Panel Analysis of Nonstationarity in Idiosyncratic and Common component (PANIC) test.

The table reports statistics based on the (MQ) statisitcs developed by Bai and Ng (2004). $(\hat{r}_1)_f$ and $(\hat{r}_1)_c$ are the numbers of nonstationary common factors estimated respectively in a parametric and nonparametric way by successive estimation of the MQ tests. MQ_f and MQ_c use parametric and nonparametric corrections, respectively, to accomodate additional serial correlations. Critical values for MQ_f and MQ_c for testing the null hypothesis of independent stochastic trends $(H_0 : r_1 = m)$ are provided by Bai and Ng (2004). MQ_f and MQ_c are tests for the number of common stochastic trends r_1.

Model 1, Model 2, Model 4 and Model 5 are specified in Banerjee and Carrion-I-Silvestre (2013) as follows. Model 1 has no linear trend and a stable cointegrating vector. Model 2 has a stable trend and a stable cointegrating vector. Model 4 has no linear trend and multiple structural breaks in the level and the cointegrating vector of the model. Model 5 is specified with a stable trend and multiple structural breaks affecting the level and the cointegrating vector of the model.

The number of common factors is estimated using the panel BIC information criterion as in Bai and Ng (2004), where the maximum number of factors allowed is 12.

	No structural breaks	One structural break				Two structural breaks			
		Model 1	Model 2	Model 4	Model 5	Model 1	Model 2	Model 4	Model 5
$(\hat{r}_1)_f$	12	12	12	12	12	12	12	12	12
$(\hat{r}_1)_c$	11	12	11	12	12	12	11	12	12
MQ_f	-99.779	-97.254	-114.796	-86.326	-103.637	-95.111	-113.979	-82.753	-99.541
MQ_c	-105.817	-107.642	-92.870	-101.268	-100.648	-95.410	-92.634	-103.361	-103.441

Table 3.2 Estimated break dates for the one structural break model specifications

The table reports the years of the estimated break dates for the one structural break model specification. Model 1, Model 2, Model 4 and Model 5 are specified in Banerjee and Carrion-I-Silvestre (2013) (see Table 3.1). Estimation of these break dates has been carried out using the model specified in equation (3.1) in first differences.

Year	Frequency			
	Model 1	Model 2	Model4	Model 5
1993	3	4	6	5
1994	3	4	3	2
1995	8	3	7	7
1996	9	6	8	9
1997	2	0	2	2
1998	2	2	2	2
1999	1	2	1	1
2000	3	3	5	5
2001	2	1	2	2
2002	0	1	0	0
2003	0	1	1	2
2004	0	1	0	0
2005	1	3	0	0
2006	17	21	14	14
2007	2	1	2	2

Table 3.3 Estimated break dates for the two structural break model specifications

The table reports the years of the estimated break dates for the case of two structural breaks. For each of the first and the second estimated break dates our analysis yield 53 estimated break dates for Model 1, Model 2, Model 4 and Model 5 as specified in Banerjee and Carrion-I-Silvestre (2013) (see Table 3.1). Estimation of these break dates has been carried out using the model specified in equation (3.1) in first differences.

First estimated break point					Second estimated break point				
Year	Frequency				Year	Frequency			
	Model 1	Model 2	Model 4	Model 5		Model1	Model 2	Model 4	Model 5
1992	2	0	1	2	1996	1	0	1	1
1993	5	9	8	8	1997	1	0	0	0
1994	5	6	3	2	1998	0	2	2	2
1995	8	8	8	7	1999	1	1	1	2
1996	12	13	12	14	2000	3	3	3	4
1997	4	2	5	4	2001	2	3	3	4
1998	6	3	3	3	2002	0	0	0	0
1999	5	2	2	2	2003	0	3	0	1
2000	5	4	7	4	2004	0	5	1	1
2001	1	1	2	4	2005	4	6	4	3
2002	0	2	2	3	2006	35	27	33	31
2003	0	2	0	0	2007	5	1	3	2
2004	0	1	0	0	2008	1	2	2	2

Table 3.4 Pesaran's CD statistic for cross-section independence among the idiosyncratic residuals

The table reports statistics based on the CD test proposed by Pesaran (2004) for testing the null hypothesis of cross-section independence among the idiosyncratic disturbance terms . (k) refers to different values of autoregressive corrections. Model 1, Model 2, Model 4 and Model 5 are specified in Banerjee and Carrion-I-Silvestre (2013) (see Table 3.1). The CD test of Pesaran (2004) is a 2−sided test distributed as $N(0,1)$ under the null hypothesis of cross-sectional independence. The order of the autoregressive corrections used in the computation of the augmented Dickey-Fuller type regression equation (equation (3.3)) is selected using the t-sig criterion in Ng and Perron (1995). At the 1% significance level, the null hypothesis of cross-sectional independent errors is rejected if $|CD| \geq 2.55$. (***) indicates rejection of the null hypothesis of cross-section independence at 1% significance level.

K	No structural breaks	One structural break				Two structural breaks			
		Model 1	Model 2	Model 4	Model 5	Model 1	Model 2	Model 4	Model 5
0	1.435	-5.791***	-1.007	-4.099***	-3.843***	-6.697***	-5.130***	-7.100***	-7.046***
1	1.361	-5.844***	-1.136	-4.-84***	-3.892***	-6.671***	-5.249***	-7.082***	-7.015***
2	1.329	-5.757***	-1.232	-4.149***	-3.918***	-6.663***	-5.343***	-6.942***	-6.850***
3	1.329	-5.576***	-1.064	-4.178***	-3.822***	-6.425***	-5.226***	-6.814***	-6.724***
4	1.108	-5.634***	-1.242	-4.138***	-3.814***	-6.461***	-5.477***	-6.887***	-6.836***
5	0.890	-5.631***	-1.097	-4.111***	-3.880***	-6.624***	-5.528***	-6.926***	-6.831***
6	0.747	-5.656***	-1.282	-4.044***	-3.915***	-6.556***	-5.466***	-6.795***	-6.705***
7	0.991	-5.605***	-1.205	-4.019***	-3.873***	-6.481***	-5.353***	-6.672***	-6.607***
8	1.196	-5.402***	-1.018	-4.006***	-3.843***	-6.342***	-5.324***	-6.542***	-6.472***
9	1.046	-5.496***	-1.120	-4.004***	-3.776***	-6.275***	-5.309***	-6.497***	-6.465***
10	0.909	-5.365***	-1.152	-3.842***	-3.563***	-6.343***	-5.358***	-6.597***	-6.517***
11	1.080	-5.391***	-1.028	-3.833***	-3.509***	-6.377***	-5.435***	-6.675***	-6.605***
12	1.130	-5.444***	-1.155	-3.810***	-3.513***	-6.394***	-5.457***	-6.707***	-6.624***

Table 3.5 Banerjee and Carrion-I-Silvestre (2013) cointegration test of Purchasing Power Parity.

The table reports results of the panel cointegration test proposed by Banerjee and Carrion-I-Silvestre (2013). Critical values for testing the null hypothesis of no coinegration are provided by Pedroni (1999) for the case of no structural breaks and by Banerjee and Carrion-I-Silvestre (2013) for the one structural break model specifications. Non-rejection of the null hypothesis of no cointegration implies that PPP does not hold. Model 2 is specified by Banerjee and Carrion-I-Silvestre (2013) with a stable trend and a stable cointegrating vector. The number of common factors is estimated using the panel BIC information criterion as in Bai and Ng (2004). The order of the autoregressive corrections used in the computation of the augmented Dickey-Fuller type regression equation (equation (3.3)) is selected using the t-sig criterion in Ng and Perron (1995).

	No structural breaks	One structural break
		Model 2
Panel cointegration test statistics	2.899	1.990

Fig. 3.1 Frequency of the estimated break date (year) for the fifty-three economies for the one structural real model specifications

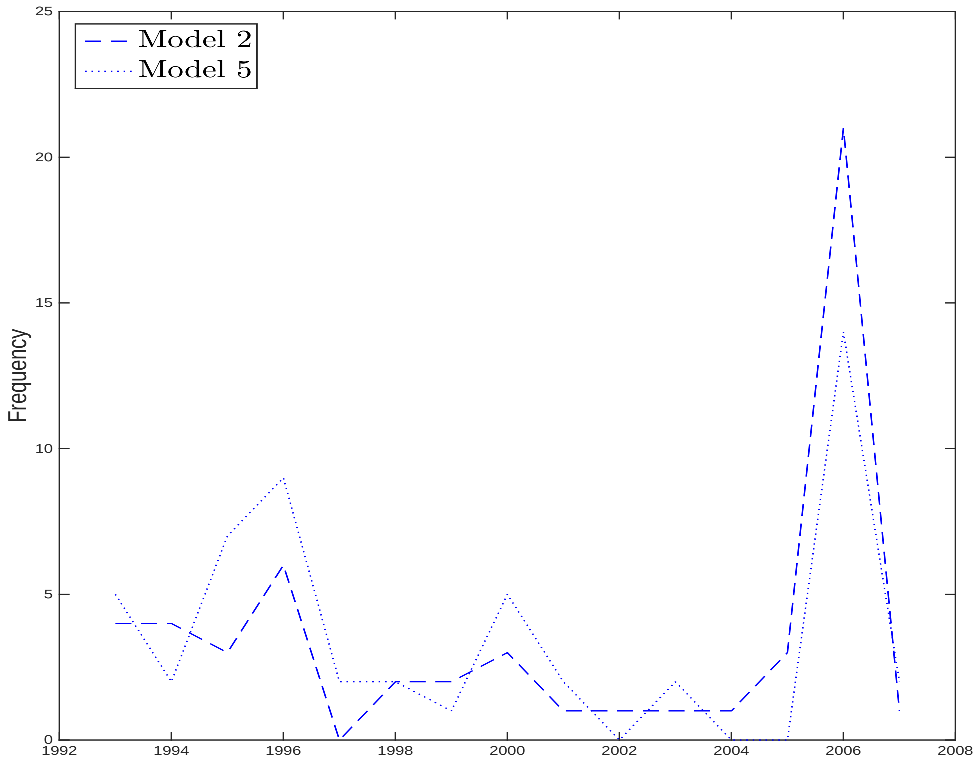
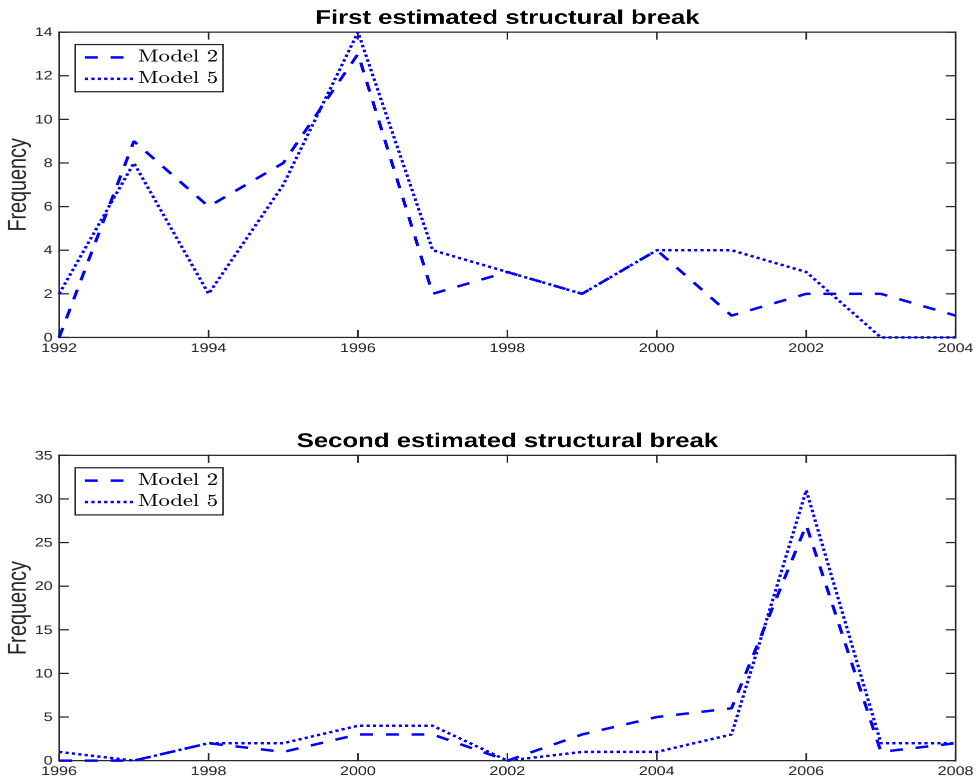


Fig. 3.2 Frequency of the estimated break date (year) for the fifty-three economies for the two structural real model specifications.



Chapter4

Forecasting exchange rates: A factor approach

4.1 Introduction

The foreign exchange market is one of the largest markets in the world. In terms of liquidity, the daily average turnover recorded in the UK in April 2013 is approximately \$2.547 billion.[1] Despite this liquidity, it is notoriously difficult to improve on the random walk model in predicting floating exchange rates. Meese and Rogoff (1983) showed that models based on fundamentals failed to beat the random walk model for a sample of three leading currencies against the US dollar over the 1973:03-1981:06 sample period. This apparent exchange rate disconnect from fundamentals remains one of the long standing puzzles in international finance. This has continued until recent models based on a factor approach introduced promising results in the field of exchange rate forecasting.

In this chapter, our analysis of exchange rate prediction builds upon factor approach proposed by Engel et al. (2015). They construct factors from a panel of 17 OECD US dollar exchange rates and they employ the idiosyncratic deviations from the factors to forecast. They show that such forecasts outperform others even in the absence of serial correlation in the univariate exchange rate processes. The panel in this chapter consists of 10 OECD currencies quoted in US dollars at a monthly frequency. Factors were extracted from the exchange rate panel only and not from a panel of the fundamentals added subsequently. The underlying rationale is that exchange rate series tend to commove over time and thus contain information that is hard to extract from observable fundamentals. The analysis builds on Engel et al. (2015) by comparing the predictions from two new models with those from the random walk model on the basis of their performance in an out-of sample predictive accuracy test. The leading Engel et al. model uses factors only with no additional fundamentals. Their remaining three models utilise factors together with different measures of observable fundamentals based on the (i) Taylor rule (ii) Purchasing power parity (PPP) and (iii) monetary models. In this chapter, we propose the

[1] A report by the London Foreign Exchange Joint Standing Committee estimated that in April 2013 the daily average turnover recorded in the UK was approximately \$2.547 billion.

separate use of forward rates and interest rate differentials as the two new sets of fundamentals to be used in conjunction with the extracted factors.

In addition, we adopt a more comprehensive forecasting exercise addressing the performance of each competing model in order to determine which model is best able to forecast spot exchange rates in each economy tested. Our measures for forecasting accuracy are the model confidence set proposed by Hansen et al. (2011) (henceforth MCS), the superior predictive ability test suggested by Hansen (2005) (henceforth SPA), the Theil's-U test, and the t_{cw} test proposed by Clark and West (2006).

Our forecasting accuracy measurements for the sample (1) (1999:01-2007:12; out of sample period 2004:01-2007:12) provide little evidence in favour of some of our candidate models over the random walk model at short horizons only (1, 3, 6, and 12 months). Over the longer horizons (18 and 24 months), none of our candidate models was able to outperform the random walk model in providing a better forecast for the spot exchange rates, a situation that is in a stark contrast to the findings of Engel et al. (2015). The latter found all their fundamental models' predictions have lower (though not significantly so) mean squared prediction error than the random walk model for long (2 and 3 year) horizon predictions over the later part (1999-2007) of their forecasting sample. However, for the samples (2) and (3) (out of sample periods are 2008:01-2013:04 and 1999:01-2013:04, respectively), our prediction accuracy tests show that the random walk model is outperformed widely on the long horizons only.

Despite the fact that our candidate models produce better forecasts for the spot exchange rates than the random walk model does (for samples (2) and (3) over the long horizons), it remains difficult to identify the best model among candidate models that is able to consistently outperform the random walk model, a situation that uncovers a high level of heterogeneity in model performance across varying countries, factors and horizons.

The remainder of this chapter is organised as follows. Section 2 summarises and reviews the relevant literature. Section 3 introduces the methodology by presenting the data, the tests, and the forecasting mechanism. Section 4 provides the empirical results. Section 5 draws conclusion out of the chapter.

4.2 Literature review

In the early stages following the collapse of Bretton Woods's system of fixed exchange rates, a considerable number of studies explored various methodologies for modelling exchange rates behaviour. Early work by Meese and Rogoff (1983) demonstrated that exchange rate models based on macro fundamentals were not able to beat the random walk model at short or medium horizons.[2] And if the candidate model does not beat the random walk, it does not provide a better forecast than the random walk model. Meese and Rogoff's findings were established by evaluating a set of various econometric models (univariate, multivariate, and structural models) based on their performance in an out-of-sample forecasting accuracy test.
Succeeding work by Chin and Meese (1995), who focused on similar models, also reported no evidence in favour of long-horizon predictability for the Sterling-Dollar exchange rate.[3] Similarly, Berben and Dijk (1998) revealed no significant evidence in favour of long horizon exchange rate predictability for the Dutch Mark, the Japanese Yen, the Canadian Dollar, and the Swiss Franc vis-à-vis the US dollar over the period 1973:Q1-1997:Q3.

In defence of the fundamental-based exchange rate models, several studies proposed using various combinations of econometric techniques and economic variables with the goal of overturning Meese and Rogoff's finding. For instance, MacDonald and Taylor (1994), based on the application of unrestricted monetary models within a multivariate cointergation framework, reported a successful forecast for the Sterling-Dollar exchange rate in a sample of monthly observations spanning the period 1976:01-1990:12. Mark (1995) also documented supporting evidence in favour of a successful long horizon forecast for the exchange rates of Canada, Germany, Japan, and Switzerland currencies against the United States currency for the period from

[2] At one to twelve month horizons.

[3] Chin and Meese (1995) found no evidence in favour of long horizon prediction for the Sterling-Dollar exchange rate in an analysis mainly based on error correction terms specifications. However, the authors noted that models with other exchange rates, such as the German Mark and the Japanese Yen vis-à-vis the US dollar, beat the random walk in providing a better forecast at long horizons.

1973:02 to 1991:04.[4] Using a univariate estimation procedure, Lothian and Taylor (1996) documented a successful exchange rate prediction for a sample of exchange rates, and this was achieved by using a very long time series, as long as two hundred years of data series. Their model has been found to explain up to 60 and 80 per cent of changes in both the Dollar-Sterling and the Franc-Sterling exchange rates, respectively. In a related manner, Evans and Lyons (1999) found that fundamental-based forecasting models could account for up to 10% of the monthly changes in exchange rates compared with a value of 60% of daily changes that could be obtained using their proposed portfolio framework. Using an out-of-sample accuracy test, the authors found that their portfolio model can improve on the random walk model in predicting movements of two exchange rates, namely the Dutch Mark and the Japanese Yen vis-à-vis the US dollar, at short horizons. In a recent study, Kilian and Taylor (2003) suggested that models that incorporate nonlinear exchange rate dynamics can improve the forecasting accuracy of fundamental models at long horizons (2 to 3 years). The authors also pointed out that such improvement in models prediction capability is difficult to be detected in an out-of-sample forecasting exercises.

Mark and Sul (2001), Groen (2005), and Engel et al. (2007) found relatively good success of exchange rate predictability using monetary-based exchnage rate models within a panel data estimation framework. However, in a recent comprehensive study, Cheung et al. (2005) examined the performance of several exchange rate models with interest rate parity, monetary, and productivity specifications and concluded that none of their candidate models consistently outperforms the random walk at any horizon. Similar results were also obtained by Groen (1999), Sarno and Taylor (2002), and Alquist and Chinn (2008), among others, who argued that standard macroeconomic models of exchange rates (conventional forecasting models) cannot predict nominal exchange rates with significantly higher accuracy than the random walk model.

[4] The analysis was established on regressing long horizon variations of exchange rates on the deviation of current exchange rates from linear combinations of money supply and real income.

A recent literature has endorsed the usefulness of using Taylor rule fundamentals in modelling exchange rates determination (see for example Groen and Matsumoto (2004), Engel and West (2006), McCracken (2007), and Galí (2008)).[5] Molodtsova and Papell (2009) documented that exchange rate models based on Taylor rules specifications improve on the standard monetary models, the purchasing power parity models, the interest rate models, and the random walk model in predicting exchange rates at short horizons. Similarly, Molodtsova et al. (2011) reported, within the Taylor rule framework, significant evidence in favour of the US dollar/Euro exchange rate predictability at short horizons using real-time data spanning the period 1999-2007.

More recently, forecasting models based on a factor approach provided promising results in predicting macro variables (see for instance the work of Stock and Watson (2004) and Ludvigson and Ng (2007) on modelling output growth and stock market returns, respectively). Greenaway et al. (2012) argued that the predictability of exchange rates appears to be more accurate when used in pooled approaches that rely on a whole set of common factors (proxied by currencies) rather than single exchange rates.[6] Recent work by Engel et al. (2015) which focused on factor models to predict currency movements provided promising results. The authors found all their fundamental models's predictions have lower (though not significantly so) mean squared prediction error than the random walk model for long (2 and 3 year) horizon predictions over the later part(1999-2007) of their forecasting sample.

[5]See Molodtsova and Papell (2012) on how Taylor rules can be used to forecast exchange rates.

[6]The study suggested that the Euro, the Swiss-Franc, and the Yen vis-à-vis the US dollar represent a set of common factors which have been found to be helpful in(i) explaining a large proportion of exchange rate changes (ii) and providing a successful forecast of exchange rates.

4.3 Methodology

4.3.1 Method and data

The following section provides a comprehensive description of the econometric framework and the data utilised in the following forecasting process. The present analysis of exchange rate prediction is based on the model proposed by Engel et al. (2015), given by equation (4.1), where they construct factors from a panel of 17 OECD US dollar exchange rates and they employ the idiosyncratic deviations from the factors to predict future movement in exchange rates.[7] The factors are constructed from unobserved variables extracted from the exchange rates panel only and not from a panel of the fundamentals added subsequently. The underlying rational is exchange rates tend to commove over time and thus contain information that is hard to extract from observable fundamentals.

In the present analysis, we follow Engel et al. (2015) approach by employing the extracted factors, as presented in the right hand side of equation 4.1, in order to predict changes in exchange rates $\Delta s_{it} = s_{it+h} - s_{it}$.

$$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \mu_{it+h} \tag{4.1}$$

where s_{it+h} is the logarithm of exchange rate in country (i) at time $(t+h)$ where (h) denotes a given horizon, s_{it} is the logarithm of exchange rate in country (i) at time (t), α_i is a fixed effect for country (i), β is a constant, $\hat{F}_{it}$ represents the estimated factors, and μ_{it+h} is the error term.

Equation (4.1) introduces the model where only estimated factors but no additional observable fundamentals are utilised in the forecasting process (henceforth equation (4.1) represents the model of "factors only"). Equations (4.2), (4.3), and (4.4) represent the models where factors are utilised together with different mea-

[7] The same approach has been previously employed in a number of studies using different specifications for the central tendency measurement (see Mark (1995), Molodtsova et al. (2008) and Engel et al. (2007)).

sures of observable fundamentals based on (1) purchasing power parity (2) monetary models and (3) Taylor rule, respectively. In general, exchange rate models based on monetary fundamentals have not fared well in producing a better forecast for the nominal exchange rates. For example, Cheung et al. (2005) found that the monetary models generally do not have significantly better forecasting power than the random walk model.[8] Besides, despite the importance of Taylor rule specifications as an accurate approximation to monetary policy setting, it has recently lost its role specially after the financial crisis (2007-2008) where the economy in many developed countries has been in the zero lower bound area. Thus, the interest rates cannot be used as a policy instrument.[9] Considering the previous two main problems, this chapter proposes two new forecasting models. In particular, we build on Engel et al. (2015) by proposing the separate use of forward rates and interest rate differentials as the two new sets of fundamentals to be used in conjunction with the extracted factors. Equations (4.5) and (4.6) represent the models where factors are combined with forward rates and interest rate differential, respectively. Across all models, factors were extracted from the exchange rates only and not from the other observable fundamentals.

$$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[(p_{it} - p_{0t}) - s_{it}] + \mu_{it+h} \tag{4.2}$$

$$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[(m_{it} - m_{0t}) - (y_{it} - y_{0t}) - s_{it}] + \mu_{it+h} \tag{4.3}$$

$$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[1.5(\pi_{it} - \pi_{0t}) + 0.5(\widetilde{y}_{it} - \widetilde{y}_{0t})] + \mu_{it+h} \tag{4.4}$$

$$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[fw_{it} - s_{it}] + \mu_{it+h} \tag{4.5}$$

$$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[(r_{it} - r_{0t}) - s_{it}] + \mu_{it+h} \tag{4.6}$$

[8] Mark and Sul (2001) and Groen (2005) have, in fact, found that panel error-correction models (ECM) based on the simple monetary model or the closely related purchasing power parity model do have power to forecast exchange rates out of sample.

[9] The Taylor rule assumes that the interest rate is the key policy instrument.

where p_{it} and p_{0t} are the logarithms of price level (Consumer Price Index CPI), y_{it} and y_{0t} are the logarithms of output, $\widetilde{y}_{it}$ and $\widetilde{y}_{0t}$ are output gaps, π_{it} and π_{0t} represent the inflation, m_{it} and m_{0t} are the logarithms of money supply, fw_{it} are the logarithms of forward exchange rate, and r_{it} and r_{0t} are the logarithms of short-term interest rates. (i) refers to any country in the sample and (0) refers to the home country which is the United States in this study.

The current analysis utilises data in monthly frequencies obtained from "Data Stream" for the period from 1999:01 to 2013:04 belong to the following countries: the United Kingdom, Canada, Switzerland, Denmark, Japan, South Korea, Norway, Sweden, Australia, and the Euro area. Three sub-samples were established from the whole panel as follows. Sample (1) includes the above ten economies with the out of sample period starts from 2004:01 and finishes in 2007:12. The aim of using this sample is to investigate the relative forecasting performance of our candidate models for the period that preceded the financial crisis which peaked in 2008, and to compare the forecasting results obtained by our four forecasting accuracy measurements to those of Engel et al. (2015) for the same ten economies. Samples (2) and (3) include the same ten economies with the out of sample periods range from 2008:01 to 2013:04 and from 2009:01 to 2013:04, respectively. One motivation of using these two samples is to reveal the performance of our competing models during and after the financial crisis.

The price level is the Consumer Price Index CPI. The industrial production is used as a proxy for the output. Output gap is constructed as in Engel et al. (2015) using Hadrick and Prescott HP detrending procedure. Money supply is represented by (M_1) for all countries except for Denmark where it is replaced by (M_0) since (M_1) is not available. Exchange rates are the spot nominal exchange rates vis-à-vis the US dollar. The interest rates are the three-month interest rates on treasury bills (or the equivalent where available) for each country. The forward rates are the forward exchange rates with three-month maturity vis-à-vis the corresponding US dollar.

Mechanism of the forecasting starts by producing time series of estimated factors and factor loadings extracted from panel of exchange rates only. The estimation method is the maximum likelihood, assuming normality.[10]

$$\hat{F}_{it} = \hat{\delta}_{1i}\hat{f}_{1t} + \hat{\delta}_{2i}\hat{f}_{2t} + \hat{\delta}_{3i}\hat{f}_{3t} \tag{4.7}$$

where $\hat{\delta}_{1i}$, $i = 1, ..., n$; $\hat{\delta}_{2i}$, $i = 1, ..., n$; $\hat{\delta}_{3i}$, $i = 1, ..., n$, are the estimated factor loadings for "n" economies, $\hat{f}_{1t}$, $\hat{f}_{2t}$, and $\hat{f}_{3t}$ are the first, the second, and the third estimated factor, respectively.

The forecasting process proceeds by identifying the horizons over which the exchange rates are predicted. In the current analysis, we base our forecasting on the horizons of one month, three months, six months, twelve months, eighteen months, and twenty-four months.

To illustrate the forecasting process, we present the following example from the sample (1) where the model of factors only (equation (4.1)) is utilised to forecast over one-month horizon. At the first stage, we use data from the period 1999:01 to 2003:12 to extract factors and factor loadings, and construct $\hat{F}_{it}$ (equation 4.7) for $i = 1, ..., 10$. The next stage is to estimate the following panel regression (i.e. $\hat{\alpha}_i$ and $\hat{\beta}$) from the period t =1999:01-2003:11 using the standard panel data regression (least squares with dummy variable).

$$s_{it+1} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \mu_{it+1} \tag{4.8}$$

The subsequent stage is to predict changes in the exchange rates over the first month. This is achieved via the application of the following formula

$$s_{i,2004:01} - s_{i,2003:12} = \hat{\alpha}_i + \hat{\beta}(\hat{F}_{i,2003:12} - s_{i,2003:12}) \tag{4.9}$$

where data of 2003:12 is used to predict the first month change in s. The process above is then repeated after adding one observation to the end of the sample which

[10] (i) We seasonally adjust the macro variables by taking a six-month average of the log level of these variables. (ii) Following Engel et al. (2015), we normalise the factors to have mean zero and unit variance.

is used in factors extraction and panel estimation. This recursive method leads to an increase in the size of the employed sample (used for factor extraction and panel estimation) every time an observation is added to the end of sample.

4.3.2 Forecasting accuracy tests

This section presents the various techniques employed in the current chapter for model performance evaluation. The evaluation is carried out by four different measurements which are the Theil's U- statistic, the Mean Squared Prediction Error (MSPE)-adjusted t-test proposed by Clark and West (2006) (t_{cw} test), the superior predictive ability studentised (SPA) test suggested by Hansen (2005), and finally the model confidence set (MCS) proposed by Hansen et al. (2011).

One objective of using the first two tests is to compare the forecasting results from the present chapter to those of Engel et al. (2015). The latter based their prediction accuracy evaluations on the Theil's-U and t_{cw} statistics to check the forecasting performance of their exchange rate models.

The Theil's U-statistic is a relative accuracy measure that compares the Mean Squared Prediction Error (MSPE) of the candidate models with the relevant MSPE of the random walk model. Equation (4.10) defines the Theil's U-statistics where the term $(\hat{x}_{t+1} - x_{t+1})$ represents the forecasting errors at time (t+1), whereas the term $(x_t - x_{t+1})$ represents the prediction errors resulting from the random walk model. Note that in the random walk model, next period $(t+1)$ prediction is assumed to be identical to the last period observation (t) i.e. $\hat{x}_{t+1} = x_t$.[11] In other words, the Theil's U-statistics could be considered as a ratio of the errors generated by candidate models to the errors resulted from using a "simplistic or "naive" forecasting technique. A U-statistic less than one implies that the candidate model is superior to the random walk model Brooks (2008).

$$U = [\sum_{t=1}^{n-1} (\frac{\hat{x}_{t+1} - x_{t+1}}{x_t})^2 / \sum_{t=1}^{n-1} (\frac{x_t - x_{t+1}}{x_t})^2]^{1/2} \tag{4.10}$$

The second test for evaluating the predictive ability for each forecasting model against the random walk models is the test proposed by Clark and West (2006). The test adjusts the point estimates of differences between MSPEs of the benchmark and

[11] The random walk model generates a forecast of no change in the exchange rates.

the candidate models to account for the noise associated with the larger of the two models in the situation when one model nests the other.[12] The t_{cw} (equation 4.11) tests the null hypothesis (H_0) of equal MSPE (i.e. equal predictive ability) against the alternative hypothesis (H_1; one-sided test) that is MSPE of the candidate model is smaller than the MSPE of the random walk model (i.e. the random walk model is outperformed) using standard normal critical values (i.e. the null hypothesis of MSPE equality is rejected when $t_{cw} > 1.28$ at the 10% significance level).

$$t_{cw} = \sqrt{P}[\hat{\sigma}_1^2 - (\hat{\sigma}_2^2 - adj.)]/\sqrt{\hat{V}} \tag{4.11}$$

where P is the number of predictions, $\hat{\sigma}_1^2$ is the out of sample MSPE of the random walk model, $\hat{\sigma}_2^2$ is the out of sample MSPE of the candidate model, "*adj.*" is the adjustment term equals to $P^{-1}\sum_{t=T-P+1}^{T}(X'_{t+1}\hat{\beta}_t)^2$.[13]

The third employed measurement for testing whether any of our forecasting models produces superior forecast to the random walk model is the SPA studentised test proposed by Hansen (2005). One advantage of using the SPA studentised test is to check whether any of the candidate models outperform the random walk model in providing a better forecast for the spot exchange rates. Hansen (2005) builds on White (2000) by constructing a test that uses a sample dependent distribution under the null hypothesis. Hansen showed that the SPA studentised test is powerful and is less sensitive to the inclusion of poor and irrelevant alternative forecasting models. The SPA tests the null hypothesis stating that the benchmark model is not inferior to any of the alternative forecast models under consideration.

The SPA studentised test statistics are computed as follows

$$SPA = max[max_{1\leq k\leq m}\sqrt{n}\bar{d}_k/\hat{\omega}_k, 0] \tag{4.12}$$

where $\hat{\omega}_k^2$ is some consistent estimator of $\omega_k^2 = var(n^{1/2}\bar{d}_k)$, $\bar{d}_k = \sum_{t=1}^{n} d_{k,t}/n$ where $d_{k,t} = L_{0,t} - L_{k,t}$ is the relative performance of model k to the benchmark model.

[12] The benchmark model in this chapter is the random walk model.

[13] See Clark and West (2006) for details on how to calculate the t_{cw} test statistics.

$L_{k,t}$ is the observed loss of model k at time t. $k = 0, 1, ..., m$ where $k = 0$ is the benchmark, and m is the number of alternative forecasting models. $t = 1, ..., n$ is the sample period for model comparison.

The last test to be used for the current model performance evaluation is the test of Model Confidence Set (MCS) proposed by Hansen et al. (2011). The test aims to produce a subset of best models ($M^*_{1-\alpha}$) from a collection of competing models (M_0) with a certain level of confidence (α). The MCS test has the advantage that it does not require to identify a benchmark model unlike the t_{cw} and the SPA tests where identification of benchmark model is substantial. Additionally, the MCS procedure recognises the limitation of the data where informative data would yield the best models. However, using less informative data would result in large confidence set including many of the competing models, a situation that leads to a difficulty in distinguishing between the candidate models on the basis of their prediction performance. The MCS procedure relies on sequential testing of the null hypothesis of equal forecasting accuracy and an elimination of the worst performing models in order to construct the confidence set. In the present chapter, we set the confidence set to 10% and report $p-$values for each of the competing models that are thresholds at which a model $i \in M^*_{1-\alpha}$ if and only if $\hat{p}_i \geq \alpha$.[14]

[14]See Hansen et al. (2011) for more detailed information on MCS procedures.

4.4 Empirical finding

Forecasting results based on the Theil's U and the t_{cw} test statistics are presented in Tables 4.2, 4.5, and 4.8 for the samples (1), (2), and (3), respectively. Included in the tables are the numbers of predictable currencies that are every time subject to a specific candidate model at a particular forecasting horizon. Every table consists of three panels; the first panel "A" contains figures indicating the number of predictable currencies when one estimated factor is utilised in the forecasting process; the second and the thirds panels "B" and "C" include numbers of predictable currencies based on the inclusion of two and three factors, respectively.

To read the Tables 4.2, 4.5, and 4.8 consider the model of "factors only" in panel "B" from Table 4.2. Using the Theil's U-statistics, figure 1 at horizon (1 month) means that the model of "factors only" outperformed the random walk model for 1 out of the 10 included currencies. In other words, the MSPE resulting from the model of "factor only" were less than the MSPE of the random walk model for only one currency. Recall that U$<$ 1 means that the candidate model has a lower MSPE than the random walk model. In a similar fashion, the figure in brackets (0) means that none of the present 10 currencies were found predictable according to the t_{cw} test i.e. the null hypothesis of equal MSPE is not rejected at 10% significance level for any of the ten currencies at one-month horizon.

Tables 4.3, 4.6, and 4.9 report results obtained by the SPA studentised test for the samples (1), (2), and (3), respectively. The tables contain p-values resulting from testing the null hypothesis stating that the benchmark model is not inferior to any of the alternative forecasting models. Significant results are in bold.

Tables 4.4, 4.7, and 4.10 provide p-values obtained by the application of the MCS procedures for the samples (1), (2), and (3), respectively. Every table includes six sections ("I", "II", "III", "IV", "V", and "VI") which report MCS results over 1, 3, 6, 12, 18, and 24 months forecasting horizons, respectively. MCS p-values are presented for each of the competing models including the random walk model, on a country basis. Figures that are in bold indicate the relevant models are contained in the set of best models $M^*_{90\%}$.

Examining predictability of our current exchange rate models starts by analysing the forecasting results obtained by the aforementioned forecasting accuracy measurements for the sample (1) (1999:01-2007:12; out of sample period 2004:01-2007:12) over the short horizons (1, 3, 6, 12 months). With the notable exception of the models of "factors +PPP" and "factors + forward premium" in panels "B" and "C", the numbers of predictable currencies obtained by Theil's U-statistics, reported in Table 4.2, seem to be relatively small across the three panels. Similarly, the t_{cw} test statistics, also reported in Table 4.2, provide relatively very small numbers of predictable currencies across the three panels.[15]

In terms of how the competing models perform against the random walk model, Table 4.3 reports results obtained by the SPA studentised test. The SPA statistics demonstrate that the null hypothesis stating that the random walk model is not inferior to any of the alternative forecasting models is not rejected for most of the included currencies i.e. most of our candidate models are outperformed by the random walk model.

To further investigate the forecasting performance of our candidate models, Table 4.4 shows the results obtained by the MCS procedure that produces the set of best models with a given level of confidence. The results of the MCS procedure show that the random walk model seems to enter the confidence set (set of the best models) for most of the included currencies. This finding is relatively consistent with the results obtained by the SPA studentised test over the same periods. According to the SPA studentised test, the random walk model is outperformed by one of our candidate models at 3 and 6 month horizons for Norway and at 6 and 12 month horizon for Canada and South-Korea, respectively. Whereas the MCS procedure provides similar results at 6 and 12 month horizon and extends the currencies to include South-Korea and Canada at 1 and 3 month horizon, respectively.

[15]For example the model of "factors + PPP" at one month horizon in panel "C" reports that six out of ten currencies were predictable.

Over the longer horizons (18 and 24 months), our forecasting accuracy measurements provide stronger evidence in favour of the random walk model over the competing models. Put differently, none of the candidate models can beat the random walk in providing a better forecast for the spot exchange rates. This breakdown in the number of predictable currencies is in contrast with the findings of Engel et al. (2015). The latter found that the predictions of all their fundamental models had lower (though not significantly so) mean squared prediction error than those of the random walk model for long (2 and 3 year) horizon predictions over the later part(1999-2007) of their forecasting sample.

For the sample (2) (1999:01-2013:04; out of sample period 2008:01-2013:04), our forecasting results produce significant evidence in favour of long horizon predictions. Theil's U-statistics, Table 4.5, suggest that the predictable currencies over 18 and 24 months horizons are relatively large. The t_{cw} statistics also show an increase in the amounts of predictable currencies specifically at 24 months horizon. The SPA studentised test statistics, Table 4.7, show that the random walk model is outperformed widely on 18 and 24 months horizons. This finding has also been corroborated by the MCS test (panels "V" and "VI" in table 8) where the random walk model was proven inferior to several of the competing models. Similar results were found for the sample (3); our forecasting accuracy measurements show the random walk is beaten by many of our candidate models over the long horizons.

Over the short horizons, our forecasting models for the samples (2) and (3) yield relatively similar results.[16] The random walk model seems to be superior to most of the candidate models. This finding is confirmed by the statistics reported from the four forecasting accuracy measurements applied. It is worth noting here that our forecasting results for the sample (2) are slightly different from those for the sample (3). Note that the out-of-sample period for the sample (1) is 2008:01-2013:04, whereas the out-of-sample period for the sample (2) is 2009:01-2013:04.

Based on our observation of the forecasting results for the samples (2) and (3), our forecasting accuracy measurements (in particular the MCS test) reveal a high

[16] Taking into account the differences in the out of sample period starting date.

degree of heterogeneity in model performance across the varying countries, factors and horizons within samples (2) and (3). Thus, it is difficult to identify the best model that is able to consistently produce the best forecasts on the long run.

A simple comparison between the forecasting accuracy statistics obtained from the three samples shows a significant difference in model performance between sample (1) on the one hand and samples (2) and (3) on the other. The aforementioned significant difference occurred when the forecasting was carried out over long horizons (18 and 24 months). In the sample (1), our candidate models fail to improve over the random walk model, whereas results obtained from samples (2) and (3) show that our candidate models tend to outperform the random walk model in providing a better forecast for the spot exchange rates. One explanation for such disparity in forecasting results could be attributed to the financial crisis that peaked in 2008 and triggered structural changes in foreign exchange markets Melvin and Taylor (2009). The absence of these structural changes before 2008 might explain the failure of our candidate models to improve over the random walk model. However, these post-crisis structural changes could provide an account for the relative success of the competing models in our study over the random walk model. Observing the results over the short horizons reveals that the immediate instability following the financial crisis in late 2007 could explain the failure to beat the random walk model in sample (2) and relatively in sample (3).

4.5 Conclusion

The present chapter analyses exchange rate predictions utilising the factor approach proposed by Engel et al. (2015). The factors were constructed only from a panel of exchange rates, and not from other observable fundamentals added to the forecasting process subsequently. The chapter proposes the separate use of forward rates and interest rate differentials as the two new sets of fundamentals to be used in conjunction with the extracted factors.

Our forecasting results show that our candidate models do not improve over the random walk model in providing a better forecast for the spot exchange rate for the forecasting sample (1) (2004-2007). The above situation overturns the findings reported by Engel et al. (2015) who found that all their fundamental models had lower mean squared predication error than the random walk model for long (2 and 3 year) horizon predictions over the later part (1999-2007) of their forecasting sample. However, significant evidence in favour of several competing models over long horizon predictions is documented for the samples (2) and (3) over the forecasting samples of (2008-2013) and (2009- 2013), respectively. One explanation for the difference in forecasting results between sample (1) on the one hand and samples (2) and (3) on the other hand could be attributed to the financial crisis that started in late 2007 and peaked in 2008, which triggered structural changes in the foreign exchange markets.

Although our candidate models produce better forecasts for the spot exchange rates than the random walk model does (for samples (2) and (3) over the long horizons), it remains difficult to identify the best model among candidate models that is able to consistently outperform the random walk model, a situation that uncovers a high level of heterogeneity in model performance across varying countries, factors and horizons.

Table 4.1 Summary of currencies, samples, and models.

The table reports a summary of samples and models that are employed in the present forecast of exchange rates, which is based on the factor approach proposed by Engel et al. (2015). Samples (1), (2), and (3) contain data from the same ten economies which are the UK, Canada, Switzerland, Denmark, Japan, Korea, Norway, Sweden, Australia, and the Euro area. The factors were constructed only from a panel of exchange rates, and not from other observable fundamentals added to the forecasting process subsequently.

A. Samples

	Sample span	Out of sample period	Number of currencies
Sample (1)	1999:01-2013:04	2004:01-2007:12	10
Sample (2)	1999:01-2013:04	2008:01-2013:04	10
Sample (3)	1999:01-2013:04	2009:01-2013:04	10

B. Models

$\hat{F}_{it} - s_{it}$ (Factors only)	$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \mu_{it+h}$
$(\hat{F}_{it} - s_{it})+$ Interest rates	$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[(r_{it} - r_{0t}) - s_{it}] + \mu_{it+h}$
$(\hat{F}_{it} - s_{it})+$ Forward premium	$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[fw_{it} - s_{it}] + \mu_{it+h}$
$(\hat{F}_{it} - s_{it})+$ Taylor rules	$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[1.5(\pi_{it} - \pi_{0t}) + 0.5(\tilde{y}_{it} - \tilde{y}_{0t})] + \mu_{it+h}$
$(\hat{F}_{it} - s_{it})+$ PPP specifications	$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[(p_{it} - p_{0t}) - s_{it}] + \mu_{it+h}$
$(\hat{F}_{it} - s_{it})+$ Monetary specifications	$s_{it+h} - s_{it} = \alpha_i + \beta(\hat{F}_{it} - s_{it}) + \gamma[(m_{it} - m_{0t}) - (y_{it} - y_{0t}) - s_{it}] + \mu_{it+h}$

Table 4.2 Numbers of predictable currencies for the forecasting sample (1) (2004:01-2007:12) using the Theil's-U and the t_{cw} test statistics.

The table shows numbers of predictable currencies using the Theil's-U and the t_{cw} test statistics at different maturities. The values in brackets indicate the number of currencies using the t_{cw} test (null hypothesis of equal MSPE) at the 10% significance level ($t > 1.28$). Numbers without brackets refer to predictable currencies resulted from the application of the Theil's U statistics. Recall that $U < 1$ means that the candidate model has a lower MSPE than the benchmark model which is the random walk model in our study. M1, M2, M3, M4, M5, and M6 indicate the model of factors only, factors + Taylor rule, factors + monetary fundamentals, factors + PPP, factors + forward premium, and factors + interest rate differentials, respectively.

Model	Test	1 month	3 months	6 months	12 months	18 months	24 months
Panel A: one factor							
M1	U<1	1	3	3	0	1	0
	t>1.28	(1)	(1)	(2)	(0)	(0)	(0)
M2	U<1	1	2	3	0	1	0
	t>1.28	(0)	(2)	(2)	(0)	(0)	(0)
M3	U<1	1	2	3	1	1	0
	t>1.28	(1)	(1)	(2)	(1)	(1)	(0)
M4	U<1	2	3	4	3	1	0
	t>1.28	(1)	(2)	(3)	(0)	(2)	(0)
M5	U<1	1	3	3	1	1	0
	t>1.28	(1)	(1)	(2)	(1)	(0)	(0)
M6	U<1	1	2	2	2	1	0
	t>1.28	(1)	(1)	(1)	(1)	(1)	(0)
Panel B: two factors							
M1	U<1	1	2	3	0	0	0
	t>1.28	(0)	(0)	(1)	(0)	(0)	(0)
M2	U<1	1	1	2	0	0	0
	t>1.28	(0)	(0)	(1)	(0)	(0)	(0)
M3	U<1	1	2	2	0	0	0
	t>1.28	(0)	(0)	(1)	(0)	(0)	(0)
M4	U<1	5	4	4	5	0	0
	t>1.28	(1)	(2)	(3)	(3)	(0)	(0)
M5	U<1	1	3	4	0	0	0
	t>1.28	(1)	(1)	(2)	(0)	(0)	(0)
M6	U<1	1	2	2	2	1	0
	t>1.28	(1)	(1)	(1)	(1)	(1)	(0)

Continued on next page ...

Table 4.2 continued from previous page

Model	Test	1 month	3 months	6 months	12 months	18 months	24 months
Panel C: three factors							
M1	U<1	0	2	3	0	1	0
	t>1.28	(0)	(0)	(1)	(0)	(0)	(0)
M2	U<1	0	1	1	1	1	1
	t>1.28	(0)	(0)	(1)	(0)	(0)	(0)
M3	U<1	1	1	2	1	1	0
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)
M4	U<1	6	3	3	0	0	0
	t>1.28	(1)	(2)	(3)	(0)	(0)	(0)
M5	U<1	1	3	4	0	1	0
	t>1.28	(1)	(1)	(2)	(0)	(0)	(0)
M6	U<1	0	1	1	0	0	0
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)

Table 4.3 Test for Superior Predictive Ability (SPA); forecasting sample (1) (2004:01-2007:12)

The table shows p-values resulting from the implementation of the SPA test proposed by Hansen (2005). (***), (**) and (*) indicate rejection of the null hypothesis that the random walk model is not inferior to any alternative forecast at the 1%, 5% and 10% significance level, respectively. The SPA test has been conducted with 10,000 bootstrap replications. A detailed explanation of the implemented bootstrap procedures in this chapter is provided by Hansen (2005) for the SPA tests and by Hansen et al. (2011) for the MCS tests.

Country	1 month	3 months	6 months	12 months	18 months	24 months
Euro	1.000	1.000	1.000	1.000	1.000	1.000
Japan	1.000	1.000	1.000	0.756	0.404	1.000
Norway	0.438	0.000***	0.001***	0.631	1.000	1.000
Canada	1.000	0.289	0.019**	1.000	1.000	1.000
Sweden	0.713	0.657	0.539	0.587	1.000	1.000
Denmark	0.631	1.000	1.000	1.000	1.000	1.000
Australia	1.000	1.000	0.485	1.000	1.000	1.000
Switzerland	0.575	0.724	0.609	1.000	1.000	1.000
South-Korea	0.256	0.207	0.121	0.001***	1.000	1.000
United Kingdom	0.454	1.000	1.000	1.000	0.174	1.000

Table 4.4 Test for Model Confidence Set (MCS); forecasting sample (1) (2004:01-2007:12).

The table shows p-values resulting from the MCS test. M1, M2, M3, M4, M5, and M6 indicate the model of factors only, factors + Taylor rule, factors + monetary fundamentals, factors + PPP, factors + forward premium, and factors + interest rate differentials, respectively. F1, F2, and F3 indicate the number of employed factors as 1, 2, and 3 factors, respectively. Numbers in bold indicate to the models that are included in the set of best models $M^*_{90\%}$. The MCS test has been conducted with 10,000 bootstrap replications.

Panel I (1 month)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.852**	**0.631**	**0.454**	**0.631**	**0.631**	**0.454**	0.027	0.030	0.030	**0.631**	**0.454**	**0.454**	**1.000**	**0.631**	**0.631**	0.027	0.027	**0.852**	**0.454**
Japan	0.053	**1.000**	**0.333**	0.065	0.065	0.063	0.053	0.053	0.345	0.065	0.065	0.065	0.003	**0.922**	**0.333**	0.003	**0.333**	**0.145**	**0.145**
Norway	0.001	0.001	0.001	0.022	**1.000**	**0.710**	0.022	0.022	0.058	**0.710**	**0.248**	**0.184**	0.022	0.022	0.001	-	-	-	**0.710**
Canada	**0.710**	**0.876**	**1.000**	**0.509**	**0.710**	**0.949**	**0.949**	**0.710**	0.949	0.011	0.068	0.011	**0.876**	**0.916**	0.011	0.068	0.068	0.068	**0.151**
Sweden	0.023	0.023	**1.000**	0.023	**0.966**	**0.442**	0.023	**0.979**	0.972	**0.442**	**0.442**	**0.442**	0.023	0.023	**0.460**	0.023	0.023	0.023	**0.442**
Denmark	**0.870**	**0.870**	**0.694**	**0.870**	**0.870**	**0.694**	**0.870**	**0.694**	0.694	**0.428**	**0.428**	**0.428**	**1.000**	**0.870**	**0.870**	-	-	-	**0.428**
Australia	**0.119**	**0.429**	**0.119**	-	-	-	0.009	0.009	0.009	-	-	-	**0.119**	**1.000**	**0.537**	0.040	0.009	0.009	**0.119**
Switzerland	0.088	0.088	0.085	-	-	-	0.088	0.088	0.085	0.083	**0.979**	**0.958**	0.088	0.088	0.085	-	-	-	**1.000**
South-Korea	**1.000**	0.088	0.088	0.079	0.088	0.088	**0.107**	0.088	0.088	0.088	0.088	0.088	**0.107**	**0.107**	0.079	-	-	-	0.088
United Kingdom	0.041	0.041	**0.186**	0.041	0.041	**1.000**	**0.727**	**0.727**	0.186	**0.186**	**0.186**	**0.186**	0.041	0.041	**0.186**	0.041	0.041	0.041	**0.186**

Panel II (3 months)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.855**	**0.301**	**0.301**	**0.855**	**0.38**	**0.301**	0	0	0	**0.855**	**0.301**	**0.38**	**0.855**	**0.85**	**0.301**	0	0	**1**	**0.301**
Japan	**0.126**	**0.126**	**0.126**	**1**	**0.462**	**0.126**	**0.462**	**0.126**	**0.126**	0.002	0.002	0.087	**0.126**	**0.126**	**0.101**	**0.462**	**0.126**	**0.126**	**0.101**
Norway	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.047	**0.512**	**0.807**	**1**	0.002	0.002	0.002	-	-	-	0.002
Canada	**0.569**	**1**	0.005	**0.569**	0.005	0.005	**0.569**	**0.569**	0.005	0.005	0.005	0.005	**0.569**	0.005	0.005	0.017	0.017	0.017	0.005
Sweden	0.017	0.017	0.017	0.017	0.017	**0.236**	0.017	**1**	**0.875**	**0.236**	**0.236**	**0.236**	0.017	0.017	**0.875**	0.017	0.017	0.017	**0.236**
Denmark	**0.678**	**0.678**	**0.678**	**0.678**	**0.678**	**0.678**	**0.725**	**0.678**	**0.678**	**0.27**	**0.27**	**0.27**	**1**	**0.678**	**0.678**	-	-	-	**0.27**
Australia	**0.85**	**0.731**	**0.85**	-	-	-	0.001	0.001	0.001	-	-	-	**0.85**	**0.85**	**0.323**	0.001	**1**	0.001	**0.117**
Switzerland	0.045	0.045	0.045	-	-	-	0.045	0.045	0.045	**1**	**0.16**	**0.678**	0.045	0.045	0.045	-	-	-	**0.678**
South-Korea	**0.137**	**0.22**	**0.22**	**0.213**	**0.22**	**0.22**	**0.137**	**0.22**	**0.22**	**1**	**0.22**	**0.22**	**0.137**	**0.137**	**0.213**	-	-	-	**0.22**
United Kingdom	**0.570**	**0.221**	**0.168**	**0.57**	**0.168**	**0.168**	**0.57**	**0.168**	**0.168**	**0.221**	**0.168**	**0.168**	**0.57**	**0.221**	**0.168**	**1**	**0.729**	**0.57**	**0.168**

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Table 4.4 continued from previous page.

								Panel III (6 month)											
Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.522**	**0.301**	**0.301**	**0.522**	**0.301**	**0.301**	0.070	**1.000**	**0.522**	**0.301**	**0.301**	**0.301**	**0.522**	**0.301**	**0.301**	**0.732**	**0.674**	**0.522**	**0.244**
Japan	**0.517**	**0.517**	**0.517**	**0.517**	**0.517**	**0.517**	**0.555**	**0.517**	**0.517**	0.005	0.007	0.001	**0.517**	**0.517**	**0.517**	**1.000**	**0.555**	**0.555**	**0.517**
Norway	**1.000**	0.001	0.001	0.001	0.028	0.002	0.001	0.002	0.002	**0.100**	**0.517**	**0.645**	0.001	0.001	0.001	-	-	-	0.001
Canada	**0.184**	**0.319**	**0.319**	**0.306**	**0.319**	0.000	**0.184**	**0.319**	**0.836**	**0.319**	**0.319**	**0.306**	**0.184**	**0.319**	**1.000**	0.000	0.032	0.032	0.000
Sweden	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.731**	**0.625**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**
Denmark	**0.552**	**0.139**	**0.552**	**0.966**	**0.139**	**0.139**	**0.139**	**0.139**	**0.139**	**0.139**	**0.139**	**0.139**	**1.000**	**0.139**	**0.876**	-	-	-	**0.139**
Australia	0.053	**0.890**	0.053	-	-	-	0.053	0.053	0.053	-	-	-	0.053	**0.827**	0.053	0.053	0.053	0.053	**1.000**
Switzerland	0.077	0.008	0.008	-	-	-	0.008	0.008	0.008	0.008	**0.588**	0.008	0.077	0.008	0.008	-	-	-	**1.000**
South-Korea	**0.272**	**0.438**	0.050	**0.272**	**0.438**	0.029	**0.109**	**0.433**	**1.000**	0.029	0.052	**0.438**	**0.240**	**0.260**	**0.433**	-	-	-	**0.438**
United Kingdom	0.053	0.053	0.053	0.063	0.053	0.053	0.063	0.053	0.053	0.053	**1.000**	0.053	0.053	0.053	0.053	0.063	0.063	0.063	**0.713**

								Panel IV (12 month)											
Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.427**	0.001	0.001	**0.427**	0.001	**1.000**	0.025	0.025	0.002	**0.116**	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	**0.116**
Japan	0.000	0.008	0.000	0.000	0.000	**0.718**	0.014	0.000	**0.718**	0.020	0.014	0.014	0.000	0.008	0.000	0.014	0.014	0.014	**1.000**
Norway	**0.153**	**0.153**	**0.153**	**0.153**	**0.670**	**0.153**	**0.153**	**1.000**	**0.153**	**0.153**	**0.153**	**0.153**	**0.153**	**0.291**	**0.153**	-	-	-	**0.153**
Canada	**1.000**	0.000	0.001	0.000	0.000	0.001	**0.775**	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001	**0.775**
Sweden	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	**0.711**	**1.000**	0.000	0.000	0.003	0.000	0.021	0.021	0.003	**0.765**
Denmark	**0.416**	0.076	**0.416**	**1.000**	0.076	0.076	**0.397**	0.076	0.072	**0.350**	0.076	0.076	0.072	0.076	0.072	-	-	-	**0.350**
Australia	**0.232**	**0.274**	0.045	-	-	-	0.045	0.045	0.045	-	-	-	**0.228**	**0.274**	**1.000**	**0.274**	0.001	0.045	**0.172**
Switzerland	0.000	0.000	0.000	-	-	-	0.000	0.000	0.000	**1.000**	**0.415**	**0.508**	0.000	0.000	0.000	-	-	-	**0.302**
South-Korea	0.000	0.001	0.009	0.000	0.001	0.001	**1.000**	0.001	0.001	0.001	0.048	0.001	0.000	0.000	0.000	-	-	-	0.000
United Kingdom	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	**0.785**	**0.946**	0.000	0.008	0.000	0.000	0.092	0.092	**0.785**

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Panel V (18 months)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.308**	0.000	0.000	**1.000**	0.000	0.000	0.000	0.036	0.000	0.000	0.010	0.036	0.000	0.000	0.000	0.000	0.000	0.000	**0.308**
Japan	**0.242**	**0.242**	**0.104**	**0.242**	**0.242**	**0.242**	**0.242**	**0.242**	**0.242**	0.063	0.038	0.000	**0.242**	**1.000**	**0.242**	0.008	0.021	0.002	**0.242**
Norway	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.093	0.000	0.000	0.000	-	-	-	**1.000**
Canada	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	**1.000**
Sweden	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.670**	**1.000**	0.000	0.000	0.000	0.000	0.000	0.002	0.000	**0.670**
Denmark	**0.326**	0.000	0.000	**1.000**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.038	0.000	0.000	0.000	-	-	-	**0.326**
Australia	0.000	0.000	0.000	-	-	-	0.000	0.020	0.000	-	-	-	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**
Switzerland	**0.391**	0.027	0.027	-	-	-	0.072	0.072	**1.000**	**0.213**	**0.213**	**0.213**	**0.213**	0.027	0.027	-	-	-	**0.156**
South-Korea	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000	-	-	-	**0.369**
United Kingdom	0.000	0.000	0.023	0.000	0.000	0.014	0.000	0.000	0.023	**0.451**	**0.451**	0.000	0.000	0.000	0.023	0.000	0.000	0.000	**1.000**

Panel VI (24 months)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**
Japan	0.000	0.000	0.000	0.000	0.000	0.000	**0.581**	0.000	0.000	0.000	**1.000**	0.000	0.000	0.000	0.000	0.006	0.006	0.000	**0.261**
Norway	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	-	-	**1.000**
Canada	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**
Sweden	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**
Denmark	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	-	-	**1.000**
Australia	0.000	0.000	0.000	-	-	-	0.000	0.000	0.000	-	-	-	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**
Switzerland	0.000	0.000	0.000	-	-	-	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	-	-	**1.000**
South-Korea	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-	-	-	**0.353**
United Kingdom	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**

Table 4.5 Numbers of predictable currencies for the forecasting sample (2) (2008:01-2013:04) using the Theil's-U and the t_{cw} test statistics.

The table shows numbers of predictable currencies using the Theil's-U and the t_{cw} test statistics at different maturities. The values in brackets indicate the number of currencies using the t_{cw} test (null hypothesis of equal MSPE) at the 10% significance level ($t > 1.28$). Numbers without brackets refer to predictable currencies resulted from the application of the Theil's U statistics. Recall that $U < 1$ means that the candidate model has a lower MSPE than the benchmark model which is the random walk model in our study. M1, M2, M3, M4, M5, and M6 indicate the model of factors only, factors + Taylor rule, factors + monetary fundamentals, factors + PPP, factors + forward premium, and factors + interest rate differentials, respectively.

Model	Test	1 month	3 months	6 months	12 months	18 months	24 months
Panel A: one factor							
M1	U<1	0	0	0	1	3	4
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)
M2	U<1	0	0	0	0	3	4
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)
M3	U<1	0	0	1	2	4	5
	t>1.28	(0)	(0)	(0)	(0)	(0)	(1)
M4	U<1	3	1	1	6	7	7
	t>1.28	(1)	(1)	(1)	(0)	(2)	(5)
M5	U<1	0	0	0	1	3	6
	t>1.28	(0)	(0)	(0)	(0)	(0)	(1)
M6	U<1	0	0	0	0	1	3
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)
Panel B: two factors							
M1	U<1	2	1	0	2	6	8
	t>1.28	(1)	(0)	(0)	(0)	(0)	(4)
M2	U<1	2	2	0	2	5	8
	t>1.28	(1)	(0)	(0)	(0)	(1)	(4)
M3	U<1	2	2	1	5	8	9
	t>1.28	(1)	(0)	(0)	(0)	(0)	(5)
M4	U<1	4	3	3	5	6	7
	t>1.28	(0)	(0)	(1)	(0)	(1)	(3)
M5	U<1	2	1	0	4	6	8
	t>1.28	(1)	(0)	(0)	(0)	(0)	(4)
M6	U<1	1	0	1	2	3	6
	t>1.28	(0)	(0)	(0)	(0)	(1)	(2)

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Table 4.5 continued from previous page

Model	Test	1 month	3 months	6 months	12 months	18 months	24 months
Panel C: three factors							
M1	U<1	2	1	0	7	7	8
	t>1.28	(0)	(0)	(0)	(0)	(2)	(4)
M2	U<1	3	2	1	5	7	8
	t>1.28	(0)	(0)	(0)	(0)	(1)	(4)
M3	U<1	4	2	1	6	7	8
	t>1.28	(0)	(0)	(1)	(1)	(3)	(4)
M4	U<1	5	3	4	6	7	8
	t>1.28	(1)	(0)	(1)	(1)	(2)	(2)
M5	U<1	3	1	0	8	8	8
	t>1.28	(0)	(0)	(0)	(0)	(2)	(6)
M6	U<1	2	1	1	5	5	6
	t>1.28	(0)	(1)	(0)	(1)	(1)	(0)

Table 4.6 Test for Superior Predictive Ability (SPA); forecasting sample (2) (2008:01-2013:04)

The table shows p-values resulting from the implementation of the SPA test proposed by Hansen (2005). (***), (**) and (*) indicate rejection of the null hypothesis that the random walk model is not inferior to any alternative forecast at the 1%, 5% and 10% significance level, respectively. The SPA test has been conducted with 10,000 bootstrap replications. A detailed explanation of the implemented bootstrap procedures in this chapter is provided by Hansen (2005) for the SPA tests and by Hansen et al. (2011) for the MCS tests.

Country	1 month	3 months	6 months	12 months	18 months	24 months
Euro	0.056*	0.498	0.309	0.000***	0.013**	0.007***
Japan	0.244	0.371	0.158	0.000***	0.000***	0.000***
Norway	1.000	1.000	1.000	0.395	0.045**	0.011**
Canada	1.000	1.000	1.000	0.874	0.219	0.084*
Sweden	0.420	0.740	0.607	0.197	0.039**	0.018**
Denmark	0.126	0.638	0.409	0.000***	0.063*	0.004***
Australia	0.761	1.000	1.000	0.202	0.044**	0.015**
Switzerland	0.588	1.000	1.000	0.354	0.153	0.001***
South-Korea	0.263	0.280	0.276	0.068*	0.008***	0.020**
United Kingdom	0.492	1.000	1.000	0.211	0.035**	0.043**

Table 4.7 Test for Model Confidence Set (MCS); forecasting sample (2) (2008:01-2013:04).

The table shows p-values resulting from the MCS test. M1, M2, M3, M4, M5, and M6 indicate the model of factors only, factors + Taylor rule, factors + monetary fundamentals, factors + PPP, factors + forward premium, and factors + interest rate differentials, respectively. F1, F2, and F3 indicate the number of employed factors as 1, 2, and 3 factors, respectively. Numbers in bold indicate to the models that are included in the set of best models $M^*_{90\%}$. The MCS test has been conducted with 10,000 bootstrap replications.

									Panel I (1 month)										
Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.209**	**0.163**	**0.163**	**0.209**	**0.209**	**0.163**	**0.163**	**0.209**	**0.245**	**0.163**	**0.163**	**0.163**	**0.163**	**0.163**	**0.163**	**1.000**	**0.444**	**0.209**	**0.163**
Japan	**0.930**	**0.542**	**0.930**	**1.000**	**0.930**	**0.930**	**0.930**	**0.602**	**0.930**	**0.256**	**0.930**	**0.930**	**0.930**	**0.542**	**0.602**	**0.930**	**0.542**	**0.256**	**0.930**
Norway	0.069	**0.984**	**0.981**	0.069	0.069	0.069	0.069	0.050	**0.984**	**0.685**	**0.420**	**0.420**	**1.000**	**0.982**	**0.685**	-	-	-	**0.420**
Canada	0.064	**0.239**	**0.239**	0.064	**0.660**	**0.660**	0.064	0.064	**0.660**	**0.239**	**0.239**	**0.239**	0.064	**0.239**	**0.239**	0.064	**1.000**	**0.239**	**0.239**
Sweden	**0.471**	**0.256**	**0.471**	**0.471**	**0.471**	0.051	**0.471**	**0.471**	**0.471**	**0.256**	**0.256**	**0.256**	**0.471**	**0.256**	**0.471**	0.051	**1.000**	0.051	**0.256**
Denmark	**0.332**	**0.332**	**0.306**	**1.000**	**0.332**	**0.332**	**0.360**	**0.332**	**0.332**	**0.302**	**0.302**	**0.302**	**0.332**	**0.306**	**0.306**	-	-	-	**0.302**
Australia	**0.810**	**0.388**	**0.810**	-	-	-	0.020	0.031	0.031	-	-	-	**0.992**	**0.388**	**0.810**	**1.000**	**0.388**	**0.564**	**0.382**
Switzerland	0.078	0.078	0.037	-	-	-	0.078	0.037	0.037	0.078	0.037	**1.000**	0.078	0.078	0.037	-	-	-	0.037
South-Korea	**0.216**	**0.216**	**0.216**	**0.216**	**0.216**	**0.216**	**0.251**	**0.216**	**0.216**	**0.216**	**0.251**	**0.216**	**1.000**	**0.216**	**0.216**	-	-	-	**0.216**
United Kingdom	**0.238**	**0.192**	**0.192**	**0.238**	**0.192**	**0.192**	**0.238**	**0.238**	**0.192**	**0.666**	**1.000**	**0.238**	**0.238**	**0.192**	**0.192**	**0.238**	**0.238**	**0.192**	**0.192**

									Panel II (3 months)										
Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.213**	**0.213**	**0.213**	**0.213**	**0.213**	**0.213**	**0.213**	**0.861**	**0.213**	**0.201**	**0.124**	**0.123**	**0.213**	**0.213**	**0.213**	**1.000**	0.081	**0.861**	**0.127**
Japan	**0.646**	**0.342**	**0.342**	**1.000**	**0.342**	**0.342**	**0.342**	**0.342**	**0.342**	**0.203**	**0.342**	**0.342**	**0.646**	**0.342**	**0.342**	**0.842**	**0.238**	**0.203**	**0.342**
Norway	**0.743**	**0.570**	**0.570**	**0.743**	**0.721**	**0.570**	**1.000**	**0.743**	**0.570**	**0.570**	**0.215**	**0.215**	**0.665**	**0.570**	**0.570**	-	-	-	**0.215**
Canada	0.073	**0.101**	**0.323**	0.073	**0.101**	**0.323**	0.073	0.073	**0.373**	0.073	0.073	0.073	0.073	**0.101**	**0.101**	0.073	**1.000**	**0.323**	**0.101**
Sweden	**0.623**	**0.456**	**0.456**	**0.623**	**0.456**	**0.623**	**0.623**	**0.456**	**0.456**	**0.456**	**0.456**	**0.152**	**0.456**	**0.456**	**0.456**	**1.000**	**0.975**	0.067	**0.152**
Denmark	**0.255**	**0.255**	**0.255**	**0.255**	**0.947**	**0.255**	**1.000**	**0.255**	**0.255**	**0.255**	**0.255**	**0.255**	**0.947**	**0.255**	**0.255**	-	-	-	**0.255**
Australia	**0.827**	**0.232**	**0.523**	-	-	-	**1.000**	0.046	0.046	-	-	-	**0.827**	**0.181**	**0.827**	**0.827**	**0.232**	**0.523**	0.100
Switzerland	**0.843**	**1.000**	**0.843**	-	-	-	0.094	**0.843**	**0.843**	0.094	0.000	**0.843**	**0.843**	**0.843**	**0.843**	-	-	-	**0.843**
South-Korea	**0.460**	**0.171**	**0.178**	**0.224**	**0.171**	**0.171**	**0.590**	**0.171**	**0.171**	**0.178**	**1.000**	**0.460**	**0.590**	**0.171**	**0.224**	-	-	-	**0.171**
United Kingdom	0.006	**0.959**	**0.210**	0.006	**0.210**	**0.210**	0.006	**0.601**	**0.210**	0.006	0.006	0.006	0.006	**0.242**	**0.210**	**1.000**	0.006	**0.767**	**0.210**

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Panel III (6 month)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.031	**0.506**	**0.133**	0.031	**0.506**	**0.133**	0.031	0.034	0.034	**0.133**	**0.133**	**0.133**	0.034	**1.000**	**0.133**	0.034	0.034	0.034	**0.133**
Japan	**1.000**	**0.923**	0.043	0.043	0.043	0.043	**0.347**	**0.844**	0.046	**0.179**	**0.179**	**0.179**	0.043	**0.939**	0.046	**0.844**	**0.179**	**0.179**	**0.289**
Norway	**0.330**	**0.330**	**0.303**	**0.639**	**0.639**	**0.529**	**1.000**	**0.639**	**0.303**	**0.111**	**0.111**	**0.111**	**0.639**	**0.330**	**0.303**	-	-	-	**0.111**
Canada	0.050	**0.382**	0.050	0.050	**1.000**	0.050	0.050	0.050	0.050	0.056	0.050	0.050	0.050	**0.382**	**0.404**	0.056	0.050	0.050	**0.382**
Sweden	**1.000**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.292**	**0.774**	**0.292**	**0.292**	0.036	0.022	0.046	**0.292**
Denmark	0.016	0.016	**1.000**	**0.562**	**0.139**	**0.139**	0.016	0.016	0.016	**0.139**	**0.139**	**0.139**	0.016	0.016	**0.562**	-	-	-	**0.139**
Australia	0.063	**0.771**	**0.771**	-	-	-	0.056	0.056	0.063	-	-	-	0.056	**0.771**	**0.771**	**1.000**	**0.449**	**0.449**	**0.154**
Switzerland	**0.747**	**0.747**	**0.747**	-	-	-	**0.747**	**0.747**	**0.747**	0.003	**1.000**	**0.747**	**0.747**	**0.747**	**0.747**	-	-	-	**0.123**
South-Korea	**0.545**	**0.475**	**0.475**	**0.545**	**0.219**	**0.219**	**0.545**	**0.202**	**0.101**	**0.528**	**1.000**	**0.545**	**0.545**	**0.475**	**0.475**	-	-	-	**0.219**
United Kingdom	0.056	0.000	**0.638**	0.000	**1.000**	**0.273**	0.056	0.000	**0.105**	0.056	0.000	0.000	0.000	0.000	**0.558**	0.000	0.000	**0.833**	**0.105**

Panel IV (12 month)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	**0.107**	0.107	0.000	0.000	0.000	0.004	0.004	0.000	0.000
Japan	0.001	0.002	0.014	0.002	0.002	0.014	0.001	0.002	0.002	**1.000**	0.001	0.001	0.001	0.002	0.014	0.001	**0.176**	**0.163**	0.001
Norway	**0.508**	**0.508**	**0.121**	**1.000**	**0.933**	**0.293**	**0.508**	**0.139**	**0.121**	**0.121**	**0.121**	**0.121**	**0.508**	**0.121**	**0.121**	-	-	-	**0.121**
Canada	0.017	**0.268**	**0.408**	0.017	**0.268**	**0.268**	0.003	**0.268**	**0.710**	**0.912**	0.017	0.017	0.017	**0.267**	**0.268**	0.017	**1.000**	**0.710**	**0.268**
Sweden	0.015	0.001	**0.561**	0.001	0.001	**1.000**	0.001	0.001	**0.345**	**0.198**	**0.287**	**0.157**	0.058	0.000	**0.345**	0.082	0.015	0.001	**0.345**
Denmark	0.001	0.012	0.001	0.001	0.001	0.001	0.001	0.012	0.001	**1.000**	**0.106**	0.106	0.001	0.001	0.001	-	-	-	0.001
Australia	0.050	0.007	**1.000**	-	-	-	0.007	0.007	0.007	-	-	-	0.028	0.007	0.007	0.007	**0.155**	**0.132**	**0.155**
Switzerland	**0.677**	**0.905**	**0.423**	-	-	-	**0.259**	**0.677**	**0.677**	0.000	**1.000**	**0.677**	**0.677**	**0.925**	**0.540**	-	-	-	**0.677**
South-Korea	0.094	**1.000**	**0.335**	0.094	0.063	0.001	0.094	0.063	**0.335**	0.094	0.094	0.094	0.094	0.023	**0.335**	-	-	-	0.023
United Kingdom	0.074	0.071	**0.293**	0.071	0.071	**1.000**	0.071	0.071	**0.285**	0.074	0.071	0.071	0.071	0.071	**0.285**	0.071	0.002	**0.285**	**0.982**

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Table 4.7 continued from previous page.

Panel V (18 months)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.024	0.014	0.002	0.024	0.024	0.012	0.008	**1.000**	0.012	**0.126**	**0.126**	**0.126**	0.024	0.012	0.002	0.051	0.051	0.024	0.000
Japan	0.000	0.000	0.000	0.000	0.000	0.052	0.001	0.000	0.000	**1.000**	0.625	**0.575**	0.000	0.000	0.000	0.000	**0.625**	**0.574**	0.000
Norway	0.004	0.004	**0.242**	0.004	0.004	**0.242**	**0.242**	0.004	**0.242**	**1.000**	**0.468**	**0.468**	0.004	0.004	**0.112**	-	-	-	0.004
Canada	0.004	**0.703**	**0.770**	0.004	**0.703**	**0.765**	**0.765**	**0.703**	**0.765**	**0.770**	**0.770**	0.004	0.004	**0.687**	**0.765**	0.004	0.004	0.004	**1.000**
Sweden	0.000	**0.701**	**0.506**	0.019	**0.506**	**0.506**	**0.506**	0.000	**0.506**	**0.110**	**0.110**	**0.110**	0.000	**0.506**	**0.295**	0.069	0.000	0.000	**1.000**
Denmark	0.079	0.012	0.010	0.027	0.016	**1.000**	**0.141**	0.012	0.012	**0.100**	**0.141**	0.100	0.079	0.012	**0.141**	-	-	-	0.141
Australia	0.001	**0.147**	0.001	-	-	-	**1.000**	0.001	0.001	-	-	-	0.001	**0.137**	0.001	0.001	**0.137**	**0.137**	0.001
Switzerland	**0.265**	0.001	**0.871**	-	-	-	**0.889**	**0.702**	**0.702**	0.025	0.001	**0.702**	**0.265**	0.025	**0.889**	-	-	-	**1.000**
South-Korea	0.038	**1.000**	**0.433**	0.047	**0.476**	**0.433**	**0.300**	0.001	**0.151**	0.038	0.001	0.047	0.047	0.001	**0.476**	-	-	-	0.004
United Kingdom	0.091	0.001	**0.179**	0.091	0.001	**0.302**	**0.235**	**1.000**	**0.179**	0.091	0.091	0.091	0.091	**0.179**	**0.179**	0.028	0.001	**0.235**	0.014

Panel VI (24 months)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.018	0.018	0.018	0.018	0.018	0.004	0.001	**1.000**	0.018	**0.307**	**0.147**	**0.141**	0.018	0.018	0.000	0.039	0.018	0.018	0.018
Japan	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**1.000**	**0.701**	**0.265**	0.000	0.001	0.000	**0.817**	**0.817**	**0.817**	0.000
Norway	**1.000**	**0.813**	**0.301**	0.050	**0.813**	**0.128**	**0.585**	**0.813**	**0.401**	**0.128**	**0.401**	**0.199**	0.044	**0.813**	**0.128**	-	-	-	0.050
Canada	0.000	**0.467**	0.010	0.010	**0.268**	0.000	0.000	**0.574**	0.000	0.000	0.071	0.071	0.000	**1.000**	0.016	0.026	0.026	0.071	0.016
Sweden	0.062	**0.106**	**0.106**	0.062	**0.710**	**0.106**	0.001	**0.106**	**0.106**	**0.106**	**0.106**	**0.106**	0.053	**0.106**	**0.106**	0.004	0.002	**1.000**	0.004
Denmark	0.095	0.095	0.008	0.095	0.040	0.008	0.008	0.030	0.030	**1.000**	**0.225**	**0.109**	0.095	0.008	0.008	-	-	-	0.095
Australia	0.001	0.000	0.020	-	-	-	0.020	0.000	0.000	-	-	-	0.000	**1.000**	0.001	0.000	**0.438**	**0.188**	0.020
Switzerland	**0.113**	0.004	0.021	-	-	-	**0.113**	0.001	0.021	0.004	0.000	0.001	**1.000**	0.021	0.027	-	-	-	0.004
South-Korea	0.013	0.013	**0.436**	0.043	0.013	0.001	0.013	0.013	1.000	0.013	0.043	0.013	0.043	0.013	0.001	-	-	-	0.013
United Kingdom	0.052	**0.694**	**0.419**	0.052	1.000	0.000	0.001	**0.419**	**0.317**	0.052	0.052	0.001	0.052	**0.419**	**0.120**	0.001	**0.282**	**0.317**	0.001

Table 4.8 Numbers of predictable currencies for the forecasting sample (3) (2009:01-2013:04) using the Theil's-U and the t_{cw} test statistics.

The table shows numbers of predictable currencies using the Theil's-U and the t_{cw} test statistics at different maturities. The values in brackets indicate the number of currencies using the t_{cw} test (null hypothesis of equal MSPE) at the 10% significance level ($t > 1.28$). Numbers without brackets refer to predictable currencies resulted from the application of the Theil's U statistics. Recall that $U < 1$ means that the candidate model has a lower MSPE than the benchmark model which is the random walk model in our study. M1, M2, M3, M4, M5, and M6 indicate the model of factors only, factors + Taylor rule, factors + monetary fundamentals, factors + PPP, factors + forward premium, and factors + interest rate differentials, respectively.

Model	Test	1 month	3 months	6 months	12 months	18 months	24 months
Panel A: one factor							
M1	U<1	0	0	1	6	4	4
	t>1.28	(0)	(0)	(0)	(3)	(0)	(3)
M2	U<1	0	1	3	7	4	4
	t>1.28	(0)	(0)	(0)	(2)	(0)	(3)
M3	U<1	0	1	1	8	7	7
	t>1.28	(0)	(0)	(0)	(5)	(1)	(5)
M4	U<1	6	7	7	6	6	6
	t>1.28	(0)	(1)	(2)	(4)	(2)	(5)
M5	U<1	0	1	3	6	4	6
	t>1.28	(0)	(0)	(0)	(3)	(0)	(3)
M6	U<1	0	0	0	1	1	2
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)
Panel B: two factors							
M1	U<1 7	5	8	9	6	8	
	t>1.28	(1)	(1)	(3)	(6)	(0)	(5)
M2	U<1	5	5	8	9	6	8
	t>1.28	(1)	(5)	(3)	(5)	(0)	(4)
M3	U<1	2	2	1	5	8	9
	t>1.28	(1)	(0)	(0)	(0)	(0)	(5)
M4	U<1	6	5	5	9	9	8
	t>1.28	(1)	(1)	(3)	(5)	(2)	(6)
M5	U<1	6	5	8	9	6	8
	t>1.28	(1)	(1)	(3)	(4)	(0)	(7)
M6	U<1	2	2	1	2	2	3
	t>1.28	(0)	(0)	(0)	(0)	(0)	(0)

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Table 4.8 continued from previous page

Model	Test	1 month	3 months	6 months	12 months	18 months	24 months
Panel C: three factors							
M1	U<1	3	7	9	9	9	8
	t>1.28	(1)	(1)	(5)	(4)	(3)	(7)
M2	U<1	1	6	7	9	9	8
	t>1.28	(0)	(1)	(3)	(5)	(2)	(7)
M3	U<1	5	6	7	9	9	8
	t>1.28	(0)	(1)	(3)	(4)	(3)	(6)
M4	U<1	9	8	8	7	8	7
	t>1.28	(2)	(3)	(3)	(2)	(3)	(4)
M5	U<1	3	7	9	9	8	8
	t>1.28	(1)	(1)	(3)	(4)	(4)	(7)
M6	U<1	2	3	4	3	3	3
	t>1.28	(0)	(0)	(0)	(0)	(0)	(1)

Table 4.9 Test for Superior Predictive Ability (SPA); forecasting sample (3) (2009:01-2013:04)

The table shows p-values resulting from the implementation of the SPA test proposed by Hansen (2005). (***), (**) and (*) indicate rejection of the null hypothesis that the random walk model is not inferior to any alternative forecast at the 1%, 5% and 10% significance level, respectively. The SPA test has been conducted with 10,000 bootstrap replications. A detailed explanation of the implemented bootstrap procedures in this chapter is provided by Hansen (2005) for the SPA tests and by Hansen et al. (2011) for the MCS tests.

Country	1 month	3 months	6 months	12 months	18 months	24 months
Euro	0.180	0.356	0.028**	0.000***	0.005***	0.000***
Japan	0.766	0.666	0.286	0.032**	0.026**	0.004***
Norway	0.285	0.578	0.081*	0.001***	0.015**	0.017**
Canada	0.633	0.208	0.130	0.059*	0.167	0.079*
Sweden	0.424	0.248	0.215	0.001***	0.005***	0.045**
Denmark	0.331	0.393	0.051*	0.000***	0.002***	0.001***
Australia	0.336	0.135	0.075*	0.031**	0.017**	0.001***
Switzerland	0.793	0.702	0.488	0.170	0.225	0.000***
South-Korea	0.311	0.032**	0.129	0.053*	0.046**	0.051*
United Kingdom	0.018**	0.062*	0.041**	0.013**	0.083*	0.128

Table 4.10 Test for Model Confidence Set (MCS); forecasting sample (3) (2009:01-2013:04).

The table shows p-values resulting from the MCS test. M1, M2, M3, M4, M5, and M6 indicate the model of factors only, factors + Taylor rule, factors + monetary fundamentals, factors + PPP, factors + forward premium, and factors + interest rate differentials, respectively. F1, F2, and F3 indicate the number of employed factors as 1, 2, and 3 factors, respectively. Numbers in bold indicate to the models that are included in the set of best models $M^*_{90\%}$. The MCS test has been conducted with 10,000 bootstrap replications.

Panel I (1 month)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.303**	**0.250**	**0.250**	**1.000**	**0.303**	**0.303**	**0.128**	0.012	0.012	**0.128**	**0.128**	**0.128**	**0.303**	**0.128**	**0.128**	0.050	0.012	**0.605**	**0.250**
Japan	**0.908**	**0.124**	**0.124**	**0.908**	**0.124**	**0.124**	**0.908**	**0.124**	**0.787**	**0.124**	**0.892**	**0.908**	**0.908**	**0.124**	**0.124**	**1.000**	**0.908**	**0.787**	**0.124**
Norway	0.093	**0.980**	**0.801**	0.093	0.093	0.093	0.093	0.093	**0.980**	**0.783**	**0.595**	**0.714**	**1.000**	**0.801**	**0.783**	-	-	-	0.093
Canada	**0.416**	**0.371**	**0.416**	**0.416**	**0.371**	**0.416**	**0.549**	**0.416**	**0.416**	**0.416**	**0.549**	**0.304**	**0.416**	**0.304**	**0.416**	**1.000**	**0.881**	**0.881**	**0.416**
Sweden	**0.329**	**0.329**	**0.329**	**0.329**	**0.329**	**0.514**	**0.514**	**0.329**	**0.329**	**0.329**	**0.250**	**0.231**	**0.329**	**0.250**	**0.329**	**0.514**	**0.329**	**1.000**	**0.329**
Denmark	**0.407**	**0.396**	**0.396**	**0.669**	**0.407**	**0.396**	**1.000**	**0.396**	**0.407**	**0.396**	**0.396**	**0.396**	**0.396**	**0.396**	**0.396**	-	-	-	**0.396**
Australia	**0.928**	**0.360**	**0.533**	-	-	-	0.008	0.008	0.001	-	-	-	**1.000**	**0.419**	**0.906**	**0.906**	**0.360**	**0.360**	**0.419**
Switzerland	**0.886**	**0.886**	**0.886**	-	-	-	**0.886**	**0.506**	**0.506**	**0.886**	**0.506**	**0.506**	**0.886**	**0.506**	**0.886**	-	-	-	**1.000**
South-Korea	**0.597**	**0.126**	**0.597**	**0.527**	**0.126**	**0.597**	**0.126**	**0.126**	**0.126**	**0.126**	**0.367**	**0.126**	**1.000**	**0.126**	**0.367**	-	-	-	**0.367**
United Kingdom	0.091	**0.109**	**0.109**	0.091	**0.109**	**0.109**	0.091	**0.835**	**0.109**	**0.109**	**0.109**	**0.109**	0.091	**0.109**	**0.109**	0.091	**0.109**	**1.000**	0.091

Panel II (3 months)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	**0.438**	**0.438**	**0.438**	**0.438**	**0.438**	**0.159**	**0.438**	0.032	0.032	**0.159**	**0.159**	**0.159**	**0.466**	**0.438**	**0.438**	**1.000**	0.032	**0.466**	**0.438**
Japan	**0.769**	**0.458**	**0.458**	**0.773**	**0.458**	**0.458**	**0.769**	**0.458**	**0.769**	**0.168**	**0.458**	**0.769**	**0.769**	**0.168**	**0.458**	**1.000**	**0.458**	**0.168**	**0.168**
Norway	0.031	**0.809**	**0.809**	0.031	**1.000**	**0.919**	0.031	0.031	**0.809**	**0.809**	**0.809**	**0.809**	0.031	**0.919**	**0.809**	-	-	-	**0.809**
Canada	0.060	**0.743**	0.060	0.060	**0.743**	0.060	0.060	0.060	0.060	0.060	0.060	0.060	0.060	**0.552**	**1.000**	0.060	0.060	0.060	0.060
Sweden	**0.504**	**0.504**	**0.504**	**0.504**	**0.365**	**0.504**	**0.504**	**0.504**	**0.504**	**0.365**	**0.278**	**0.126**	**0.504**	**0.504**	**0.504**	**0.504**	**0.504**	**1.000**	**0.504**
Denmark	**0.469**	**0.469**	**0.278**	**0.469**	**0.469**	**0.469**	0.076	**0.469**	**0.469**	**0.278**	**0.278**	**0.278**	**1.000**	**0.469**	**0.278**	-	-	-	**0.469**
Australia	**0.816**	**0.228**	**0.228**	-	-	-	0.044	0.027	0.027	-	-	-	**1.000**	**0.228**	**0.816**	**0.816**	**0.228**	**0.228**	**0.228**
Switzerland	**0.386**	**0.949**	**0.949**	-	-	-	**0.949**	**0.944**	**0.949**	0.003	**1.000**	**0.918**	**0.944**	**0.949**	**0.983**	-	-	-	**0.949**
South-Korea	0.020	0.016	0.016	0.020	**0.413**	0.016	0.016	**1.000**	0.016	**0.413**	0.020	**0.413**	0.020	**0.413**	0.016	-	-	-	0.020
United Kingdom	0.011	**0.292**	**0.114**	**1.000**	**0.114**	**0.114**	0.011	**0.292**	**0.292**	**0.903**	**0.114**	**0.114**	0.011	**0.114**	**0.114**	0.011	0.011	**0.684**	**0.903**

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Panel III (6 month)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.019	**1.000**	**0.287**	**0.417**	**0.417**	**0.287**	0.000	0.048	0.048	**0.287**	**0.287**	**0.287**	0.019	0.000	**0.287**	0.048	0.048	0.048	0.048
Japan	**1.000**	0.002	0.002	0.002	0.002	0.002	0.002	**0.881**	0.002	**0.452**	**0.121**	**0.830**	0.002	**0.881**	0.040	0.002	**0.474**	**0.121**	**0.830**
Norway	**0.702**	**0.702**	**0.170**	0.016	0.016	**0.702**	0.016	0.016	**0.702**	**0.170**	**0.170**	**0.170**	**1.000**	**0.702**	**0.696**	-	-	-	**0.702**
Canada	**0.241**	**0.241**	**0.241**	**0.241**	**0.241**	**0.241**	**1.000**	**0.241**	**0.241**	**0.805**	0.097	0.089	**0.241**	**0.192**	**0.241**	0.097	0.066	0.097	**0.495**
Sweden	**0.511**	**0.423**	**0.504**	**0.511**	**0.423**	**0.504**	**1.000**	**0.511**	**0.504**	**0.220**	**0.423**	**0.220**	**0.511**	**0.423**	**0.504**	0.076	**0.940**	0.047	**0.511**
Denmark	**0.318**	**0.318**	**0.236**	**0.318**	**0.135**	**0.135**	0.038	0.038	**0.318**	**0.135**	**0.129**	**0.129**	**0.590**	**0.590**	**0.318**	-	-	-	**1.000**
Australia	0.032	**0.188**	**0.424**	-	-	-	0.032	**0.894**	0.032	-	-	-	0.032	**0.188**	**0.227**	**0.424**	**0.188**	**0.146**	**1.000**
Switzerland	**0.573**	**0.862**	**0.862**	-	-	-	**0.862**	**0.862**	**0.862**	0.011	**1.000**	**0.862**	**0.862**	**0.862**	**0.862**	-	-	-	**0.862**
South-Korea	**0.362**	**0.153**	**0.153**	**1.000**	**0.153**	**0.153**	**0.153**	**0.153**	**0.153**	**0.153**	0.015	**0.153**	**0.362**	**0.153**	**0.153**	-	-	-	**0.362**
United Kingdom	0.001	0.000	**0.401**	0.001	**1.000**	**0.401**	0.001	0.000	0.000	0.001	**0.365**	**0.160**	0.001	0.000	**0.401**	0.001	0.001	0.001	0.001

Panel IV (12 month)

Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.000	0.000	**1.000**	0.001	0.001	0.001	0.027	0.013	0.001	0.027
Japan	0.001	0.001	0.086	0.001	0.025	0.086	0.025	0.025	0.025	0.001	0.001	0.001	0.001	0.001	0.086	0.025	**1.000**	**0.301**	0.001
Norway	0.025	0.025	**0.425**	0.046	0.025	0.025	**1.000**	0.004	**0.425**	**0.425**	0.025	0.025	0.025	0.025	**0.653**	-	-	-	0.046
Canada	0.002	**0.155**	**0.399**	**0.399**	**0.155**	**0.399**	0.002	0.399	**1.000**	0.008	0.008	0.008	0.002	**0.155**	0.002	0.008	0.008	0.008	0.002
Sweden	0.010	0.003	0.003	0.003	0.003	0.000	0.003	0.004	0.003	**1.000**	0.000	0.000	0.010	0.003	0.003	0.076	0.011	0.076	0.004
Denmark	0.038	0.058	0.038	0.038	0.058	0.024	0.058	0.058	0.040	0.004	0.000	**1.000**	0.038	0.058	0.040	-	-	-	0.058
Australia	0.079	0.079	0.079	-	-	-	0.082	0.079	0.079	-	-	-	0.079	0.005	0.079	0.079	**1.000**	**0.177**	0.082
Switzerland	**0.263**	0.003	**0.276**	-	-	-	**0.263**	0.000	**0.472**	0.017	0.001	0.000	**0.276**	0.017	**1.000**	-	-	-	0.017
South-Korea	**0.128**	**0.128**	**0.128**	**1.000**	**0.128**	**0.128**	**0.128**	**0.128**	**0.128**	**0.112**	0.000	**0.128**	**0.128**	**0.128**	**0.119**	-	-	-	**0.128**
United Kingdom	0.003	**1.000**	**0.449**	**0.754**	0.007	**0.614**	**0.116**	**0.754**	**0.449**	0.092	**0.449**	**0.116**	0.011	0.011	**0.449**	0.055	0.092	0.055	0.092

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Table 4.10 continued from previous page.

Panel V (18 months)																		
Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.009	0.000	**1.000**	0.015	0.000	**0.901**	**0.525**	**0.109**	0.000	**0.109**	**0.109**	**0.109**	0.000	0.000	**0.525**	0.098	0.079	0.085	0.000
Japan	0.000	0.001	0.001	0.000	0.001	0.062	0.001	0.000	0.001	**1.000**	**0.522**	**0.314**	0.000	0.001	0.001	0.000	**0.522**	**0.314**	0.000
Norway	0.000	0.000	**0.294**	0.000	0.000	0.000	0.000	0.000	**0.294**	0.000	**1.000**	0.000	0.000	0.000	**0.294**	-	-	-	0.000
Canada	0.000	**0.251**	0.000	0.000	**0.251**	**0.671**	**0.659**	**0.251**	**0.659**	0.032	0.000	0.045	0.000	**0.251**	0.032	0.089	0.032	0.032	**1.000**
Sweden	0.007	0.007	0.000	0.007	0.000	0.000	0.000	0.000	0.000	**0.151**	**0.707**	**1.000**	0.007	0.007	0.000	0.043	0.043	0.007	0.000
Denmark	0.050	0.010	1.000	0.050	0.010	**0.454**	**0.454**	0.048	0.010	**0.248**	**0.248**	**0.108**	0.050	0.010	**0.248**	-	-	-	0.050
Australia	0.092	0.001	0.008	-	-	-	0.001	0.092	0.008	-	-	-	0.092	0.001	0.001	0.001	0.001	**1.000**	0.092
Swtizerland	**0.129**	0.001	**0.384**	-	-	-	**0.384**	**0.190**	**0.384**	**1.000**	**0.384**	**0.190**	**0.190**	0.027	**0.384**	-	-	-	**0.384**
South-Korea	0.052	0.012	0.012	0.083	0.012	**0.158**	**0.158**	0.012	**1.000**	**0.158**	**0.158**	0.083	0.052	0.012	**0.158**	-	-	-	0.012
United Kingdom	0.010	0.000	0.010	0.010	**0.358**	0.000	0.000	**0.358**	**1.000**	0.052	0.052	0.010	0.050	0.008	0.010	0.026	0.010	0.052	0.010

Panel VI (24 months)																		
Country	M1F1	M1F2	M1F3	M2F1	M2F2	M2F3	M3F1	M3F2	M3F3	M4F1	M4F2	M4F3	M5F1	M5F2	M5F3	M6F1	M6F2	M6F3	RW
Euro	0.001	0.000	**0.733**	0.001	0.000	**0.395**	0.000	**0.395**	**0.395**	**0.395**	**0.359**	**0.395**	0.001	**1.000**	**0.395**	0.040	0.040	0.040	0.001
Japan	0.000	0.000	0.012	0.000	0.000	0.012	0.000	0.000	0.012	0.000	0.000	**0.483**	0.000	0.012	0.012	0.000	**1.000**	0.000	0.000
Norway	0.004	**1.000**	**0.243**	0.017	0.004	**0.243**	**0.507**	0.004	**0.507**	**0.243**	0.004	0.017	0.017	0.004	0.004	-	-	-	0.017
Canada	0.000	**1.000**	0.003	0.000	**0.802**	0.002	0.000	0.000	0.000	0.000	0.040	0.040	0.000	0.000	0.003	0.040	0.003	0.040	0.003
Sweden	0.010	0.010	0.010	0.013	0.010	0.010	0.010	0.010	0.010	**1.000**	0.005	0.002	0.013	0.010	0.010	0.013	0.013	0.010	0.010
Denmark	0.044	0.031	0.003	0.044	0.031	0.001	0.031	0.002	0.011	**0.785**	**0.312**	1.000	0.039	0.031	0.003	-	-	-	0.031
Australia	0.000	0.000	0.000	-	-	-	0.002	0.000	0.000	-	-	-	0.000	0.000	0.000	0.000	**1.000**	**0.201**	0.000
Switzerland	0.000	0.000	0.000	-	-	-	**1.000**	0.000	0.006	0.000	0.000	0.000	0.000	0.000	0.062	-	-	-	0.000
South-Korea	0.094	**0.179**	**0.179**	0.048	**0.179**	**0.179**	**0.332**	**0.179**	**0.332**	**0.179**	0.002	0.001	0.000	**0.179**	**0.179**	-	-	-	**1.000**
United Kingdom	0.009	**0.275**	0.000	0.009	0.000	0.003	**0.126**	**0.126**	0.000	0.082	0.006	0.003	0.009	**1.000**	0.002	0.006	0.003	0.009	0.002

Chapter5

Conclusion

Over the last few decades, there has been a growing interest in modelling and forecasting exchange rate movements as well as searching for evidence of PPP. Despite extensive research, it has been found that most conventional forecasting models (have) failed to predict floating exchange rates with significantly higher accuracy compared with the random walk model. In search of PPP, early panel unit root and panel cointegration tests were ill-equipped to handle the potential presence of cross-sectional dependence and structural breaks. This presence has adversely affected the statistical power of the corresponding panel test statistics and potenatially led to invalid conclusions about PPP.

The present thesis addresses the above issues by presenting a collection of three essays. The first essay examines long-run PPP in a panel of 13 OECD countries 1989:07-2012:11, and this task is accomplished by utilising three panel unit root tests; the IPS test of Im et al. (2003) under the assumption of cross-sectional independence; the CIPS test of Pesaran (2007) which accounts for cross-sectional dependence via a single unobserved common factor approach; and finally the novel panel unit root test CIPSM of Pesaran et al. (2013) that allows for cross-section dependence through a multifactor error structure approach.

When using cross-sectional-dependence-robust panel unit root tests, the estimation results suggest no significant evidence favouring long-run PPP. Conversely, there is clear evidence supporting PPP when using panel unit root tests under the assumption of cross-sectional independence. This indicates that the overwhelming influence on (non) rejection of the null unit root hypothesis stems from ignoring or allowing for cross-sectional dependence (in our testing criteria). Further, given the fact that the estimation results from the three panel unit root tests are relatively consistent across the two panel sections of real exchange rates (1989:07-2012:11, 1989:07-2006:12), we carefully conclude that the financial crisis (2007-2008) did not affect this conclusion on long-run PPP.

The second essay examines long-run PPP but eschews the typical real exchange rate approach. Instead it tests for a cointegrating relatioship between nominal exchange rates and price ratios in a panel estimation framework. Unlike earlier panel cointegration tests of PPP, which failed to account for the potential presence of structural breaks and cross-section dependence, we test the null of no cointegration using the novel panel cointegration test of Banerjee and Carrion-I-Silvestre (2013), which allows for (i) heterogeneous and multiple structural breaks and (ii) cross-sectional dependence.

Several important results emerge from the application of the above panel cointegration test. In particular, drawing upon a panel of monthly data covering 53 countries between 1992:01 and 2014:05, we cannot find evidence supporting cointegration between nominal exchange rates and relative price ratios. Thus the implication is that long-run PPP does not hold. Interestingly, this evidence against PPP is obtained by two types of models that were equipped/ill-equipped to handle the potential presence of structural breaks in the data, a situation that could lead to the conclusion that structural breaks are not key determinants of (non) rejection of the no-cointegration null hypothesis.

Finally, the third essay employs an empirical framework for forecasting exchange rates which is based on the factor approach proposed by Engel et al. (2015). Our analysis builds on Engel et al.'s method by comparing the predictions from two new models with those from the random walk model on the basis of their performance in an out-of-sample predictive accuracy test. To be more precise, we propose the separate use of forward rates and interest rate differentials as the two new sets of fundamentals to be used in conjunction with the extracted factors.

Initially, it is found that exchange rate models based on a factor approach can outperform the random walk model in providing better forecasts at long horizons. However, our results do not support one of our candidate models being the best model to consistently outperform the random walk model. This situation points to a high level of heterogeneity in model performance across varying prediction accuracy measurements, currencies, factors, and horizons.

5.1 Limitations and future research areas

One practical limitation of the testing procedure in Chapter (2) is that the estimated number of non-stationary common stochastic trends is relatively large. Specifically, the presence of 12 global stochastic trends may cast serious doubt on the performance of the Bai and Ng (2004)'s unit root testing technique that is applied in the chapter. As an agenda for future research the true number of non-stationary common factors could be selected using different and possibly more robust information criterion.

Another potential limitation of the work done in Chapter (4) is that the Taylor rule weights on inflation and output (Equation 4.4) are fixed. As an extension for future work it would be desirable to enhance the fit of Taylor rule specifications by allowing for more flexible specification of the parameters in Taylor rule models and using data dependent method for estimating the optimal number of factors for the forecasting framework.

Further research on forecasting exchange rates (Chapter 4) could be achieved by using various forms of technical trading rules (e.g. moving average rules, support and resistance levels) as a new set of variables to be added in conjunction with the extracted factors that have been used in the current study. There is a fairly large literature on using technical trading rules in modelling foreign exchange markets. A sample of papers includes, among others, Gencay (1999) and Gradojevic (2007).

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Table A.1 Panel unit root tests statistics to test the null unit root hypothesis using homogenous autoregressive lags (Case I: intercept and trend)

This table reports statistics based on the application of various panel unit root tests for investigating the validity of PPP using homogenous number of autoregressive lags (p) across the individual series of real exchange rates in the panel. The IPS statistic is the standardised $t-$bar test of Im et al. (2003), defined by (1.11), under the assumption of cross-section independence. The CIPS test is the cross-sectionally augmented IPS test proposed by Pesaran (2007), defined by (1.14), where cross-section dependence is accommodated through a single unobserved common factor approach. The CIPSM(q), CIPSM(r) and CIPSM are the panel unit root tests suggested by Pesaran et al. (2013), defined by (1.16), where cross-section dependence is accommodated through multifactor error structure approach. The latter three tests are established using, in addition to the real exchange rates, additional regressors of real equity prices eq_{it}, real interest rates r_{it}, and both eq_{it} and r_{it}, respectively.
(***), (**) and (*) indicate rejection of the null unit root hypothesis at 1%, 5% and 10% significance level, respectively.

Lag order\Test	IPS	$CIPS$	$CIPSM(q)$	$CIPSM(r)$	$CIPSM$
Panel A: full sample (1989:07-2012:11)					
p=0	-2.17	-2.69*	-2.73**	-2.71**	-2.76
p=1	-2.32	-2.84**	-2.73**	-2.88***	-2.78
p=2	-2.31	-2.90**	-2.70**	-2.95***	-2.76
p=3	-2.41	-2.83**	-2.63*	-2.86***	-2.68
p=4	-2.23	-2.63	-2.41	-2.66*	-2.48
p=5	-2.14	-2.49	.	.	.
p=6	-2.11	-2.43	.	.	.
p=7	-1.99	-2.46	.	.	.
p=8	-2.13	-2.62	.	.	.
Panel B: sub-sample (1989:07-2006:12)					
p=0	-1.72	-2.46	-2.48	-2.42	-2.49
p=1	-1.93	-2.57	-2.49	-2.58	-2.55
p=2	-1.89	-2.71*	-2.52	-2.71**	-2.55
p=3	-1.93	-2.64	-2.44	-2.63*	-2.44
p=4	-1.75	-2.43	-2.25	-2.44	-2.29
p=5	-1.65	-2.36	.	.	.
p=6	-1.60	-2.27	.	.	.
p=7	-1.54	-2.35	.	.	.
p=8	-1.69	-2.43	.	.	.

Table A.2 Panel unit root tests statistics to test the null unit root hypothesis using homogenous autoregressive lags (Case II: intercept only)

This table reports statistics based on the application of various panel unit root tests for investigating the validity of PPP using homogenous number of autoregressive lags (p) across the individual series of real exchange rates in the panel. The IPS statistic is the standardised $t-$bar test of Im et al. (2003), defined by (1.11), under the assumption of cross-section independence. The CIPS test is the cross-sectionally augmented IPS test proposed by Pesaran (2007), defined by (1.14), where cross-section dependence is accommodated through a single unobserved common factor approach. The CIPSM(q), CIPSM(r) and CIPSM are the panel unit root tests suggested by Pesaran et al. (2013), defined by (1.16), where cross-section dependence is accommodated through multifactor error structure approach. The latter three tests are established using, in addition to the real exchange rates, additional regressors of real equity prices eq_{it}, real interest rates r_{it}, and both eq_{it} and r_{it}, respectively.
(***), (**) and (*) indicate rejection of the null unit root hypothesis at 1%, 5% and 10% significance level, respectively.

Lag order\Test	IPS	$CIPS$	$CIPSM(q)$	$CIPSM(r)$	$CIPSM$
Panel A: full sample (1989:07-2012:11)					
p=0	-2.00**	-2.18*	-2.30**	-2.35**	-2.38*
p=1	-2.13***	-2.27**	-2.35**	-2.44***	-2.44*
p=2	-2.13***	-2.31**	-2.36***	-2.49***	-2.45*
p=3	-2.22***	–2.25*	-2.31**	-2.39***	-2.39*
p=4	-2.06**	-2.06	-2.14*	-2.22**	-2.22
p=5	-1.97**	-1.94	.	.	.
p=6	-1.94**	-1.88	.	.	.
p=7	-1.84*	-1.90	.	.	.
p=8	-1.96**	-2.03	.	.	.
Panel B: sub-sample (1989:07-2006:12)					
p=0	-1.61	-2.15	-2.15*	-2.15*	-2.14
p=1	-1.79	-2.24*	-2.15*	-2.28**	-2.19
p=2	-1.76	-2.37**	-2.19**	-2.39***	-2.20
p=3	-1.80	-2.31**	-2.15*	-2.33**	-2.16
p=4	-1.65	-2.11	-1.96	-2.15*	-2.00
p=5	-1.55	-2.07	.	.	.
p=6	-1.51	-1.97	.	.	.
p=7	-1.47	-2.07	.	.	.
p=8	-1.60	-2.13	.	.	.