Testing for Unit Root Processes for South American Countries

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Abstract

In this thesis, we aim to test the Purchasing Power Parity (PPP) hypothesis on data from ten different South American countries, using different statistical methods. We begin by testing the hypothesis using the standard linear tests augmented Dickey-Fuller and Phillips-Perron. We then continue to test in case of nonlinear processes with methods developed to increase the power of the tests; exponential smooth transition autoregressive (ESTAR) and assymetric ESTAR (AESTAR). Finally, the panel unit root Choi test is applied. We use monthly real effective exchange rate data from 10 different South American countries, provided by Bruegel. Our results show that the p-values generally increase when comparing the linear Dickey-Fuller and Phillips-Perron test to the ESTAR and AESTAR tests. We reject the null hypothesis of a unit root for one country using the ESTAR test and for three countries using the AESTAR. We have ambiguous changes in the p-values when comparing the AESTAR to the ESTAR. For the Choi test, we reject the null hypothesis of a unit root for all tests but the ESTAR test. Rejecting the null hypothesis of a unit root indicates that the PPP hypothesis holds. Hence, new tests, e.g. nonlinear and panel data tests that have a higher power compared to the standard linear tests, may lead to the vindication of the PPP hypothesis.

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1 Introduction

Our aim with this thesis is to apply a range of different tests to test for a unit root process and evaluate their performances. The tests are applied to time series data on the real effective exchange rates (REER) of ten different South American countries. The rationale of choosing to test for unit root processes in REER data is the fact that it is connected to the purchasing power parity (PPP) hypothesis. Crownover et al. (1996) defines the purchasing power parity as "an equilibrium condition equating the nominal exchange rate between two countries with the price ratio of an identical bundle of goods in each country". When able to reject the null hypothesis of a unit root, it is an indication that the PPP hypothesis holds. Therefore, researchers have been trying to determine whether there is a unit root process in REER data.

In some cases when testing for relative PPP, researchers are trying to determine whether a unit root exists between nominal exchange rate and a ratio of price indices. If the researchers fail to reject the null hypothesis of a unit root it suggests that arbitrage does not eliminate the difference between the nominal exchange rate and the ratio of price indices which would be evidence that relative PPP would not hold (Crownover et al., 1996).

The first attempts to validate the PPP hypothesis used the augmented Dickey-Fuller (ADF) unit root test and failed to reject the null hypothesis, i.e. implicitly rejecting the PPP hypothesis. This outcome was attributed to the low power of the ADF-test. Since then, the literature has gone separate ways; nonlinear tests have been introduced and some researchers have instead turned to panel unit root tests (Bahmani-Oskooee et al., 2008).

For this thesis, we will apply and evaluate a total of five different tests to determine whether the time series contains a unit root process. Two of these tests are the often-used augmented Dickey-Fuller test by Dickey and Fuller (1979) and the Phillips-Perron test, originated by Phillips and Perron (1988). We will also apply two newer, non-linear tests: a test for an exponential smoothing transitional autoregressive (ESTAR) process (Kapetanios et al., 2003) and the asymmetric exponential smoothing transitional autoregressive (Sollis, 2009). Finally, we will also apply a panel test for a unit root developed by Choi (2001).

These tests are then applied on real effective exchange rate data from bruegel.org, from which we have chosen ten different South American countries. We chose all South American countries for which we could retrieve sufficient data, and these are: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay and Venezuela. As far as we know, this is the first thesis to make use of data from South American countries, which are all developing countries as well, and apply the ESTAR, AESTAR and Choi tests. We have 541 monthly observations for all countries with the exception of Brazil, Paraguay and Peru. Brazil has 422 observations and Paraguay and Peru both have 289 observations each. Countries with 541 observations have data from January 1970, Brazil has data from December 1979 while Paraguay and Peru has data from January 1991. The data continues until January 2015.

We find that with the Dickey-Fuller test, we can reject the null hypothesis of a unit root in 2 out of 10 countries. There is only a slight change when applying the Phillips-Perron test, where it is possible to reject the null hypothesis in 3 out of 10 countries. With the standard tests for a unit root process, we do not manage to reject the hypothesis of a unit root process for 7 out of 10 countries.

The results for the ESTAR test shows a significant difference: it is now possible to reject the hypothesis of a unit root process for 1 out of 10 countries. This shows a decreased power of the ESTAR test compared to the previous tests. Results for the AESTAR shows an increase in the power of the test and we can reject the null for 2 out of 10 countries. These results differ somewhat from those found by Bahmani-Oskooee et al. (2008). There does not seem to be nonlinearities for South American countries. It should also be noted that we take GARCH effects into account which Bahmani-Oskooee et al. (2008) does not.

Finally, the results of the Choi test show that we can reject the null hypothesis in all cases when using the p-values derived from the tests with no corrected standard errors. After having corrected for heteroskedasticity and serial correlation, the null hypothesis is rejected for all tests but the ESTAR.

2 Literature review

One of the first observations of the purchasing power parity was made by Cassel (1918). In the article, Cassel argues that the exchange rate between two countries is determined foremost by "the quotient between the internal purchasing power against goods of the money of each country". He also proposes the name purchasing power parity for this parity (Cassel, 1918). Cassel goes on to state that in order for the exchange rate not to deviate (to a large degree) from the purchasing power parity, two conditions must be met: free movement of merchandise as well as some sort of trade volume between the two countries. The condition of free movement of merchandise is not violated unless there is a disturbance in trade that affects one country more than the other (Cassel, 1918).

There are two measures of PPP; absolute and relative. Absolute PPP indicates that the nominal exchange rate is solely determined by the ratio of price levels while relative PPP states that the change in the nominal exchange rate is determined by the change in the countries respective price levels, i.e the inflation. Sometimes PPP is also referred to as the law of one price (Crownover et al., 1996).

The absolute purchasing power parity can be formally expressed as follows:

$$P_t = \frac{P_t^*}{S_t} \tag{1}$$

where P_t denotes the price level of in one country, ${P_t}^*$ denotes the price level in a foreign country and S_t denotes the nominal exchange rate between the currencies of the two countries, all at time t. Price level is usually represented by a Consumer Price Index (CPI).

Relative purchasing power parity on the other hand can be expressed as follows:

$$\frac{\Delta P_t^*}{P_{t-1}^*} = \frac{\Delta S_t}{S_{t-1}} + \frac{\Delta P_t}{P_{t-1}} \tag{2}$$

where the change in the nominal exchange rate and the change in domestic price level equals the change in the foreign price level.

Testing whether the PPP hypothesis holds in the long-run have commonly been performed through analyzing real effective exchange rates (REER), e.g. through testing the null hypothesis of a random walk process in REER data. Later, testing for the presence of a unit root, using e.g. augmented Dickey-Fuller, was used since the earlier tests failed to reject the null hypothesis (Taylor, 2003). The Dickey-Fuller test was developed by Dickey and Fuller (1979) and tests for the presence of a unit root process for an autoregressive model. If the null hypothesis of a unit root cannot be rejected, it also implies that the time series is non-stationary.

A common problem with these tests is that they have suffered from a lack of power. Using Monte-Carlo simulations, Lothian and Taylor (1997) find that these two conventional unit-root tests have a low degree of power with regards to sample sizes of both 20 and 50 as well as two different cases of first order autocorrelations. When increasing the sample size to 100 observations, the power of the test also increases, but stil remains very low for higher values of autocorrelation; around 50 percent, i.e. a fifty percent chance of rejecting the null hypothesis of a unit root. Only at a sample size of 200 does the tests demonstrate a high power for both cases of first order autocorrelation (Lothian and Taylor, 1997).

Possible solutions to the problem of the lack of power when using the aforementioned tests have included using longer spans of data, which bears the problem that there is a higher chance of having structural changes in the data. There is also the possibility that the exchange rate regime could have changed when the time span is longer. Another attempt to solve the problem has been to use panel data to increase the number of REERs to test (Taylor, 2003).

More recently, studies on purchasing power parity and real exchange rates have indicated that real exchange rates can exhibit nonlinearity rather than linearity. There are at least three different sources of nonlinearity in real exchange rates: the first is due to nonlinearities in international goods arbitrage, causing the goods of markets that are geographically separated to differentiate. The second is the interaction of heterogeneous agents in foreign exchange markets, i.e. agents exhibiting different opinions regarding exchange rates. The third source of nonlinearity could be political interventions in the foreign exchange markets (Taylor, 2003).

An exchange rate is the price of one currency expressed in another currency. This is called the nominal exchange rate, and it differs from the real exchange rate. The real exchange rate is measure of the relative price of two countries' goods; it shows how much of a (or several) good that is needed in country A to purchase the same good in another country B. In order to construct a real exchange rate that reflects the weight each trading partner has with a country. This can be done by creating a weighted average measure of the price of goods for the foreign countries relative to the prices domestic country. A trade weight is applied to the bilateral exchange rate of every country to create a measure of the real effective exchange rate (Feenstra and Taylor, 2008).

In order to deal with nonlinearity in real exchange rates, researchers have developed and proposed new statistical tests. One test proposed to deal with nonlinearities is the test developed by Kapetanios et al. (2003). The test is developed to detect nonstationarity against an alternative hypothesis of nonlinear and globally stationary exponential smoothing transition autoregressive processes. The test is most commonly referred to as the ESTAR but is also referred to as the KSS-test. Through Monte-Carlo simulations, Kapetanios et al. (2003) find that their test has more power around the null hypothesis when compared to the standard Dickey-Fuller test.

Apart from applications on simulated data, the ESTAR test has also been put to test by Bahmani-Oskooee et al. (2008), who applies both the ESTAR test and the conventional augmented Dickey-Fuller test to test the validity of the PPP hypothesis for 88 different countries, using monthly real effective exchange rate data. His sample consists of developing countries, which is argued to fill a gap in the literature, since most of the previous studies have been done on data from industrialized countries. Bahmani-Oskooee et al. (2008) find support for the PPP hypothesis for 12 out of 88 countries using the ADF test. Using the ESTAR test, support is found for another 19 countries, i.e. a total of 31 countries.

Bahmani-Oskooee et al. (2008) also suggest that for developing countries, there is a higher degree of nonlinear adjustment towards PPP, due to more foreign exchange interventions as well as more barriers to trade in developing countries.

A further development of the ESTAR test has been provided by Sollis (2009). While some tests test a unit root hypothesis against the alternative of an ESTAR process is "implicitly symmetric", the author proposes an asymmetric exponential smooth transition autoregressive (AESTAR) test in order to test against the alternative of a symmetric or asymmetric process. Using Monte-Carlo simulations, the author finds that the AESTAR test has more power than the test developed by Kapetanios et al. (2003), provided the data generating process (DGP) is an asymmetric ESTAR model. Furthermore, applying the test to real exchange rates from Nordic countries, Sollis (2009) finds that while neither the Dickey-Fuller test nor the ESTAR is able to reject the null hypothesis of a unit root. AESTAR on the other hand is able to reject the null hypothesis in two countries (Sollis, 2009).

As previously mentioned, panel data tests were considered one possible solution for the problem of low power (Taylor, 2003). The weakness of these multivariate tests is that since the null hypothesis is, normally, that all of the time series contain a unit root process. Therefore, a rejection of the null hypothesis will not determine how many of the time series that are stationary. Taylor and Sarno (1998) showed that in a sample of four series, one stationary process along with three unit root processes, the single stationary process lead to a rejection of the null hypothesis at a 5 % significance level.

Unlike many other panel data unit root tests, Choi (2001) devised a test aimed to work under more general assumptions. For this test, the number of groups can be either finite or infinite (as opposed to only infinite) and the time span for the groups is assumed to be different. In Choi (2001), the p-values of a unit root test, that has been applied to each group, are combined and tested. Choi also apply the test to real exchange rate data, and find evidence in favor of the PPP hypothesis, suggesting that the test could have improved power in small samples.

3 Method

In this section, the methods used to test for PPP that were introduced in the previous section are more thoroughly discussed. We start by introducing what a unit root process is and continue with the Dickey-Fuller and Phillips-Perron tests before moving on to present the non-linear ESTAR and AESTAR tests. We finish this section by describing the Choi test and the model diagnostics.

3.1 Linear testing for unit root processes

In time series analysis one is concerned with whether a process changes over time or not. A process is said to be stationary if the time series exhibits mean reversion, has a finite variance and has a theoretical correlogram that diminishes as lag length increases (Enders, 2010).

A nonstationary series has no long-run mean, the variance is dependent on time and goes to infinity when time increases towards infinity as well as theoretical autocorrelations in finite samples dies out slowly. A unit root process is non-stationary (Enders, 2010).

The Dickey-Fuller test was developed by Dickey and Fuller (1979) and it is widely used in order to find the prevalence of unit root processes in time series data. This test was further developed by Elliott et al. (1992), resulting in the Augmented Dickey-Fuller test.

In Dickey and Fuller (1979) considered three equations for testing the prevalence of a unit root;

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{3}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + \varepsilon_t \tag{4}$$

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \varepsilon_t \tag{5}$$

The difference between the three equations concerns the presence of the deterministic elements of a_0 and $a_2 t$. The first equation is a pure random walk model, the second one includes an intercept or drift term while the third equation includes both a drift and a linear trend. When testing the PPP hypothesis we are testing the null hypothesis $\gamma = 0$ or not in Equation 4 (Enders, 2010). If the null is not rejected the time series has a unit root process. When testing for a unit root one needs to be aware that the critical t-values depend on whether an intercept is included and/or if a time trend is included. The t-values in a Dickey-Fuller has its own distribution because a non-stationary process has infinite variance compared to the regular t-distribution which has a finite variance. For a sample size of 100 we have that the 5 percent critical value is -2.89 and the 1 percent critical value is -3.51 (Enders, 2010).

There is also an augmented version of the Dickey-Fuller test, which controls for potential higher-order autocorrelations. It is formalized as

$$\Delta y_t = a_0 + \gamma y_{t-1} + \sum_{i=2}^{p} \beta_i \Delta y_{t-1+1} + \varepsilon_t \tag{6}$$

and thus allows for autoregressive processes up until the pth order. (Enders, 2010)

The second linear test we will apply in this thesis is the Phillips-Perron test for a unit root process. The test, developed by Phillips and Perron (1988), tests for a unit root process in univariate time series against the alternatives of stationarity or a deterministic trend. The reasoning to include the Phillips-Perron test is that, compared to the Augmented Dickey-Fuller, it uses Newey-West standard errors and is thus robust against serial correlation and heteroskedasticity. (StataCorp, 2013) Newey-West standard errors are heteroskedasticity and autocorrelation consistent (HAC). The standard errors must be calculated conditional on a choice of maximum lag length. The autocovariances of the standard errors are computed at the chosen maximum lag length. Usually the lag length is chosen to exceed the periodicity of the data, and for monthly data then at least 12 lags are sufficient. (Wooldridge, 2009)

Let us consider two least-squares regression equations

$$y_t = \hat{\mu} + \hat{\alpha} y_{t-1} + \hat{u}_t, \tag{7}$$

$$y_t = \tilde{\mu} + \tilde{\beta}(t - {}^1/{}_2T) + \tilde{\alpha} y_{t-1} + \tilde{u}_t, \tag{8}$$

where $(\hat{\mu}, \hat{\alpha})$ and $(\tilde{\mu}, \tilde{\beta}, \tilde{\alpha})$ are the conventional least-squares regression coefficients.

The null hypothesis of the coefficients in the regression models is thus $\alpha = 1$ and $\mu = \beta = 0$. Introducing a non-zero drift $\mu \neq 0$ in the generating process does not effect $\tilde{\alpha}$ and its t-statistic. Following, we can rewrite Equation 8 above as

$$y_t = \mu + \alpha y_{t-1} + u_t \tag{9}$$

where the distributions of the above-mentioned statistics are unchanged. Thus, we use Equation 9 to test for a unit root in our time series.

3.2 Nonlinear testing of a unit root process

Linear tests, such as the standard Dickey-Fuller test, persistently fails to reject the null of a unit root when applied to economic data, which has led some researchers to reconsider the economic theories tested, while some researchers have turned to developing alternative methodologies (Kapetanios et al., 2003). An example of a new test is the ESTAR test; Kapetanios et al. (2003) have developed a nonlinear test for a unit root against the alternative of a nonlinear exponential smooth transition autoregressive process (ESTAR) which is globally stationary. Through Monte Carlo simulations the authors find that the power of the ESTAR test is better than the Dickey-Fuller around the null hypothesis.

In order to formalize the ESTAR model we first need to introduce a STAR(1) model,

$$\Delta y_t = \alpha + \beta y_{t-1} + \gamma y_{t-1} \vartheta(\theta; y_{t-d}) + \varepsilon_t \tag{10}$$

where β and γ are unknown parameters and the error term is independently and identically distributed with mean 0 and variance σ^2.

The transition function adopted in this case is of the exponential form, and is defined as follows

$$\vartheta(\theta; y_{t-d}) = 1 - exp(-\theta y_{t-d}^2) \tag{11}$$

Where we assume $\theta \geq 0$, and $d \geq 1$ is the delay parameter. Also, $\theta : \mathbf{R} \in (0, 1)$.

By joining the two previous equations we then get the exponential STAR, i.e. ESTAR, model,

$$y_t = \alpha + \beta y_{t-1} + \gamma y_{t-1}[1 - exp(-\theta y_{t-d}^2)] + \varepsilon_t \tag{12}$$

The above equation can be converted into:

$$\Delta y_t = \gamma y_{t-1}[1 - exp(-\theta y_{t-d}^2)] + \varepsilon_t \tag{13}$$

where $\theta = \beta - 1$. If we add an intercept and impose $\theta = 0$ and $d = 1$, our ESTAR will look as follows,

$$\Delta y_t = \alpha + \gamma y_{t-1}[1 - exp(-\theta y_{t-d}^2)] + \varepsilon_t. \tag{14}$$

The reason for these impositions is that the Augmented Dickey-Fuller test is not very powerful in the case where the process is stationary but nonlinear. This develops a powerful framework (Kapetanios et al., 2003).

If θ is positive it determines the speed of the mean reversion. Many economic models predict that the reversion towards equilibrium is faster when being far away from it, but a rather unstable reversion the closer it is to equilibrium.

In Equation 14 above, we would test whether $\theta = 0$ against the alternative $\theta > 0$. However, it is not feasible since we have another unobserved parameter, γ, in the equation. Kapetanios et al. (2003) derived a first order Taylor series approximation to test for unit root under the ESTAR framework with the null being $\delta = 0$ against the alternative $\delta < 0$

$$\Delta y_t = \alpha + \delta y_{t-1}^3 + \varepsilon_t \tag{15}$$

As we can see this is much easier to test and to do so we need a t-statistic which is obtained as follows:

$$t_{NL} = \frac{\hat{\delta}}{s.e.(\hat{\delta})} \tag{16}$$

where $\hat{\delta}$ is the OLS estimate of δ and $s.e(\hat{\delta})$ is the standard error of $\hat{\delta}$. Unlike when testing linearity against nonlinearity for the stationary process, the t_{NL} test does not have an asymptotic standard normal distribution. Since the t_{NL} does not have an asymptotic standard normal distribution, the t_{NL} distribution has to be simulated in order to allow for valid conclusions from the ESTAR tests.

However, a more general case can be presented where the errors in Equation are serially correlated. If the serially correlated errors enter in a linear fashion, we can use the corrections established by Dickey and Fuller (1979) and to extend Equation into

$$\Delta y_t = \alpha + \sum_{j=1}^{p} \rho_i \Delta y_{t-i} + \gamma y_{t-1}[1 - exp(-\theta y_{t-1}^2)] + \varepsilon_t \tag{17}$$

where $\varepsilon_t \sim \text{iid}(0, \sigma^2)$. The t_{NL} statistic for testing $\theta = 0$ for this equation is found in the same manner as in Equation 16 where $\hat{\gamma}$ is the OLS estimate of γ and $s.e(\hat{\gamma})$ is the standard error of $\hat{\gamma}$ obtained from the following auxiliary regression with the p augmentations:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \rho_j \Delta y_{t-j} + \delta y_{t-1}^3 + u_t. \tag{18}$$

The null hypothesis is that $\Delta = 0$ and if this is rejected, we conclude that the time series contains a unit root. This equation is used to determine whether our time series contains a unit root process.

There are reasons to believe that real exchange rates will have an asymmetric adjustment if policymakers behave asymmetrically in the international exchange markets. To test whether this is true or not we will make use of the asymmetrical ESTAR, AESTAR. The AESTAR model employs both an exponential function and a logistic function. (Sollis, 2009)

$$\Delta y_t = G_t(\theta_1, y_{t-1})[(S_t(\theta_2, y_{t-1})\rho_1 + (1 - S_t(\theta_2, y_{t-1}))\rho_2]y_{t-1} + \varepsilon_t \tag{19}$$

$$G_t(\theta_1, y_{t-1}) = 1 - exp(-\theta_1(y_{t-1}^2)), \text{ where } \theta_1 \geq 0 \tag{20}$$

$$S_t(\theta_2, y_{t-1}) = [1 + exp(-\theta_2 y_{t-1})]^{-1}, \text{ where } \theta_2 \geq 0 \tag{21}$$

$$\varepsilon_t \sim iid(0, \sigma^2) \tag{22}$$

To test this for a unit root we need an auxiliary model by taking a Taylor expansion of the exponential function in the original model around $\gamma = 0$. This is done by Sollis (2009). The derivations are outside the scope of this thesis but can be found in the aforementioned article. In essence, the author conducts a few Taylor expansions and end up with the following Taylor approximation,

$$\Delta y_t = \alpha + \phi_1 y_{t-1}^3 + \phi_2 y_{t-1}^4 + \sum_{i=1}^{k} K_i \Delta y_{t-i} + \eta_t \tag{23}$$

where α is the intercept, $\phi_1 = \rho_2^* \gamma_1$, $\phi_2 = a(\rho_2^* - \rho_1^*)$, and $\eta_t = \varepsilon + R_t$, where R_t is what is left after the Taylor approximation.

When calculating the F-value for the AESTAR test in Equation 23 is the unrestricted model. The restricted model tests wether $\phi_1 = \phi_2 = 0$. Thus, it follows that the restricted model drops ϕ_1 and ϕ_2. Also, for the F-statistic to be valid, ϕ_1 in Equation 23 needs to be smaller than zero. An asymptotic F-distribution has been simulated to provide correct p-values since the AESTAR does not follow a conventional F-distribution.

The lag lengths chosen when applying both the linear and nonlinear unit root tests are determined using the the Schwarz Bayesian information criterion (SBIC) (Schwarz et al., 1978), which we can be formally defined as follows:

$$SBIC = ln(\hat{\sigma}^2) + \frac{k}{T} ln(T) \tag{24}$$

The SBIC is considered to be the most conservative of the information criteria: in comparison to Akaike information criteria(AIC), it yields an asymptotically correct model while the AIC will suggest too large of a model. The SBIC delivers a more conservative model because it has a larger penalty term. The SBIC is also strongly consistent, meaning that it asymptotically delivers the correct model order, while the AIC is more efficient. AIC will on average deliver too large models, even with infinite amount of data (Brooks, 2008).

3.3 Panel data test

As previously mentioned, the direction of research to improve upon unit root tests seems to have gone in two ways: either focusing on panel data tests or to the development of nonlinear tests (Bahmani-Oskooee et al., 2008). While the focus in this thesis is on alternative and non linear tests, one panel unit root test is applied as well: the Choi panel unit root test developed by Choi (2001). Although the Choi test has been applied to the p-values of more standard tests of unit root processes, e.g. ADF, there are to our knowledge no examples where it has been applied to p-values resulting from nonlinear testing. Hence, we are interested in seeing if the results of the test are different when applied to the linear and nonlinear tests.

Choi's test posits the null hypothesis that all the time series are unit root non stationary against the alternative hypothesis that at least one time series is non stationary while the others are not, in the case of finite N, i.e. number of groups Choi (2001). In the case where N is finite, the following test statistics are appropriate Choi (2001) (following the notation of Choi (2001)):

- P is called the inverse chi-square test, developed by Fisher in 1932:

$$P = -2 \sum_{i=1}^{N} ln(p_i) \tag{25}$$

- Z is called the inverse normal test, developed by Stouffer et al. (1949):

$$Z = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \Phi^{-1}(p_i) \tag{26}$$

where $\Phi()$ is the standard normal cumulative distribution function, and $\Phi^{-1}()$ is its inverse.

- L is the logit test developed by George (1977):

$$L = \sum_{i=1}^{N} ln(\frac{p_i}{1-p_i}) \tag{27}$$

The p_i for all test statistics are the p-values derived from a unit root test, e.g. augmented Dickey-Fuller or Phillips-Perron. In our case, we have also used the p-values derived from the ESTAR and AESTAR test.

The rejection rules are as follows, where $c_{i\alpha}$ represents the critical values at significance level α:

$$P > c_{p\alpha} \tag{28}$$

$c_{p\alpha}$ is the value of the upper tail of chi-square distribution, and the degrees of freedom is $2N$

$$Z < c_{z\alpha} \tag{29}$$

$c_{z\alpha}$ is the value of the lower tail of the normal distribution,

$$L^* < c_{l\alpha} \tag{30}$$

$c_{l\alpha}$ is the value of the lower tail of the t-distribution, and the degrees of freedom is determined by $5N + 4$.

3.4 Model diagnostics

There are three central assumptions concerning the residuals of time series regressions:

- the error terms are homoskedastic,
- the errors are not serially correlated,
- the errors are normally distributed.

A standard approach to test for the presence of correlation in errors for two time periods (serial correlation) is the Durban-Watson test Durbin and Watson (1971) and the Breusch-Godfrey test developed by Breusch (1978) and Godfrey (1978). In this thesis we have employed the Breusch-Godfrey test for serial correlation seeing as we have dynamic models and the Durbin-Watson is biased for such models. (Wooldridge, 2009)

Heteroskedasticity can be tested using the Breusch-Pagan test developed by Breusch and Pagan (1979). Serial correlation and heteroskedasticity can be corrected with the Newey-West method, developed by Newey and West (1986). After concluding heteroskedasticity or serial correlation in our ESTAR models, we have corrected the residuals by using Newey-West standard errors. Also, GARCH effects can be corrected with Newey-West standard errors. This was shown by Kim and Schmidt (1993).

However, we are unable to use Newey-West standard errors for our AESTAR since the correction does not provide sum of squares and therefore we cannot compute a F-test. Instead, we have used sandwich covariance matrices to correct for heteroskedasticity as well as autocorrelation. The sandwich covariance matrix was introduced by Huber (1967), Eicker (1967) and White (1980). White developed the commonly known White test for heteroskedasticity. The sandwich covariance matrix is used in the Phillips-Perron test, it corrects for both heteroskedasticity as well as autocorrelation. (StataCorp, 2013).

Some time series displays autoregressive conditional heteroskedasticity (ARCH) and this needs to be tested for; ARCH was developed by Robert Engle (1982), and it was later developed to a generalized ARCH (GARCH) by Bollerslev (1986). ARCH processes are stochastic processes which have a mean of zero and are serially uncorrelated processes. ARCH processes also have non constant variances conditional on the past as well as constant unconditional variances. Since the ARCH model allows for the forecast variance to change over time and since the variance is predicted by past forecast errors, it is considered useful Engle (1982).

3.5 Structural change

A structural change or structural break is a change in the parameters of a time series model. While an assumption of stationarity in time series data signifies that parameters are constant over time, a structural break happens when one or more of the parameters changes at a certain date, called the break date. The impact of a change in a parameter will of course depend on the model in question and the parameter that has changed and it is important to account for the possibility of a structural change in time series since it can be harmful to inference, forecasting as well as policy recommendations (Hansen, 2001).

One of the earliest tests for a structural break, where the break date is modelled as unknown, was introduced by Chow (1960) and is commonly referred to as the Chow test. The Chow test was later developed by Quandt (1960). The most relevant aspect for this thesis is the possible effect of structural changes on unit root tests: under the presence of a structural break, e.g. the Dickey-Fuller test is biased towards not rejecting the null hypothesis of a unit root process (Enders, 2010).

In order to control for structural changes, the time series plots of all countries are inspected visually. We also apply a formal test: the supF-test of Andrews (1993) for multiple structural changes. The null hypothesis for the supF-test is that there is no structural change in the time series.

In order to adjust for these structural changes, the breakpoint, i.e. the observation where the change occurred, is needed. The breakpoint is calculated using Zeileis et al. (2001), which implements the methodology of Bai and Perron (2003). Zeileis et al. (2001) computes the breakpoints through minimizing the residual sum of squares of the equation:

$$y_t = {x_t}^\top \beta + u_t \tag{31}$$

4 Data

The data used is real effective exchange rates (REER) for ten South American countries: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay and Venezuela. The data set is provided by Bruegel, and contains monthly observations, computed using annual CPI's. There are two versions of the data: the "broad index", which is calculated using 172 trading partners, and the "narrow index" which is calculated using 67 trading partners. The broad index is available from 1960 and forward, and the narrow index is available from 1995 (Darvas, 2012).

Table 1: Number of observations and the selected lag length.

Countries	Observations	Lag length	Time span
Argentina	541	2	Jan 1970 - Jan 2015
Bolivia	541	6	Jan 1970 - Jan 2015
Brazil	422	1	Dec 1979 - Jan 2015
Chile	541	3	Jan 1970 - Jan 2015
Colombia	541	1	Jan 1970 - Jan 2015
Ecuador	541	1	Jan 1970 - Jan 2015
Paraguay	289	1	Jan 1991 - Jan 2015
Peru	289	5	Jan 1991 - Jan 2015
Uruguay	541	0	Jan 1970 - Jan 2015
Venezuela	541	1	Jan 1970 - Jan 2015

Table 1 shows the countries included in the analysis, along with the number of available monthly observations, as well as the lag length chosen for each country. We have 541 REER observations for most countries. However, Brazil has 422 observations and there are 289 observations for Peru and Paraguay.

The time period of the data spans between January 1970 and January 2015 for all countries with 541 observations, whereas the time period for Brazil starts in

December 1979, and Chile and Colombia have observations from January 1991. The time series plots are shown in Figure 1 through 10.

We easily detect sudden changes in the data. For Bolivia, there is an increase from one month to another; from a value of 144 in the end of 1984 to a value of over 1500 towards the end of 1985. This rather drastic change is caused by hyperinflation. There is also a similar situation for Chile, where there is a large increase in value in the fall months of 1973 before the value plummets again: from 1024 in October of 1973 to 204 in November.

5 Results

5.1 Test for the presence of structural change

The presence of structural change in time series can lead to erroneous inference and cause unit root tests, e.g. the Dickey-Fuller test, to be biased. Therefore, we are interested in discovering and testing for any possible structural changes in our data. The first step is the visual inspection of each country's REER development over time in a time series plot, as can be seen in Figure 1 through 10. Through visual inspection of the graphs it is easy to spot sudden changes in the trend of some of the data. The time-series graphs show that the REER has been quite volatile over time in all countries. For most, if not all, countries, it is also easy to draw the conclusion that we have structural breaks in the data set. We also test for the presence of structural change using the supF-test Andrews (1993).

Below, Table 2 is presented, containing the results of the supF-test; the supF-statistic is presented along with the p-values. As can be seen in the table, the p-values of all time series are 0, which tells us that the null hypothesis of no structural change can be rejected for all time series. Therefore, the conclusion is that there is a structural change in the time series, which must be accounted for.

When we have calculated the breakpoints or break dates for each country, we can adjust the Augmented Dickey-Fuller test to take the structural change into account. This adjustment is done as shown in (Enders, 2010, Chapter 4), and the results of this adjustment are presented in Table 4.

5.2 Test for the presence of a unit root process

The following tables contains the p-values from the four tests, i.e. the Augmented Dickey-Fuller, Phillips-Perron, ESTAR and AESTAR test, for the presence of a unit root process. Table 3 presents the p-values without any corrections made to the

Table 2: supF-test of structural change: supF-statistic and p-value.

Country	supF-statistic	P-value
Argentina	277.1307	0
Bolivia	111.7408	0
Brazil	206.8212	0
Chile	725.9274	0
Colombia	569.4104	0
Ecuador	1901.053	0
Paraguay	390.7971	0
Peru	169.3872	0
Uruguay	402.5082	0
Venezuela	196.5973	0

residuals. The test have been applied to all ten of the South American countries. When applicable, the number of lags used is shown in Table 1. The p-values displayed in Table 3 suffer from heteroskedastic and in some cases also autocorrelated residuals. We decided to present this Table to illustrate the large differences between uncorrected residuals and corrected residuals. P-values that are correct, in the sense that the residuals have been corrected for heteroskedasticity and autocorrelation, are displayed in Table 4. The p-values for the tests of heteroskedasticity and serial correlation can be found in Table 6 in the Appendix. Only the ESTAR and AESTAR estimates are different.

In order to calculate the p-values, we have generated a t-distribution for the ESTAR test and a F-distribution for the AESTAR tests.This has been done with a Monte Carlo simulation in which we have simulated 10 000 t-values to obtain the correct t-distribution and F-distribution.

Table 3 displays the results from the tests of unit root. Both of the linear tests, the Dickey-Fuller and the Phillips-Perron, display similar results. Using these tests, we can reject the null hypothesis of a unit root for only two countries with the Dickey-Fuller, Bolivia and Chile, and for Peru when using the Phillips-Perron test. Argentina is significant at the ten percent level in the Dickey-Fuller test but not in the Phillips-Perron. Moving on to our non-linear tests, the ESTAR and the AESTAR, we have very different results. With the ESTAR test we can reject the null hypothesis of a unit root for four countries; Argentina, Bolivia, Brazil, and Chile. Using the AESTAR test, rejection of the null hypothesis is made for seven countries at the 5 percent level. Generally, the AESTAR test increased the power for all countries

Table 3: P-values from unit root tests without correcting the residual.

Countries	Dickey-Fuller	Phillips-Perron	ESTAR	AESTAR
Argentina	0.0700	0.1144	0.0057	0.0100
Bolivia	0.0000	0.0000	0.0000	0.0000
Brazil	0.0843	0.2101	0.0464	0.0360
Chile	0.0131	0.0002	0.0000	0.0000
Colombia	0.2953	0.4220	0.4095	0.2893
Ecuador	0.1388	0.1623	0.0514	0.0032
Paraguay	0.8540	0.9360	0.8246	0.8465
Peru	0.1558	0.0315	0.1171	0.0267
Uruguay	0.2457	0.2457	0.2474	0.3267
Venezuela	0.9803	0.9933	1.0000	0.0018

except for Paraguay and Uruguay.

In Table 4, we display the p-values where we have corrected the residuals for heteroskedasticity and serial correlation. The Dickey-Fuller values has been corrected for structural breaks and the t-statistics has been compared to the ones found in Perron (1989). Note that we do not use p-values since we could more easily compare our t-statistics to the ones found in Perron (1989) without simulating the appropriate distribution.

We can reject the null for Bolivia and Colombia, while all other countries are insignificant at the 10 percent level, while there are very few significant countries. We can reject the null hypothesis of a unit root for only one country using the ESTAR test, namely Bolivia. Chile has a p-value of 0.0611 and can thus be rejected at the ten percent level. Regarding the AESTAR test, we can reject the null in three countries; Bolivia, Peru and Venezuela. After correcting the residuals we can see that the p-values are generally very high and evidence for PPP is thus very weak. Also, we can see that the ESTAR and the AESTAR tests have decreased power compared to the linear tests for some countries, which was not expected. It should be noted that nonlinear tests are robust to structural change.

Comparing Table 3 and Table 4 there is a drastic change. For example, Argentina had very low p-values using both the ESTAR and the AESTAR but when correcting the residual, the p-value increased tenfold and this pattern is clear for all countries.

We have also run the analysis on data supplied by the BIS and found similar results. Unfortunately, the data from BIS only has observations for six South American countries and for a shorter time span. The results were similar to the ones

Table 4: P-values from unit root tests with corrected residuals.

Countries	Dickey-Fuller (t-statistic)	Phillips-Perron	ESTAR	AESTAR
Argentina	-2.8634	0.1144	0.5615	0.6040
Bolivia	-10.6707*	0.0000	0.0000	0.0000
Brazil	-2.1151	0.2101	0.1691	0.1668
Chile	-1.5831	0.0002	0.0611	0.0000
Colombia	-6.8406*	0.4220	0.2445	0.1119
Ecuador	-2.2116	0.1623	0.6420	0.7675
Paraguay	-.7046	0.9360	0.8602	0.9135
Peru	-2.9350	0.0315	0.1869	0.4350
Uruguay	-2.7927	0.2457	0.6597	0.7144
Venezuela	1.2374	0.9933	1.0000	0.0392

* significant at the 1% level.

presented above and can be found on the last page of the Appendix.

Below, we find a table over the observed test statistics (P, Z, L) for the Choi test and their respective critical values at $\alpha = 0.01$. The null hypothesis that all time series are unit root non stationary will be evaluated according to the rejection rules given in Choi (2001), i.e.: $P > c_{p\alpha}$, $Z < c_{z\alpha}$ and $L < c_{l\alpha}$.

For the p-values derived from tests without correcting for heteroskedasticity and serial correlation, the decision is to reject the null hypothesis for all tests at the 1 % significance level. For the p-values where standard errors are corrected, the null hypothesis can be rejected in 3 out of 4 cases, only for the ESTAR p-values is it not possible to reject the null hypothesis.

Table 5: Choi test statistics and critical values.

Test	P	Z	L
Augmented Dickey-Fuller	52.0530	-2.9033	-19.0506
Phillips-Perron	59.5689	-2.9027	-20.6331
ESTAR	71.3608	-2.9060	-14.4774
AESTAR	91.9802	-6.1566	-43.3001
Test, corrected standard errors.			
Augmented Dickey-Fuller	52.0530	-2.9033	-19.0506
Phillips-Perron	59.5689	-2.9027	-20.6331
ESTAR	38.3376	-0.3843	0.2794
AESTAR	58.1911	-2.8381	-22.0974
Critical values	37.5662	-2.3974	-2.3263

6 Conclusion

The results presented in the previous section, are somewhat consistent with many other studies on the subject. Linear tests, in this case the Dickey-Fuller and Phillips-Perron test for a unit root process, fails to reject the hypothesis in most cases. There is a difference in P-values for both of the tests, and the p-values are generally higher using the Phillips-Perron test due to the Newey-West corrected errors. For some countries, the P-values decrease, e.g. Peru and Chile.

When correcting for heteroskedasticity and autocorrelation in the ESTAR test, the P-values are higher for many countries when compared to the two linear tests. Colombia is the only country to display a large decrease in p-value and only one country is significant.

The ESTAR and the AESTAR generally display similar results, however we can see that the p-value for Peru increases and that the p-value for Venezuela dramatically decreases. Notably, we can only reject the null hypothesis for three countries with the AESTAR test.

Without correcting the residuals for the nonlinear tests the results are quite different when compared to (Bahmani-Oskooee et al., 2008). After correcting the residuals for serial correlation and heteroskedasticity, our results remain rather different from the results obtained in the previously mentioned study. In Bahmani-Oskooee et al. (2008), the null hypothesis is rejected for two countries in South America: Chile and Ecuador.

In contrast, we are able to reject the null hypothesis for only one country with the ESTAR test, Bolivia. However, we find that Ecuador has a p-value of 0.6420, which means that we can no longer reject the null hypothesis of a unit root processs. Chile has a p-value of 0.06 which is fairly close to being significant. When residuals are corrected, we can only reject the null hypothesis of a unit root process for one country; which indicates that these nonlinear tests are not able to confirm the PPP hypothesis when correcting the residuals.

The Choi test is also applied on the p-values derived from the above mentioned tests. The result, at a 1 % significance level, is that we find evidence to reject the null hypothesis in for all tests except for the ESTAR test. The conclusion we can draw from this is that by applying this panel unit root test, we do find evidence in support of the PPP hypothesis when applying ADF, PP and the AESTAR test.

When rejecting the hypothesis of a unit root process, we implicitly find evidence in favor of the power purchasing parity hypothesis. Using the other tests included in this thesis, we have not found evidence for PPP, due to lack of power. Another possible explanation for not being able to reject the hypothesis for the Dickey-Fuller test could be the presence of structural breaks. It should also be noted that the failure to vindicate the PPP hypothesis could be the simple explanation that the nations in question violate the assumptions of the hypothesis through barriers to trade or similar interventions.

Possible weaknesses in this thesis is the choice of data: while we have tried to corroborate our results using data from the Bank of International Settlements, we still have the problem of possible exchange regime changes in the period of the chosen countries. This could affect our results, as mentioned by Taylor (2003). Another weakness lies in the application of the Choi panel data test: when we have p-values that are practically zero, it influences the test strongly towards rejecting the null hypothesis.

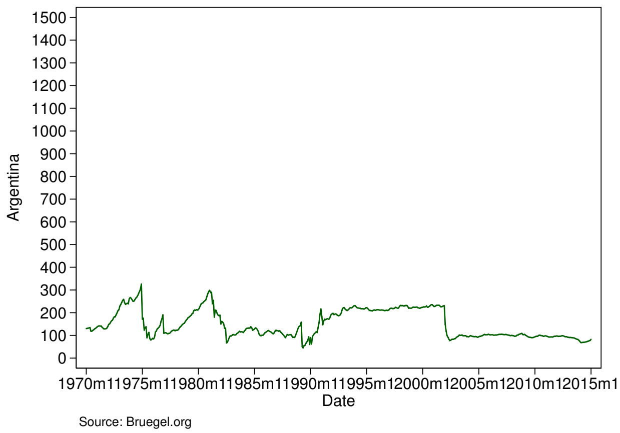

Figure 1: Argentina

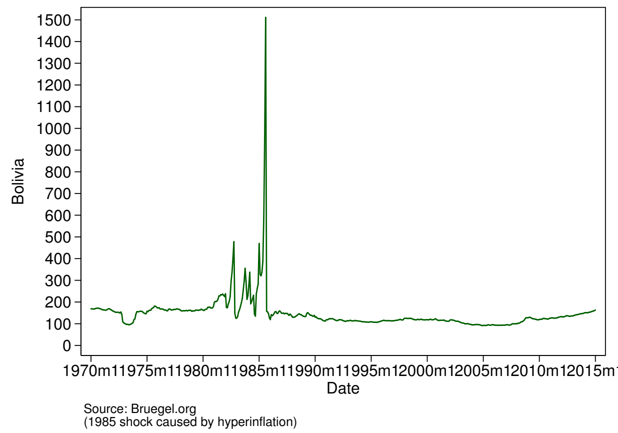

Figure 2: Bolivia

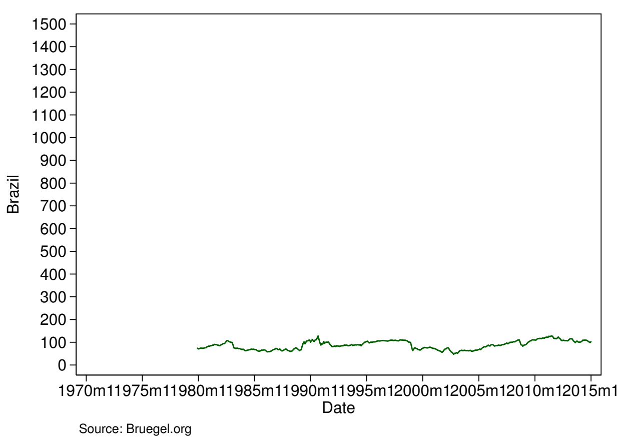

Figure 3: Brazil.

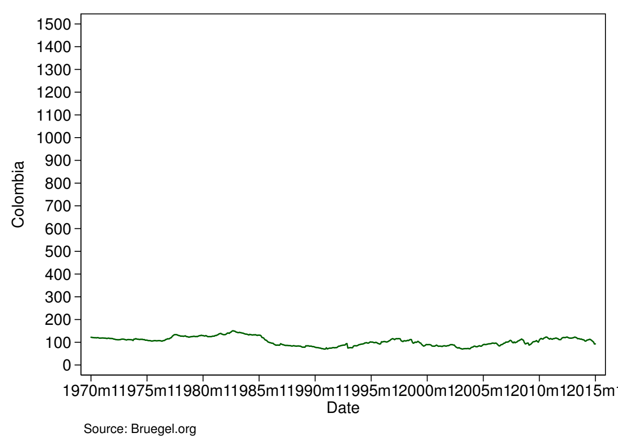

Figure 4: Colombia

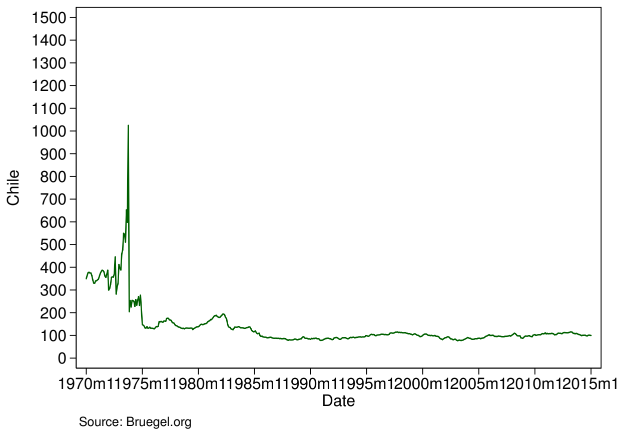

Figure 5: Chile.

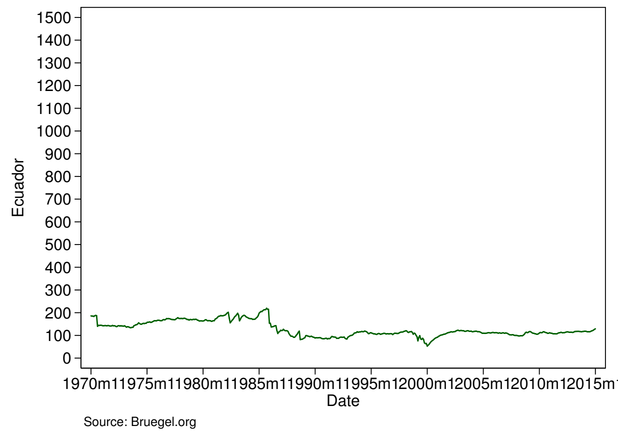

Figure 6: Ecuador

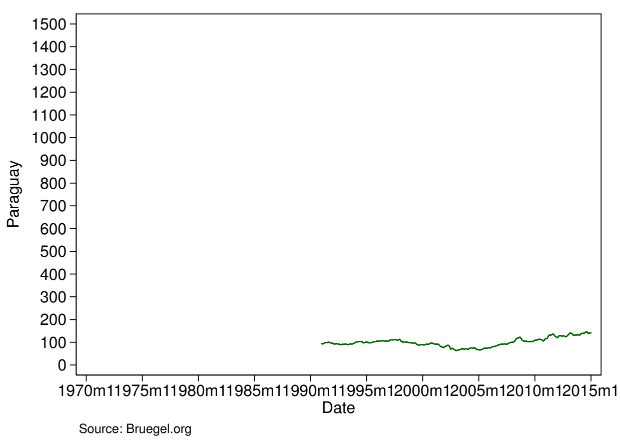

Figure 7: Paraguay.

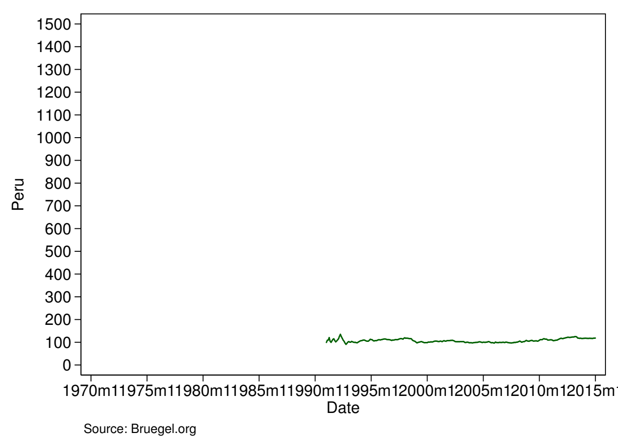

Figure 8: Peru

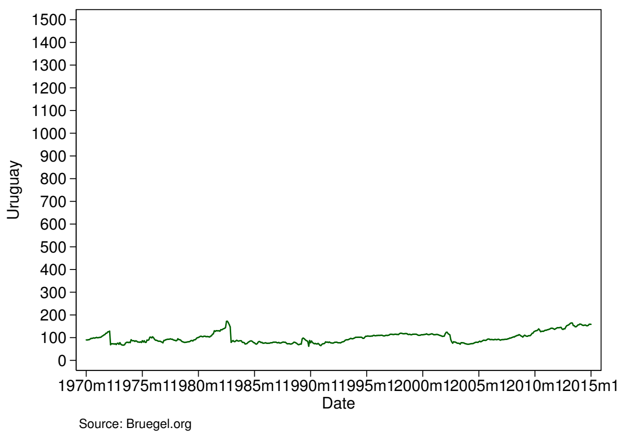

Figure 9: Uruguay.

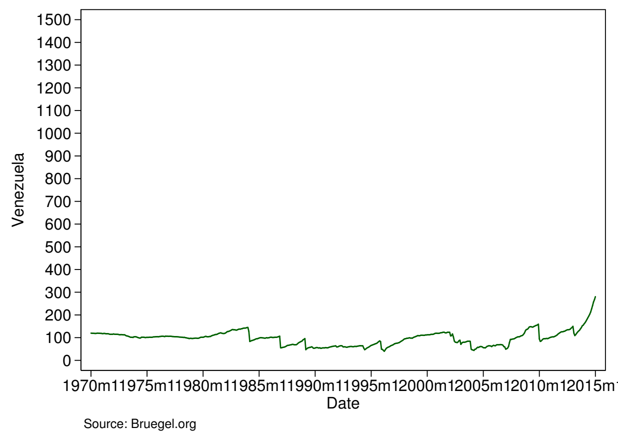

Figure 10: Venezuela

References

Andrews, D. W. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica: Journal of the Econometric Society*, 821–856.

Bahmani-Oskooee, M., A. M. Kutan, and S. Zhou (2008). Do real exchange rates follow a nonlinear mean reverting process in developing countries? *Southern Economic Journal*, 1049–1062.

Bai, J. and P. Perron (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics 18*(1), 1–22.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics 31*(3), 307–327.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models*. *Australian Economic Papers 17*(31), 334–355.

Breusch, T. S. and A. R. Pagan (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the Econometric Society*, 1287–1294.

Brooks, C. (2008). *Introductory econometrics for finance.* Cambridge University Press.

Cassel, G. (1918). Abnormal deviations in international exchanges. *The Economic Journal*, 413–415.

Choi, I. (2001). Unit root tests for panel data. *Journal of international money and Finance 20*(2), 249–272.

Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica: Journal of the Econometric Society*, 591–605.

Crownover, C., J. Pippenger, and D. G. Steigerwald (1996). Testing for absolute purchasing power parity. *Journal of International Money and Finance 15*(5), 783–796.

Darvas, Z. (2012, June). Real effective exchange rates for 178 countries: a new database.

Dickey, D. A. and W. A. Fuller (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association 74*(366a), 427–431.

Durbin, J. and G. Watson (1971). Testing for serial correlation in least squares regression. iii. *Biometrika 58*(1), 1–19.

Eicker, F. (1967). Limit theorems for regressions with unequal and dependent errors. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, Volume 1, pp. 59–82.

Elliott, G., T. J. Rothenberg, and J. H. Stock (1992). Efficient tests for an autoregressive unit root.

Enders, W. (2010). *Applied econometric time series*. John Wiley & Sons.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987–1007.

Feenstra, R. C. and A. M. Taylor (2008). *International economics*. Worth Publishers.

George, E. O. (1977). *Combining independent one-sided and two-sided statistical tests-Some theory and applications*. Ph. D. thesis, University of Rochester. Department of Statistics.

Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica: Journal of the Econometric Society*, 1293–1301.

Hansen, B. E. (2001). The new econometrics of structural change: Dating breaks in us labor productivity. *Journal of Economic perspectives*, 117–128.

Huber, P. J. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, Volume 1, pp. 221–233.

Kapetanios, G., Y. Shin, and A. Snell (2003). Testing for a unit root in the nonlinear star framework. *Journal of Econometrics 112*(2), 359–379.

Kim, K. and P. Schmidt (1993). Unit root tests with conditional heteroskedasticity. *Journal of Econometrics 59*(3), 287–300.

Lothian, J. R. and M. P. Taylor (1997). Real exchange rate behavior. *Journal of International Money and Finance 16*(6), 945–954.

Newey, W. K. and K. D. West (1986). *A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix.* National Bureau of Economic Research Cambridge, Mass., USA.

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica: Journal of the Econometric Society*, 1361–1401.

Phillips, P. C. and P. Perron (1988). Testing for a unit root in time series regression. *Biometrika 75*(2), 335–346.

Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American statistical Association 55*(290), 324–330.

Schwarz, G. et al. (1978). Estimating the dimension of a model. *The annals of statistics 6*(2), 461–464.

Sollis, R. (2009). A simple unit root test against asymmetric star nonlinearity with an application to real exchange rates in nordic countries. *Economic modelling 26*(1), 118–125.

StataCorp, L. (2013). *Stata: Release 13. Statistical software.* Stata Press.

Stouffer, S. A., A. A. Lumsdaine, M. H. Lumsdaine, R. M. Williams Jr, M. B. Smith, I. L. Janis, S. A. Star, and L. S. Cottrell Jr (1949). The american soldier: combat and its aftermath.(studies in social psychology in world war ii, vol. 2.).

Taylor, M. P. (2003). Purchasing power parity. *Review of International Economics 11*(3), 436–452.

Taylor, M. P. and L. Sarno (1998). The behavior of real exchange rates during the post-bretton woods period. *Journal of international Economics 46*(2), 281–312.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica: Journal of the Econometric Society*, 817–838.

Wooldridge, J. (2009). *Introductory econometrics: A modern approach.* Cengage Learning.

Zeileis, A., F. Leisch, K. Hornik, and C. Kleiber (2001). strucchange. an r package for testing for structural change in linear regression models.

A Appendix

A.1 Tables

Table 6: Tests of autocorrelation, heteroskedasticity, and ARCH

Country	Test	Autocorrelation	Heteroskedasticity	ARCH
Argentina	ESTAR	0.7203	0.0000	0.3016
	AESTAR	0.1697	0.0000	0.0293
Bolivia	ESTAR	0.0000	0.0000	0.0000
	AESTAR	0.0243	0.0000	0.2427
Brazil	ESTAR	0.1691	0.0000	0.0000
	AESTAR	0.1484	0.0000	0.0000
Chile	ESTAR	0.0000	0.0000	0.0000
	AESTAR	0.0001	0.0000	0.6882
Colombia	ESTAR	0.3296	0.0008	0.2281
	AESTAR	0.2998	0.0001	0.2732
Ecuador	ESTAR	0.8439	0.0000	0.4644
	AESTAR	0.3789	0.0000	0.3465
Paraguay	ESTAR	0.1356	0.0000	0.0000
	AESTAR	0.1357	0.0000	0.0000
Peru	ESTAR	0.0020	0.0000	0.0033
	AESTAR	0.0018	0.0000	0.0002
Uruguay	ESTAR	0.7016	0.0000	0.7300
	AESTAR	0.7227	0.0000	0.7313
Venezuela	ESTAR	0.2399	0.0000	0.5713
	AESTAR	0.3313	0.0000	0.6185

A.2 Bank of International Settlements Data

Table 7: Number of observations and the selected lag length.

Countries	Observations	Lag length	Time span
Argentina	252	1	Jan 1994 - Mar 2015
Brazil	252	2	Jan 1994 - Mar 2015
Chile	252	1	Jan 1994 - Mar 2015
Colombia	252	1	Jan 1994 - Mar 2015
Peru	252	1	Jan 1994 - Mar 2015
Venezuela	252	1	Jan 1994 - Mar 2015

Table 8: P-values from unit root tests without correcting the residual.

Countries	Dickey-Fuller	Phillips-Perron	ESTAR	AESTAR
Argentina	0.5885	0.6527	0.3917	0.0495
Brazil	0.4565	0.4534	0.4181	0.5094
Chile	0.0654	0.1260	0.0726	0.1001
Colombia	0.0889	0.1566	0.071	0.0869
Peru	0.1401	0.2494	0.1326	0.1941
Venezuela	0.9934	0.9968	1.0000	0.0097

Table 9: P-values from unit root tests with corrected residuals.

Countries	Dickey-Fuller	Phillips-Perron	ESTAR	AESTAR
Argentina	0.5885	0.6527	0.7686	0.5440
Brazil	0.4565	0.4534	0.3573	0.4641
Chile	0.0654	0.1260	0.0726	0.1001
Colombia	0.0889	0.1566	0.071	0.0461
Peru	0.1401	0.2494	0.1326	0.2145
Venezuela	0.9934	0.9968	1.0000	0.0051

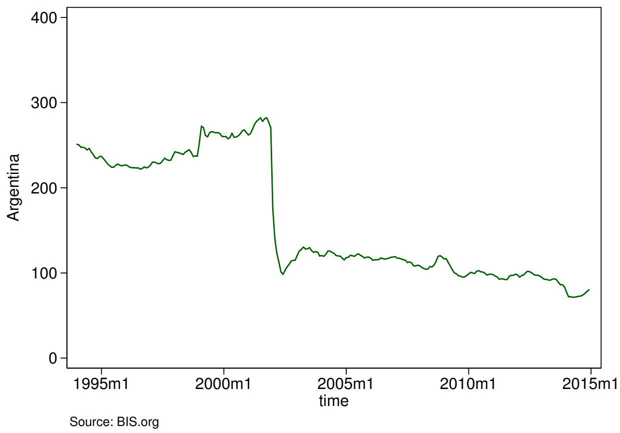

Figure 11: Argentina

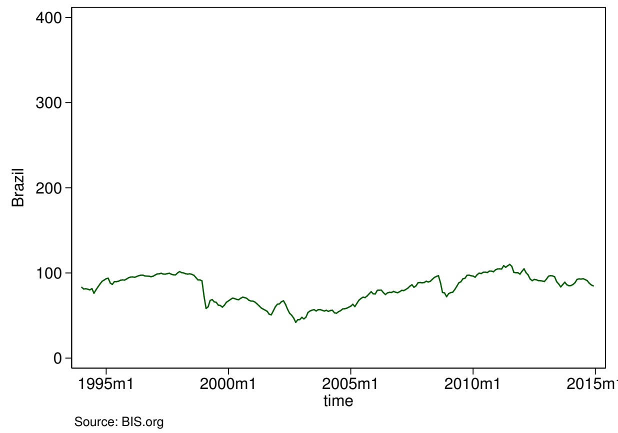

Figure 12: Bolivia

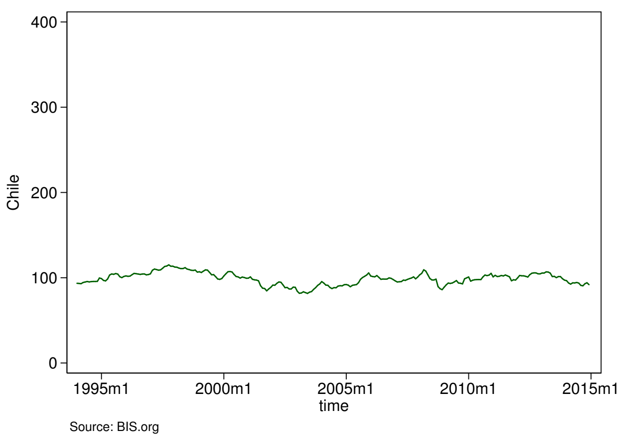

Figure 13: Brazil.

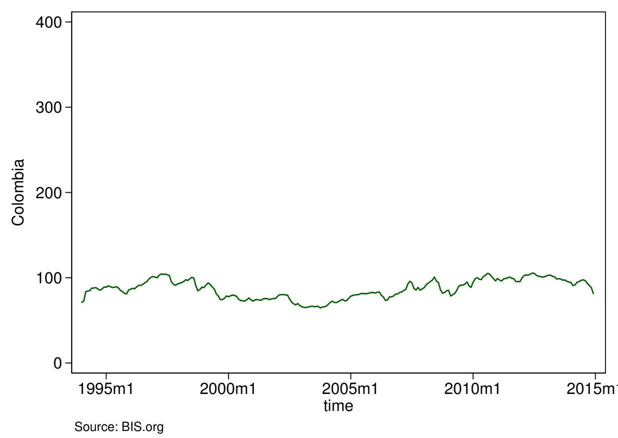

Figure 14: Colombia

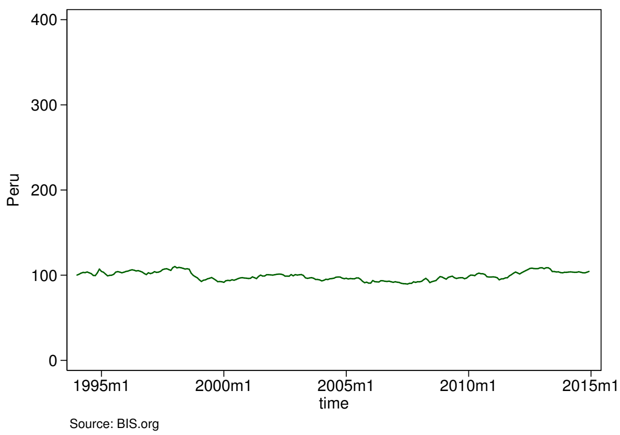

Figure 15: Chile.

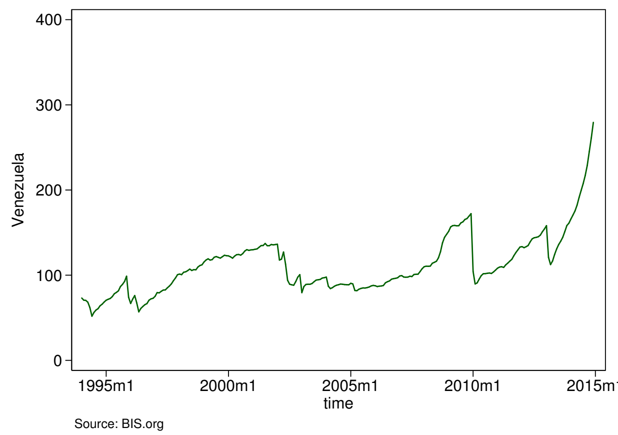

Figure 16: Ecuador