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Explosiveness in G11 currencies*

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Abstract

This paper tests for explosiveness in G11 currencies in daily data using a methodology that accounts for the possibility of non-stationary volatility. The results suggest that bouts of explosiveness in exchange rates are uncommon at a daily frequency. However, periods of explosiveness tend to last for several days. Such episodes only involve small changes in actual currency levels, which usually reverse shortly after. This paper identifies the currency in a currency pair that is experiencing explosive dynamics by also considering the dynamics of effective exchange rates of different currencies. There is high concordance with explosiveness in the broad value of the US dollar exchange rate, suggesting that there are relatively few instances where explosiveness in individual cross-rates reflected country-specific factors.

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Non-technical summary

One definition of a 'bubble' in an asset price is that the price exhibits explosive (i.e. exponential) dynamics. Econometric tests for explosiveness have been widely used in assessing the behaviour of asset prices such as stocks and housing. The tests developed by Phillips et al. (2015a) and Phillips et al. (2015b) provide an accurate way to gauge whether asset prices are experiencing explosive dynamics. These tests have not previously been applied to exchange rates at a high frequency. This paper applies tests for explosiveness to eleven of the most commonly traded exchange rates at a daily frequency and over a long sample.

The volatility of exchange rates tends to be high at a daily frequency. This volatility can weaken the power of these tests to discriminate between periods when an exchange rate is explosive and ones where it is not. To address this, a wild bootstrapping technique is used to assess the statistical significance of the test results.

The results suggest that bouts of explosiveness in exchange rates are uncommon at a daily frequency. However, periods of explosiveness tend to last for several days. Such episodes only involve small changes in actual currency levels, which usually reverse shortly after. To identify the currency that is experiencing explosive dynamics in a currency pair, the tests are also applied to effective exchange rates of different currencies as these capture the broad value of a specific currency. There is strong similarity between explosive periods in the broad value of the US dollar exchange rate and cross-rates, suggesting that there are relatively few instances where explosiveness in individual currencies reflected country-specific factors. There is also evidence that explosive episodes have tended to coincide with periods of high market volatility.

1 Introduction

Recently developed tests by Phillips et al. (2015a) and Phillips et al. (2015b) provide an accurate way to gauge whether asset prices are experiencing explosive dynamics. There are two important advantages of these tests over standard unit root tests. The first is that these tests have been shown to be good at correctly identifying such periods, especially when there are multiple periods of explosive dynamics over the full sample. Secondly, unlike many of the earlier tests for bubbles, the validity of these tests for explosiveness is not dependent on the model used to determine the economic fundamentals that determine the value of the asset price under consideration.

These tests have already been used in a large number of studies to demonstrate that many asset prices are prone to periods of explosive behaviour. Explosiveness implies that there is an explosive root in the autoregressive representation of a time series, such that $a > 0$ in $x_t = (1 + a)x_{t-1} + \varepsilon_t$ for some subperiod of the sample. The intuition behind these tests is that an asset price contains a component which is driven fundamentals and whose time series properties are distinguishable from those of any potential bubble component (which will be explosive process). If the fundamental component behaves like a random walk with drift (as is the case for many asset price series), but the asset price also contains a bubble component, then the asset price series would inherit explosiveness from its bubble component during the period considered.

Unlike other asset prices, exchange rates do not typically exhibit explosive growth for extended periods.[1] But they can experience explosive dynamics over short sub-samples.[2]

This paper makes two contributions to the literature. Firstly, recently developed tests for explosiveness are applied to eleven of the most commonly traded exchange rates at a daily frequency and over a long sample. Particularly at high frequencies such as daily, the volatility of the exchange rate tends to be high and potentially non-stationary, and there may be a size distortion in unit root tests causing them to over-reject the null that the series is explosive.

[1] With the exception, of course, of the currencies of countries experiencing hyper-inflation (see Pavlidis et al. 2012) or prolonged bouts of macroeconomic instability. Some central banks also intervene in foreign exchange markets, which may reduce the volatility of some currency pairs.

[2] Bettendorf and Chen (2013), Jiang et al. (2015) and Hu and Oxley (2017, *forthcoming*) apply the tests from Phillips et al. (2011) and Phillips et al. (2015b) to exchange rate series.

For this reason, wild bootstrapping is used to compute critical values for statistical interference.[3]

Secondly, explosive increases (or collapses) in a given base currency implies a corresponding collapse (or increase) in the quote currency. This paper considers the possibility of both expansion and crash periods and identifies the currency experiencing explosive dynamics by considering the dynamics of effective exchange rates of different currencies.

This paper is focussed on describing short-term exchange rate volatility. A large literature attempts to identify 'rational' bubbles in asset prices by looking for significant departures from their theoretically consistent fundamental value. However, explosive behaviour in an asset price can reflect a host of different factors, including explosiveness in unobserved fundamentals or large changes in the discount rate (see Pavlidis et al. 2015), 'irrational exuberance' (as described by Shiller 2005) or the possibility of 'intrinsic bubbles' (see Froot and Obstfeld 1991). Following the recent literature, this paper does not question the nature of the explosiveness identified and takes the existence of bubbles as an empirical question.

2 Tests for explosiveness

This paper applies Phillips et al.'s (2015b) test for identifying periods when asset prices are experiencing exponential growth. The null hypothesis is that an asset price or returns series (y_t) is AR(1) process with drift:

$$y_t = dT^{-\eta} + \theta y_{t-j} + e_t \tag{1}$$

where smallcase letters denote logarithms, d is the intercept, T is the sample size, η determines the magnitude of the drift as T tends to infinity, and

[3] That said, there may be other limitations to modelling high frequency financial data in this way, such as the possibility that noise affects the asymptotic properties of the test.

$e_t \sim NID(0, \sigma_e^2)$.[4] A right-tailed ADF test is applied over recursive sub-samples

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{j=1}^{k} \delta_{r_1,r_2}^{j} \Delta y_{t-j} + \varepsilon_t \quad (2)$$

where k is the number of lags, Δ is the difference operator, ε_t is the error term and r_1 and r_2 span the estimation range. The null that $\beta = 1$ (i.e. y_t has a unit root) is tested against the alternative $\beta > 1$ (i.e. implying local explosiveness). These tests are run recursively over a flexible sample window to detect breaks in the AR(1) coefficient. To calculate the distribution of the ADF statistics under the null of a random walk data generating process with normal *iid* errors, the corresponding critical values from the right tail of the limit distribution are simulated.[5] Explosiveness is determined by comparing the calculated test statistic for each period to the simulated critical values.

Phillips et al. (2015b) assume that the data generating process for the alternative distribution exhibits potentially multiple explosive episodes, and when explosive periods terminate, that the series reverts back to its pre-explosive level plus a small perturbation and continues to behave like a random walk with drift: $y^*_{\tau_{i,f}} = y_{\tau_{i,e}} + O_p(1)$, where $y_{\tau_{i,e}}$ and $y_{\tau_{i,f}}$ are the emergence (e) and termination (f) levels of the explosive period, respectively, $O_p(1)$ is a small perturbation and $y^*_{\tau_i}$ is the value on termination of the K^{th} explosive episodes for $i = (1, ..., K)$. Following Harvey et al. (2015), a more general alternative specification that permits gradual collapses is used in this paper. The alternative data generating process assumes that the series reverts back to random walk behaviour immediately from its termination level: $y^*_{\tau_i} = y_{\tau_{i,f}} + \varepsilon_t$

[4] Phillips et al. (2015b) focus on the pure random walk case where $\eta = 1$ and set $d = 1$ and $\theta = 1$, while Phillips et al. (2011) focus on $\eta \to \infty$ (random walk without drift). Phillips et al. (2015a) show that the distribution of the ADF statistic does not change significantly for values of $\eta > \frac{1}{2}$. In the currencies considered, any deterministic drift component is unlikely to dominate the other components of the series. Phillips et al. (2014b) show that even for asset prices such as stocks, that have significant stochastic trends over the sample considered, bubble components can clearly be distinguished using right-tailed unit root tests. Testing whether a drift component reflecting risk premia in specific cross-rates can explain deviations from random walk behaviour in exchange rates is left to future research.

[5] Simulations are necessary as the limit distributions of these tests are Brownian motion and depend on the window size and regression model specification. Specifically, Phillips et al. (2015b) show that the asymptotic distribution of the BSADF statistic is a Wiener process, which they approximate using partial sums of *iid* random draws with 2000 steps.

where $\varepsilon_t \sim N(0, \sigma^2)$. In the context of asset price modeling, Phillips et al.'s (2015a) assumption implies a return to fundamentals-consistent price level following the termination of an explosive period. The advantage of Harvey et al.'s (2015) approach is that it permits a range of price correction processes and allows an explosive episode to persist until the end of the sample.[6]

Whereas Phillips et al.'s (2011) earlier SADF test (commonly referred to as the PWY test) uses an expanding window with the starting point fixed at the beginning of the sample, Phillips et al.'s (2015b) and Phillips et al.'s (2015a) more recent approach involves a double recursive approach, nesting the SADF test in a loop and using rolling samples with an expanding window and moving starting point (known as the PSY approach). Phillips et al. (2015b) show, using Monte Carlo simulations, that the PSY approach is significantly better at detecting explosive periods when there are multiple episodes in the full sample and that the power of the test to correctly identify such episodes improves as the sample size expands.

To date-stamp the origination and termination dates of explosive periods, a 'Backward Sup ADF' (BSADF) test statistic is calculated as the sup value of the ADF statistic calculated over the interval:

$$BSADF_{r_2}(r_0) = sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \tag{3}$$

where the value of the BSADF test statistic is the supremum value of the sequence of ADF tests (i.e. the maximum value of the set of tests over the full sample)[7]. Origination and collapse dates of the ith explosive period are determined using the infimum (largest lower bound) dating rule used by PSY:

$$\tilde{r}^{ie} = inf_{r \in [r^{i-1f}, 1]} r : BSADF_r(r_0) > CV_r^{\kappa} \tag{4}$$

and

$$\tilde{r}^{if} = inf_{r \in [r^{ie} + L_t, 1]} r : BSADF_r(r_0) < CV_r^{\kappa} \tag{5}$$

[6] A similar approach is used by Phillips and Shi (2017, *forthcoming*), who also discuss the implications of alternative assumptions about the nature of a bubble implosion in more detail. There are several alternative approaches that attempt to model the inherent non-linearity of bubble periods, such as using regime switching models that allow asset price dynamics to differ depending on bubbles size (see Schaller and Norden 1997, or more recently Brooks and Katsaris 2005 or Shi 2013).

[7] Where an ADF statistic is calculated as $ADF_{r1}^{r2} = \frac{\hat{\beta}_{r1,r2}}{se(\hat{\beta}_{r1,r2})}$ under the null and when lags are added to remove serial correlation from the error term.

where $\tilde{r}^{ie}$ and $\tilde{r}^{if}$ are the date fractions of origination and collapse and CV^{κ} are the $100(1-\kappa)\%$ critical values for significance level κ which are based on the BSADF statistic for observation fraction r. The start date of an explosive period is the earliest observation with an BSADF statistic that exceeds the corresponding critical value under the distribution of the null, while the collapse date of the explosiveness is taken to be the first time that the BSADF statistic declines to below the critical value.

A key assumption of these tests is that the volatility of the error term of the equation for an asset price being modeled is stationary. If this assumption does not hold it can lead to Type 1 errors (false rejections of the null that there is no explosiveness present in the sub-sample). Heteroscedasticity is a common phenomenon in high frequency financial series such as exchange rates (see for example, Figure 44 in the Appendix).[8] In the presence of heteroscedasticity, the standard PSY test may therefore not be valid for inference.[9] However, Cavaliere and Taylor (2008) show that inference for (left-sided) unit root testing is robust to non-stationary volatility when a wild bootstrap is applied.[10] This paper uses a wild bootstrap to simulate critical values for the PSY test that will be applied to exchange rate series.

3 Wild bootstrap procedure for the PSY approach

Whereas the critical values for the PSY approach depend only on the sample size, minimum sample fraction r_0 and the test specification, in this paper the wild bootstrapped critical values also depend on the differenced series being

[8] The Figure shows that the NZD has the highest nominal volatility in its cross rate with the USD over the sample period, while the CAD, CHF and USD all have relatively high volatility in their effective exchange rates.

[9] Standard tests for heteroscedasticity, such as the Breusch-Pagan-Godfrey and White tests, reject the null of no heteroscedasticity for several test specifications for the daily cross rates considered in this paper. If a series has explosive dynamics, standard tests for heteroscedasticity or breaks in volatility may not produce consistent results. However, the wild bootstrap critical values produced for inference in this paper will provide consistent results whether heteroscedasticity is present in the series or not.

[10] Specifically, they show that wild bootstrap test statistics replicate the limit distribution under the unit root null and non-stationary volatility. Likewise, Goncalves and Kilian (2004) show that a wild bootstrap estimator is asymptotically valid (i.e. their sizes unaffected) for univariate autoregressions in the presence of conditional heteroskedasticity, while Xu (2008) demonstrates the same conclusion holds under unconditional heteroskedasticity.

tested. Following Harvey et al. (2015), a wild bootstrap algorithm is used to compute critical values for inference:

1. For each series, T bootstrap residuals ε_t^* are generated as $\varepsilon_t^* = w_t \Delta y_t$ with $\varepsilon_1^* = 0$ and $t = 2, ..., T$, after drawing w_t from an auxiliary distribution such that $\{w_t\}_{t=2}^T \sim N(0,1)$.[11]

2. Bootstrap sample $(y_0^*, ..., y_T^*)$ computed as the partial sum of the bootstrap residuals: $y_t^* = \sum_{j=1}^t \varepsilon_j^*$, where $t = 1, .., T$.

3. Bootstrap test statistics computed as in equations 3 and 4 using y_t^* over the sample window with the starting point $r_1 = 1, .., r_2 - r_0 + 1$ and end-point $r_2 = r_0, .., T$.

4. Steps 1 to 3 are repeated 2000 times to produce the bootstrap distribution used to calculate the critical values for the BSADF statistic.

This approach ensures that the bootstrap residuals account for any heteroskedasticity present in the series under consideration as they depend on Δy_t and ε_t^* are an *iid* sequence with zero mean and unit variance.[12]

4 Results

The sample spans 3 January 2000 to 13 July 2016 (4177 observations) for all G11 currencies.[13] Effective exchange rates are based on the Bank of England Effective Exchange Rate Indices, which have the advantage of being available

[11] This paper presents results using a standard normal distribution, but in line with Cavaliere and Taylor (2008), simulations based on other error distributions (such as that proposed by Mammen 1993) produced similar results.

[12] Caspi (2017, *forthcoming*) provides an Eviews implementation of a version of the PSY test that allows for bootstrapping using Harvey et al.'s (2015) approach, as well as several alternatives. Etienne et al. (2014) and Milunovich et al. (2016) also apply a wild bootstrap procedure to the PSY test but base the wild bootstrap residuals instead on the residuals from the AR model in equation 2. Instead of specifically modeling the process governing volatility, Harvey et al. (2015) show that wild bootstrapping the PWY test based on the differenced series under consideration to obtain critical values produces results robust to the possibility of non-stationary volatility. They show that their variant of the PWY test maintains the size and power properties of the test when there is heteroscedasticity present in a time series. Following Harvey et al. (2015), sub-sample regressions are amended when allowing for serial correlation in ε_t, although they note that their approach to bootstrapping leaves the asymptotic properties of their test unaffected when ε_t is weakly dependent.

[13] Daily exchange rates are taken from the Bank of England website and quoted as middle rates observed in the late afternoon.

at a daily frequency for a large range of countries and can easily matched to the daily exchange rate data used.[14] For all cross-rates, lag length length of the test is set to one in equation 2.[15] As is typical when modeling financial market data, a constant is added to the AR regressions in this paper to account for non-random drift. Critical values are simulated using on 2000 replications. The size of the initial test window needs to be big enough to provide consistent estimates. In this paper, r_0 is set at 158 days, using the rule of thumb suggested by Phillips et al. (2014a).[16] Given the use of daily data, a minimum period of 1 day is imposed.[17] Exchange rates are quoted in terms of USD, and effective exchange rate indices are indexed to ensure that values for 1990 average equal 100.

4.1 Tests applied to nominal exchange rates

Appendix A shows results for all nominal exchange rates quoted relative to USD. The shaded bars in the top panels show the days on which nominal USD cross rates exhibited explosive behaviour. In the bottom panel, the red line plots the BSADF test sequence, while the blue line plots the 95 percent simulated critical values. Table 1 compares the number of days with explosive dynamics in each currency pair. Periods of explosiveness are fairly uncommon. Between January 2000 and July 2016, less than 7 percent of days exhibited explosive dynamics on average across the 11 cross-rates. Periods of explosiveness are most common in the USD:DKK, USD:EUR, USD:CAD and USD:SEK cross rates, and occur least frequently in the USD:GBP and

[14] These indices are constructed by weighting bilateral exchange rates against sterling for 21 currencies, 13 of which are EU currencies, with weights based on each country's relative importance to UK trade in manufactures in 1989-1991 (with weights also capturing third country effects).

[15] In the benchmark results, a fixed lag order is one used since Phillips et al. (2015a) show that the high orders of lags generate a size distortion in the test statistic that increases with sample size, but that is minimised when using fixed lag lengths. The judgements reached based on such specifications for the USD:NZD based on zero lags, as well as specifications selected using a Bayesian information criterion, are similar.

[16] The initial window needs to be large enough to ensure that the actual sampling distribution is not too different from its asymptotic distribution (reducing the risk of comparing the statistics to incorrect critical values for the first runs of the test), while not being so large that short-lived bubbles early in the sample are not detected. Phillips et al. (2014a) suggest that the starting window size should be inversely proportional to the sample size, and propose the following size rule: $r_0 = 0.01 + \frac{1.8}{\sqrt{T}}$.

[17] Phillips et al. (2015b) suggest using $L_t = \delta\frac{log(T)}{T}$ to determine the minimum period to use, with the scaling factor δ depending on the frequency of the data in case the user wishes to impose a minimum of one year, for example (see Phillips et al. 2015a).

USD:CHF cross-rates.

Table 1 also summarises the characteristics of explosive periods in each currency pair for days of explosive 'expansions' and 'collapses', respectively. Explosive periods are 'expansions' ('crashes') if the mean of the exchange rate is higher (lower) over the explosive period than at the start. As all cross rates are quoted relative to one USD, an increase represents a depreciation relative to the USD. Expansions are therefor associated with an increase in the value of the USD, while crashes are associated with an increase in the quote currency. For G11 currencies overall, explosive appreciations are more common than explosive depreciations. With the exception of the CAD, JPY, NOK and SEK, the other seven cross-rates have more explosive episodes in which the quote currency appreciates than explosive episodes where it depreciates. The USD:CHF currency pair experienced the highest proportion of explosive periods involving quote currency depreciation, while the USD:JPY experienced the highest proportion of appreciation episodes. Explosive periods lasted longer on average for crashes than for expansions. Such periods were longest overall on average in the USD:AUD cross-rate. This reflects two very long periods of explosiveness: 44 days beginning 6 May 2003 and 79 days beginning on 10 November 2003. The USD:NZD pair has the largest number of individual explosive episodes, although these have a shorter duration than some other cross-rates.

These tests identify days during which a series changes from a random walk process to one with an explosive root. As such, it would be interesting to assess the speed and magnitude of reversion back to random walk behaviour. Unfortunately, the test statistics from the test applied in this paper are not directly related to the size of the explosive period. To compare the characteristics of periods of explosiveness, Table 1 shows actual changes in the exchange rate start-to-peak and start-to-trough for each identified period of explosiveness. Most explosive periods themselves are associated with relatively small changes in currency levels: usually only single digits in percentage points between the emergence of explosiveness to its peak/trough. These are also followed by rapid bounce-backs in the currency over the days that followed, and the magnitude of adjustments are not particularly large either.[18] On average across the G11 currencies, quote currency depreciations

[18] In contrast, for monthly data for G10 currencies, Hu and Oxley (2017, *forthcoming*) find explosive periods where some currencies collapse without recovering. They argue that this motivates the use of a specification without an intercept to exclude such episodes, although the asymptotic properties of such an approach is not studied. In this paper, when an intercept is excluded from the specification used for the daily USD:NZD for example, results are similar to the benchmark results.

are larger during expansions than quote currency appreciations during crashes. Depreciations were especially large during late October 2008, when currencies like the NZD and AUD depreciated by almost 10 percent start-to-peak. On average, depreciations in the value of the EUR during explosive episodes are largest out of the G11 currencies at 4 percent, while the NZD appreciated the most on average during crashes in the USD:NZD pair, at 3.4 percent.

Another interesting question is whether rapid changes in exchange rates represent reversion back to levels implied by relative prices, changes in which could cause shifts in the mean level of real exchange rates over time. Although this paper does not explicitly address whether identified explosiveness forms part of mean reverting behaviour as such, the figures in Appendix B suggest that there are several explosive episodes that have followed periods where specific exchange rates have been far away from their sample mean.[19]

There is synchronicity in explosiveness across G11 exchange rates (Figure 1), particularly when distinguishing between expansion and crashing periods in different currency pairs (Tables 2 and 3 in the Appendix). While there does not appear to have been distinct changes in the frequency of explosive periods over time, there are several explosive periods that are common across the majority of cross-rates. For example, periods of explosiveness are clustered during September and October 2000 (all expansions), the first half of 2003 (all crashes), October 2008 (all expansions), June and July 2002 (all crashes) and the final months of 2014 to first few months of 2015 (all expansions).

[19] Although exchange rates are expressed here in nominal terms, they will be very highly correlated with real exchange rates at a high frequency such as daily.

Table 1
Characteristics of explosive periods by cross-rate (vs USD)

	NZD	**AUD**	**GBP**	**CAD**	**DKK**	**EUR**	**JPY**	**NOK**	**CHF**	**SEK**
Number of bubble episodes	43	33	22	37	36	32	39	30	25	32
Number of bubble days	302	295	128	328	351	347	258	307	184	314
Percentage of bubble days in sample (%)	7.2	7.1	3.1	7.9	8.4	8.3	6.6	7.3	4.4	7.5
Proportion of expansions	0.3	0.4	0.5	0.5	0.4	0.4	0.9	0.5	0.2	0.6
Average length expansions (days)	3.3	5.4	4.1	11.2	14.2	15.4	7.4	8.7	5.5	9.7
Average length -ve periods (days)	15.6	17.0	8.8	7.3	8.0	8.8	2.3	12.8	7.9	9.9
Expansions: avg actual % change (start-peak)	2.2	2.9	2.5	2.9	3.9	4.0	1.9	3.9	1.6	3.2
Expansions: avg actual % change (peak-end)	-1.7	-1.9	-1.5	-1.7	-1.7	-1.8	-1.1	-1.9	-2.5	-1.6
Crashes: avg actual % change (start-trough)	-3.4	-3.2	-2.1	-1.9	-1.9	-2.1	-0.9	-2.7	-2.4	-2.2
Crashes: avg actual % change (trough-end)	1.9	1.9	1.4	1.1	1.4	1.4	0.4	1.9	1.5	1.4

Note: The sample is 3 January 2000 to 13 July 2016. Percentage changes are based on actual currency values and not those of the transformed series being tested. Start and end values chosen as the day before- and day after identified explosive days. Test statistics are based on the PSY test with wild bootstrap critical values where the test specification includes 1 lag and critical values are simulated using 2000 iterations.

4.2 Tests applied to effective exchange rates

The existence of an expansion period in a given base currency generally implies a crash in the other currency in the pair (compare Figures 34 and 45).[20] To investigate which currency is responsible for a given cross-rate's explosive dynamics, this section compares tests for explosiveness to G11 base currencies and considers the dynamics of effective exchange rates, which measures the broad value of different currencies.

In line with Figure 1, there is significant concordance in the incidence of explosive dynamics across the base currencies considered here (Figure 2). Appendix A plots the individual results for the effective exchange rates of each G11 currency. For all currencies, an increase in the effective exchange rate index represents an appreciation and explosive expansions would be associated with an appreciation in the broad value of that currency. For several cross-rates, periods of explosiveness occurred simultaneously in the effective exchange rate of the quote currency.

The results suggest that many of the instances of explosiveness that identified in daily cross rates with the USD may have reflected changes in the broad value of the quote currencies. Figure 23 in the Appendix also suggests that most of the crashes in G11 cross-rates correspond to rapid increases in the broad value of the USD. For example, the crashes (associated with depreciation in quote rates) identified in all G11 currencies in the first quarter of 2015 in Figure 1 is mirrored in expansions in the effective USD (indicating an appreciation in its broad value). Instances of explosiveness in individual cross-rates not matched by explosiveness in the effective USD are relatively rare, suggesting that there are not many periods where G11 cross-rate explosiveness reflected country-specific factors. Examples of such episodes include the expansions in the AUD and NZD in late 2000, expansions in the CHF, DKK and EUR in May 2010, and crashes in the CHF in June and August 2011.[21]

[20] As discussed earlier, the test applied in this paper are robust to multiple episodes of expansion and collapse and are not overly sensitive to the way exchange rates are quoted.

[21] The large jumps in the effective measures of the DKK in May 2001 and June 2001 and CHF in January 2015 also occur in other measures such as the Barclay's real effective rate, and reflect developments in their EUR cross rates. While the USD:CHF cross rate is explosive during the period around the unpegging of the CHF to the EUR in January 2015, no explosiveness is identified in the effective value of the CHF, in spite of its dramatic appreciation.

Figure 1: Concordance of explosive periods in cross-rates

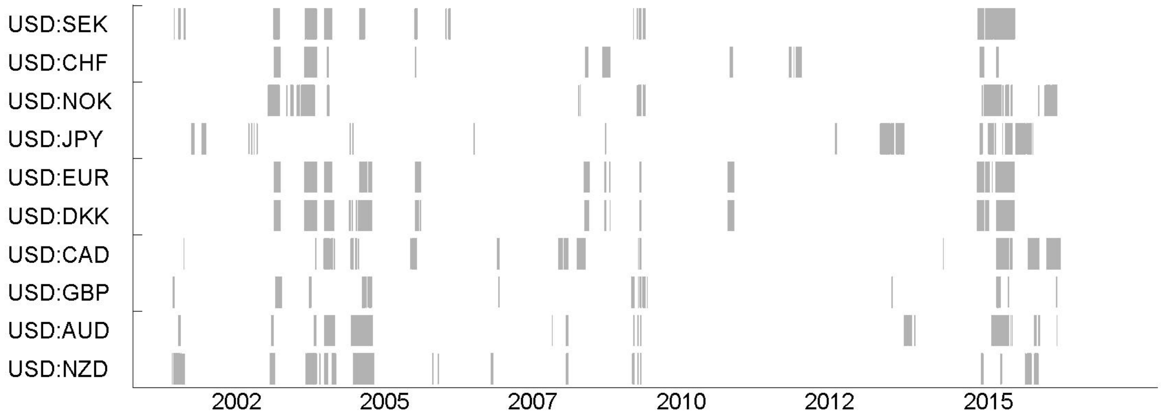
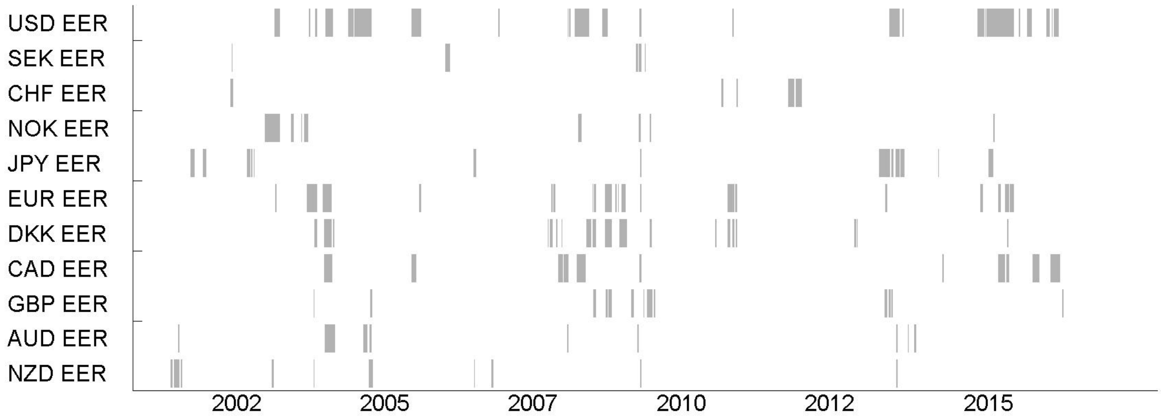


Figure 2: Concordance of explosive periods in effective rates



The focus of this paper is to document the occurrence of bouts of explosiveness in exchange rates. Determining the factors responsible for driving specific bouts of rapid exchange rate change is beyond the scope of this research. That said, to assess the possibility that expansions and collapses of explosive periods could reflect 'flight to safety' in currency markets during periods of high volatility or risk aversion, Appendix C compares cross-rate explosive episodes to the VIX index. Such episodes indeed appear to be synchronised to changes in the VIX. At least one G11 currency experiences an explosive period during each of the large spikes observed in the VIX.

5 Conclusion

To test for explosiveness in highly volatile series, this paper applies an equivalent of the PSY test based on wild-bootstrap critical values. Using a wild bootstrap is particularly important when applying tests for explosiveness to exchange rates since volatility of exchange rates tend to vary over time, especially when measured at high frequencies. Non-stationary volatility could cause a size distortion in unit root tests. The paper applies a wild bootstrap-based tests to a range of highly traded exchange rates over a long sample.

This paper finds that bouts of explosiveness in exchange rates are uncommon at a daily frequency. Periods of explosiveness tend last for several days but involve only small changes in currency levels. These also usually reverse shortly after. There is high concordance with explosiveness in the broad value of the US dollar exchange rate, suggesting that there are relatively few instances where explosiveness in individual cross-rates reflected country-specific factors. There is also evidence that explosive episodes in currency markets coincide with periods of high market volatility.

This paper is focused on identifying periods of explosiveness in G11 exchange rates at high frequency and over a long sample. Whether rapid exchange rate changes have been accompanied by explosive improvements in the macroeconomic fundamentals is left for future research. For the New Zealand dollar, for example, Steenkamp (2017) applies these tests to three models of exchange rate determination to test whether there have been periods when changes in the exchange rate have been disconnected from changes in relative economic fundamentals. Another area warranting research is understanding which factors are responsible for driving specific bouts of rapid exchange rate change. It would be useful, for example, to assess whether these represent adjustments following periods of exchange rate overvaluation, spikes in financial market risk, or shocks to relative fundamentals.

References

Bettendorf, T. and W. Chen (2013). Are there bubbles in the Sterling-dollar exchange rate? New evidence from sequential ADF tests. *Economics Letters 120*(2), 350–353.

Brooks, C. and A. Katsaris (2005). A three-regime model of speculative behaviour: Modelling the evolution of the s&p 500 composite index. *The Economic Journal 115*(505), 767–797.

Caspi, I. (2017 *forthcoming*). Rtadf: Testing for Bubbles with EViews. *Journal of Statistical Software*.

Cavaliere, G. and R. Taylor (2008). Bootstrap unit root tests for time series with nonstationary volatility. *Econometric Theory 24*(1), 43–71.

Etienne, X. L., S. H. Irwin, and P. Garcia (2014). Bubbles in food commodity markets: Four decades of evidence. *Journal of International Money and Finance 42*(1), 129–155.

Froot, K. A. and M. Obstfeld (1991, December). Intrinsic Bubbles: The Case of Stock Prices. *American Economic Review 81*(5), 1189–214.

Goncalves, S. and L. Kilian (2004, November). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics 123*(1), 89–120.

Harvey, D. I., S. J. Leybourne, R. Sollis, and A. R. Taylor (2015, September). Tests for explosive financial bubbles in the presence of nonstationary volatility. *Journal of Empirical Finance*.

Hu, Y. and L. Oxley (2017 *forthcoming*). Are there bubbles in exchange rates? Some new evidence from G10 and emerging market economies. *Economic Modelling*.

Jiang, C., Y. Wang, T. Chang, and C.-W. Su (2015). Are there bubbles in chinese rmb-dollar exchange rate? evidence from generalized sup adf tests. *Applied Economics 47*(56), 6120–6135.

Mammen, E. (1993, 03). Bootstrap and wild bootstrap for high dimensional linear models. *Ann. Statist. 21*(1), 255–285.

Milunovich, G., S.-P. Shi, and D. Tan (2016). Bubble detection and sector trading in real time. Technical report.

Pavlidis, E., I. Paya, and D. Peel (2012). A New Test for Rational Speculative Bubbles using Forward Exchange Rates: The Case of the Interwar German Hyperinflation. Technical report.

Pavlidis, E., A. Yusupova, I. Paya, D. Peel, E. Martínez-García, A. Mack, and V. Grossman (2015). Episodes of exuberance in housing markets: In search of the smoking gun. *The Journal of Real Estate Finance and Economics*, 1–31.

Phillips, P., S.-P. Shi, and J. Yu (2015a). Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500. *International Economic Review 56*, 1043–1078.

Phillips, P. C. and S.-P. Shi (2017 *forthcoming*). Financial Bubble Implosion and Reverse Regression. *Econometric Theory*.

Phillips, P. C., S.-P. Shi, and J. Yu (2014a, October). Supplement to Two Papers on Multiple Bubbles. Technical report.

Phillips, P. C., S.-P. Shi, and J. Yu (2015b). Testing for Multiple Bubbles: Limit Theory of Real Time Detectors. *International Economic Review 56*, 1079–1134.

Phillips, P. C. B., S. Shi, and J. Yu (2014b, 06). Specification Sensitivity in Right-Tailed Unit Root Testing for Explosive Behaviour. *Oxford Bulletin of Economics and Statistics 76*(3), 315–333.

Phillips, P. C. B., Y. Wu, and J. Yu (2011). Explosive behavior in the 1990s nasdaq: When did exuberance escalate asset values? *International Economic Review 52*, 201–226.

Schaller, H. and S. V. Norden (1997). Regime switching in stock market returns. *Applied Financial Economics 7*(2), 177–191.

Shi, S.-P. (2013). Specification sensitivities in the markov-switching unit root test for bubbles. *Empirical Economics 45*(2), 697–713.

Shiller, R. J. (2005). *Irrational Exuberance: (Second Edition)*. Princeton University Press.

Steenkamp, D. (2017). How bubbly is the New Zealand dollar? Reserve Bank of New Zealand Discussion Paper.

Xu, K.-L. (2008). Bootstrapping autoregression under non-stationary volatility. *Econometrics Journal 11*(1), 1–26.

Appendix A Tests to cross rates and effective exchange rates

Figure 3: USD:NZD (log)

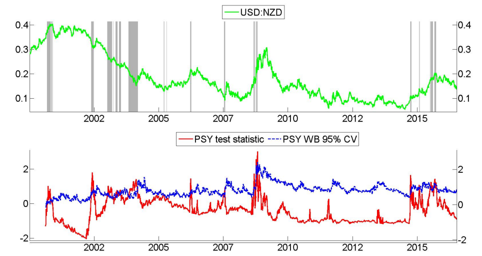


Figure 4: Effective NZD (log)

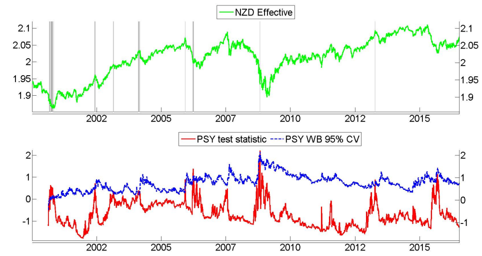


Figure 5: USD:AUD (log)

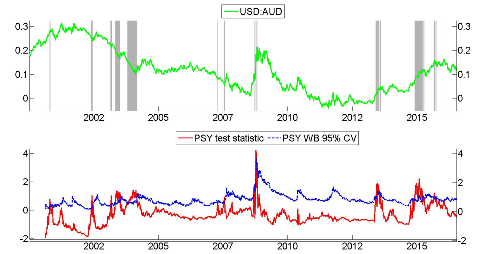


Figure 6: Effective AUD (log)

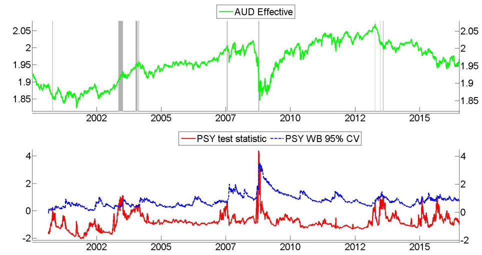


Figure 7: USD:GBP (log)

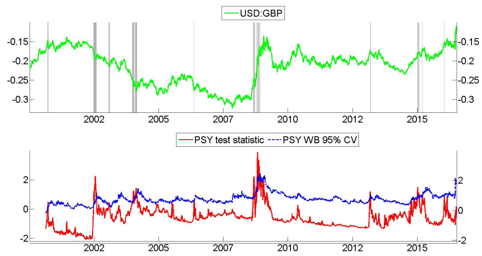


Figure 8: Effective GBP (log)

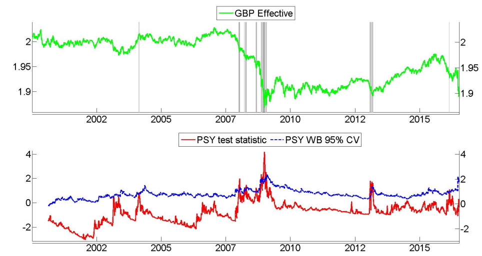


Figure 9: USD:CAD (log)

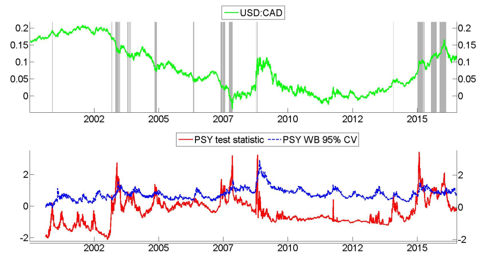


Figure 10: Effective CAD (log)

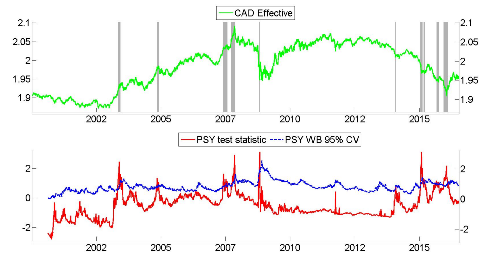


Figure 11: USD:DKK (log)

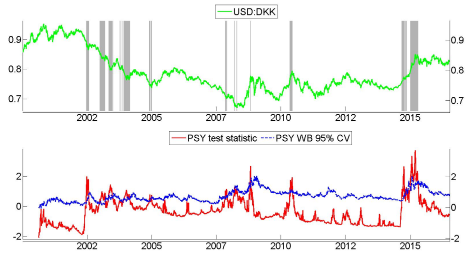


Figure 12: Effective DKK (log)

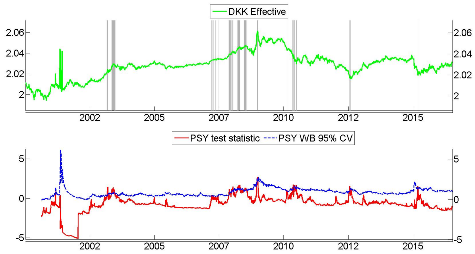


Figure 13: USD:EUR (log)

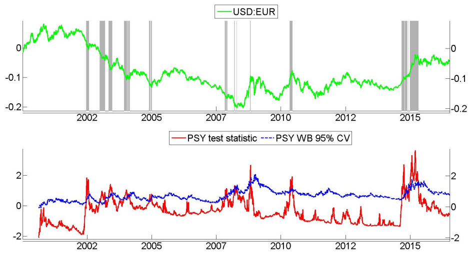


Figure 14: Effective EUR (log)

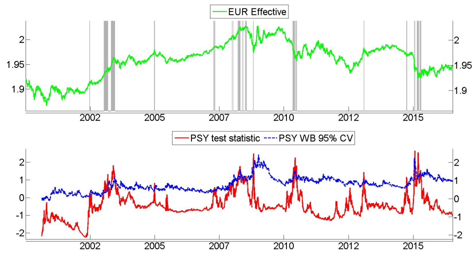


Figure 15: USD:JPY (log)

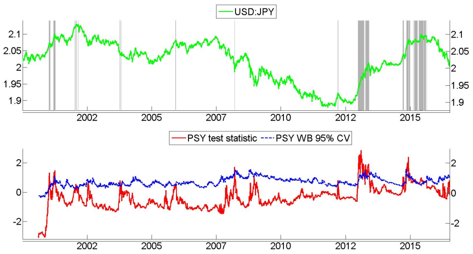


Figure 16: Effective JPY (log)

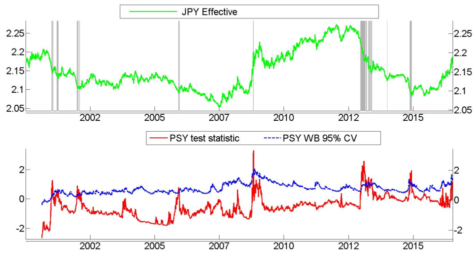


Figure 17: USD:NOK (log)

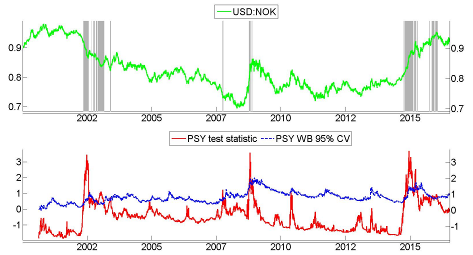


Figure 18: Effective NOK (log)

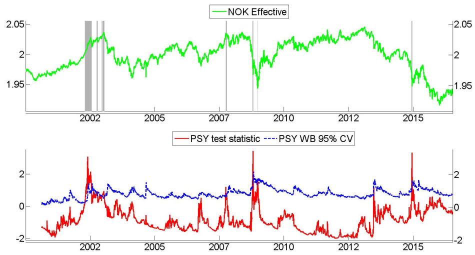


Figure 19: USD:CHF (log)

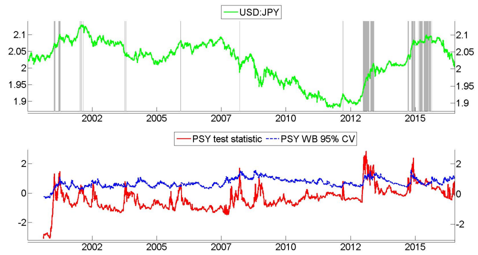


Figure 20: Effective CHF (log)

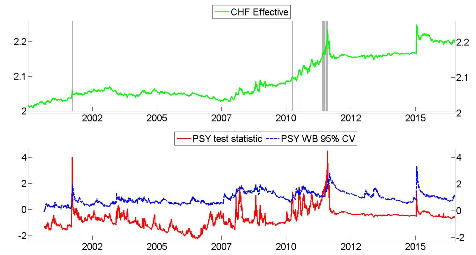


Figure 21: USD:SEK (log)

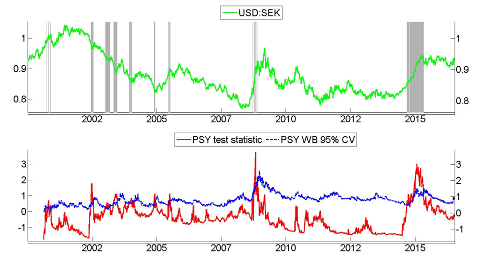


Figure 22: Effective SEK (log)

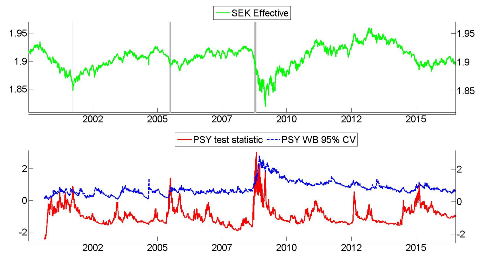
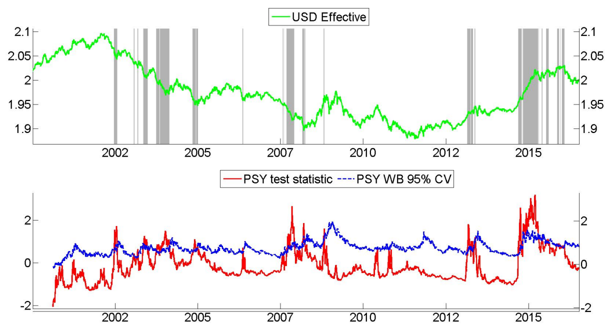


Figure 23: USD Effective exchange rate (log)



Note: Results based on a specification with 1 lag.

Table 2
Incidence of explosive periods by year and cross-rate: Expansions (vs USD)

	NZD	**AUD**	**GBP**	**CAD**	**DKK**	**EUR**	**JPY**	**NOK**	**CHF**	**SEK**
2000	38	6	6	2						14
2001							25			
2002							7			
2003										
2004										
2005							4			8
2006	6									
2007										
2008	14	8	32	7	5	5		18		16
2009										
2010					22	23			8	
2011										
2012							3			
2013		25	4				88			
2014	7				38	44	35	1	16	55
2015	34	85	15	111	77	82	82	131	9	92
2016		1	1	48				16		
Sum	99	125	58	168	142	154	244	166	33	185

Note: The sample is 3 January 2000 to 13 July 2016. Test statistics are based on the PSY test with wild bootstrap critical values where the test specification includes 1 lag and critical values are simulated using 2000 iterations.

Table 3

Incidence of explosive periods by year and cross-rate: Crashes (vs USD)

	NZD	**AUD**	**GBP**	**CAD**	**DKK**	**EUR**	**JPY**	**NOK**	**CHF**	**SEK**
2000										
2001										
2002	21	10	29		29	29		72	30	24
2003	80	68	10	54	98	85	6	66	48	81
2004	88	79	30	18	61	54			5	24
2005	5									
2006			1	10						
2007	9	11		74	15	19		3	14	
2008					6	6	2		24	
2009										
2010										
2011									30	
2012										
2013										
2014				1						
2015		2		3			6			
2016										
Sum	203	170	70	160	209	193	14	141	151	129

Note: The sample is 3 January 2000 to 13 July 2016. Test statistics are based on the PSY test with wild bootstrap critical values where the test specification includes 1 lag and critical values are simulated using 2000 iterations.

Appendix B Concordance between deviations from sample mean and explosive periods

Figure 24: USD:NZD (log)

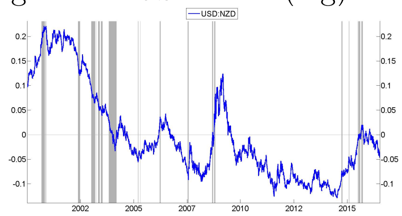


Figure 25: USD:AUD (log)

Figure 26: USD:GBP (log)

Figure 27: USD:CAD (log)

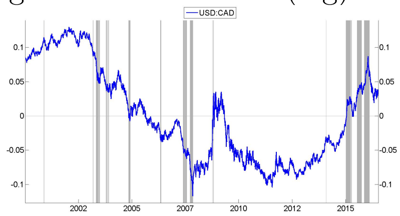


Figure 28: USD:DKK (log)

Figure 29: USD:EUR (log)

Figure 30: USD:JPY (log)

Figure 31: USD:NOK (log)

Figure 32: USD:CHF (log)

Figure 33: USD:SEK (log)

Note: Shaded bars represent explosive periods for each currency and blue line is the deviation from sample mean.

Appendix C Concordance between explosive dates in currencies and VIX

Figure 34: USD:NZD

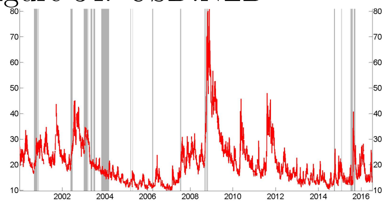


Figure 35: USD:AUD

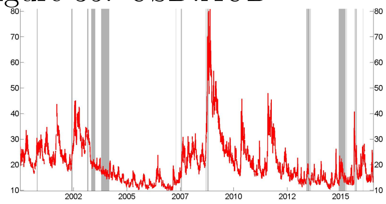


Figure 36: USD:GBP

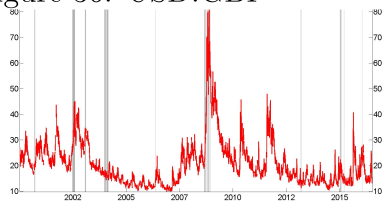


Figure 37: USD:CAD

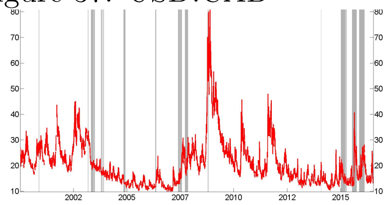


Figure 38: USD:DKK

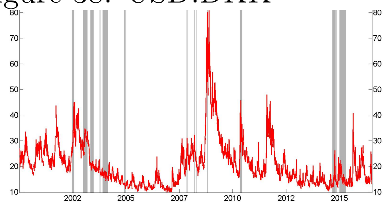


Figure 39: USD:EUR

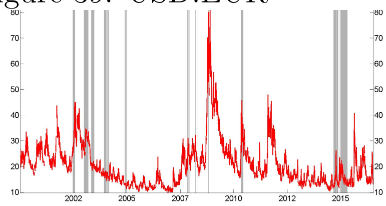


Figure 40: USD:JPY

Figure 41: USD:NOK

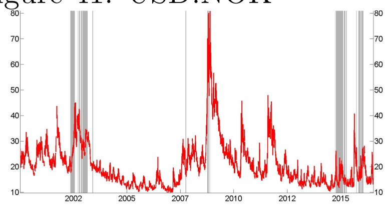


Figure 42: USD:CHF

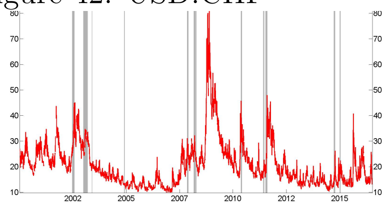


Figure 43: USD:SEK

Note: Shaded bars represent explosive periods for each currency and VIX in red.

Appendix D Additional Figures

Figure 44: Volatility of daily exchange rates

Residuals from ADF test for USD:NZD

Coefficient of variation

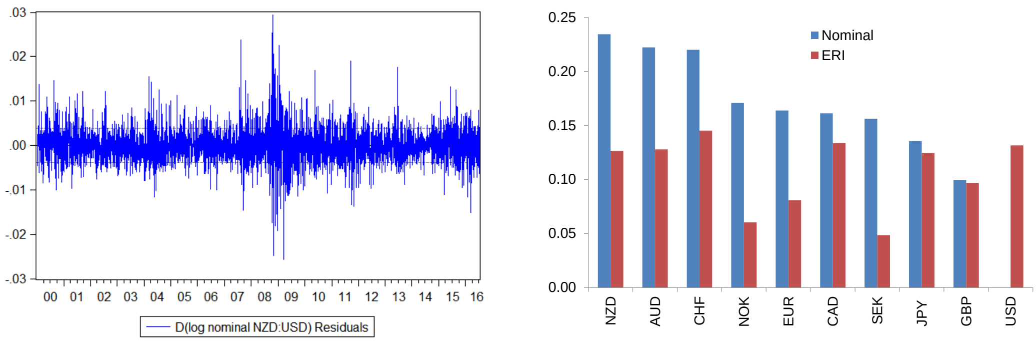
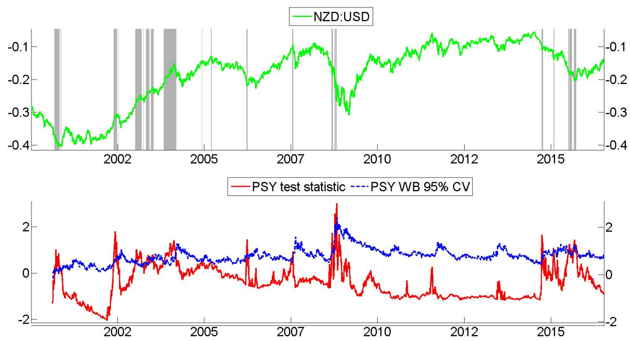


Figure 45: Implication of quotation



Note: Results based on PSY test with wild bootstrap, 1 lag and 2000 iterations.