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An Analysis of the Relationship Between Sovereign Credit Default Swaps, National Stock Indices, and Interest Rate Differentials with Respect to Exchange Rate

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Abstract

The goal of this study is to observe the relationship between sovereign credit default swaps (CDS), national stock indices (Index), interest rate differentials (INTDIF) and foreign exchange rates. The study uses weekly data of five currencies, the Australian Dollar (AUD), Brazilian Real (BRL), Mexican Peso (MXN), Japanese Yen (JPY), and British Pound (GBP), in terms of the US Dollar (USD), each country's 5-year CDS contracts, a stock index representative of each nation's stock market, and a short-term interest rate differential between the home country and the United States, from January 2007 through December 2011.

Similar to the existing literature, we find data supporting the fact that sovereign CDS, national stock indices, and interest rate differentials can help explain exchange rates. With the help of the Stata statistical software program, we run a multiple regression model for each country, with the three independent (explanatory) variables being CDS, Index, and INTDIF, and the dependent variable being the exchange rate. The first multiple regression test we run is an ordinary least squares regression. We then test for autocorrelation using the Durbin-Watson test, and when needed retest the significance level using first differencing. In conclusion, we find significant t-test and f-test statistics indicating that our models do indeed help explain exchange rates.

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I. Introduction and Literature Review

Early in 2007, the implosion of the US subprime mortgage crisis would develop into a worldwide credit crisis, sending global financial markets into panic. During this time, global currency markets experienced unparalleled swings as market participants ran to unwind massive carry trade[1] positions, and seek safety. Theoretically, there are expectations of what certain economic or financial variables should be able to tell us about the strength of an economy and thus its currency. However, given the dynamic nature of the financial markets over the past five years, it is important to see how these variables actually moved and if they really can tell us something about exchange rates. In this paper, we have selected a few variables that we believe should give us an idea of the strength and climate of a given economy and thus the health of its exchange rate. The three explanatory variables that we will look at are sovereign credit default swaps (CDS), stock market indices, and interest rate differentials. Through a series of regression analyses we hope to find statistical significance in the ability of these three explanatory variables to explain exchange rates.

Before diving into the various models' and hypothesis, it is important to establish a clear understanding of each explanatory variable. According to the International Swaps and Derivatives Association (ISDA) a credit default swap (CDS) is, "a bilateral agreement designed explicitly to shift credit risk between two parties. In a CDS, one party (protection buyer) pays a periodic fee to another party (protection seller) in return for compensation for default (or similar credit event) by a reference entity" (About The CDS Market, 2009). Figure 1 provides a visual representation of the aforementioned swap (How Credit Default Swaps Work, 2009).

[1] Currency carry-trade: a strategy in which an investor borrows the currency of a country whose interest rate is low (i.e. short the currency) and invests in the currency of a country whose interest rate is high (i.e. long the currency), thus profiting from the interest rate differential of the two countries.

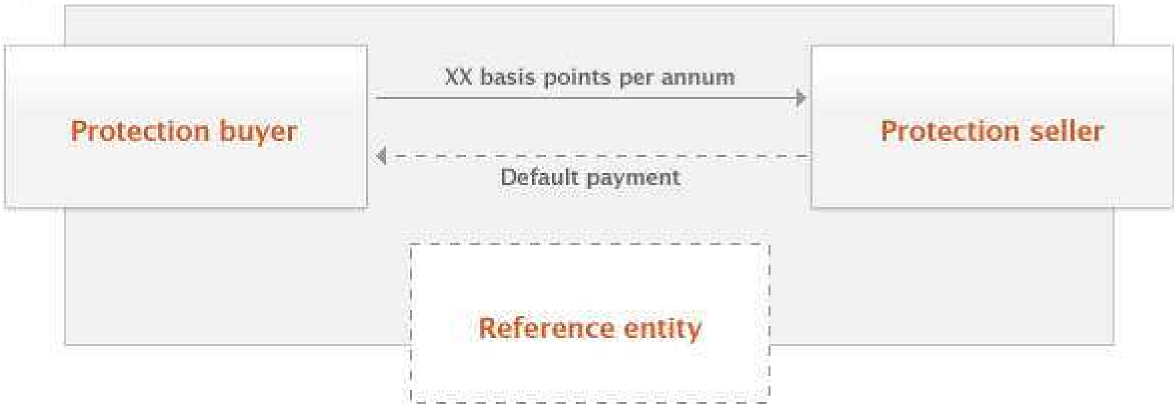

Figure 1: How Credit Default Swaps Work

Credit default swaps were first written in the early 1990s as a means for financial institutions to hedge and diversify their credit risks. In theory, credit default swaps strengthen the financial system and offer unique economic value by enabling participants to transfer credit risk. For example, by entering into a CDS contract banks can pass on credit risks to other risk takers, thus freeing up more capital to be available for financing. Similarly, CDS contracts strengthen the financial system by spreading risk throughout the entire system, preventing large concentrations of risk that may occur otherwise. Lastly, CDS serve as a gauge of credit market conditions, allowing banks and policymakers to monitor the health of the financial system (Key CDS Facts, 2009).

Later on however, the CDS market began to experience additional growth from investors looking for a low-cost means of taking on credit exposure. Over the years, this caused the CDS market to grow substantially, making credit risk highly liquid. As reported by the ISDA, the notional amount[2] of CDS grew from $918.9 billion in 2001 to a peak of $62.2 trillion during the height of the financial crisis. Much of this increase in notional CDS volume was due to naked

[2] Notional: for CDS, notional amount refers to the par amount of credit protection bought or sold, equivalent to debt or bond amounts, and is used to derive the premium payment calculations for each payment period and the recovery amounts in the event of a default.

credit default swaps[3], which were estimated to make up almost 80% of the CDS market in 2009 (Harrington, 2009).

In lieu of the financial crisis and ensuing global sovereign debt crisis, naked credit default swaps have been a subject of controversy amongst regulators and market participants. While, it is evident that naked CDS provide liquidity to the credit risk markets, some critics including hedge-fund billionaire George Soros view them as vile financial instruments that allow speculators to bet against companies and countries (Kirchfeld, 2010). More recently, European officials have backed these claims, blaming naked CDS buyers on making the Greek debt crisis worse (Jacobs, 2010).

With an understanding of credit default swaps and their role within financial markets, we can now begin to understand what they can tell us about the underlying institutions which they help provide insurance for. Because a CDS is essentially an insurance contract on an outstanding debt instrument, the higher the likelihood of default of the underlying institution the more expensive it is to insure through the use of a CDS contract. Therefore, CDS spreads for institutions will widen when the market detects deterioration of credit risk and tighten when the market perceives less credit risk. For this reason, a widening of sovereign CDS would implicate that the market perceives that a country is experiencing increasing risk. Regardless of whether this risk is stemming from economic or political instability, its currency should decline to reflect the perception or reality of increasing risk. Because of this, we believe that sovereign CDS should, to some extent, help explain exchange rates.

[3] Naked credit default swaps: in a naked credit default swap, the buyer does not own the underlying debt.

While the goal of our study is not to prove whether our explanatory variables can predict exchange rates, there is some existing literature that delves into this. The hypothesis as posed in the small but existing literature, Zhang, 2010, states that the health of the credit market, as measured by CDS, can predict currency values because the currency value of a country will experience a decline as investments take a flight to safety in other countries if credit risks in the country are perceived to be rising (Gaiyan Zhang, 2010). Zhang's study used daily data of four currencies (Japanese Yen (JPY), Euro (EUR), British Pound (GBP) and Australian Dollar (AUD)) in terms of the US Dollar (USD), and JPY, USD, GBP and AUD in terms of the EUR from January 2004 to February 2008 to examine the lead-lag relationship between the CDS market and the currency market. Zhang used the North American investment-grade (IG) and high-yield (HY) corporate CDS indices as indicators of the CDS market.

Through the use of a Vector Auto-regressive (VAR) analysis[4] Zhang's results indicated significant Granger-causality[5] effects coming from changes in both the North American Investment Grade (IG) and High Yield (HY) CDS indices to changes in the JPY, EUR and AUD exchange rates in terms of the USD. However, significant Granger-causality was only found in the AUD in terms of the EUR. More practically, Zhang's study helped uncover the fact that changes in CDS index spreads can give light to important carry-trade information on some currencies, but not others. Furthermore, this lead-lag relationship between CDS and currency markets is stronger during periods of credit deterioration, like the one experienced during the recent financial crisis, as investors will unwind their carry-trade positions in the face of extreme risk and volatility. Lastly, Zhang concluded that because of the policy coordination in interest

[4] Vector auto-regression (VAR): a statistical model used to capture the linear interdependencies among multiple time series.

[5] Granger-causality: a statistical concept of causality in which it is determined if one time series is useful in forecasting another.

rates among similar countries (like the US and the UK), carry trades are less likely to occur in similar economies. Therefore, the lead-lag relationship between CDS and currency markets is more likely to hold true between dissimilar economies which offer larger carry trade opportunities due to increased interest rate arbitrage.

A second study in the existing literature, Carr and Wu (2007) found strong contemporaneous correlation between sovereign CDS spreads and the implied volatility of currency options for Mexico and Brazil (Peter Carr, 2007). With regards to the general behavior of exchange rates, there have been several studies which support the belief that exchange rates are in fact predictable as opposed to unpredictable as maintained by the random walk hypothesis[6]. Most recently, Killian and Taylor's tests provided strong empirical evidence against the random walk model at currency predictability horizons of 2 to 3 years (Lutz Kilian, 2003). Again, while the goal of our study is not to prove whether our explanatory variables can be used to predict exchange rate movements, it aims to answer a similar but more basic question: how well does our model explain exchange rates.

The second explanatory variable that we incorporate into our model is a stock market index. We believe that taking an index representative of the equity market for each of the country's whose currency we analyze, will also help explain the exchange rate. The rationale behind this is that it is expected that a higher equity market index level is associated with a stronger domestic economy and thus a stronger exchange rate. Similarly, in his study Zhang points out that a higher equity market index should be associated with tighter CDS spreads due to the lower default probability of firms (Gaiyan Zhang, 2010). Another study done by Liu,

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[6] Random-walk hypothesis: the theory that stock price changes have the same distribution and are independent of each other; therefore past stock price or market movements or trends cannot be used to predict future movements.

Margaritis, and Tourani-Rad, found that equity indexes, especially the Dow Jones Industrial Average, plays an important role in determining the Yen cross rates for the most popular carry-trade currencies, i.e. NZD/JPY, AUD/JPY and GBP/JPY (Ming-Hua Liu, 2012). More specifically, they found that long-term changes in equity indices have more influence on exchange rates than the implied volatility (VIX) index. While we will not be analyzing the JPY cross rates that Liu, Margaritis, and Tourani-Rad, used in their study, we hope to find similar findings in that exchange rates can in fact help explain exchange rates.

Our third explanatory variable is the short-term interest rate differential between each country and the United States. As a proxy for short-term interest rates, we have used the equivalent of a 3-month T-bill from each country. In calculating each differential, we have subtracted the 3-month rate for a US T-bill from the 3-month rate of each country, thus giving us a positive or negative number representing the difference in yields. A positive number means that a country has higher short-term interest rates than the U.S., while a negative number implies that the country has lower short-term interest rates than the U.S. Theoretically, it is expected that interest rate differential is negatively related to the value of the foreign currency against the USD, because the currency of a country with a lower relative nominal interest rate is expected to appreciate according to the International Fisher Effect[7]. However, as outlined by Zhang, the inverse of this relationship can also be true because a greater interest rate differential could also imply a higher real risk-free interest rate, thus representing a more attractive investment opportunity and attracting more foreign capital inflows (Gaiyan Zhang, 2010). Because of this,

[7] International Fisher Effect: an economic theory that states that an expected change in the current exchange rate between any two currencies is approximately equivalent to the difference between the two countries' nominal interest rates for that time – Investopedia.com.

while we do expect that interest rate differentials will indeed help explain exchange rates, we are not entirely sure whether the relationship will be positive or negative.

Historically, interest rate differentials have played a significant role within the global currency markets through the use of the carry trade investing strategy. As explained previously, in a typical carry trade investors borrow the currency of a country whose interest rate is low (i.e. short the currency) and invests in the currency of a country whose interest rate is high (i.e. long the currency), thus profiting from the interest rate differential of the two countries. This form of riskless arbitrage became popular over the last decade as some countries like Japan exhibited extraordinarily low interest rates while others held interest rates substantially higher.

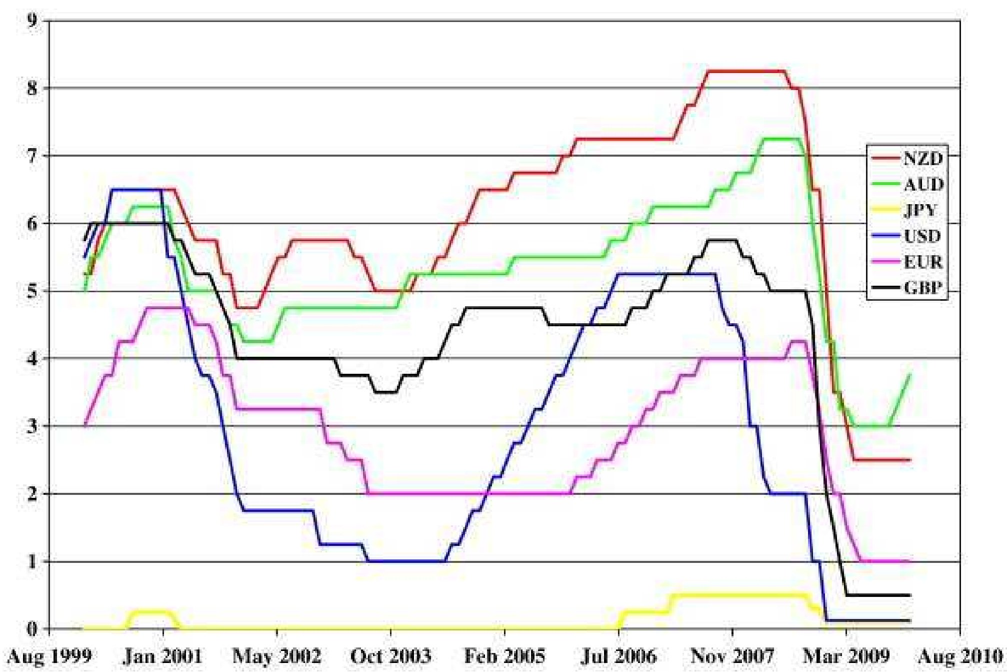

Figure 2: Official interest rates of major currencies **(Ming-Hua Liu, 2012)**

As we can see from Figure 2, the interest rate differential between Japan and New Zealand was as high as eight percent at times, making Japan the ideal funding currency for the carry trade. Not only this, but during this time frame, investors were also benefiting from the appreciation of other currencies (like the USD) versus the JPY. An August 2007 article from MoneyWeek put it quite simply, “Anyone borrowing for next to nothing in yen and putting the money into US Treasuries (US government bonds) has received a double pay-off: from an interest rate difference of more than three percentage points and from the dollar’s rise against the yen” (Stuart, 2007). However as monetary authorities pushed for a normalizing of interest rates worldwide, and Japan began to return to steady growth during the first half of 2007, suddenly an end to Japan’s zero interest rate policy seemed evident. As the global financial crisis worsened, Yen-carry traders rushed to unwind their positions, and the JPY appreciated while other currencies, like the NZD and AUD tanked.

As previously mentioned, in theory, according to the International Fisher Effect (IFE), and uncovered interest parity (UIP), the currency with higher interest rate is expected to depreciate against the one with the lower interest rate. However, in reality, as is seen through the success of the carry trade, the opposite tends to occur. This violation of the UIP as coined by Engle (1996) and Froot & Thaler (1990) is known as the forward premium puzzle (Froot & Thaler, 1990) and (Engel, 1996). Regardless of the whether interest rate differentials exhibit a positive or negative relationship with exchange rates, we hope to prove that they are a statistically significant variable that can help explain exchange rates

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II. Thesis

Using a series of multiple regression models we arrive at results that indicate that sovereign CDS, stock market indices and interest rate differentials do in fact help explain exchange rates. We measure the strength of our models by looking at various statistical measures including t-test and f-test[8] statistics, r-squares, and root mean square errors (RMSE).

III. Methodology (Materials and Methods)

This study looks at five countries, Australia, Brazil, Mexico, Japan, and Great Britain. All data used in the study is weekly and was compiled from Bloomberg for the time period beginning in January 2007 through December of 2012[9]. For the sovereign CDS explanatory variable, we use the 5-year CDS tranche because they are the most liquid in the CDS market (John Hull, 2004). For the stock market index explanatory variable, we use the ASX 200 Index (ASX 200) for Australia, the Bovespa Stock Exchange Index (IBOV) for Brazil, the Mexican IPC (Indice de Precios y Cotizaciones) Index (MEXBOL), the Nikkei-225 Index (NIKKEI 225) for Japan, and the FTSE 100 Index (FTSE 100) for Great Britain.

This study uses a multiple regression model to investigate the relationship between sovereign CDS, domestic equity markets, and interest rate differentials, with respect to exchange rates. The general multiple regression model is (Carter Hill, 1997):

$$Y_t = \beta_1 + \beta_2 (CDS)_t + \beta_3(Index)_t + \beta_4(INTDIF)_t + e_t$$

Before we state our null and alternative hypothesis, it is important to ensure we understand some standard assumptions about the probability distribution of the random errors, e_t. They are:

1. $E[e_t] = 0$. Each random error has a probability distribution with zero mean. Some errors will be positive, some will be negative, and over a large number

[8] F-test: used to test for the overall significance of the regression model.

[9] Note: for Great Britain, there was insufficient data until August of 2008. Similarly, the data for some countries was quoted less frequently than others.

of observations they will average out to zero. In other words we are stating that our model is correct on average

2. var(e_t) = σ^2. Each random error has a probability distribution with variance σ^2. The variance σ^2 is an unknown parameter and it measures the uncertainty in the statistical model. Errors with this property are said to be homoskedastic.
3. cov(e_t, e_s) = 0. The covariance between the two random errors corresponding to any two different observations is zero. Therefore, any pair of errors is uncorrelated.
4. We will sometimes further assume that the random errors e_t have normal probability distributions. That is, $e_t \sim N(0, \sigma^2)$

Similarly, because each observation of the dependent variable y_t depends on the random error term of e_t, each y_t is also a random variable. The statistical properties of y_t are similar to those of e_t. They are:

1. $E(y_t) = \beta_1 + \beta_2(CDS)_t + \beta_3(Index)_t + \beta_4(INTDIF)_t$. This assumption means that the expected (average) value of y_t depends on the values of the explanatory variables and the unknown parameters.
2. var(y_t) = var(e_t) = σ^2. This assumption means that the variance of the probability distribution of y_t does not change with each observation.
3. cov(y_t, y_s) = cov(e_t, e_s) = 0. This assumption means that any two observations on the dependent variable are uncorrelated.
4. We will sometimes assume that the values of y_t are normally distributed about their mean. That is, $y_t \sim [(\beta_1 + \beta_2(CDS)_t + \beta_3(Index)_t + \beta_4(INTDIF)_t), \sigma_2]$

In addition to the above assumptions about the error term (e_t) and the dependent variable (y_t), we must make two assumptions about the explanatory variables. The first is that they are not random variables, meaning that the values of the explanatory variables are known to us prior to observing the values of the dependent variable. The second assumption is that any one of the explanatory variables is not an exact linear function of any of the others.

To examine whether we have a viable explanatory model, we set up the following null and alternative hypotheses.

Null hypotheses H_0: $\beta_2 = 0$, $\beta_3 = 0$, $\beta_4 = 0$

Alternative hypotheses H_1: at least one of the β's is nonzero

In carrying out our statistical analysis we use Stata, a general purpose statistical software package. Having loaded the data onto Stata, we run an ordinary least square (OLS) regression. The OLS regression is a classical linear regression model that minimizes the sum of the squared residuals.

OLS minimizes $\sum e_t^2$

The residual, e, is the difference between the actual Y (the exchange rate) and the predicted Y. In other words, OLS calculates the slope coefficients so that the difference between the predicted Y and the actual Y is minimized. The residuals are squared in order to facilitate the comparison of negative errors to positive errors.

After calculating the OLS for all of the data we run a Durbin-Watson test in order to test for autocorrelation. Because we are dealing with time-series data, it is important to check for autocorrelation. While number three under the assumptions about the probability distribution of the random errors, found above, states that any pair of error terms will be uncorrelated, many times this is violated when using time series data. This is because when using time series data many times the variables under consideration follow a natural ordering through time, meaning that there is always the possibility that successive errors will be correlated with each other. For example, let's take one of our independent variables, CDS. Let's say that we are looking at Mexico 5Y CDS. If S&P decides to downgrade Mexico's credit rating one day, then naturally Mexico's 5Y CDS will increase on that day. However, this increase will not disappear the next day; most likely it will continue to affect the value of Mexico's CDS for an extended period of time. This carryover will be related too, or correlated with, the effects of the earlier shock, in this case the credit downgrade. When circumstances like these arise, leading to correlated error terms, we say that autocorrelation exists. The problem with autocorrelation is that it can lead us to misleading t-test, f-test, root means square errors (RMSE), and standard errors (se).

The Durbin-Watson test is a common way to test for autocorrelation, also known as serial correlation. The d-statistic is measured on a scale of 0 to 4, with 2 indicating no autocorrelation. Values less than 1 indicate that there is positive autocorrelation, while values greater than 3 indicate that there exists negative autocorrelation. Although positive autocorrelation does not affect the consistency of the estimated regression coefficients, it does affect our ability to conduct valid statistical tests, and therefore to accept or reject our null hypothesis. On one hand, the f-statistic may be inflated because the mean squared error (MSE) will tend to underestimate error variance. Secondly, positive autocorrelation typically causes the OLS standard errors to underestimate the true standard errors; in other words it may lead us to compute artificially small standard errors. In turn, these small standard errors will cause the t-statistic to be inflated, demonstrating that there is significance when there may not be. Lastly, an inflated t-statistic may in turn lead us to incorrectly reject the null hypotheses. On the other hand, negative autocorrelation, implies that a positive error for one observation increases the chance of a negative error for another observation and a negative error for one observation increases the chances of a positive error for another.

After reading the results of the Durbin-Watson test we then analyze each countries d-statistic to see if autocorrelation is a significant problem. In the case that autocorrelation exists we then use first differencing to retest the significance of the multiple regression model. First differencing is a method used to help eliminate autocorrelation. After running the first differencing command on Stata, we then run another Durbin-Watson test to see if autocorrelation has been eliminated. We find that most of all the autocorrelation has been eliminated. Using the first differencing output, we then compare the calculated value of the f-test statistic to the critical value from the f-distribution to test the overall significance of the regression model. If the value of the f-test statistic is greater than the critical value of the f-distribution then we can reject the null hypothesis and accept the alternative hypothesis, thus concluding that our model helps explain exchange rate movements. Similarly, we can then use the first differencing output, to compare the calculated value of the t-test statistic for each explanatory variable to the critical value from the t-distribution. If the absolute value of the calculated t-test statistic is greater than the critical value, then we can conclude that that particular independent variable helps the overall significance of the model. However, if the calculated t-statistic demonstrates that a given independent variable does not help explain the overall significance of the model, we can remove the variable and attempt to run the regression again. Lastly, in presenting our final results we use the root mean square error (RMSE) given to us by the first differencing output

IV. Results and Discussion

We created and ran six distinct models, one for each country or zone, to test whether sovereign CDS, national stock indexes, and interest rate differentials can form a viable model to explain exchange rates. We compare all t-test and f-test statistics to the critical values needed for a 95 percent confidence interval.

The first multiple regression model that we run is for Australia; Stata output results can be found at Appendix A[10]. Looking at the results we can note a few things. Looking at the OLS regression we can see that the f-test statistic which measures the overall fit of the model indicates that the model is statistically significant. When we look at the t-statistics for our explanatory variables we find that all of our independent variables, except for x2 (Index), are statistically significant. While this should seem to indicate that x2 adds no value to the model, and thus we should remove it, we must first test for autocorrelation to see if our test statistics are indeed accurate. By running the Durbin-Watson test we received a value 0.050722, thus indicating significantly strong positive autocorrelation. As mentioned previously, because autocorrelation can lead us to false conclusions we must remove the autocorrelation by using first differencing to retest the significance of the model. After running the first differences in Stata we arrived at results indicating that both f- and t-statistics were statistically significant, thus we can reject the null hypothesis and accept the alternative hypothesis.

The importance of removing autocorrelation by running a first differences test is shown here as we arrive at conclusions different from those found in our original OLS regression. While originally our t-statistics had indicated that x2 (INDEX) had no true importance in our model, after using least differencing, we found that it actually did add value to our model. Similarly, we can see that autocorrelation had been artificially inflating our f-test statistic, our r-squared, and

[10] All future results discussed can be found in the Appendix.

our RMSE. Lastly, in order to confirm that our least differencing model removed enough autocorrelation, we ran another Durbin-Watson test. Our d-statistic of 2.251766 indicates that enough autocorrelation was removed in order to validate our results.

We can also make a few observations from looking at the coefficients of our regression model for Australia:

$Y_{AUD/USD}$ =	- 0.0007339	+ 0.0009381(CDS)	- 0.2126136 (Index)	- 0.0875643 (INTDIF)
t-statistic:	-0.46	3.51	-4.29	-2.40

By looking at these coefficients we can say that Australia 5Y CDS is positively related to the AUD/USD exchange rate, while the ASX 200 (Index) and INTDIF are negatively related to the AUD/USD exchange rate. If we compare this to the initial assumptions we had made about the relationship that each independent variable should exhibit with respect to the exchange rate we can notice the following. Initially, we had stated that all else equal, an increase in a country's CDS should lead to a depreciation in the value of that country's currency. The positive CDS coefficient proves states just this: as CDS increases, the AUD/USD exchange rate increases, meaning that the AUD depreciates with respect to the USD. A graphical representation of these two variables over the tested time period can be seen in Figure 3, found below.

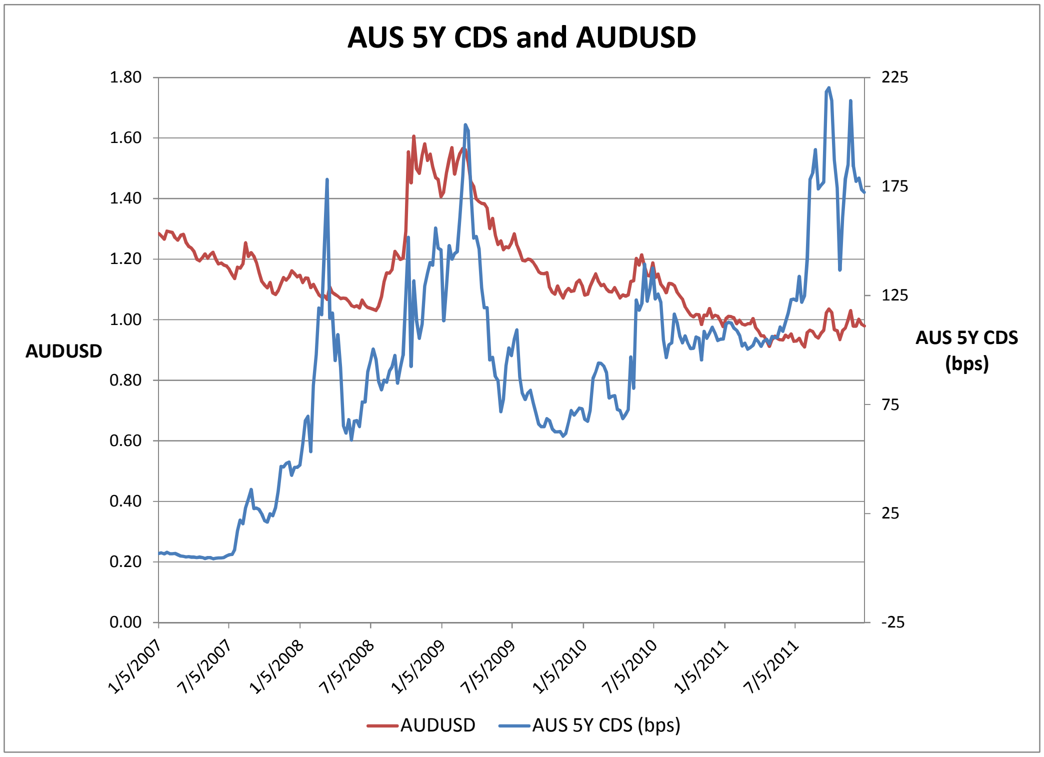

Figure 3: AUS 5Y CDS & AUDUSD

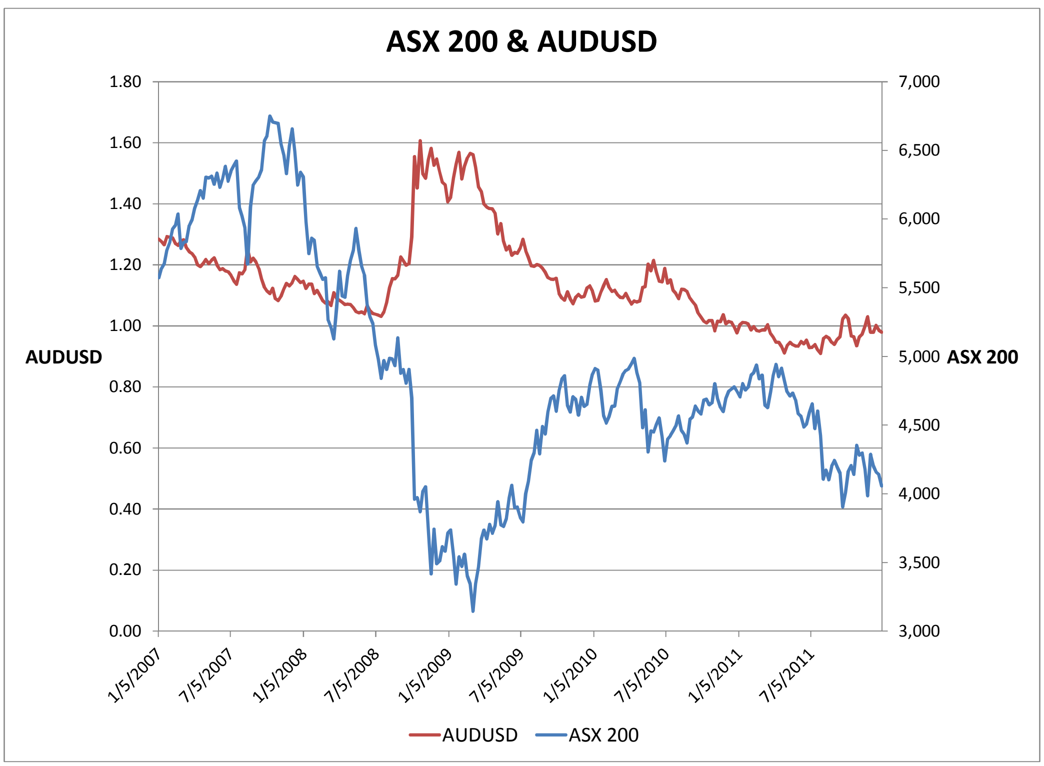

Figure 4: ASX 200 & AUDUSD

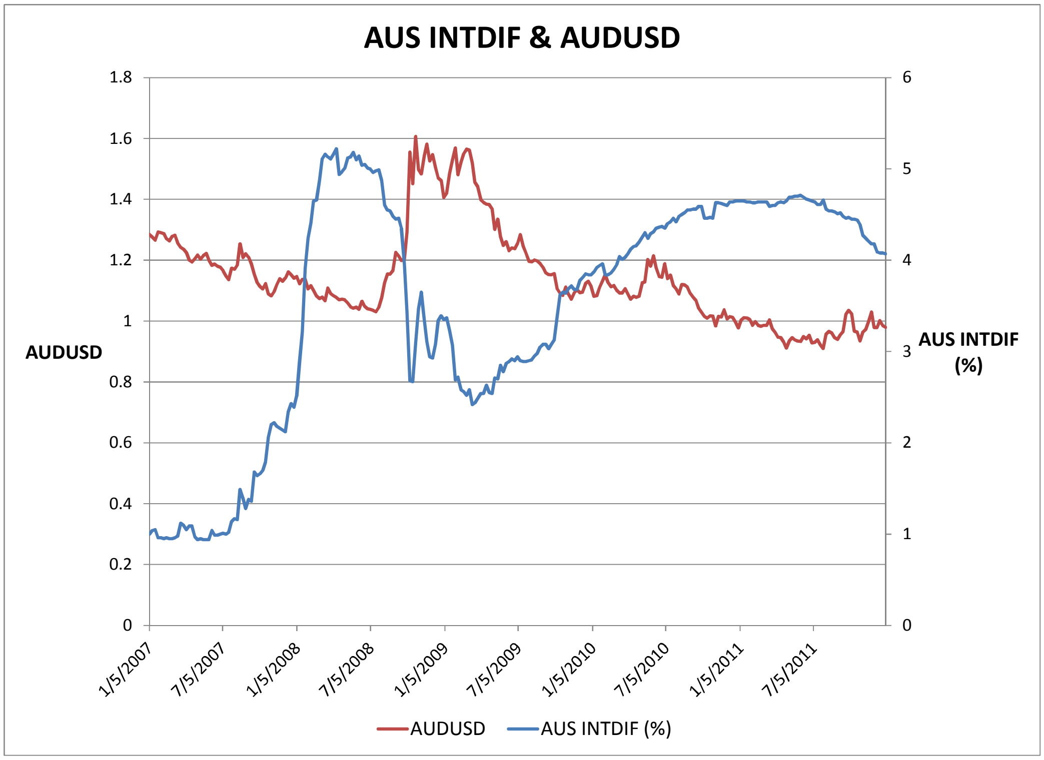

Figure 5: AUS INTDIF & AUDUSD

When we first made our assumptions about the relationship between stock indices and exchange rates we said that, all else equal, we should observe an positive relationship between the stock index of a country and the strength of that country's exchange rate. Looking at the coefficient for Australia Index, – 0.3096, we can see that this is true. As the Australia stock index, ASX 200, decreases the AUD/USD exchange rate increases; in other words the AUD depreciates versus the USD. A graphical representation of these two variables over the tested time period can be seen in Figure 4, found above.

The last pair that we need to analyze is that of the relationship between the interest rate differential and the exchange rate. Previously we mentioned that, theoretically, according to the International Fisher Effect, we should be able to observe an inverse relationship between the interest rate differential of a foreign country and the US and the value of that foreign country's currency versus the USD. However, we also mentioned that due to the effects of carry trades the observed relationship could actually be the opposite. The coefficient for Australia's INTDIF of -0.0875643 indicates that there is indeed an inverse relationship between the interest rate differential and the exchange rate. This means that as the interest rate differential between Australia's short-term (3-month) interest rate and that of the US's increases, the AUDUSD exchange rate decreases, implying that the AUD appreciates versus the USD. A graphical representation of these two variables over the tested time period can be seen in Figure 5, found above.

The second multiple regression model that we ran was for Brazil; Stata output results can be found in Appendix B. Looking at the results we can note a few things. First, the f-test statistic for the OLS regression model indicates that the model is statistically significant. Similarly to that of Australia's output, when we look at the t-statistics for our explanatory variables we find that all of our independent variables, except for x2 (Index), are statistically significant. As done with the Australia model we then tested for autocorrelation by running the Durbin-Watson test for which we received a value of 0.1847, indicating significantly strong positive autocorrelation. We then retested the significance using first differencing to minimize the effects of autocorrelation. Just like the case was for the Australia model, our first differences output indicated that both f- and t-statistics were statistically significant, thus we can reject the null hypothesis and accept the alternative hypothesis. In order to ensure that enough autocorrelation was removed from our model, we then ran the Durbin-Watson test again arriving at a d-statistic of 1.985338, indicating almost no correlation. Although our original OLS regression had indicated that our x2 (Index) variable had no true importance in our model, least differencing once again showed that it actually did add value to our model. We can also see how our original OLS regression had artificially inflated our f-test statistic, our r-squared, and our RMSE.

We can also make a few observations from looking at the coefficients of our regression model for Brazil:

$Y_{BRL/USD}$ =	-0.0009779	+ 0.0009646 (CDS)	-0.188445 (Index)	-0.0421293 (INTDIF)
t-statistic:	-0.48	5.76	-5.09	-2.93

By looking at the CDS coefficient we can say that CDS is positively related to the BRL/USD exchange rate. In other words, as Brazil 5Y CDS increases the BRL/USD exchange rate increases as well, meaning that the BRL depreciates versus the USD. This is in line with our initial assumptions. A graphical representation of these two variables over the tested time period can be seen in Figure 6, found below. The Index variable coefficient indicates that there is a negative relationship between the IBOV and the BRL/USD exchange rate. This is also in line with our expectations, because as the IBOV increases, the BRL/USD exchange rate decreases,

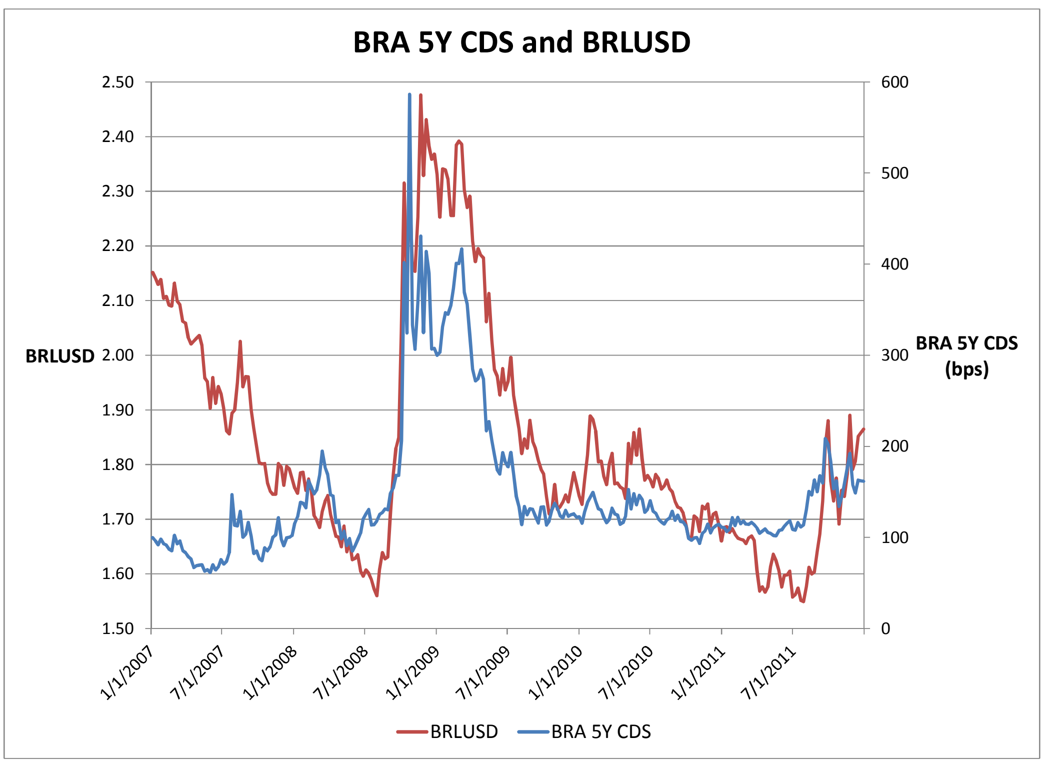

Figure 6: BRA 5Y CDS & BRLUSD

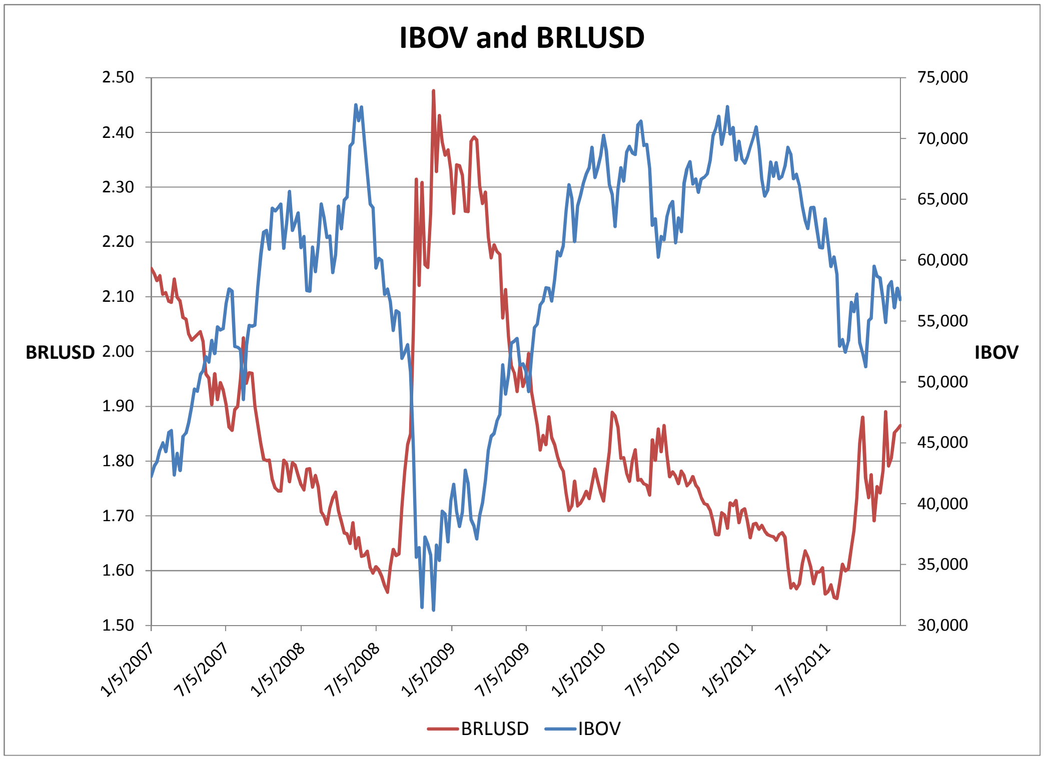

Figure 7: IBOV & BRLUSD

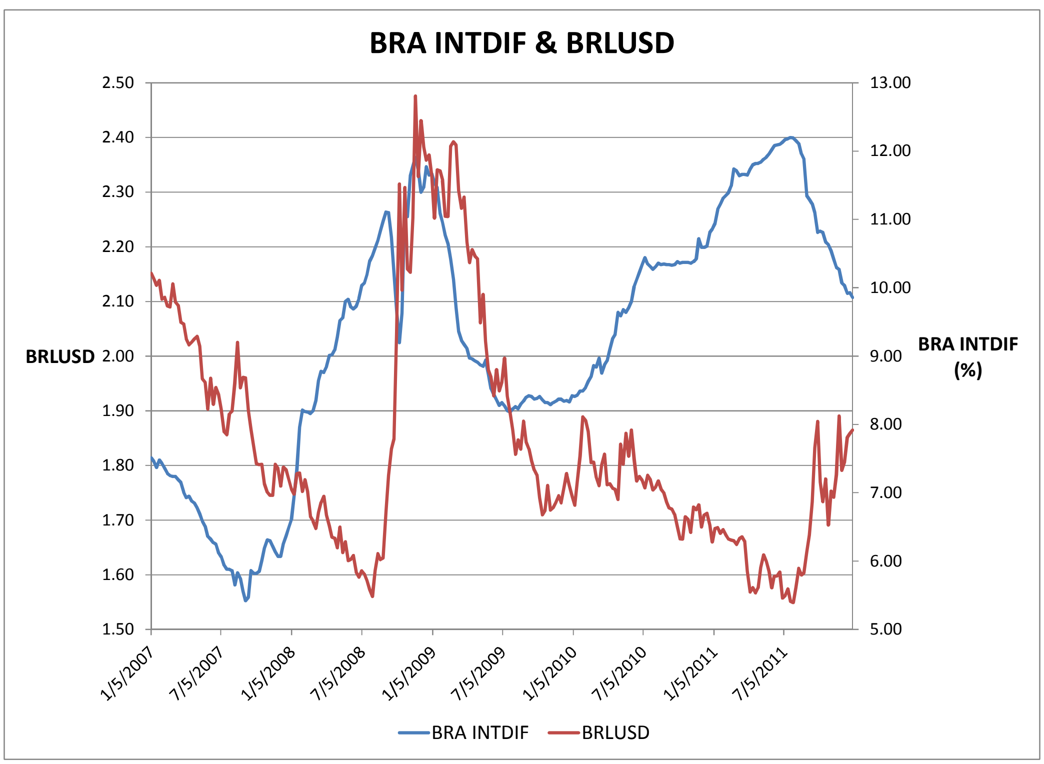

Figure 8: BRA INTDIF & BRLUSD

meaning that the BRL appreciates against the USD. We can observe how these two variables move with respect to one another over the tested time period in Figure 7, found above. Lastly, the coefficient for INTDIF indicates that there is an inverse relationship between the Brazilian INTDIF and the BRL/USD exchange rate. This implies that as the Brazilian INTDIF increases the BRL/USD decreases meaning that the BRL appreciates versus the USD. We can observe how these two variables move over the tested time period in Figure 8, found above.

The third multiple regression model that we run is for Mexico; Stata output results can be found in Appendix C. Looking at the results we can note a few things. According to the f-test statistic from the OLS regression, we can see that we have a viable explanatory model. However, we can see that the absolute values of the t-test statistics for both x2 (Index) and x3 (INTDIF) are not greater than the t-critical values. While at first this would seem to indicate that neither of these variables adds any value to our model, it is important to first test for autocorrelation. After running the Durbin-Watson test, we arrived to a d-statistic of 0.1015287, indicating strong positive autocorrelation. In order to correct for autocorrelation and thus retest the significance of our model we used first differencing. However, even after using first differencing we can see that the absolute values of the t-statistics for x2 and x3 are less than the t-critical values. Thus, this would seem to indicate that for the Mexico regression model, x2 (Index) and x3 (INTDIF) add no value to our model. However, overall we have a viable explanatory model as is seen through the f-statistic given from the least differences model. Similar to Australia and Brazil, we can see that the OLS regression model overstated our f-statistic, our r-squared, and our RMSE, as is expected. Finally, in order to ensure that enough autocorrelation was removed from our model we ran the Durbin-Watson test again, arriving at a d-statistic of 2.27671, indicating almost no correlation.

We can also make a few observations from looking at the coefficients of our regression model for Mexico:

$Y_{MXN/USD} =$	0.0111546	+ 0.0048371 (CDS)	+ 0.3722066 (Index)	- 0.1402256 (INTDIF)
t-statistic:	1.00	4.34	0.40	-1.49

By looking at the CDS coefficient we can say that CDS is positively related to the MXN/USD exchange rate. As explained various times earlier this is in line with our initial assumptions; as Mexico CDS increases the MXN depreciates versus the USD. A graphical representation of these two variables over the tested time period can be seen in Figure 9, found below. The positive Index variable coefficient implies that there is a positive relationship between the MEXBOL and the MXN/USD exchange rate. Much like in the case of Brazil, this is opposite to what we initially expected; as it indicates that as the MEXBOL increases the MXN depreciates versus the

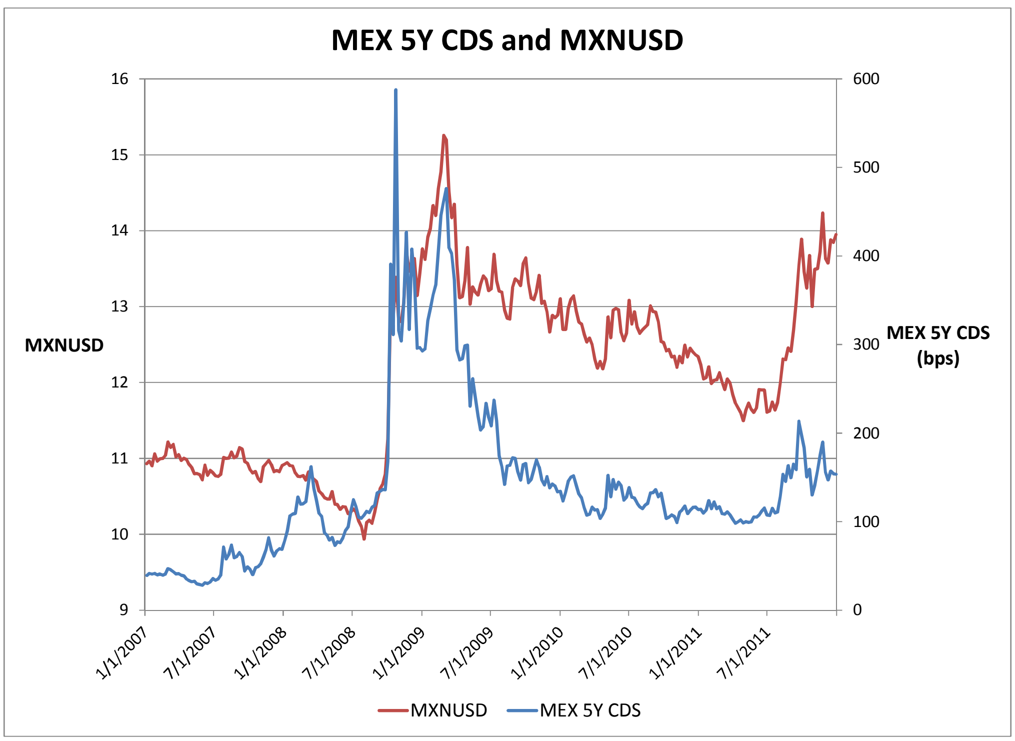

Figure 9: MEX 5Y CDS & MXNUSD

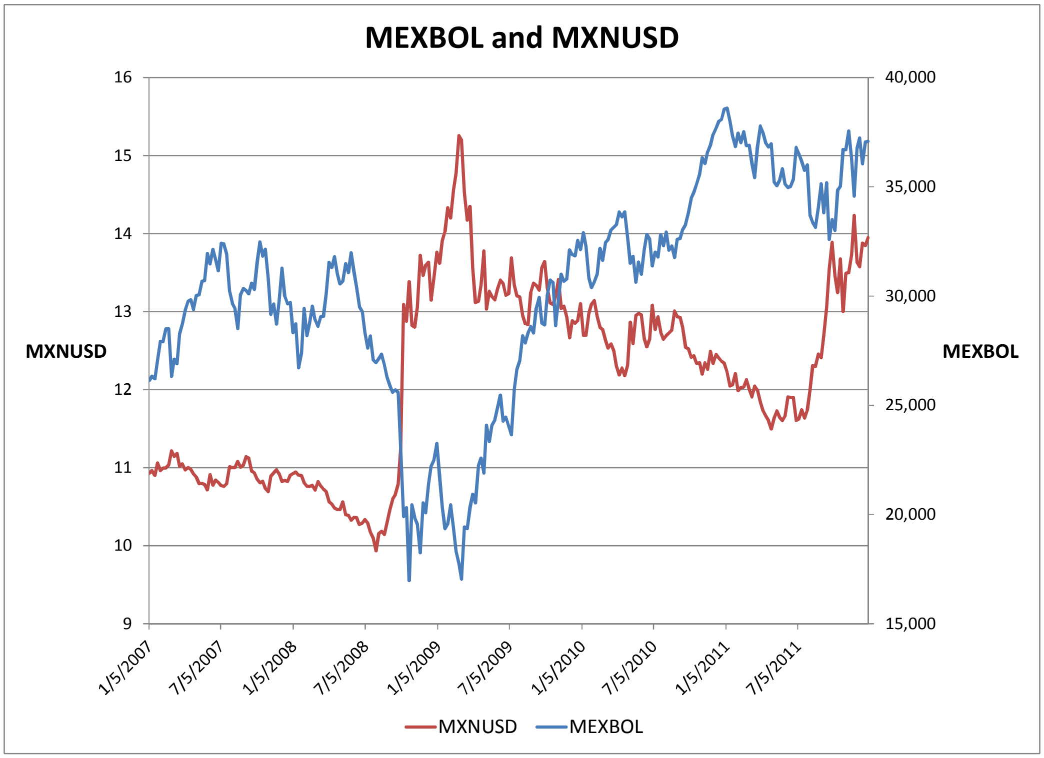

Figure 10: MEXBOL & MXNUSD

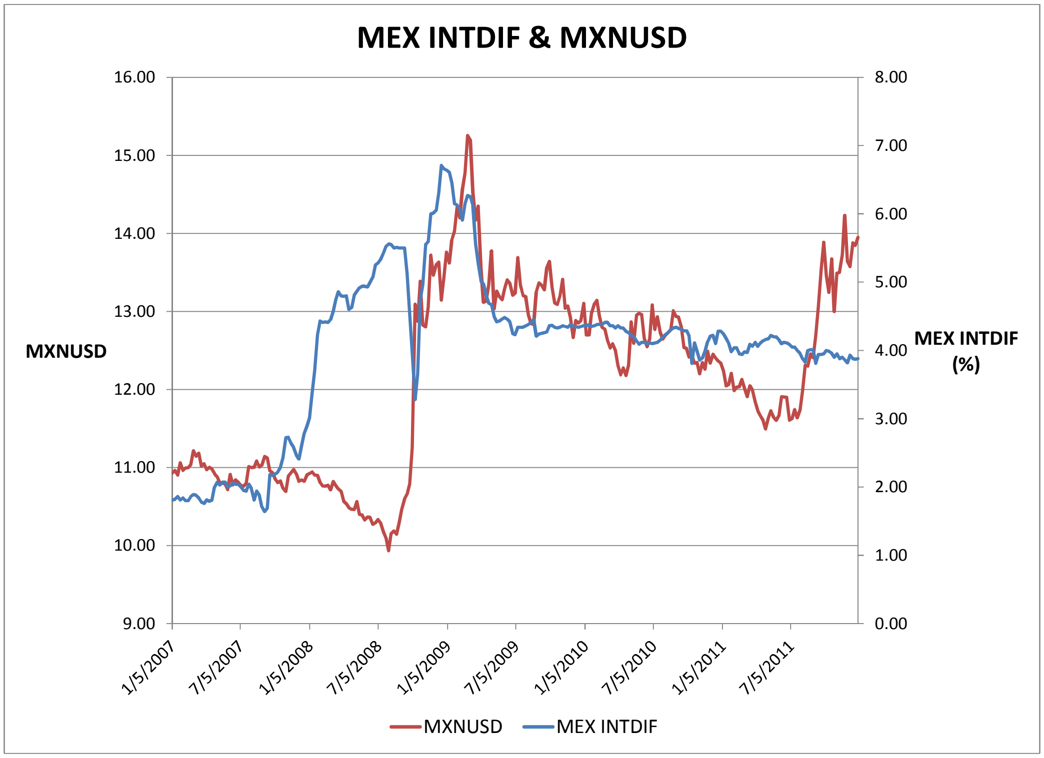

Figure 11: MEX INTDIF & MXNUSD

USD. We can see these two variables plotted over the tested time period in Figure 10 above. Lastly, the -0.1109 coefficient for INTDIF indicates that there is an inverse relationship between the Mexican INTDIF and the MXN/USD exchange rate. Much like the case for Brazil, this means that as the INTDIF for Mexico increases, the MXN/USD exchange rate decreases; in other words the MXN appreciates against the USD. These two variables can be observed in Figure 11, found above.

The fourth multiple regression model that we ran was for Japan; output data can be found in Appendix D. The output for the OLS regression indicates that all explanatory variables are statistically significant and that overall, we have a viable explanatory model. We can also see that our r-squared is significantly, high 0.9004; the highest for any of our OLS regressions. However, after running the Durbin-Watson test we realized that the data suffered from positive autocorrelation; d-statistic of 0.169168. Following our research methodology presented earlier, we then retested the significance of the model by using first differencing. After doing so we quickly realized that the majority of the model's fit was due to autocorrelation. Looking at the t-test statistics for our explanatory variables we realized that only x2 (Index) was larger than the t-critical value. This indicates that x1 (CDS) and x3 (INTDIF) for Japan, do not add value to our model. However, overall we still have a viable explanatory model as measured by the f-test statistic. Also, just like in all other regression models, we can see that the OLS regression model once again overstated our f-statistic, our r-squared, and our RMSE. Lastly, after rerunning the Durbin-Watson test on the first differencing output, we arrived at a d-statistic of 2.158158, indicating almost no autocorrelation.

The coefficients of our regression model for Japan can also help us draw some conclusions.

$$Y_{JPY/USD} = -0.1196342 \quad -0.206828\,(\text{CDS}) \quad +11.59272\,(\text{Index}) \quad -1.817079\,(\text{INTDIF})$$

t-statistic: -1.35 -1.25 5.38 -1.58

The CDS coefficient tells us that it is negatively related to the JPY/USD exchange rate. Thus, contrary to our expectations, as Japan CDS increases, the JPY appreciates versus the USD. We can see these two variables graphed over our tested time period in Figure 12 found below. The positive Index coefficient means that as the Japanese Index (Nikkei 225) increases the JPY depreciates against the USD. This is similar to the case of Brazil and Mexico where the opposite of the expected relationship is observed. Both of these variables can be observed in Figure 13. Lastly, the coefficient for INTDIF supports the notion that as INTDIF for Japan increase, the JPY/USD exchange rate decreases, implying that the JPY appreciates versus the USD. These two variables can be observed in figure 14 found below.

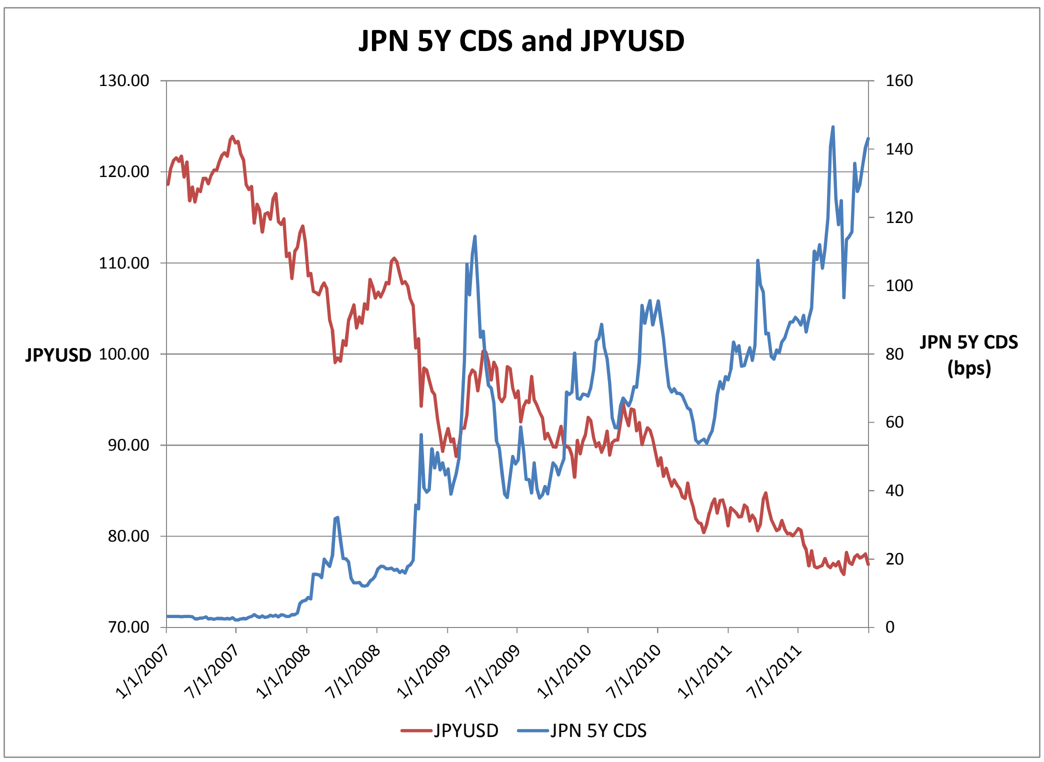

Figure 12: JPN 5Y CDS & JPYUSD

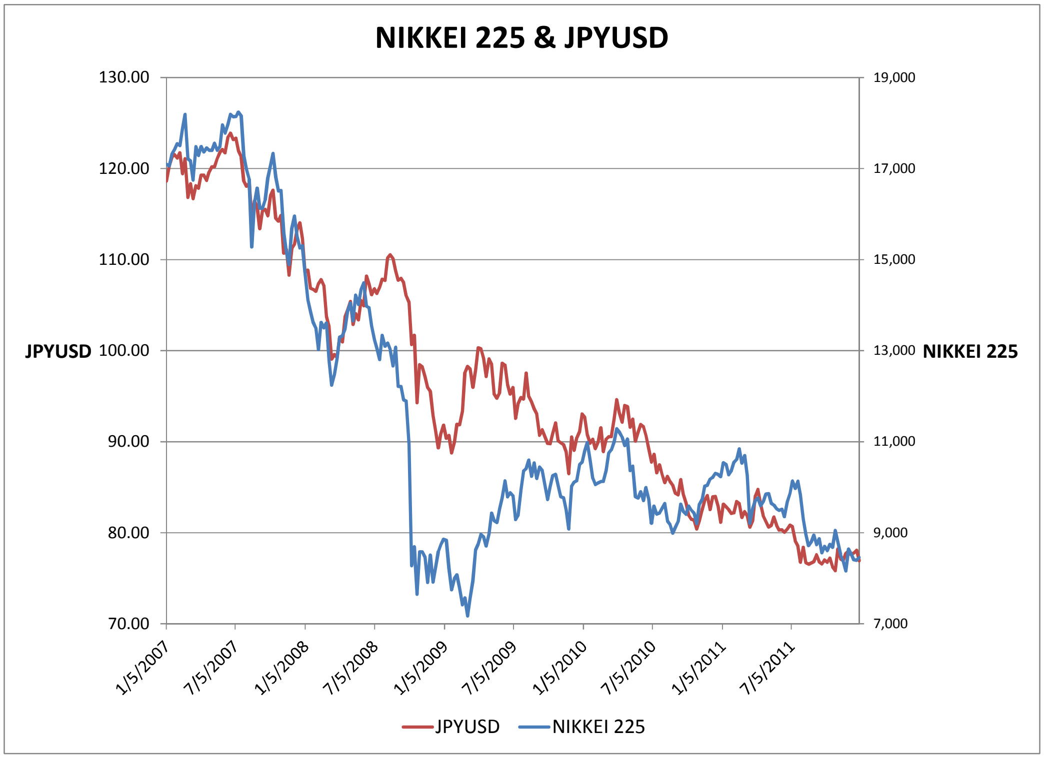

Figure 13: NIKKEI 225 & JPYUSD

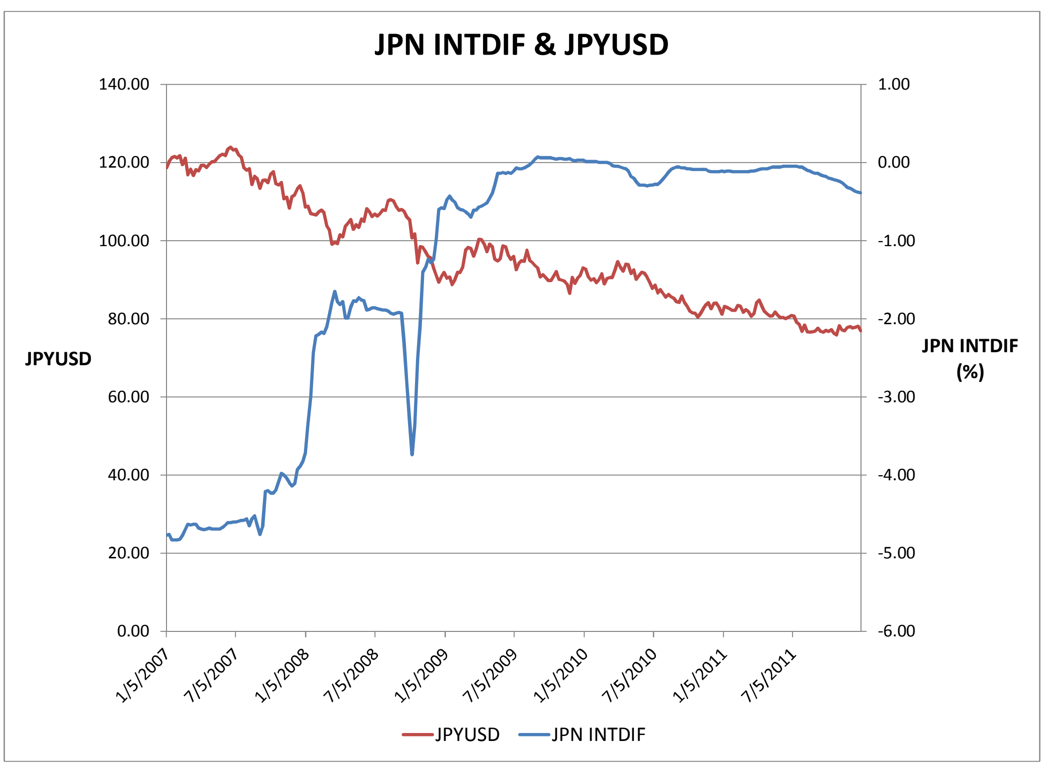

Figure 14: JPN INTDIF & JPYUSD

The final multiple regression model that we run is for the UK; Stata output results can be found in Appendix E. The OLS regression output indicates that we have a viable explanatory model given our f-test statistic. However, looking at the t-test values for our three explanatory variables, we can see that the value for x2 (Index) was not greater than the t-critical value. As we have mentioned in the analysis of all our other regression models, we must first test for autocorrelation in order to understand whether our results are truly indicative of our model. After running a Durbin-Watson test we found our model does suffer from positive autocorrelation; d-statistic of 0.3836621. As we have done in all other cases, we then retested the significance of our model using first differencing. Different from all other cases presented before, our first differencing output changed the significance of various explanatory variables. While according to our OLS regression output x2 did not add value to our model, after using first differencing we found that it actually did help our model. Secondly, while after our OLS regression we thought that x3 (INTDIF) helped our model, after using first differencing we found that this variable is actually redundant and provides no additional value to our model. Overall, our f-test statistic indicates that we have a viable explanatory model for GBP/USD exchange rate. Similar to all previous cases the OLS regression model overstated our f-statistic, r-squared, and RMSE. Lastly, to ensure that autocorrelation was removed from our model we ran the Durbin-Watson test again, arriving at a d-statistic of 2.093403, indicating almost no autocorrelation.

The coefficients of our regression model for the UK can also help us draw some conclusions.

$Y_{GBP/USD}$ =	0.0004612	+ 0.0003425 (CDS)	-0.0537683 (Index)	-0.0052177 (INTDIF)
t-statistic:	0.53	2.38	-2.71	-0.29

By looking at the CDS coefficient we can tell that UK 5Y CDS is positively related to the GBP/USD exchange rate. In other words, as UK CDS increases the GBP depreciates versus the USD as is expected. The relationship between these two variables over the tested time period can be seen in Figure 13 found below. Opposite to the CDS coefficient, the Index coefficient indicates that there is a negative relationship between the FTSE 100 (Index) and the GBP/USD exchange rate. This means that as the FTSE 100 increases, the GBP appreciates versus the USD, like we had expected. A graphical representation of these variables can be seen in Figure 14. The third explanatory variable, INTDIF indicates that there is an inverse relationship between UK INTDIF and the GBP/USD exchange rate. In other words as the UK INTDIF increases the GBP appreciates relative to the USD. This relationship can be observed in Figure 15 found below.

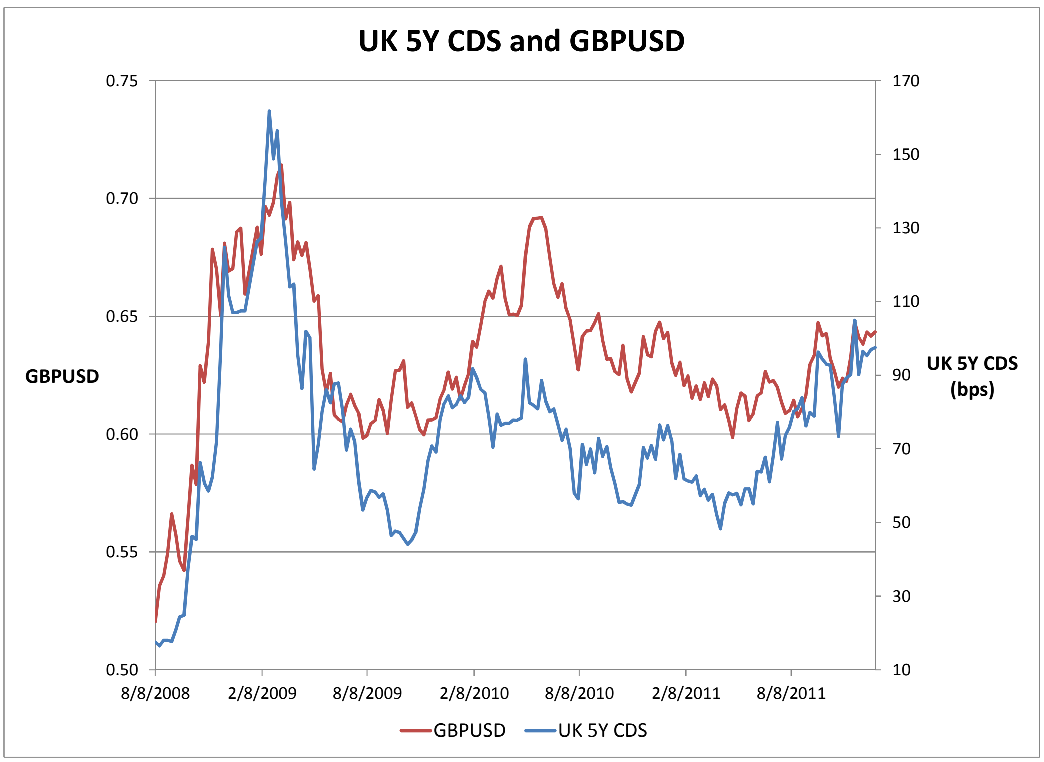

Figure 15: UK 5Y CDS & GBPUSD

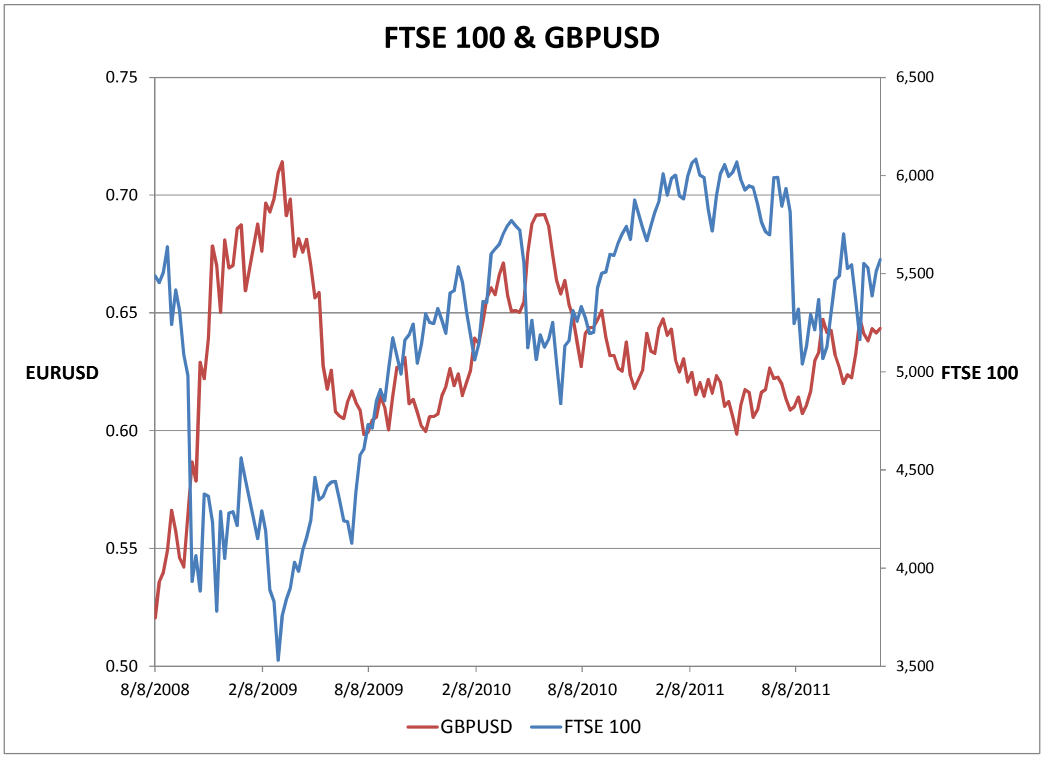

Figure 16: FTSE 100 & GBPUSD

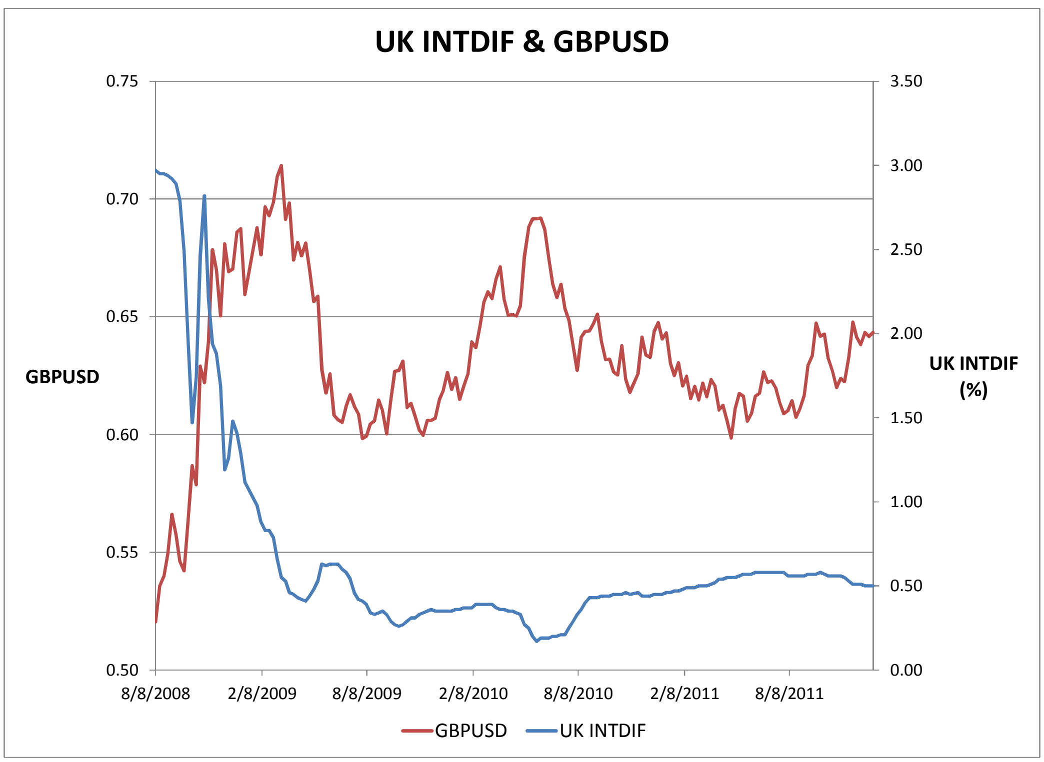

Figure 17: UK INTDIF & GBPUSD

V. Conclusions

After having run multiple regression models for Australia, Brazil, Mexico, Japan and the UK there are a few conclusions we can draw. First, we can accurately state that all of our models were viable and helped explain the exchange rate. However, even though the f-statistic values for all of our models were larger than the f-critical values, in many instances our explanatory variables' t-statistics were not larger than the t-critical values. Similarly, even when our explanatory variables were statistically significant, many times they exhibited opposite relationships with respect to the exchange rate than what we would have expected. For example, Japan's independent variables experienced the most unexpected relationships with respect to its exchange rate. One possible explanation for this could be due to the massive unwinding of JPY carry trades during the peak of the financial crisis.

Up until 2007, the JPY was the funding currency for the carry trade, due to Japan's near-zero interest rate policy. However, as Japan began to experience growth once again in early 2007, there came an end to monetary easing in Japan and rates began to hike upwards. As the Japan-US interest rate differential shrunk rapidly, desperate carry traders, who had borrowed Japanese funds, rushed into the market to repay their loans which were soaring in value. As more and more investors poured into the Japanese market to pay off their JPY denominated loans, the JPY skyrocketed in value versus the USD. Altogether, from the beginning of 2007 to the end of 2008, Japan 5Y CDS spiked from 3.25 to 44.5 bps, the Japan-US interest rate differential dropped from 4.5 percent to less than one percent, and the JPY appreciated about 23% versus the USD. While both the increase in CDS and decrease in interest rate differentials should in theory cause the home country's currency to depreciate all of these factors were negated by the amount of investors that were entering the Japanese market to exchange funds into JPY to repay JPY denominated loans, thus causing the JPY to appreciate against the USD. This is just one example of outside factors that can cause certain variables to move in unexpected ways. However, variables such as the ones observed in this study are determined by so many different factors that it is almost near impossible to determine their movements. However, in conclusion we can state that observing sovereign CDS, national stock indices, and interest rate differentials for the five countries observed in this study can indeed help explain exchange rates. A question to consider for future research is whether certain explanations like the JPY carry trade can serve as explanations for the unexpected relationships between our explanatory variables (CDS, Index, and INTDIF) and the exchange rate.

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VII. Appendix

Appendix A

Australia

y = AUD/USD x1 = Australia 5Y CDS x2 = ASX 200 x3 = INTDIF

Ordinary Least Squares (OLS)

```
Linear regression                                      Number of obs =     261
                                                       F(  3,   257) =   92.34
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4434
                                                       Root MSE      =  .11804
```

y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1	.0014798	.0002675	5.53	0.000	.000953	.0020065
x2	-.309629	.3486728	-0.89	0.375	-.9962485	.3769905
x3	-.1021499	.0075493	-13.53	0.000	-.1170162	-.0872835
_cons	1.367443	.0157945	86.58	0.000	1.33634	1.398547

```
Durbin-Watson d-statistic(  4,   261) =   .050722
```

First differences

```
Linear regression                                      Number of obs =     260
                                                       F(  3,   256) =   14.72
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.4177
                                                       Root MSE      =  .02491
```

D.y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1						
D1.	.0009381	.0002671	3.51	0.001	.0004121	.0014641
x2						
D1.	-.2126136	.0495147	-4.29	0.000	-.3101216	-.1151055
x3						
D1.	-.0875643	.0364478	-2.40	0.017	-.1593399	-.0157886
_cons	-.0007339	.0015953	-0.46	0.646	-.0038755	.0024076

```
Durbin-Watson d-statistic(  4,   260) =  2.251766
```

Appendix B

<u>Brazil</u>

y = BRL/USD x1 = Brazil 5Y CDS x2 = IBOV x3 = INTDIF

Ordinary Least Squares (OLS)

```
Linear regression                                      Number of obs =     261
                                                       F(  3,   257) =  257.77
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.7160
                                                       Root MSE      =  .11352
```

y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1	.0022851	.0001244	18.37	0.000	.0020401	.0025301
x2	.3674692	.1940665	1.89	0.059	-.0146939	.7496323
x3	-.0561281	.0036571	-15.35	0.000	-.0633297	-.0489264
_cons	2.021523	.0420209	48.11	0.000	1.938774	2.104272

```
Durbin-Watson d-statistic(  4,   261) =  .1846739
```

First differences

```
Linear regression                                      Number of obs =     260
                                                       F(  3,   256) =   21.53
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.5784
                                                       Root MSE      =  .03254
```

D.y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1 D1.	.0009646	.0001674	5.76	0.000	.0006349	.0012944
x2 D1.	-.188445	.0370539	-5.09	0.000	-.2614143	-.1154756
x3 D1.	-.0421293	.0143817	-2.93	0.004	-.0704507	-.0138078
_cons	-.0009779	.002053	-0.48	0.634	-.0050209	.0030651

```
Durbin-Watson d-statistic(  4,   260) =  1.985338
```

Appendix C

Mexico

y = MXN/USD x1 = Mexico 5Y CDS x2 = MEXBOL x3 = INTDIF

Ordinary Least Squares (OLS)

```
Linear regression                                    Number of obs =     261
                                                     F(  3,   257) =  113.90
                                                     Prob > F      =  0.0000
                                                     R-squared     =  0.5583
                                                     Root MSE      =  .79796
```

y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1	.0104724	.0011968	8.75	0.000	.0081157	.012829
x2	3.534283	1.92529	1.84	0.068	-.2570706	7.325636
x3	-.1108663	.0789666	-1.40	0.162	-.2663704	.0446378
_cons	11.08855	.1719011	64.51	0.000	10.75003	11.42706

```
Durbin-Watson d-statistic(  4,   261) =  .1015287
```

First differences

```
Linear regression                                    Number of obs =     260
                                                     F(  3,   256) =    7.44
                                                     Prob > F      =  0.0001
                                                     R-squared     =  0.4462
                                                     Root MSE      =  .17951
```

D.y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1						
D1.	.0048371	.001114	4.34	0.000	.0026434	.0070308
x2						
D1.	.1501802	.3722066	0.40	0.687	-.5827965	.8831569
x3						
D1.	-.2090957	.1402256	-1.49	0.137	-.4852383	.0670468
_cons	.0111546	.0111715	1.00	0.319	-.0108453	.0331544

```
Durbin-Watson d-statistic(  4,   260) =   2.27671
```

Appendix D

Japan

y = JPY/USD x1 = Japan 5Y CDS x2 = NIKKEI 225 x3 = INTDIF

Ordinary Least Squares (OLS)

```
Linear regression                                    Number of obs =     260
                                                     F(  3,   256) = 1138.43
                                                     Prob > F      =  0.0000
                                                     R-squared     =  0.9004
                                                     Root MSE      =  4.3839
```

y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1	-.1634207	.0124467	-13.13	0.000	-.1879317	-.1389097
x2	17.54224	8.459331	2.07	0.039	.8835006	34.20098
x3	-4.381721	.2339465	-18.73	0.000	-4.842426	-3.921017
_cons	98.81463	.9157775	107.90	0.000	97.01122	100.6181

```
Durbin-Watson d-statistic(  4,   260) =   .169168
```

First differences

```
Linear regression                                    Number of obs =     259
                                                     F(  3,   255) =   11.11
                                                     Prob > F      =  0.0000
                                                     R-squared     =  0.1903
                                                     Root MSE      =  1.4279
```

D.y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1						
D1.	-.0206828	.0165908	-1.25	0.214	-.0533553	.0119897
x2						
D1.	11.59272	2.155019	5.38	0.000	7.348817	15.83662
x3						
D1.	-1.817079	1.151315	-1.58	0.116	-4.084375	.4502171
_cons	-.1196342	.0889284	-1.35	0.180	-.2947619	.0554935

```
Durbin-Watson d-statistic(  4,   259) =  2.158158
```

Appendix E

United Kingdom

y = GBP/USD x1 = UK 5Y CDS x2 = FTSE 100 x3 = INTDIF

Ordinary Least Squares (OLS)

```
Linear regression                                      Number of obs =     175
                                                       F(  3,   171) =  158.89
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.6573
                                                       Root MSE      =  .01987
```

y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1	.0010049	.0000492	20.41	0.000	.0009077	.0011021
x2	.0290035	.042077	0.69	0.492	-.0540537	.1120607
x3	-.0097642	.0029065	-3.36	0.001	-.0155015	-.004027
_cons	.5647969	.0044029	128.28	0.000	.5561058	.5734881

```
Durbin-Watson d-statistic(  4,   175) =  .3836621
```

First differences

```
Linear regression                                      Number of obs =     174
                                                       F(  3,   170) =   10.43
                                                       Prob > F      =  0.0000
                                                       R-squared     =  0.1695
                                                       Root MSE      =  .01076
```

D.y	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
x1 D1.	.0003425	.000144	2.38	0.019	.0000582	.0006269
x2 D1.	-.0537683	.019836	-2.71	0.007	-.092925	-.0146117
x3 D1.	-.0052177	.0178481	-0.29	0.770	-.0404501	.0300148
_cons	.0004612	.0008649	0.53	0.595	-.0012461	.0021685

```
Durbin-Watson d-statistic(  4,   174) =  2.093403
```