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CHANGING ELASTICITY OF EXCHANGE RATES

FUNDAMENTAL OR SENTIMENTAL?

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PREFACE AND ACKNOWLEDGEMENTS

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ABSTRACT

I use high frequency data for 7 exchange rates between 2003-2011 to study how are the elasticities of exchange rates with respect to macroeconomic surprises changing. My results indicate that elasticities for US announcements react similarly irrespective of exchange rate, change very slowly normally but their changes were unpredictable and significant during the crisis of 2007-2009.

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1 Introduction

In this work I will attempt to find what are the determinants that govern the changes in the responses of exchange rates to surprising macroeconomic news. There have been some studies in the past such as Vrugt 2010 and Nathan 2012 which have determined that the elasticities of some macroeconomic variables change but as far as I know this is the first study that tries to determine whether specific economic factors influence those elasticities.

In this work I use high frequency data from the Bloomberg forecast monitor to determine how 7 exchange rates react to macroeconomic surprises in monthly US announcements over the period 2003-11. I define a macroeconomic surprise as the difference between the forecasted value of macroeconomic variable e.g inflation and the actual value that was announced. My analysis is divided into 3 parts. In the first I estimate the elasticities to macroeconomic surprises via regressions conducted with the Kalman filter and unify then with principal component analysis. Then I conduct regression in order to find determinants that might influence those elasticities from 3 groups of possible determinants economic fundamentals, investor sentiment and economic cyclicality. Finally I also use those specifications in an attempt to conduct an out of sample forecast of the elasticities.

My results suggest that the different elasticities were determined by a group of common factors irrespectively of the exchange rate considered. This suggests that US specific or global conditions affect the elasticities. Furthermore I determined that a strong break occurred around the time of the Global economic crisis which suggests that the during that period the determinants of the elasticities changed.

Overall my results suggest that economic fundamentals influenced to some extent the elasticities but that in the period after the crisis their role decreased while that of sentiment increased. This is likely due to aftershocks from the crisis which has not ended as of 2011. Furthermore the out of sample section strongly suggests that elasticilies have autocorrelation and all of the specifications tested failed to perform better.

The rest of the paper is divided as follows: section 2 will look at the theoretical consideration behind economic surprises and the determinants of exchange rate elasticities. Section 3 will look at the data that will be used in the analysis and section 4 will look at the analytical methodology. Section 5 will describe the limitations of this paper and section 6 its results. Finally section 7 will conclude with some discussion and recommendations.

2 Theory and Literature Review

In this section I will review the key papers in the field of exchange rates and macroeconomic announcements. Further, I will introduce the important publications which outline the determinants of exchange rate elasticity and inspire my research. The section will focus on the methodologies and the key insights of the literature.

2.1 Macroeconomic News Announcements and the reaction of the Economy

Economic surprises and their effect on different sides of the economy have been a hot topic since researchers gained access to high-frequency data. One of the key publications is by Andersen et al (2007). The authors explore the effects of twenty-five US macroeconomic news announcements while making use of high-frequency data for the stock markets, bond markets and the domestic exchange rate. They particularly focus on very short time spans (5-minute returns) after the announcement in the attempt to isolate the announcement effect from any other fluctuations. Firstly, they focus on the significance of macroeconomic news and estimate simple OLS regressions which assume static relationship between the economic surprise and the asset's returns. The results strongly support the hypothesis that there is a significant link and therefore fundamental economic variables such as GDP, Industrial Production, Trade Balance, Inflation and Unemployment are linked to the financial markets. Furthermore, they explore the specific links between announcements and different asset classes. They find that the reaction of equity markets strongly depends on the business cycle of the economy. Having that in mind Andersen et al make use of a two-step weighted least squares regression in the attempt to capture dynamic effects of the macroeconomic news. The results from this section only confirm the observed relationships in the first part, thus confirming the cyclical nature of the link between equities and announcement news. Finally, the authors consider a structural GARCH specification in order to address the microstructure of the markets and identify any spill-over and contagion effects. This last part of their analysis increases the robustness of their results and confirms the conclusions. Overall, their research has two key implications, or namely: the macroeconomic surprises constitute to a conditional mean jump of the assets' returns; the effect of the news announcements is highly conditional on the economic climate and business cycle conditions.

Further research on the topic has been done by James & Kasikov (2007). In comparison to Andersen et al, their analysis is conducted incorporating even shorter time-span data, or namely introducing the 1-minute frequency. The dataset in this case covers more than 100 economic surprises and 9 major currencies which allows the researchers to differentiate between big/small economies and group the announcements data into categories. While the methodology is somewhat simpler than in Andersen et al, their findings confirm the significant effect of macroeconomic surprises on the exchange rate. Furthermore, the authors have shown that smaller economies exhibit an upward trend in their exchange rate elasticities while bigger economies such as the Euro-zone and the US remain in their range. Another point of interest is that the Euro-Zone and Norway are the only countries in the sample which show significant effect of business surveys (in this case from the IFO and ZEW institute).

While most of the literature would focus on the US solely, i.e. analyzing changing elasticity with US macroeconomic announcements, Vrught(2008) expands the research to Germany, Euro-area, Japan, UK and Canada and covers a significant time period between 1996 and 2009. This is an important expansion since the cross-country dynamics and economic differences might produce surprisingly different results. Furthermore, this allows for a more general perception of the effect in question along with broader and stronger conclusions for it. In this research Vrught firstly calculates a static value of the elasticity of the exchange rate towards a series of macroeconomic news announcements by using a simple OLS regression. However, since the elasticity is hypothesized to vary over time, he uses the unknown structural break test methodology developed by Andrews (1993) which suggests that the elasticity indeed exhibits breaks in time. Therefore, the author employs the state-space (kalman filter) methodology in order to allow the elasticity coefficient to change over time.

(1) $\Delta(\ln e_\tau) = \alpha\tau + \beta_\tau S_\tau + \varepsilon_\tau \qquad \varepsilon \sim NID(0,\sigma 2)$

(2) $\alpha_\tau +1 = \alpha_\tau$

(3) $\beta_\tau +1 = \beta_\tau + \eta_\tau +1 , \qquad \eta\tau \sim NID(0,\sigma\eta)$

where $\Delta(\ln e_\tau)$ represents the change in the exchange rate, S_τ is the standardized surprise.

Without going deeper into the methodology, the research arrives to several important conclusions. Firstly, the significance of non-US macroeconomic announcements is proven. Secondly, Vrught shows that announcements concerning real economic variables are more important than consumer/producer variables. This carries an insight that real macroeconomics should be in a tight relation with the changing elasticity of the exchange rate. Finally, the author examines the relationship between size and sign factors of the news announcement when he arrives to the conclusion that both of them have significant effects on the elasticity of the exchange rate. However, unlike previous papers, Vrught uses daily data. As it was shown by James & Kasikov while analyzing the issue at the 1-minute interval, the speed of the announcement digesting can influence the results.

Another approach to the research in question would be to consider only one macroeconomic announcement and evaluate its effect in different economic conditions. Boyd et al (2005) focus entirely on Unemployment rate and the effect of this announcement on the stock market. The varying conditional mean jumps are well documented in their analysis listing several important conclusions. First of all, they confirm the results of Andersen et al that the economic state of contraction or expansion plays a crucial role of the announcement digestion by the market. However, the factors which contribute to this change remain unexplained since their results conclude significance only for expansion periods. Secondly, they find that stocks growth expectations and the equity risk premium are clearly linked to the changing elasticities of the exchange rate. Finally, they conclude that the important factor affecting the exchange rate and the direction of the effect are the expectations of investors for the future state of the market. This leads to interesting insights that fundamental economic variables are surely a determinant of the elasticity, but sentiments in the market would also play a key role.

Last but not least, Nathan (2012) conducts an analysis in attempt to answer the question if economic news announcements have an effect on the currency fluctuations. The author uses macroeconomic news for the period between 2005 and 2011 for three countries (USA, Australia, Canada) and announcement data for a variety of fundamental country indicators. While the author arrives to the definite conclusion that surprises do affect exchange rates, he dives deeper into various financial phenomena such as the difference in effect according to the direction of the surprise, the size of the surprise, the business cycle condition, and immediate vs. 1-hour returns. His results are weak with respect to asymmetric responses, nonlinearity and liquidity tests. However, Nathan emphasizes that the financial stress, i.e. crisis period, has a significant effect on the exchange rate reactions. His results show that for Australia the news gained a premium, or in other words had a greater impact on the exchange rate movement, while in the USA and Canada the news gained a discount, thus having a lower impact during the crisis. Seeing this conclusion alone does not lead to a direct explanation why we observe this phenomenon. However, his exchange-rate specificity tests proves significance as well which in plain words means that single country announcements generate different exchange rate movements of the domestic currency towards the various reference currencies. Therefore, the author suggests that the differing liquidity across currency pairs could be a strong determinant to these results. Overall, Nathan concludes that macroeconomic news are the key drivers of the exchange rate movements post those announcements.

All of the above research papers deal mostly with the issue of changing elasticity and testing against that. The main conclusions come around the facts that conditional mean would definitely spike right after an announcement, and that not only US currency exhibits that anomaly. Moreover, we saw that economic cycles, conditions and market expectations can influence that change in an adverse way. Therefore, it is of crucial importance that we examine more carefully the problem in question and conduct an analysis establishing the factors responsible for that change. In order to elaborate on the issues we need to review several fundamental publications in the field of exchange rate forecasting.

2.2 Macroeconomic Fundamentals and Exchange rate Forecasting

Firstly, it is the basic intuition to indicate that macroeconomic fundamentals might influence the elasticity of exchange rates. One of the key publications in this respect is by Messe and Rogoff (1983) where they analyze structural models in order to attempt exchange rate forecasting. The authors base their analysis on several models pioneered by Hooper and Morton, Dornbusch and Frankel, and Bilson and Frankel. All of those models are based around the idea that the future exchange rate would be a function of key fundamental indicators, or more precisely the first order differentials between domestic and foreign countries. The semi-reduced form of the representative equation for all models is:

$$s = a_0 + a_1 * (m - \overline{m}) + a_2 * (y - \bar{y}) + a_3 * (r - \bar{r}) + a_4 * (\pi - \bar{\pi}) + a_5 * TB + a_6 * \overline{TB} + u$$

where s is the log of the domestic price of the foreign currency, $(m - \overline{m})$ is the log of the ratio of the domestic to foreign money supply, $(y - \bar{y})$ is the log of the ratio of domestic to foreign income, $(r - \bar{r})$ is the short term interest rate differential, $(\pi - \bar{\pi})$ is the expected long term inflation differential, represented by a proxy of long-term interest rate differentials, $TB - \overline{TB}$ represents the net current trade balance and u is a disturbance term which may be serially correlated.

The difference between the three models is that the Bilson-Frankel model assumes PPP, while Dornbusch-Frankel allow for a slow adjustment of the domestic prices. Contrary, Hooper-Morton specification has no restrictions.

Further, Messe and Rogoff hypothesize that in-sample the coefficients of the models might be unstable or miss-specified. Therefore, they continue with evaluating the out-of-sample forecasting capabilities of the model by estimating OLS and GLS rolling window regressions and computing their forecasts. To enable better comparison and a broader analysis they include several other specifications such as a random walk with drift, vector autoregressive specification and other. They compare all the forecasted series to the random walk model. For criteria they use the mean error, root mean squared error and mean absolute error statistics. Although the fundamentals model is computed using observed values for all variables, it fails to outperform the Random Walk on all short horizons. All other specifications fail to outperform the Random Walk as well. As an overall insight it is good to note that the fundamental model increased in forecasting power at longer horizons.

2.3 Market Sentiment

Another main hypothesis about exchange rate elasticities concerns market sentiment. Hooper (1997) reviews the key literature in exchange rate forecasting emphasizing on the point that fundamental-based models tend to fail and a naïve strategy (the exchange rate will be what it is today) outperforms all forecasting tools. Further, he develops a theory that market expectations, or in other words sentiment, is the key to forecast exchange rates in the short term. The key implication here is that if we could observe the overall market expectation, then we could forecast the exchange rates. However, since this is impossible, one can only try forecasting the more predictable patterns of exchange rate volatility and correlations using various GARCH specifications.

On the other hand market sentiment is far from insignificant in the equity pricing. For example, Baker and Wurgler (2006) conduct an analysis on a very broad dataset covering all common stock in the US for the period between 1962 and 2001. The research in question includes sentiment proxies such as the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. The authors employ a conditional characteristics model which estimates the returns of equities as their characteristics and sentiment proxies.

$$E_{t-1}[R_{it}] = a + a_1 T_{t-1} + \mathbf{b}_1' \mathbf{x}_{it-1} + \mathbf{b}_2' T_{t-1} \mathbf{x}_{it-1},$$

where i indexes firms, t denotes time, **x** is a vector of characteristics, and **T** is a proxy for sentiment.

Baker and Wurgler arrive to the conclusion that stock returns are conditional to the beginning-of-period proxies for sentiment. Further, they develop the hypothesis and conclusion that small stocks which tend to be attractive to optimists and speculators, earn on average low returns when sentiment is estimated to be high. The patterns reverse or attenuate when considering low sentiment in the market. The important insights from this paper converge in the idea that market sentiment has been part of equity prices since a long time ago.

Further research by Brauchler (2010) analyses the significance of sentiment indexes. The paper is based solely on the USD/JPY exchange rate while the author uses a stationary autoregressive model in order to “explain” the daily returns of the currency couple. The author notices a significant increase of the regression power when sentiment variables are included, such as the US consumer sentiment index, US consumer expectations index, US and Japanese consumer confidence indexes and business condition indexes. Finally the author tests for joint significance the sentiment proxies and finds that they are significant. This is just another analysis that proves the hypothesis that market sentiment is part of the asset pricing process.

Lately, a more modern approach to investor sentiment proxies was developed by Da et al (2011). The authors make use of a relatively new data source, or namely Google Trends, which provides search volume indexes for specified terms. The idea in this case is that retail investors would search on Google information about the companies they are looking to trade with, thus spikes in the search volume indexes would represent high interest in the specific company. In order to target only specific people, they would look on Google Trends for the ticker names of the companies they are interested in, therefore limiting the number of searches only to the people who are actually interested in the pure financial data of the company. Their conclusions show that the Search Volume Index approach is different from existing measures and has a significant predictive power for stock price increases and large first-day returns of a sample of IPOs. Therefore, we can conjecture that the Google Trends search database is a viable investor attention proxy which could be incorporated in further research.

2.4 Liquidity and its effect on Asset Pricing

In addition to Fundamentals and Market Sentiment, other factors could affect the changes in exchange rate elasticities over time. The most relevant factor would be to examine the financial market conditions. Hence, I would like to review several publications with respect to market liquidity and its theoretical implications on different asset classes. Finally, several new liquidity measures are introduced.

One of the key publications exploring theoretically the liquidity effects onto the exchange rate was developed by Grilli and Roubini (1992). The economists develop their analysis around a two-country, open economy extension of the Lucas (1988) model while they introduce temporary separation between the goods market and the asset market, both of which would use money for transactions. Without going into details about their theoretical approach, the outcome is strong and clear – the liquidity of the financial sector has a significant effect on the exchange rate, or more precisely – the more liquid the asset market is, the stronger is the domestic currency.

Further into the topic, Goyenko et al (2009) has developed several new measures of liquidity including both high-frequency and low-frequency versions. The general purpose of the research is to prove that low-frequency approaches to liquidity can be found as good proxies and useful measures for statistical and financial analysis. Therefore, those newly developed proxies are calculated using vast datasets depending on the frequency of the measure. Overall, in the low-frequency approaches, the statistics Effective Tick, Holden and LOT Y-split dominate. Out of those measures the first one is the simplest and requires the least computational power, however, Holden liquidity proxy would produce the best results. The definition and derivation of those statistics is too vast to be included in this section, hence I would advise to refer to the Methodology section for the definition of the statistics that I will be using, or to the original research paper for the elaboration on deriving the criteria. It is worth mentioning that Goyenko et al conduct robustness analysis which concludes that the criteria are suitable for econometric analyses especially on the lower-frequency end.

In this section I reviewed the key publications in the sphere of exchange rate forecasting and the significance of macroeconomic news announcements. In the first part I have shown previous literature that proves the significance of surprises and their effects on different asset classes. We saw different approaches evaluating datasets from the single country/single announcement approach to vast datasets covering multiple years of high-frequency data. The general conclusion from all of the publications is that economic announcements have a significant effect on various asset classes, but the determinants of those changes can differ. In the second part of the literature review I have listed three ways in which the problem can be approached, or namely considering the fundamental economic indicators as factors, market sentiment and the different approaches to use it, and finally liquidity as a key market measure which cannot be linked to sentiment or fundamentals.

3 Data

My dataset includes data from August 2003 till July 2011 with monthly frequency. During my analysis for sections 5.2 and 5.3 the sample will be further split into 3 samples- August 2003 till May 2006, June 2006 till December 2009 and January 2010 till July 2011.This is done in order to isolate the economic crisis in a separate sample that will be large enough to include most of its immediate before and after effects. A full list of all variables will be provided as an Appendix table and the variables that need additional calculation will be described below. The rest of the section will be divided into 4 parts describing the different types of variables according to the way in which they will be used – Surprise, Fundamental, Sentiment and Cyclical.

3.1 Surprise

This part of the dataset has been graciously provided to me by my supervisor JustinasBrazys. It constitutes standardized surprises for the US macroeconomic announcements included in the Bloomberg US forecast monitor. That is the surprises are the difference between the actual announcement and the forecast for this particular announcement from the Bloomberg survey. This monitor includes over 90 different announcements but for the purpose of this study I have singled out those that have monthly frequency which leaves me with 33 announcements from various fields including retail, the labor market, manufacturing and many others. Previous research by Nathan 2010 has determined that the Bloomberg forecasts do include information about the actual outcomes which means that they reflect to some extent market expectations.

This dataset furthermore contains the returns of the exchange rates for a period of 5 minutes immediately after an announcement. This data will be used to calculate the elasticities of the exchange rates of 9 different countries with respect to the US dollar[1].

3.2 Fundamental

This dataset will be used for the calculation of the fundamental model in section 5.2. I have acquired all of the data used here from Thompson Reuters with the exception of style MSCI indexes which were acquired from MSCI Barra. The fundamental variables used follow the Hooper-Morton model from a classical paper (Meese and Rogoff 1983) plus some additional factors taken from the financial markets. The variables are mostly M1 as money supply, industrial production, one month interest rates, CPI, and current accounts mostly from sources such as the OECD. In addition I have included an index of primary commodities prices calculated by the IMF in order to account for possible influences of such products to

[1] The countries included are Australia, the Eurozone, the UK, New Zealand, Canada, Switzerland, Japan, Norway and Sweden

the exchange rates of commodity producing countries. Finally I have used data from MSCI Barra to calculate the market and HML and SMB factors for the United States and for the foreign countries following the famous Fama and French model.

3.3 Sentiment

In this dataset I include mostly variables that serve as proxies for investors sentiment. Most of the variables are inspired by two works (Brown and Cliff 2004) (Yardeni 2012).

Firstly I take data from the American Association of Individual Investors (AAII). This organization conducts a regular survey among retail investors with questions about their opinion of the market and the composition of their portfolio. I will take two variables from them one is the ration of investors who are bullish to the number of investors who are bearish and the second is the average percentage of investors portfolio that is kept in cash holdings.

Next I will use Thompson Reuters data to calculate the so called bust and boom barometer. This variable is attempting to predict the economic cycle by looking at factor inputs and is often cited as a measure that investors follow. This barometer is the ratio between the Commodity Research Bureau Spot Index Raw Industrials and initial unemployment claims from the US Bureau of Labor statistics.

Next I look at institutional investors sentiment. I do this by calculating the DJ ratio. This is the ratio between the traded volume of the closest to maturity put option versus the volume traded of the closest to maturity call option of the Dow Jones Industrial Average. This measure is usually believed to indicate the sentiment of institutional investors because of their dominance on the options market. Furthermore I will use market based measure for sentiment in the case of the advanced and declining issues measure. It is essentially the number of stocks that have positive returns in the previous month divided by the number of stocks that have experienced negative returns in the previous month. I have calculated this by using monthly prices of all stocks traded on NYSE and on the major exchanges of each specific country[2].

I have also included some measures based on Initial public offerings (IPO) for the United States. The success and occurrence of such offerings is often regarded as a measure for the markets risk aversion. I have used the dataset of Prof. Jay Ritter from the University of Florida.I include two variables the number of IPO in a given month and the average first day return of those IPOs.

Furthermore I use data from Thompson Reuters for the CESI index. This is the Citigroup Economic Surprise index. The idea here is that elasticities might be dependent on the extent to which surprises have occurred in the recent past.

Finally I have also constructed a measure of my own based on the tool Google Trends. This tool gives the frequency with which certain words or phrases are searched for in Google by country and specific period.

[2] The Frankfurt Stock exchange was used as a proxy for the Eurozone.

This gives an excellent opportunity to measure the overall sentiment. Nevertheless as explained in(The Economist 2012) the search of economic terms has two biases. The first one is a downward trend in searches that is due to the fact that the data is given as a percentage of all searches and therefore as the popularity of the internet increased specialized terms percentage decreased. The second bias is the influence of searches by students who are working on assignments or preparing for exams. Therefore before I can use such data I will have to remove those biases.

Firstly I have looked for the searches from certain countries[3] for various economic terms. The terms are firstly the worldwide searches of the variations of the name of the local currency, the name of the local central bank and the most important stock index of this country. In addition I look at the searches from this country for the terms gold and economy.

In order to remove biases each of those searches will be regressed on :

$$econ_{term} = c + c_1 * trend + c_n * university_{term}$$

where university term depicts I will use the local searches for the following terms definition, theory and exam[4] expressed in local language. Then I take the residuals of those regressions standardize them by removing their means and dividing them by their standard deviation and compiling them in groups for each country. Then I perform a principal component analysis and take the first principal components as the measure of sentiment for that currency.

3.4 Cyclical

In this dataset I will consider variables that are connected to the crisis.All of the data used is from Thompson Reuters.

Firstly I will consider measures of liquidity. Liquidity has been theorized to be influential for exchange rate dynamics but is very hard to measure due to requirements for a high frequency data. Fortunately some proxies have been developed for liquidity that are measurable with daily data.(Goyenko et al 2008) Those measures can be divided into two groups price impact and effective spread. The first measures what would be the impact of one transaction and the second measures transaction costs. I will use daily data for all stocks traded on NYSE to estimate the two recommended measures from the Goyenko et al paper the Amihud measure and the effective tick. Both measures are estimated for each stock and then a market wide value weighted average is taken.

Amihud also refered as liq_simple is calculated as

$$Illiquidity = Average(\frac{abs(r)}{Volume})$$

[3] Germany was used as a proxy for the Eurozone.

[4] Due to the relative unavailability of data for Switzerland I use the German university searches as a proxy assuming that the school year would be similar in the 2 countries.

Where r is the stocks daily return and Volume is the daily trading volume.

The effective tick refered as liq_r is somewhat harder to calculate. I will provide a brief explanation on how Goyenko et al define it below.

Let S_t be the realization of the effective spread at the closing trade of day t. Assume that the realization of the spread on the closing trade of day is randomly drawn from a set of possible spreads $s_j, j = 1, 2, \ldots, J$ with corresponding probabilities $\gamma_j, j = 1, 2, \ldots, J$. By convention, the possible effective spreads $s_1 s_2, \ldots s_J$ are ordered from smallest to largest. For example on a $\$\frac{1}{8}$ price grid, S_t is modeled as having a probability γ_1 of $s_1 = \$\frac{1}{8}$ spread, γ_2 of $s_2 = \$\frac{1}{4}$ spread, γ_3 of $s_3 = \$\frac{1}{2}$ spread, and γ_4 of $s_4 = \$1$ spread.

Assume that price clustering is completely determined by spread size. For example, if the spread is $\$\frac{1}{4}$, the model assumes that the bid and ask prices employ only even quarters. The quote could be $\$25\frac{1}{4}$ bid, $\$25\frac{1}{2}$ offered, but never $\$25\frac{3}{8}$ bid, $\$25\frac{5}{8}$ offered. Thus, if odd-eighth transaction prices are observed, one infers that the spread must be $\$\frac{1}{8}$. This implies that the simple frequency with which closing prices occur in particular price clusters can be used to estimate the spread probabilities $\hat{\gamma}_j, j = 1, 2, \ldots, J$. For example on a $\$\frac{1}{8}$ fractional price grid, the frequency with which trades occur in four, mutually exclusive price sets ($\text{odd } \frac{1}{8}\text{s}, \text{odd } \frac{1}{4}\text{s}, \text{odd } \frac{1}{2}\text{s},$ and whole dollars) can be used to estimate the probability of a $\$\frac{1}{8}$ spread, $\$\frac{1}{4}$ spread, $\$\frac{1}{2}$ spread, and a $1 spread. Similarly for a decimal price grid, the frequency with which trades occur in five, mutually exclusive sets (off pennies, off nickels, off dimes, off half-dollars, and whole dollars) can be used to estimate the probability of a penny spread, nickel spread, dime spread, quarter spread, and whole dollar spread.

Let N_j be the number of trades on prices corresponding to the jth spread (j=1,2,…,J) using only positive-volume days in the time interval. In the $\$\frac{1}{8}$ price grid example (where J=4), N_1 through N_4 are the number of trades on $\text{odd } \frac{1}{8}$ prices, the number of trades on $\text{odd } \frac{1}{4}$ prices, the number of trades on $\text{odd } \frac{1}{2}$ prices, and the number of trades on whole dollar prices, respectively.

Let F_j be the probabilities of trades on prices corresponding to the jth spread (j=1,2,…,J). These empirical probabilities are computed as

$$F_j = \frac{N_j}{\sum_{j=1}^{J} N_j} \quad \text{for } j = 1, 2, \ldots, J. \qquad (13)$$

Let U_j be the unconstrained probability of the jth spread (j=1,2,…,J). The unconstrained probability of the effective spread is

$$U_j = \begin{cases} 2F_j, & j = 1 \\ 2F_j - F_{j-1}, & j = 2, 3, \ldots, J-1 \\ F_j - F_{j-1}, & j = J. \end{cases} \qquad (14)$$

The effective tick model directly assumes price clustering (i.e., a higher frequency on rounder increments). However, in small samples it is possible that *reverse* price clustering may be realized (i.e., a lower frequency on rounder increments). Reverse price clustering unintentionally causes the unconstrained probability of one or more effective spread sizes to go above one or below zero. Thus, constraints are added to generate proper probabilities. Let $\hat{\gamma}_j$ be the *constrained* probability of the *j*th spread (j=1,2,…,J). It is computed in order from smallest to largest as follows:

$$\hat{\gamma}_j = \begin{cases} \text{Min}[\text{Max}\{U_j, 0\}, 1], & j = 1 \\ \text{Min}\left[\text{Max}\{U_j, 0\}, 1 - \sum_{k=1}^{j-1} \hat{\gamma}_k\right], & j = 2, 3, \ldots, J. \end{cases}$$

Finally, the effective tick measure is simply a probability-weighted average of each effective spread size divided by $\bar{P}_i$, the average price in time interval *i*

$$Effective\ Tick = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\bar{P}_i}.$$

In addition, to those liquidity measures I will estimate several other variables that might be connected with the economic cycle. Financial stress is an index developed by the Federal Reserve Bank of Kansas City that incorporates 11 financial market variables and measures the fragility of the US financial sector.

Unemployment rates are also used due to their political impact that high unemployment has at times of crisis.

Last but not least I will consider several industries that have high betas according to the database of Prof. Damodaran from the Stern School namely automobiles and entertainment. I will employ several variables. Firstly new_car is the number of newly registered cars in the country. Ent is the return of an value weighted index that consists of all stocks traded on the respective country exchange that are valued in local currency and are considered entertainment by the Thompson Reuters Industry classification. I also useliv_ent which is the personal consumption expenditure for live entertainment in the US.Movies is similar measue of expenditure for movies and drinks is the sales of full service restaurants again in the US.

4 Methodology

In the following section I will describe the types of analysis that I have conducted. The first part is about the specific measurement of the elasticities. The second section will involve studying the determinants of those elasticities. Finally I will conduct attempt to forecast the elasticities via the use of out of sample coefficients.

4.1 Elasticity measurement

For the measurement of elasticities I will follow (Vrugt 2010). All surprises will be measured on available days with the definition

$$\Delta(\ln(e)) = \alpha_i^n + \beta_i^n * S_{i,t}^n + \gamma_i^n * I_{i,w}^n + \varepsilon_t$$

where e is the exchange rate Δ is the 5 minute return after the announcement and S is the standardized surprise. Following (Nathan 2012) I have added *I* as dummy variables that mark the day of the week. This is done in order to ensure that the elasticities are not influenced by calendar anomalies such as the Monday effect. Then I perform for each currency and announcements the test of AvrF(Andrews 1993) in order to determine which elasticities (β) vary through time. This test essentially runs a Chow breakpoint test for every point of the period in order to determine whether the coefficient in the previous period of that point and the coefficient of the rest of the sample differ. Then the results are aggregated into a single p-value with a null that the coefficient varies over time. I will discard all announcements whose elasticities are constant and will only use the varying ones for the remainder of the analysis.

I will use a quasi-maximum likelihood function known as the Kalman filter to calculate the time varying betas:

$$\Delta(\ln(e)) = \alpha_i^n + \beta_i^n * S_{i,t}^n + \gamma_i^n * I_{i,w}^n + \varepsilon_t \quad \varepsilon_t \sim NID(0, \sigma_{\varepsilon_t})$$

$$\alpha_{i,t+1}^n = \alpha_{i,t}^n$$

$$\beta_{i,t+1}^n = \beta_{i,t}^n + \eta_{i,t+1}^n \quad \eta_{i,t}^n \sim NID(0, \sigma_{\eta_{i,t}^n})$$

$$\gamma_{i,t+1}^n = \gamma_{i,t}^n$$

The announcements are then grouped with a monthly frequency. This can be done despite the different days of the announcements because all of them are made only once a month. Then I group each announcement with two dummy variables that measure the size and sign of the surprise in that month. The first dummy takes the value of 1 if the surprise is negative and 0 otherwise. The second dummy takes the value of 1 if the absolute value of the surprise in that month is in the top 20% of the surprises for this announcement in the last 2 years. I do this because the analysis of Nathan 2012 has established that elasticities depend on whether the surprise was positive or negative and on its size. Then I will conduct a principal component analysis for each currency of the elasticities of the surprises of all announcements together with their corresponding dummy variables. Then I will take the first principal component and will use it as a proxy for the elasticities in this particular currency.[5]

4.2 Determinants

In this part I will examine what factors influence the elasticities. This will be done via regression analysis following three possible models: a fundamental model, sentiment model and a cyclical model.All of those models where calculated as cross sections and in panel setting for the whole sample. Nevertheless it was discovered that when the whole sample is used virtually no factors appeared to be significant. Therefore the sample was split on 3 parts August 2003 till May 2006, June 2006 till December 2009 and January 2010 till July 2011.

The fundamental model is based on macroeconomic fundamental based on the theory of exchange rates. The model that will be followed is inspired by the paper of Meese and Rogoff 1983 with a first difference specification of:

$$s = a_0 + \alpha_1 * AR(1) + \alpha_2 * Trend + \alpha_3 * (m - \overline{m}) + a_4 * (y - \bar{y}) + a_5 * r + \alpha_6 * \bar{r} + \alpha_7 * (\pi - \bar{\pi}) + a_8 * TB + a_9 * \overline{TB} + a_{10} * Commodities + \alpha_{11} * \overline{MSCI} + \alpha_{12} * MSCI + \alpha_{13} * SMB + \alpha_{14} * \overline{SMB} + \alpha_{15} * \overline{HML} + \alpha_{16} * HML$$

where s is the first principal component of the elasticities, ar(1) is a 1 period autoregressive term , trend is a linear trend variable, m is the money supply, y is industrial production which is used as a proxy for gdp due to non-availability of monthly gdpdata, r is the interest rate for 1 month, π is inflation , TB is net trade balance and Commodities is the primary commodities index. MSCI is the standard country MSCI equity index and SMB and HML are factors from (Fama and French 1992). All variables without a bar represent the United States whereas all variables with bars stand for the respective foreign country. The inflation, money supply, industrial production and trade balances are lagged 2 periods[6] in order to make sure that they will be known to traders at the time of the announcements.

The second model is based on sentiments and will consist of various proxies for such measures mostly inspired by (Brown and Cliff 2004)(Yardeni 2012). This model is intended to measure whether investors' uncertainty or speculative behavior might be responsible for the varying elasticities.

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[5] I will show in the results section that this will result in the shedding of variance in the elasticities that is associated with the sign and size of surprises.

[6] One might notice that I am using the lags according to the local announcements as opposed to the later ones used by the oecd but ultimately the oecd data is only used to provide consistency across countries and traders will likely use the earlier arriving local announcements.

$$\Delta s = a_0 + \alpha_1 * AR(1) + \alpha_2 * Trend + \alpha_3 * AAII\_bear\_bull\_r + \alpha_4 * AAII\_cash\_r + \alpha_5 * barometer\_r + \alpha_6 * CESI\_r + \alpha_7 * \overline{CESI_r} + \alpha_8 * DJ\_ratio\_r + \alpha_9 * \overline{sentiment_r} + \alpha_{10} * IPO\_count + \alpha_{11} * IPO\_returns + \alpha_{12} * equity\_ratio\_r + \alpha_{13} * \overline{equity\_ratio\_r}$$

where Δs is the exchange rate return, variables without bar refer to the USA and _r stands for return. AAII is data from the American association of individual investors. Bear-bull is the ratio of bearish to bullish investors, cash is the percentage of investors' portfolios that is in cash holdings. The calculation of the barometer and sentiment variables is described in detail in section 4.3. IPO count is the number of IPOs undertaken in a given month, the DJ ratio is the ratio of the volume traded of put options on the Dow Jones Industrial Average to the volume traded of call options and equity ratio is the ratio of the number of stocks that have positive returns during the previous month to those that have had negative returns.

Finally, the cyclical model is based on various measures that could account for the state of the economy.

$$\Delta s = a_0 + \alpha_1 * AR(1) + \alpha_2 * Trend + \alpha_3 * liq_{simple_r} + \alpha_4 * liq_r + \alpha_5 * fin_{stress_r} + \alpha_6 * ur_r + \alpha_7 * \overline{ur_r} + \alpha_8 * new_{car} + \alpha_9 * \overline{new_{car}} + \alpha_{10} * ent + \alpha_{11} * \overline{ent} + \alpha_{12} * live_{ent} + \alpha_{13} * movies + \alpha_{1143} * drinks$$

Where Δs is the return of the exchange rate and variables without a barare standing for the USA. Liq_simple is the Amahud measure for price impact and liq_r is the effective tick measure. Fin_stress is the financial stress index of the Federal Reserve, ur is the unemployment rate, new car is the number of new car registrations, ent is the return of the entertainment index described in the Data section, live ent , drinks and movies personal consumption expenditures for live entertainment , movies and restaurant and drinking places respectively.

4.3 Prediction

In this section I will attempt to forecast the elasticities in an "out of sample" setting. This is done in order to see whether the conclusion drawn from the regression framework will hold out of sample and for different periods.

I will use 5 different models to create one-step ahead forecasts for the elasticities. The models will be done in 3 different scenarios. In the first scenario the first and second period will be in sample and the third period will be forecasted. In the second scenario the first period will be in sample and the second and third periods will be forecasted out of sample. Finally in the third scenario I will have the second period in sample and the third period will be forecasted out of sample. Each model will have an estimation window dependant on the scenario and after that the forecast will be estimated with a rolling model where the estimation window will move forward each time with one month without changing its length. All models will be estimated separately for each scenario. The models are inspired by (Rapach et al2010)

The first model that I will use will be a kitchen sink. That is essentially a regression which will include all predictor variables from section 4.2 as independent variables

The second model is a unified forecast. I will use each of the predictor variables in a univariate regression of the type

$s = c(1) + c(2) * predictor$

Then I will create a group of all of those regressions and the forecasts of all specifications will be used in combination to create one single forecast. The weights given to each model will be time variant and will be calculated as follows

$$\omega_{i,t} = \phi_{i,t}^{-1} / \sum_{j=1}^{n} \phi_{j,t}^{-1}$$

$$\phi_{i,t} = \sum_{c=m}^{t-1} (s_{c+1} - \hat{s}_{c+1})^2$$

Where s is the principal component, $\hat{s}$ is the forecasted principal component, t is the time which we will be forecasting, n is the total number of models and m is the time 6 months before t. Those weights are useful because they change according to a models forecasting out of sample performance in the last 6 months allowing for some structural breaks in predictability.

The third model will be an equally weighted forecast made of the forecasts of theunivariate regressions of the predictor variables.

The fourth and fifth model will be similar to the second and third except that instead of using univariate regressions I will use the fundamental, sentiment and cyclical models that I have estimated in section 4.2

In order to compare the extent to which my forecasts are similar I will conduct simple encompassing test inspired by the Rapach et al 2010 paper separately for each scenario. This involves the calculation of the so called MHLN statistic.

Define $d_{t+1} = (u_{i,t+1} - u_{j,t+1})\, u_{i,t+1}$, *where* $u_{i,t+1} = s_{t+1} - s_{i,t+1}$ *and* $u_{j,t+1} = s_{t+1} - s_{j,t+1}$. *Letting* $\bar{\bar{d}} = [1/(q - q0)] \sum_{k=q0+1}^{q} d_{R+k}$

MHLN= *[(q −q0 − 1)/(q −q0)][ˆV (¯d)−1/2]* $\bar{\bar{d}}$,

where ˆV (¯d) = (q −q0)$^{-1}$*φ0 and φ0 =* $(q - q0)^{-\frac{1}{2}} \sum_{k=q0+1}^{q} \quad (d_{\quad R+k} - \bar{\bar{d}})$

k=q0+1(dR+k− ¯d)2. HLN using the MHLN statistic and the t_{q-q0-1} *distribution to assess statistical significance.* q= the number of forecasted values, s is the elasticity and q0 is the initial hold out period which is assumed to be 6 despite the fact that only the fourth model uses it. In essence, if we reject the null hypothesis of encompassing, then it is useful to combine forecasts from models *i*and *j* instead of relying solely on the model *i*forecast.

Finally the different forecasts will be evaluated for their accuracy with a number of criteria that will compare their ability to forecast elasticities.

Firstly I will follow again Rapach and will draw the time-series plots of thedifferences between the cumulative square prediction error for a benchmark forecast and the cumulative square prediction error for theforecasts based on the individual predictive regression specifications that I have calculated. This is an informative graphical device that provides a visualimpression of the consistency of an individual predictive regression model'sout-of-sample forecasting performance over time.

I will calculate two benchmark forecasts a long AR and a random walk. The long AR is inspired by Meese and Rogoff 1983 and is an unconstrained regression which will regress the principal component return on its own lagged value plus a constant. The number of lags M to be used will be based on a rule M=N/ln(N) where N is the size of the sample.The random walk states that the principal component evolves in a random manner, therefore making it impossible to correctly predict future values. A random walk process basically describes that each period's value is equal to last period's value plus a constant drift term. If the drift term is set to be 0, then it is called a driftless random walk. The random-walk specification in this paper is generated by drawing a random number from a normal distribution with the mean and standard deviations from the estimation period of the respective principal component.

Then I will calculate the squared prediction errors which are equal to

$$MSPE = (a - f)^2$$

Where a is the actual value of the principal component return and f is the forecasted value. I will use this statistic for the cumulative plots described in the previous paragraph and for the calculation of squared Ros again from Rapach et al

$R^2_{os} = 1 - (\frac{\sum MSPE_{specification}}{\sum MSPE_{benchmark}})$

It measures the reduction in MSPE for the predictive regression model or combination forecast relative to the benchmark forecast. Thus, when it is >0, the specification forecast outperforms the benchmark forecast according to the MSPE metric. Finally in order to determine whether the result is significant I will perform a significance test which was developed by Clarkand West (2007). It is an adjusted version of the Diebold and Mariano (1995)and West (1996) statistic—what they label the *MSPE-adjusted* statistic—that in conjunction with the standard normal distribution generates asymptotically valid inferences when comparing forecasts from nested linear models. Firstly we have to define

$f_{t+1} = (r_{t+1} - \bar{r}_{t+1})2 - [(r_{t+1} - \hat{r}_{t+1})2 - (\bar{r}_{t+1} - \hat{r}_{t+1})2]$.

where$\hat{r}_{t+1}$ is the forecast and $\bar{r}_{t+1}$ is the benchmark forecast. Then we regress $\{f_{s+1}\}_{s=m+q0}^{T-1}$on a constant and calculating the *t*-statistic correspondingto the constant, a *p*-value for a one-sided (upper-tail) test is obtainedwith the standard normal distribution.

5 Limitations

In this work I have strived to achieve the highest possible rigor Nevertheless it is not without some flaws that we should be aware of before considering the results.

Firstly the biggest limitation of this work is the period during which it is conducted. It includes a major economic crisis which could have easily led to changes in the way in which exchange rates react to macroeconomic surprises.

Secondly, another important limitation is that I am considering only surprises to US statements. The inclusion of foreign statements might lead to a more balanced view as suggested in Vrugt2010.Furthermore it is possible that the reaction to US statements is atypical due to its role in the global economy.

Thirdly in my analysis I am only considering the currencies of developed countries therefore it is possible that my results would not be applicable to developing countries. I suggest a future research into that specific field.

Fourthly, as explained in the next section I removed two countries from my sample Australia and Japan due to their atypicality. It is therefore possible there are several groups of exchange rates whose elasticities behave similarly to each other. Therefore I recommend more research in this area too.

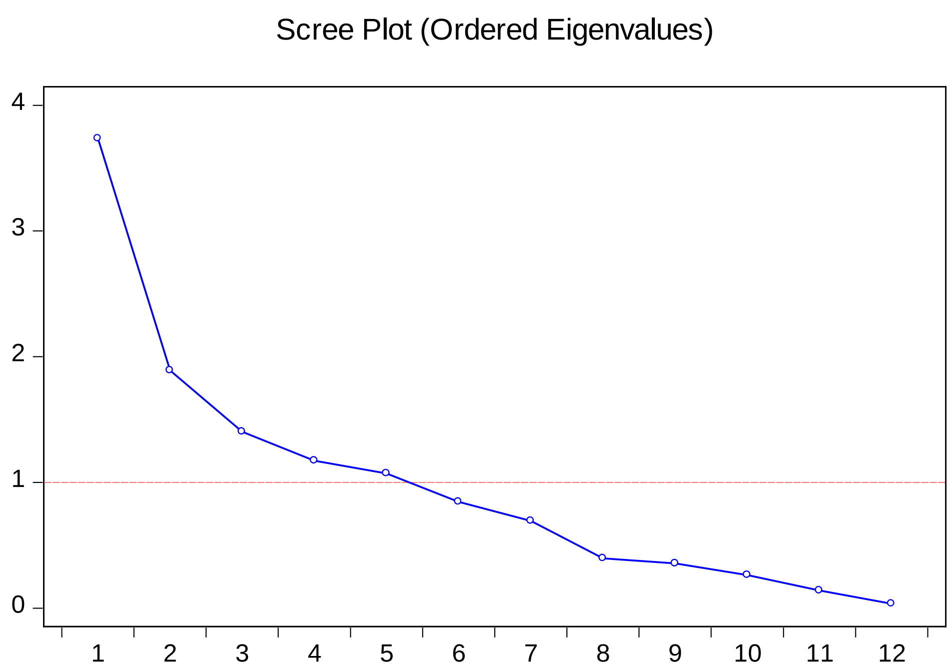
Fifthly, in this work I operate without a prior theoretical framework therefore it is possible that my empirical modeling of the relationships is wrong. A further examination on why investors might react differently should be able to uncover other factors to be tested empirically.

Last but not least, future researchers who have an abundance of computing power might be interested in performing the analysis with a maximum likelihood function as opposed to the Kalman filter that I have used. Overall Kalman is used as a standard but it might be interesting to see whether the results would change if a maximum likelihood is performed.

6 Results

6.1 Elasticity Measurement

Firstly we will look at the principal components formation. I will use the Euro zone as an illustration but virtually all of the exchange rates exhibit qualitatively the same behavior[7]. Graph 6.1 shows us a plot of the eigenvalues. It becomes apparent that despite the large number of variables just a couple of factors are able to explain a huge amount of the variance. In table 6.1 we can see the individual variance explained by the first 9 components. The first one explains over 80 % of the variances of the elasticities but almost none from the dummy variables. Furthermore by definition it has 0 correlation with the others which implies that the sign and size effects observed by Nathan shouldn't appear in it.



Graph 6.1 The eigenvalues of the elasticities for the EUR/USD exchange rate

[7] Those results are available upon request from the author

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9
CUR_2_ANN29	0.89	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00
CUR_2_ANN30	0.86	0.02	0.00	0.02	0.00	0.00	0.00	0.00	0.04
CUR_2_ANN36	0.73	0.03	0.00	0.01	0.00	0.00	0.03	0.01	0.10
CUR_2_ANN4	0.83	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.04
DSIGN_4	0.02	0.10	0.08	0.24	0.05	0.49	0.00	0.00	0.01
DSIZE_4	0.07	0.05	0.21	0.33	0.02	0.08	0.20	0.00	0.04
DSIZE_36	0.14	0.01	0.01	0.28	0.17	0.11	0.29	0.01	0.00
DSIZE_30	0.10	0.33	0.23	0.11	0.00	0.00	0.08	0.07	0.04
DSIZE_29	0.06	0.44	0.26	0.02	0.02	0.02	0.00	0.10	0.06
DSIGN_36	0.00	0.02	0.01	0.06	0.77	0.02	0.10	0.01	0.00
DSIGN_29	0.02	0.29	0.42	0.04	0.01	0.07	0.00	0.10	0.02
DSIGN_30	0.01	0.53	0.16	0.07	0.03	0.04	0.00	0.09	0.02

Table 6.1 Individual variance explained by the first 9 components the currency is the euro

We can see the results of the Anderson test in table 6.2. Overall the same types of announcements have varying elasticities across currencies with the exception of Japan. Overall they appear to be related mostly with trade suggesting that the relationships between the exchange rate and various sales in the economy are dynamic. Figure 6.2 shows the principal components taken separately for each currency. Overall all of the components are indeed similar with the exception of Japan whose elasticities are clearly radically different from all of the others. This implies that the changes in elasticities move in an aggregate manner across currencies as opposed to the findings of Nathan where he has found exchange rate specificity.

Another thing that we notice is that all of the non-Japanese PCAs appear to undergo a change during the middle of the period and ultimately arrive at a new state. This period coincides with a major economic crisis which is why I have tested my analysis by splitting the sample into 3 periods. Ultimately I have determined that trying to study the whole sample yield meaningless results. Once a split is done relationships emerge but as due to the small size of the sample (around 30 observations or less) I can only conduct this analysis in a panel dataset. From now on

I will create and use a panel dataset though Japan will be excluded from it due to the radical differences that it has with the other countries. One last thing is an outlier present in Australia data which can be seen clearly when we plot all components as a panel in fig 6.3.

This is clearly some sort of error therefore I have decided to also exclude Australia leaving me with seven currencies. I will proceed with this sample and conduct the analyses in sections 6.2 and 6.3.

Currency		Announcement	
AUD	4,20,29,30,36	Conference Board Consumer Confidence SA 1985=100	**4**
EUR	4,29,30,36	ISM Manufacturing PMI SA	**18**
GBP	4,29,30,36	ISM Manufacturing Report on Business Prices Index NSA	**19**
NZD	4,18,20,29,30,36	US Employees on Nonfarm Payrolls Total MoM Net Change SA	**20**
CAD	4,18,20,24,29,30,36	Philadelphia Fed Business Outlook Survey Diffusion Index General Conditions	**24**
CHF	29,30,36	Adjusted Retail & Food Services Sales SA Total Monthly % Change	**29**
JPY	18,19	Adjusted Retail Sales Less Autos SA Monthly % Change	**30**
NOK	4,20,29,30,36	US Trade Balance Balance Of Payments SA	**36**
SEK	4,20,29,30,36		

Table 6.2 Announcements with varying elasticities. On the left is indicated which announcement has a varying elasticity with which currency and on the right is the legend for the different announcements

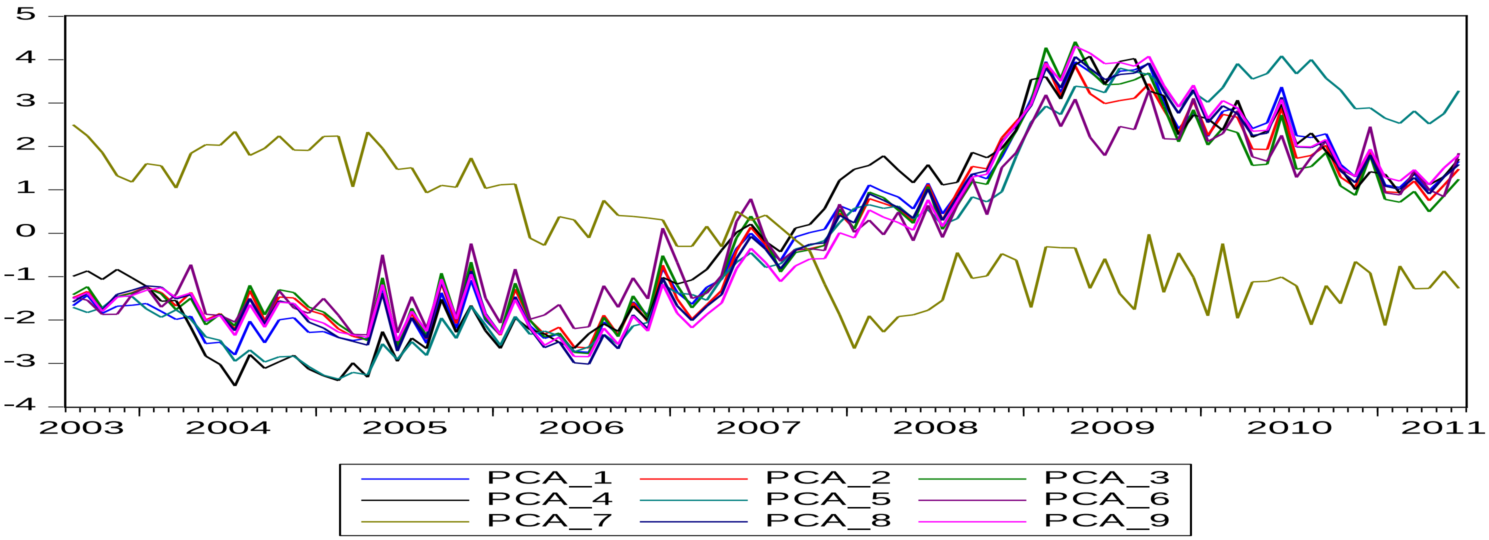


Figure 6.2Elasticities for different currencies PCA_7 is the Japanese Yen

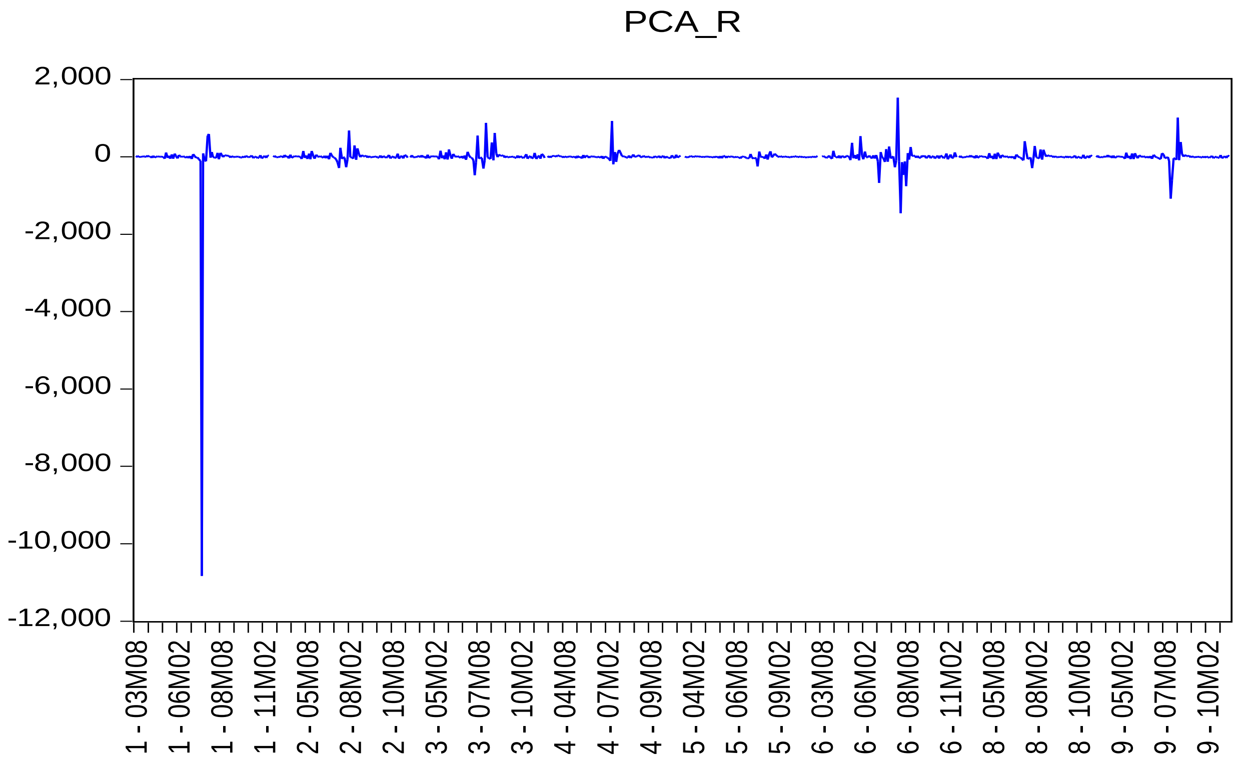


Fig. 6.3 All principal components drawn as a panel dataset. The outlier is for Australia in July 2007.

6.2 Determinants

In this section we will look at regressions of various factors in order to determine which ones influence exchange rate elasticities/ They will be grouped into three groups fundamental, cyclical and sentiment and each will be considered for each one of the three periods in my sample.

We can see the fundamental models for the three periods in tables 6.3-5.

During the first period we can clearly see that the principal components had a strong trend and autoregressive terms. Most of the fundamentals do not appear to be significant with the exception of the American current account, the returns of the equity markets for both the US and abroad, the Small minis big phenomenon and the prices of primary commodities. Interestingly commodities appear to be important only in conjunction with equity markets. This seems to indicate that elasticities were influenced by the state of the economy as a whole as opposed to the fundamentals that are normally theorized to influence exchange rates. R^2 are relatively low but this might be due to error in variables since the elasticities are estimated with Kalman filter.

Spec N	1	2	3	4	5	6	7	8	9	10
Variable Name										
C	-0.20	-49.49	-42.01	-63.46	-62.50	-47.56	-33.32	-54.95	-54.93	-63.85
	0.97	0.79	0.77	0.66	0.66	0.74	0.82	0.68	0.67	0.62
	1.00	1.04	1.07	1.11	1.13	1.28	1.29	1.38	1.42	1.49
TREND	0.71	0.79	0.67	0.75	0.60	0.54	0.57	0.88	0.82	0.85
	0.01	**0.02**	**0.02**	**0.01**	**0.04**	**0.09**	**0.07**	**0.00**	**0.00**	**0.00**
	1.00	1.04	1.05	1.06	1.06	1.07	1.08	1.08	1.09	1.10
M1		47.69	41.40	66.09	68.09	54.69	34.15	45.38	44.79	53.21
		0.79	0.77	0.64	0.64	0.71	0.81	0.73	0.73	0.68
		1.00	1.02	1.02	1.03	1.07	1.08	1.10	1.10	1.14
Ind Prod			0.29	0.28	0.25	0.23	0.16	0.18	0.21	0.18
			0.42	0.44	0.49	0.54	0.67	0.59	0.52	0.60
			1.00	1.10	1.11	1.12	1.18	1.27	1.26	1.29
IR US				-0.79	-0.86	-0.87	-0.66	-0.20	-0.14	-0.18
				0.14	0.12	0.11	0.24	0.70	0.78	0.73
				1.14	1.16	1.17	1.17	1.17	1.20	1.31
IR				-0.27	-0.27	-0.25	-0.25	-0.24	-0.23	-0.26
				0.52	0.51	0.55	0.54	0.52	0.54	0.49
				1.01	1.05	1.06	1.07	1.08	1.08	1.09
CPI					-0.54	-0.54	-0.47	-0.39	-0.31	-0.33
					0.20	0.19	0.26	0.31	0.40	0.38
					1.01	1.19	1.41	1.57	1.65	1.65
CA_US						-0.37	0.27	1.31	2.14	2.14
						0.67	0.78	0.15	**0.02**	**0.02**
						1.02	1.02	1.03	1.04	1.10
CA						0.01	0.01	0.01	0.00	0.00
						0.45	0.40	0.56	0.86	0.77
						1.02	1.34	1.78	1.78	1.80
Commodities Primary							1.60	3.47	3.41	3.35
							0.10	**0.00**	**0.00**	**0.00**
							1.04	2.19	2.29	2.41
MSCI US								7.92	6.64	6.92
								0.00	**0.00**	**0.00**
								2.55	2.74	3.15
MSCI								-4.28	-3.72	-3.73
								0.00	**0.00**	**0.00**
								1.06	1.19	1.26
SMB US									-5.07	-5.28
									0.00	**0.00**
									1.20	1.20
SMB									-0.26	-0.24
									0.54	0.57
									1.06	1.48
HML US										0.32
										0.65
										1.61
HML										-0.29
										0.56
										1.09
AR(1)	-0.39542	-0.39424	-0.54093	-0.54534	-0.56125	-0.56819	-0.55442	-0.64689	-0.62973	-0.62685
	0	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
R^2	0.156443	0.149727	0.274716	0.281123	0.287866	0.282027	0.289957	0.371336	0.418481	0.412518
N	224	210	169	169	164	164	164	164	164	164

Table 6.3 Fundamentals for first period.

Spec N										
Variable Name										
C	-27.35	349.55	345.32	386.04	392.94	392.52	468.26	559.30	603.81	551.62
	0.63	0.19	0.23	0.19	0.18	0.18	0.12	**0.07**	**0.05**	**0.06**
	1.00	1.03	1.04	1.13	1.13	1.13	1.13	1.14	1.19	1.22
TREND	0.58	0.83	1.19	0.83	0.81	0.81	0.74	0.83	0.41	0.79
	0.56	0.42	0.34	0.53	0.54	0.54	0.58	0.53	0.76	0.51
	1.00	1.05	1.08	1.08	1.08	1.08	1.12	1.18	1.19	1.20
M1		-391.39	-408.24	-431.59	-436.56	-436.25	-506.77	-604.40	-624.75	-591.72
		0.15	0.16	0.14	0.14	0.14	**0.09**	**0.05**	**0.04**	**0.04**
		1.02	1.01	1.03	1.03	1.03	1.04	1.05	1.06	1.05
Ind Prod			0.58	0.56	0.25	0.27	-0.15	1.32	0.89	1.05
			0.94	0.94	0.97	0.97	0.98	0.86	0.91	0.88
			1.02	1.02	1.02	1.03	1.05	1.07	1.25	1.46
IR US				-0.21	-0.24	-0.24	-0.32	-0.38	-0.04	0.28
				0.70	0.66	0.66	0.55	0.49	0.95	0.64
				1.11	1.11	1.15	1.22	1.24	1.26	1.29
IR				-0.82	-0.89	-0.88	-1.16	-1.28	-1.34	-1.50
				0.38	0.35	0.36	0.24	0.20	0.18	0.11
				1.02	1.01	1.01	1.01	1.03	1.03	1.03
CPI					1.31	1.32	1.32	1.25	1.27	1.38
					0.37	0.37	0.37	0.40	0.39	0.32
					1.03	1.06	1.15	1.26	1.26	1.28
CA_US						-0.06	0.75	1.33	1.11	0.35
						0.98	0.75	0.58	0.65	0.88
						1.00	1.01	1.01	1.03	1.04
CA						0.00	0.00	0.00	0.01	0.00
						0.94	0.98	0.86	0.70	0.85
						1.03	1.16	1.62	1.68	1.82
Commodities Primary							-2.94	-0.72	0.07	-0.08
							0.21	0.79	0.98	0.98
							1.03	3.99	4.00	4.24
MSCI US								-0.34	0.16	2.88
								0.94	0.97	0.51
								4.57	4.64	4.84
MSCI								-3.12	-2.51	-1.85
								0.35	0.46	0.56
								1.04	1.78	2.26
SMB US									-5.97	-1.45
									0.16	0.74
									1.33	1.42
SMB									0.05	1.82
									0.97	0.19
									1.07	1.92
HML US										-0.87
										0.64
										1.37
HML										-5.69
										0.00
										1.14
AR(1)	0.009561	0.0283	0.036332	0.044398	0.05073	0.05048	0.052258	0.050206	0.048678	-0.01256
	0.869	0.6287	0.618	0.545	0.4905	0.4952	0.4799	0.5033	0.5228	0.8622
R^2	-0.00546	-0.00201	-0.00649	-0.01109	-0.01198	-0.02075	-0.01818	-0.01452	-0.01303	0.122728
N	301	301	240	240	240	240	240	240	240	240

Table 6.4 Fundamentals for second period.

Spec N										
Variable Name										
C	-75.67	-35.75	-44.73	-46.38	-46.26	-29.74	-100.87	-112.82	-106.70	-154.85
	0.01	0.64	0.61	0.60	0.60	0.74	0.23	0.15	0.18	**0.04**
	1.00	1.06	1.10	1.15	1.16	1.18	1.18	1.20	1.39	1.43
TREND	0.91	0.95	1.05	0.96	0.98	1.04	1.06	0.96	0.92	1.13
	0.01	**0.01**	**0.01**	**0.02**	**0.02**	**0.02**	**0.01**	**0.01**	**0.02**	**0.00**
	1.00	1.06	1.33	1.33	1.33	1.40	1.48	1.47	1.47	1.52
M1		-43.58	-43.47	-34.99	-36.79	-58.25	18.15	36.76	34.33	67.38
		0.57	0.63	0.70	0.68	0.53	0.83	0.65	0.67	0.37
		1.01	1.23	1.23	1.23	1.24	1.25	1.27	1.28	1.31
Ind Prod			0.80	1.03	1.05	0.83	0.23	-0.22	0.10	1.69
			0.79	0.73	0.73	0.78	0.93	0.93	0.97	0.48
			1.01	1.12	1.12	1.19	1.31	1.46	1.49	1.55
IR US				-0.12	-0.12	-0.16	-0.26	-0.42	-0.43	-0.56
				0.36	0.36	0.23	**0.04**	**0.00**	**0.00**	**0.00**
				1.01	1.05	1.06	1.07	1.09	1.12	1.13
IR				0.08	0.09	0.09	0.08	0.09	0.08	0.09
				0.28	0.24	0.26	0.25	0.16	0.24	0.13
				1.07	1.05	1.05	1.06	1.06	1.06	1.07
CPI					-0.19	-0.18	-0.16	-0.24	-0.28	-0.25
					0.56	0.58	0.59	0.39	0.32	0.32
					1.07	1.29	1.29	1.39	1.50	1.72
CA_US						0.19	-0.12	-0.13	-0.10	-0.61
						0.75	0.83	0.81	0.85	0.26
						1.10	1.11	1.17	1.17	1.20
CA						0.00	0.00	0.01	0.01	0.00
						0.23	0.19	**0.08**	**0.07**	0.30
						1.28	1.28	2.63	2.59	3.67
Commodities Primary							-2.88	-0.14	-0.20	-2.18
							0.00	0.88	0.82	**0.03**
							1.34	3.05	3.11	3.26
MSCI US								-1.09	-1.22	-1.53
								0.30	0.25	0.13
								2.78	3.34	3.59
MSCI								-2.48	-2.57	-1.75
								0.00	**0.00**	**0.02**
								1.46	1.78	1.83
SMB US									0.88	0.46
									0.22	0.49
									1.38	1.41
SMB									-0.41	-0.53
									0.16	**0.05**
									1.46	2.17
HML US										1.56
										0.00
										1.07
HML										0.01
										0.56
										1.49
AR(1)	-0.43921	-0.44317	-0.44572	-0.43574	-0.4367	-0.43341	-0.47212	-0.43295	-0.41599	-0.4338
	0	**0**	**0**	**0**	**0**	**0.0001**	**0**	**0.0002**	**0.0005**	**0.0002**
R^2	0.209367	0.205099	0.19424	0.195238	0.189913	0.186227	0.318801	0.427017	0.431278	0.516076
N	129	129	108	108	108	108	108	108	108	108

Table 6.5 Fundamentals for third period.

During the second period we again observe a strong trend though the autoregressive term is now insignificant. This might be due to the fact that during the crisis the elasticities were changing in a manner that had a direction but was very volatile in any specific month. The only significant fundamentals were the money supply and the High minus growth phenomenon and in the case of the money supply that is true only after commodities inflation is included. The overall R^2 are non-existent until the introduction of the HML. This suggests that during the crisis elasticities were not dependent on fundamentals. The HML factor might suggest some influence of risk aversion but overall it is possible that we are looking at spurious correlation.

During the third period seen in table 6.5 we again have a significant trend and a significant autocorrelation which suggests that indeed the crisis is characterized by a break in the behavior of the elasticities. The significant fundamentals are the interest rate differential, the foreign equity market, and in some cases the commodities prices, the foreign smb and the foreign current account. The commodities and the foreign current account are never significant together which suggests that they might measure a similar effect. Furthermore just like M1 in the second period the interest rate differential is significant only when commodities are included. This implies that the more traditional fundamentals from old exchange rate models are only significant with a relation to commodity prices. It is also interesting to note that the smb is only significant when hml is included. This might suggest that we have a combination of the effects that existed before and during the crisis at least with respect to equity market phenomenon. Last but not least it is interesting to note that the domestic equity market is still not significant which again might mean that some effect from the crisis persist during the third period.

Next we will look at the cyclical model in Tables 6.6-8.

During the first period the trend and autoregressive terms are both significant just like the fundamental model though the R^2 appear to be smaller. The significant measures are the effective tick for liquidity, as well as the American measures for entertainment with the exception of live entertainment. New cars and unemployment for the US are significant at times but do not appear to be robust.

Spec N									
Variable Name									
C	-0.2012	4.3699	4.3699	4.611	-1.845	-0.0113	-5.9519	-1.4091	-6.4442
	0.97	0.46	0.46	0.45	0.8	1	0.47	0.87	0.45
	1	1	1	1	1	1	1	1	1
TREND	0.7059	0.567	0.567	0.5616	0.7343	0.6609	0.9089	0.7188	0.7827
	0.01	**0.05**	**0.05**	**0.05**	**0.03**	**0.04**	**0.01**	**0.04**	**0.03**
	1	1	1	1	1	1	1	1	1
Liquidity Simple		-3.259	-3.259	-3.3191	-3.4003	-3.1681	-2.7862	-4.021	-3.7535
		0.12	0.12	0.12	0.15	0.19	0.25	0.1	0.11
		1	1	1	1	2	2	2	2
Liquidity Spread			96.0646	95.6411	71.9527	107.1501	94.9435	113.5301	129.5248
			0	**0**	**0.05**	**0.01**	**0.02**	**0.01**	**0**
			1	1	1	1	1	1	1
Financial Stress				-0.0418	0.0663	0.1723	-0.0369	-0.0378	-0.1491
				0.84	0.78	0.47	0.88	0.88	0.53
				1	1	1	2	2	2
UR US					-4.6825	-3.2217	-4.444	-3.6664	-2.0973
					0.01	0.1	**0.03**	**0.07**	0.31
					1	1	1	1	1
UR					1.6502	1.625	1.9041	1.6307	1.217
					0.24	0.24	0.17	0.23	0.36
					1	2	2	2	2
New Car US						1.8276	0.8625	0.8114	-0.1862
						0.07	0.4	0.42	0.85
						1	1	1	1
New Car						1.6393	1.3211	1.2446	1.117
						0.14	0.22	0.24	0.28
						1	1	1	1
Entertainment US							3.085	3.3115	4.5303
							0.01	**0**	**0**
							1	1	1
Entertainment							-0.2328	0.3471	0.4744
							0.77	0.67	0.56
							1	1	1
Live Entertainment							-15.6393	-16.5788	-17.9544
							0.17	0.13	0.1
							1	1	1
Movies								-1.2163	-0.8374
								0.01	**0.07**
								1	2
Drinks									14.6474
									0
									1
AR(1)	-0.3954	96.0646	-0.3684	-0.3662	-0.3465	-0.3603	-0.2717	-0.2807	-0.2283
	0	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
R^2	0.16	0.21	0.21	0.2	0.21	0.24	0.26	0.28	0.31
N	224	224	224	224	192	192	192	192	192

Table 6.6. Cyclical for the first period

Spec N									
Variable Name									
C	-27.3501	-53.8879	-55.8085	-59.0372	-60.0158	-72.4546	-59.3482	-59.1176	-43.8611
	0.63	0.34	0.32	0.3	0.39	0.31	0.42	0.43	0.56
	1	1	1	1	1	1	1	1	1
TREND	0.5761	0.9926	1.0658	1.1247	1.1331	1.393	1.2286	1.2229	0.9199
	0.56	0.32	0.28	0.26	0.38	0.29	0.36	0.37	0.5
	1	1	1	1	1	1	2	2	2
Liquidity Simple		129.4403	139.6058	149.6558	164.4701	171.754	160.9361	160.6225	160.9447
		0	**0**	**0**	**0**	**0**	**0**	**0**	**0**
		1	1	1	1	1	1	1	1
Liquidity Spread			-186.728	-193.148	-210.537	-232.598	-249.795	-249.198	-287.01
			0.01	**0.01**	**0.02**	**0.01**	**0.01**	**0.01**	**0**
			1	1	1	1	1	1	1
Financial Stress				0.1147	0.1552	0.1595	0.1464	0.1478	0.1285
				0.6	0.54	0.53	0.58	0.58	0.63
				1	1	1	1	1	1
UR US					-1.189	-2.1221	-2.225	-2.2193	-2.1801
					0.76	0.59	0.57	0.58	0.58
					1	1	1	1	1
UR					2.2763	1.9761	2.1169	2.1014	2.1702
					0.58	0.64	0.62	0.63	0.61
					1	1	1	1	1
New Car US						-1.9555	-1.4519	-1.4478	-1.3097
						0.2	0.38	0.38	0.43
						1	1	1	1
New Car						-0.4914	-0.6504	-0.6388	-0.1767
						0.84	0.8	0.8	0.95
						1	2	2	2
Entertainment US							-0.4349	-0.4502	-0.434
							0.87	0.87	0.87
							2	2	2
Entertainment							-0.6701	-0.667	-1.0745
							0.79	0.79	0.67
							1	1	1
Live Entertainment							-16.0854	-16.2236	-18.3129
							0.46	0.46	0.41
							1	1	1
Movies								-0.0453	-0.1262
								0.97	0.91
								1	1
Drinks									-15.4242
									0.19
									1
AR(1)	0.0096	0.0184	0.0293	0.0293	0.0351	0.0385	0.0415	0.0415	0.0412
	0.87	0.75	0.62	0.62	0.58	0.55	0.52	0.52	0.53
R^2	-0.01	0.03	0.05	0.05	0.04	0.04	0.03	0.03	0.03
N	301	301	301	301	258	258	258	258	258

Table 6.7.Cyclical for the second period.

Spec N									
Variable Name									
C	-75.6663	-75.99	-77.3188	-67.3882	-64.3912	-62.8322	-107.815	-95.2999	-58.1038
	0.01	**0.01**	**0.01**	**0.03**	**0.06**	**0.08**	**0**	**0**	**0.03**
	1	1	1	1	1	1	1	1	2
TREND	0.9089	0.9145	0.9325	0.8269	0.7978	0.7848	1.2459	1.1941	0.7248
	0.01	**0.01**	**0.01**	**0.02**	**0.05**	**0.05**	**0**	**0**	**0.02**
	1	1	1	1	1	1	4	8	11
Liquidity Simple		-1.2837	-1.0767	0.9686	5.5325	5.125	-51.9165	-81.4646	-127.535
		0.84	0.86	0.88	0.43	0.48	**0**	**0**	**0**
		1	1	1	1	1	4	5	4
Liquidity Spread			27.4778	32.4167	54.1414	59.3201	-179.584	-216.128	-174.46
			0.4	0.32	0.13	0.14	**0**	**0**	**0**
			1	1	2	2	5	7	7
Financial Stress				0.0166	0.0164	0.02	-0.0483	-0.0151	0.0722
				0.33	0.45	0.42	0.14	0.67	**0.03**
				1	2	2	3	7	8
UR US					0.9186	1.1358	4.4887	9.698	14.7236
					0.52	0.47	**0.01**	**0**	**0**
					1	1	1	1	1
UR					0.4327	0.5004	0.7753	0.4095	0.5082
					0.69	0.65	0.43	0.65	0.51
					1	2	3	4	3
New Car US						0.363	-0.4186	-1.4079	-0.7899
						0.66	0.66	0.19	0.34
						1	1	1	1
New Car						-0.1401	-0.56	-0.3724	-0.0502
						0.84	0.36	0.53	0.92
						1	4	4	7
Entertainment US							0.4854	0.9127	4.3672
							0.61	0.35	**0**
							2	2	2
Entertainment							-0.9239	-0.3021	-0.9604
							0.15	0.63	**0.09**
							5	10	13
Live Entertainment							57.0837	85.9997	127.5175
							0	**0**	**0**
							2	5	5
Movies								-0.8033	-1.1851
								0	**0**
								2	3
Drinks									18.6208
									0
									1
AR(1)	-0.4392	-0.4394	-0.4414	-0.4415	-0.2882	-0.2831	-0.5149	-0.6162	-0.6247
	0	**0**	**0**	**0**	**0**	**0.01**	**0**	**0**	**0**
R^2	0.21	0.2	0.2	0.2	0.13	0.12	0.36	0.4	0.56
N	129	129	129	129	111	111	111	111	111

Table 6.8. Cyclical for the third period

The second period can be seen in Table 6.7. Neither the trend not the autoregressive term are significant indicating a clear break during this period. The equations R^2 are nonexistent. The only significant terms are the two liquidity measures both of which have stable coefficients indicating the important role of liquidity during the crisis.

The third period can be seen in Table 6.8. Both the trend and the autoregressive terms are significant again in line with the fundamental model. The significant variables are the US expenditure variables for entertainment and once they have been added, the US unemployment and the two liquidity measures. For the fullest specificationthe equity indices for entertainment and financial stress also appear important. Those expenditure in entertainment measures increase substantially the R^2 which indicates that those measures give more predictive power to the cyclical equation in the 3rd period then it had during the first one prior to the crisis again suggesting mixed effects in the third period.

Finally we will look at the sentiment model in tables 6.9-11.

In the first period we observe the trend and autoregressive terms being significant again. The R^2 are relatively small and stay small which suggests that almost all of the explained variance is from autoregression and the trend. The only significant variable is the bear bull questionnaire of individual investors. This suggests that during this period sentiment played a marginal role in explaining the elasticities of exchange rates.

The second period can be seen in Table 6.10. Again the trend and autoregressive term are not significant in line with the previous two models. The R^2 are almost non-existent with the US CESI and the individual investors cash ratio being the only significant variables but only until first day IPOreturns are introduced in which case both become insignificant and the IPO returns becomes the only significant variable. Overall this means that sentiment matters but does not appear to be more than marginally better than the cyclical equation and underperforms the fundamental equation that includes foreign hml.

Finally we can see the third period in table 6.11. The trend and autoregressive terms are significant again. The US CESI, the Dow Jones option ratio, the IPO returns and count, as well as the individual investors bear and bull ratio are all significant. The individual investors cash ratio is also significant until the introduction of the US CESI. Overall this gives us the highest R^2 for the third period with followed by that of the cyclical equation.

To sum up this section, there appears to be an important break during the crisis whereas clear trend and autoregression exist in the first and third period they disappear during the crisis. None of my models are able to explain accurately changes during the crisis though some indications about the importance of liquidity, the hml and ipo returns seem to emerge. During the first period the fundamental model appears best and during the third one the sentiment model. There is some indication of lingering effect from the crisis though all models do well during the third period. In the next section I will attempt to model those with an out of sample forecasting.

Spec N									
Variable Name									
C	-0.2012	3.7515	3.6518	6.9809	7.1982	7.6432	11.2592	41.8606	43.4028
	0.97	0.51	0.52	0.26	0.25	0.23	0.23	**0.07**	**0.06**
	1	1	1	1	1	1	1	1	1
TREND	0.7059	0.6913	0.7027	0.6505	0.6333	0.6311	0.4953	0.3216	0.2167
	0.01	**0.02**	**0.01**	**0.03**	**0.03**	**0.04**	0.24	0.47	0.65
	1	1	1	1	1	1	2	2	2
AAII Bear Bull		-0.1127	-0.109	-0.1091	-0.1279	-0.127	-0.1355	-0.1485	-0.1559
		0	**0**	**0**	**0**	**0**	**0.01**	**0.01**	**0.01**
		1	1	1	1	1	1	2	2
AAII CASH			-0.1052	-0.2562	-0.2342	-0.243	-0.2596	-0.4437	-0.5008
			0.6	0.26	0.31	0.3	0.32	0.13	0.1
			1	1	1	1	2	2	2
Barometer				-0.9248	-0.9609	-1.0043	-0.9895	-1.1191	-1.1419
				0.13	0.12	0.1	0.19	0.19	0.2
				1	1	1	1	1	2
CESI US					-0.002	-0.0018	-0.0018	-0.0014	-0.0018
					0.42	0.48	0.51	0.61	0.52
					1	1	1	1	1
CESI					0.0001	0.0003	0.0003	-0.0001	0
					0.92	0.86	0.86	0.97	0.99
					1	1	1	1	2
DJ Ratio						-0.0943	-0.1143	-0.188	-0.1063
						0.54	0.5	0.3	0.63
						1	1	1	1
Sentiments Google							0.0001	0.0005	0.0003
							0.95	0.83	0.88
							1	1	2
IPO COUNT								-1.2221	-1.1281
								0.21	0.26
								2	2
IPO RETURNS								-0.7949	-1.0013
								0.42	0.33
								1	3
Equity Ratio US									1.3047
									0.7
									2
Equity Ratio									0.7365
									0.76
									1
AR(1)	-0.3954	-0.3707	-0.3769	-0.3348	-0.3277	-0.3283	-0.3311	-0.3147	-0.3261
	0	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
R^2	0.16	0.19	0.18	0.19	0.18	0.18	0.17	0.18	0.17
N	224	224	224	224	224	224	189	189	189

Table 6.9. Sentiments for the first period

Spec N									
Variable Name									
C	-27.3501	-29.0477	-37.9151	-36.1307	-14.7066	-13.0637	-14.5418	151.7131	149.9249
	0.63	0.61	0.5	0.52	0.8	0.82	0.8	0.13	0.14
	1	1	1	1	1	1	1	2	2
TREND	0.5761	0.5833	0.7143	0.6807	0.1911	0.1061	0.136	-2.0247	-1.999
	0.56	0.56	0.47	0.49	0.85	0.92	0.9	0.22	0.24
	1	1	1	1	1	1	1	1	1
AAII Bear Bull		0.1068	0.1074	0.1182	0.1883	0.2126	0.2157	0.3916	0.3811
		0.63	0.62	0.59	0.39	0.33	0.33	0.15	0.17
		1	1	1	1	1	1	1	1
AAII CASH			1.5585	1.5587	1.6336	1.4774	1.4675	1.1247	1.0988
			0.01	**0.01**	**0**	**0.01**	**0.01**	0.17	0.19
			1	1	1	1	1	1	2
Barometer				0.8644	0.76	0.9722	0.9871	3.3812	3.5926
				0.53	0.58	0.48	0.48	0.18	0.19
				1	1	1	1	1	2
CESI US					0.0648	0.0717	0.073	0.0641	0.0609
					0.03	**0.02**	**0.02**	0.17	0.21
					1	1	1	1	1
CESI					0.0028	0.003	0.003	0.0049	0.0049
					0.33	0.29	0.29	0.25	0.26
					1	1	1	1	1
DJ Ratio						0.3483	0.3472	0.6142	0.6176
						0.32	0.32	0.16	0.16
						1	1	1	1
Sentiments Google							0.0024	0.0015	0.0014
							0.77	0.88	0.89
							1	1	1
IPO COUNT								-2.8452	-2.8836
								0.29	0.29
								1	1
IPO RETURNS								-3.3911	-3.4158
								0.01	**0.02**
								1	2
Equity Ratio US									-0.2927
									0.84
									1
Equity Ratio									2.7663
									0.75
									1
AR(1)	0.0096	0.0114	0.0091	0.0105	0.0146	0.0225	0.0211	0.0651	0.0668
	0.87	0.84	0.88	0.86	0.8	0.7	0.72	0.37	0.36
R^2	-0.01	-0.01	0.01	0.01	0.02	0.02	0.02	0.05	0.04
N	301	301	301	301	301	301	301	231	231

Table 6.10. Sentiments for the second period

Spec N									
Variable Name									
C	-75.6663	-73.576	-76.0338	-75.5109	-96.1718	-72.646	-70.3008	-130.619	-118.666
	0.01	**0.01**	**0.01**	**0.01**	**0**	**0**	**0.01**	**0**	**0**
	1	1	1	1	1	1	1	4	4
TREND	0.9089	0.845	0.8775	0.8739	1.1263	0.888	0.8613	1.504	1.3828
	0.01	**0.01**	**0.01**	**0.01**	**0**	**0**	**0**	**0**	**0**
	1	1	1	1	1	1	1	1	2
AAII Bear Bull		0.1629	0.1263	0.1248	0.1011	0.1018	0.1027	0.1125	0.1446
		0	**0**	**0**	**0.01**	**0**	**0**	**0**	**0**
		1	1	1	1	1	1	2	3
AAII CASH			0.4934	0.4813	0.477	0.1713	0.1679	-0.0604	-0.2976
			0.01	**0.01**	**0.02**	0.3	0.31	0.75	0.18
			1	1	2	2	2	2	2
Barometer				-0.0688	0.2441	-0.259	-0.2649	-0.2459	-0.2736
				0.84	0.51	0.4	0.39	0.43	0.38
				1	2	2	2	2	2
CESI US					-0.0088	-0.009	-0.0089	-0.0125	-0.011
					0.05	**0.02**	**0.02**	**0**	**0**
					1	1	1	1	1
CESI					-0.0004	-0.0003	-0.0004	-0.0009	-0.0009
					0.81	0.84	0.77	0.45	0.43
					1	1	1	1	1
DJ Ratio						-0.5564	-0.5571	-0.6298	-0.6744
						0	**0**	**0**	**0**
						1	1	1	1
Sentiments Google							0.0015	0.0012	0.0011
							0.5	0.58	0.59
							1	2	2
IPO COUNT								2.353	2.3346
								0	**0**
								4	4
IPO RETURNS								-1.3314	-1.3184
								0.01	**0.01**
								1	2
Equity Ratio US									-0.678
									0.11
									2
Equity Ratio									-0.3498
									0.45
									1
AR(1)	-0.4392	-0.4036	-0.4163	-0.4168	-0.3804	-0.4565	-0.4476	-0.4371	-0.4576
	0	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
R^2	0.21	0.32	0.35	0.34	0.35	0.55	0.55	0.6	0.61
N	129	129	129	129	129	129	129	129	129

Table 6.11. Sentiments for the third period

6.3 *Prediction*

In this section I will study the extent to which I can predict the elasticities out of sample. Of course I have already used regression to study the determinants but attempting to use out of sample coefficients will allow me to test my results outside the traditional regression framework.

Firstly we will look at the extent to which our forecasts encompass each other. If a forecast J is encompassed by forecast I then it means that all of the useful information of j is already contained in I and therefore we can discard the j model. J is encompassed if the null of MHLN is not rejected. We can see the tests for our first scenario in table 6.12

i	j	MHLN	p-val
Kitchen	Univariate EQW	-4.470272	0.00
Kitchen	Univariate Weighted	-4.428399	0.00
Kitchen	Models EQW	-2.547522	0.01
Kitchen	Models Weighted	-1.751188	0.05
Univariate EQW	Kitchen	-1481.608	0.00
Univariate EQW	Univariate Weighted	-2.959569	0.01
Univariate EQW	Models EQW	-0.810802	**0.22**
Univariate EQW	Models Weighted	-17.4151	0.00
Univariate Weighted	Kitchen	-28.69585	0.00
Univariate Weighted	Univariate EQW	-0.015051	**0.49**
Univariate Weighted	Models EQW	-6.387245	0.00
Univariate Weighted	Models Weighted	-10.27953	0.00
Models EQW	Kitchen	-2.968467	0.01
Models EQW	Univariate EQW	-0.131662	**0.45**
Models EQW	Univariate Weighted	-0.063852	**0.48**
Models EQW	Models Weighted	-0.026713	**0.49**
Models Weighted	Kitchen	-5.852585	0.00
Models Weighted	Univariate EQW	-0.045027	**0.48**
Models Weighted	Univariate Weighted	-0.055929	**0.48**
Models Weighted	Models EQW	-0.011449	**0.50**

Table 6.12 MHLN statistic for scenario 1.the first and second period will be in sample and the third period will be forecasted

Overall the best models appear to be the equally and varying weights with the three models. This indicates that dividing the variables into three different models has proven beneficial. The kitchen sink model suffers from having too many variables and the univariate regressions appear to miss some interactions. Surprisingly the equally weighted and varying weighted models appear to encompass each other. This suggests that the two weight types are very similar to each other and therefore no specific model fundamental, sentiment or cyclical appears to be explaining the elasticities best.

	SCENARIO 1		
	WEIGHTS_FUND_1	WEIGHTS_MM_1	WEIGHTS_SENT_1
Mean	0.392772	0.349367	0.257861
Std. Dev.	0.187853	0.118084	0.108229

Table 6.13 Model Weights Scenario 1

SCENARIO 1

Var Name	WEIGHTS_M1_DIFF_1	WEIGHTS_IND_DIFF_1	WEIGHTS_IR_US_R_1	WEIGHTS_IR_R_1	WEIGHTS_CPI_DIFF_1	WEIGHTS_CA_US_R_1	WEIGHTS_CA_R_1	WEIGHTS_COM_R_1	WEIGHTS_MSCI_US_R_1	WEIGHTS_MSCI_R_1
Mean	0.03	0.02	0.02	0.03	0.03	0.02	0.02	0.02	0.02	0.02
Std. Dev.	0.01	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00
Var Name	WEIGHTS_SMB_US_R_1	WEIGHTS_SMB_R_1	WEIGHTS_HML_US_R_1	WEIGHTS_HML_R_1	WEIGHTS_AAII_BB_R_1	WEIGHTS_AAII_CASH_R_	WEIGHTS_BAROMETER_	WEIGHTS_CESI_US_R_1	WEIGHTS_CESI_R_1	WEIGHTS_DJ_RATIO_R_1
Mean	0.03	0.02	0.03	0.03	0.03	0.02	0.02	0.03	0.02	0.03
Std. Dev.	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.01
Var Name	WEIGHTS_SENTIMENT_R	WEIGHTS_IPO_COUNT_1	WEIGHTS_IPO_RETURNS	WEIGHTS_EQ_RAT_US_R	WEIGHTS_EQ_RAT_R_1	WEIGHTS_LIQ_SIMPLE_R	WEIGHTS_LIQ_US_R_1	WEIGHTS_FIN_STRESS_R	WEIGHTS_UR_US_R_1	WEIGHTS_UR_R_1
Mean	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.07	0.02	0.02
Std. Dev.	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.06	0.00	0.01
Var Name	WEIGHTS_NEW_CAR_US	WEIGHTS_NEW_CAR_1	WEIGHTS_ENT_US_1	WEIGHTS_ENT_1	WEIGHTS_LIVE_ENT_1	WEIGHTS_MOVIES_1	WEIGHTS_DRINKS_1	WEIGHTS_AR_1	WEIGHTS_TREND_1	
Mean	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.02	0.02	
Std. Dev.	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	

Table 6.14 Weights for univariate regressions scenario 1 the first and second period will be in sample and the third period will be forecasted. Red indicates a weight higher than 4 % and yellow a weight lower than 2 %.

We can see those weights in table 6.13. Overall they appear to be close to equal and their variability is similar which again confirms the result that using all three models appears to be a good idea. When we look at table 6.14 we can also see the weights for the univariate regressions. Overall none of the variables has a low weight and the only one with a high weight is financial stress.

We can see scenario 2 in Tables 6.15-17. In this scenario we are attempting to forecast our crisis period so the results will indicate to what extent our specifications can deal with it. The only specification that never encompasses any of the others is the kitchen sink model which remains quite different from all of the other specifications. All of the other specifications encompass each other with the exception of equally weighted univariate regressions who fail to encompass the weighted models. This implies that most of the specifications do not appear to produce different forecasts.

SCENARIO 2

i	j	MHLN	p-val
Kitchen	Univariate EQW	-53.25394	0.00
Kitchen	Univariate Weighted	-51.54909	0.00
Kitchen	Models EQW	-120.5883	0.00
Kitchen	Models Weighted	-94.82176	0.00
Univariate EQW	Kitchen	-589.6429	0.00
Univariate EQW	Univariate Weighted	-0.016304	**0.49**
Univariate EQW	Models EQW	-0.872819	**0.19**
Univariate EQW	Models Weighted	-3.526713	0.00
Univariate Weighted	Kitchen	-410.9835	0.00
Univariate Weighted	Univariate EQW	-0.000228	**0.50**
Univariate Weighted	Models EQW	-0.795624	**0.21**
Univariate Weighted	Models Weighted	-0.80838	**0.21**
Models EQW	Kitchen	-3.117305	0.00
Models EQW	Univariate EQW	-0.382613	**0.35**
Models EQW	Univariate Weighted	-0.328633	**0.37**
Models EQW	Models Weighted	-0.000145	**0.50**
Models Weighted	Kitchen	-8.80063	0.00
Models Weighted	Univariate EQW	-0.000519	**0.50**
Models Weighted	Univariate Weighted	-0.001414	**0.50**
Models Weighted	Models EQW	-0.021433	**0.49**

Table 6.15MHLN statistic for scenario 2.the first period will be in sample and the second and third periods will be forecasted out of sample

	SCENARIO 2		
	WEIGHTS_FUND_2	WEIGHTS_MM_2	WEIGHTS_SENT_2
Mean	0.279660914	0.359100675	0.3612384
Std. Dev.	0.115384967	0.134220301	0.1606505

Table 6.16 Model Weights Scenario 2

SCENARIO 2

Var Name	WEIGHTS_M1_DIFF_2	WEIGHTS_IND_DIFF_2	WEIGHTS_IR_US_R_2	WEIGHTS_IR_R_2	WEIGHTS_CPI_DIFF_2	WEIGHTS_CA_US_R_2	WEIGHTS_CA_R_2	WEIGHTS_COM_R_2	WEIGHTS_MSCI_US_R_2	WEIGHTS_MSCI_R_2
Mean	0.023051771	0.024166286	0.021261284	0.022888466	0.031235303	0.021106196	0.021863025	0.021256439	0.020173474	0.01997245
Std. Dev.	0.008841727	0.017743754	0.006905868	0.008009477	0.056469901	0.006228831	0.010123084	0.007945078	0.006870661	0.006893985
Var Name	WEIGHTS_SMB_US_R_2	WEIGHTS_SMB_R_2	WEIGHTS_HML_US_R_2	WEIGHTS_HML_R_2	WEIGHTS_AAII_BB_R_2	WEIGHTS_AAII_CASH_R_	WEIGHTS_BAROMETER_	WEIGHTS_CESI_US_R_2	WEIGHTS_CESI_R_2	WEIGHTS_DJ_RATIO_R_2
Mean	0.024978771	0.022339265	0.023190655	0.024468459	0.020823799	0.033039838	0.022975837	0.066801397	0.022155203	0.025412403
Std. Dev.	0.006876829	0.005418598	0.009171127	0.015731402	0.007711226	0.026619434	0.004873203	0.080714538	0.010300494	0.006839749
Var Name	WEIGHTS_SENTIMENT_R	WEIGHTS_IPO_COUNT_2	WEIGHTS_IPO_RETURNS	WEIGHTS_EQ_RAT_US_R	WEIGHTS_EQ_RAT_R_2	WEIGHTS_LIQ_SIMPLE_R	WEIGHTS_LIQ_US_R_2	WEIGHTS_FIN_STRESS_R	WEIGHTS_UR_US_R_2	WEIGHTS_UR_R_2
Mean	0.023276951	0.022357047	0.030542212	0.021082678	0.021657064	0.051955861	0.026194375	0.034872506	0.024030379	0.021470532
Std. Dev.	0.012265188	0.007443406	0.016601161	0.005932734	0.006627711	0.048557659	0.006934073	0.025087971	0.010178115	0.006568912
Var Name	WEIGHTS_NEW_CAR_US	WEIGHTS_NEW_CAR_2	WEIGHTS_ENT_US_2	WEIGHTS_ENT_2	WEIGHTS_LIVE_ENT_2	WEIGHTS_MOVIES_2	WEIGHTS_DRINKS_2	WEIGHTS_AR_2	WEIGHTS_TREND_2	
Mean	0.024941463	0.022140558	0.022859921	0.020900616	0.02180219	0.024165863	0.025657422	0.02117226	0.025759779	
Std. Dev.	0.017627733	0.007409844	0.007527439	0.00635773	0.005498605	0.005608634	0.011868219	0.005985808	0.00764922	

Table 6.17 Weights for univariate regressions scenario 2. the first period will be in sample and the second and third periods will be forecasted out of sample Red indicates a weight higher than 4 % and yellow a weight lower than 2 %.

In this scenario fundamentals appear to receive substantially smaller weights which suggest that during the crisis they lost some of their predictive power. The cyclical and sentiment models on the other hand appear to have similar weights though the cyclical factors have more volatile weights. Among the univariate regressions the only ones with large weights are the price impact liquidity measure and the American CESI index. This seems to suggest that the commonality between elasticities that we observed in the 6.1 section might be due to the crisis.

SCENARIO 3

i	j	MHLN	p-val
Kitchen	Univariate EQW	-2.32515	0.02
Kitchen	Univariate Weighted	-2.266287	0.02
Kitchen	Models EQW	-2.297443	0.02
Kitchen	Models Weighted	-2.424357	0.02
Univariate EQW	Kitchen	-4182.344	0.00
Univariate EQW	Univariate Weighted	-100.1203	0.00
Univariate EQW	Models EQW	-4176.519	0.00
Univariate EQW	Models Weighted	-2165.956	0.00
Univariate Weighted	Kitchen	-20.908	0.00
Univariate Weighted	Univariate EQW	-0.002731	**0.50**
Univariate Weighted	Models EQW	-1.619523	0.07
Univariate Weighted	Models Weighted	-3.153374	0.00
Models EQW	Kitchen	-0.273219	**0.39**
Models EQW	Univariate EQW	-2.963617	0.01
Models EQW	Univariate Weighted	-2.093569	0.03
Models EQW	Models Weighted	-0.385165	**0.35**
Models Weighted	Kitchen	-0.070418	**0.47**
Models Weighted	Univariate EQW	-0.031537	**0.49**
Models Weighted	Univariate Weighted	-0.040884	**0.48**
Models Weighted	Models EQW	-0.113552	**0.46**

Table 6.18MHLN statistic for scenario 3.second period in sample and the third period will be forecasted out of sample

Next we will look at the third scenario which includes only the second period in its estimation and tries to forecast the last period. Those can be found in tables 6.18-20. It can be clearly seen that in this case the weighted models appear to encompass all of the other specifications. This suggests that when limited samples are used only the weighted models are capable of predicting well the elasticities.

	SCENARIO 3		
	WEIGHTS_FUND_3	WEIGHTS_MM_3	WEIGHTS_SENT_3
Mean	0.269013439	0.356018098	0.3749685
Std. Dev.	0.146998	0.147146778	0.1517072

Table 6.19 Model Weights Scenario 3

As we can see in table 6.19 the fundamental models again receive lower weights which indicates that their predictive power is disrupted when estimations are made using mostly data from the crisis. In the case of the univariate regressions large weights are given to the same measures as in the previous scenarios namely the financial stress and CESI indexes and the price impact liquidity measure. In addition the inflation differential has received a large weight whereas a large number of variables have received small weights.

Next we will look at the cumulative error plots which can be seen for Scenario 1 in Fig. 6.4. I will use again the Eurozone as an illustration. The kitchen sink model will be omitted in all comparisons with the long AR because of its enormous errors.

Var Name	WEIGHTS_M1_DIFF_3	WEIGHTS_IND_DIFF_3	WEIGHTS_IR_US_R_3	WEIGHTS_IR_R_3	WEIGHTS_CPI_DIFF_3	WEIGHTS_CA_US_R_3	WEIGHTS_CA_R_3	WEIGHTS_COM_R_3	WEIGHTS_MSCI_US_R_3	WEIGHTS_MSCI_R_3
Mean	0.023384464	0.024530924	0.018646484	0.026186721	0.048100937	0.018989297	0.019537062	0.018030937	0.016840755	0.015757548
Std. Dev.	0.011209995	0.016267585	0.005184301	0.01663022	0.081751447	0.005701066	0.00496095	0.006020045	0.006165576	0.005649611
Var Name	WEIGHTS_SMB_US_R_3	WEIGHTS_SMB_R_3	WEIGHTS_HML_US_R_3	WEIGHTS_HML_R_3	WEIGHTS_AAII_BB_R_3	WEIGHTS_AAII_CASH_R_	WEIGHTS_BAROMETER_	WEIGHTS_CESI_US_R_3	WEIGHTS_CESI_R_3	WEIGHTS_DJ_RATIO_R_3
Mean	0.026901396	0.018953373	0.027945131	0.022730684	0.017748091	0.020853482	0.021743226	0.066558136	0.019817357	0.02654655
Std. Dev.	0.008099419	0.006631482	0.011339291	0.009675532	0.004465176	0.007959467	0.004353616	0.05513413	0.005166209	0.00836718
Var Name	WEIGHTS_SENTIMENT_R	WEIGHTS_IPO_COUNT_3	WEIGHTS_IPO_RETURNS	WEIGHTS_EQ_RAT_US_R	WEIGHTS_EQ_RAT_R_3	WEIGHTS_LIQ_SIMPLE_R	WEIGHTS_LIQ_US_R_3	WEIGHTS_FIN_STRESS_R	WEIGHTS_UR_US_R_3	WEIGHTS_UR_R_3
Mean	0.019493486	0.020261174	0.021899084	0.019490261	0.019737405	0.084101431	0.025390378	0.056684718	0.019380295	0.021050832
Std. Dev.	0.005275273	0.005874703	0.006573964	0.005277831	0.005627146	0.060741349	0.006261748	0.034088901	0.005600183	0.007356265
Var Name	WEIGHTS_NEW_CAR_US	WEIGHTS_NEW_CAR_3	WEIGHTS_ENT_US_3	WEIGHTS_ENT_3	WEIGHTS_LIVE_ENT_3	WEIGHTS_MOVIES_3	WEIGHTS_DRINKS_3	WEIGHTS_AR_3	WEIGHTS_TREND_3	
Mean	0.01977452	0.020097669	0.019020809	0.018682168	0.022715879	0.027527614	0.020852185	0.019480119	0.024557421	
Std. Dev.	0.005351959	0.005692178	0.005271005	0.005676723	0.004827757	0.004599916	0.007271999	0.005332684	0.004549058	

Table 6.20 Weights for univariate regressions scenario 3second period in sample and the third period will be forecasted out of sample. Red indicates a weight higher than 4 % and yellow a weight lower than 2 %.

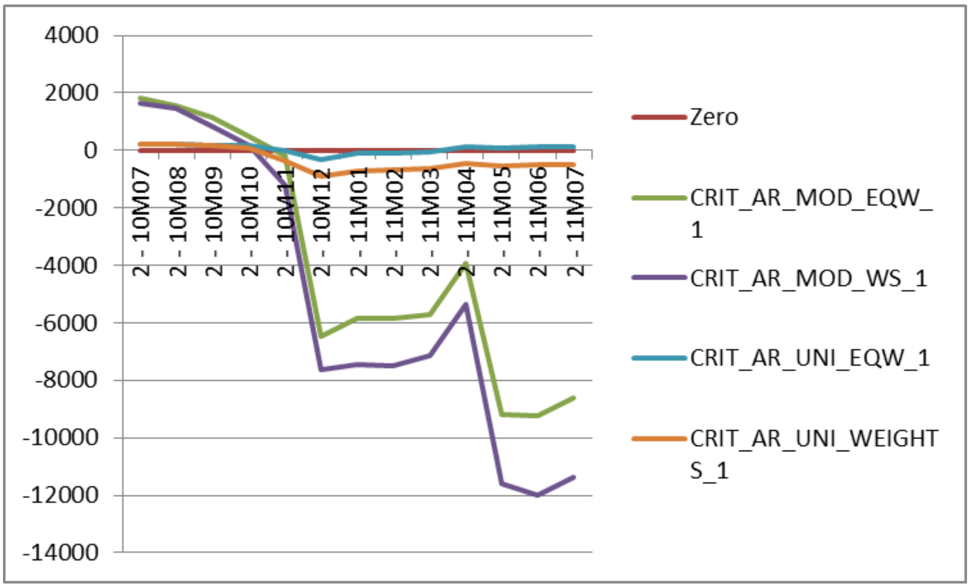


Fig 6.4 Cumulative squared errors First Scenario with benchmark the long AR. Kitchen sink is omitted.

Overall it does look like the Models do substantially better than the univariate regressions though the performance of all deteriorates with time. Fig. 6.5 gives us the comparison with respect to the random walk. It does appear that the kitchen sink is still the worst model though the others are tied really close and have and all models have better performance that the random walk which suggests that elasticities should be predictable. We can see the extent to which this is significant in Table 6.21

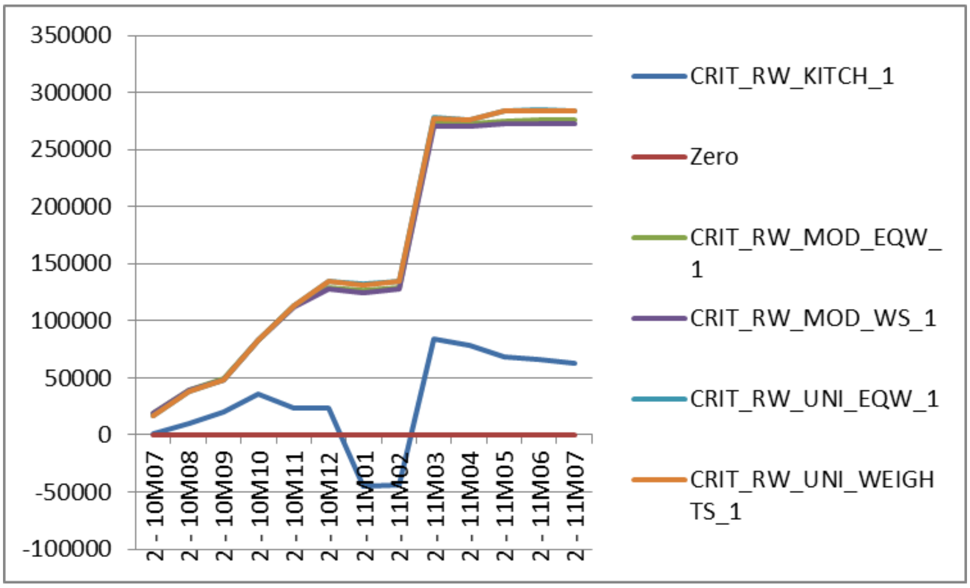


Fig 6.5 Cumulative squared errors First Scenario with benchmark the Random Walk.

specification	R	p_val
Kitchen, AR	-11.1846	0.27
Kitchen, RW	0.361388	**0.00**
Models Weights		
AR	-0.58749	0.72
Models Weights		
RW	0.916797	**0.00**
Models EQW AR	-0.28548	0.74
Models EQW RW	0.932627	**0.00**
Uni EQW AR	0.196897	0.27
Uni EQW RW	0.957908	**0.00**
Uni EQW AR	0.169068	0.83
Uni EQW RW	0.95645	**0.00**

Table 6.21 The forecast evaluation. First scenario.The first column is the Rsquared os. The second column is the p value of MSPE adjusted. If the null is rejected then the specification is outperforming the benchmark

In here the null hypothesis is that the specification performs worse than the benchmark model. Overall most of the specification do better than the random walk but fail to outperform the long AR.

Next we will look at scenario 2 where an attempt is made to forecast during the crisis Fig 6.6-7 and Table 6.21 are of relevance. It appears to be the case that the models specification sees a large deterioration in its performance whereas the univariate regressions appear to be outperforming the Long AR this could be be due to the univariate regression being able to react to the new conditions created by the crisis faster despite the fact that they include the same variables as the models. When looking at the random walk the only apparent result is that the kitchen sink model is not appropriate. Table 6.22 gives us the same result as the first scenario with all specifications outperforming the Random Walk and none the Long AR.

Next we will look at the third scenario which incorporates the least amount of data. The results can be seen in Fig. 6.8-9 and Table 6.22 Overall most of the specifications underperform the Long AR but the models are again the worst performers after the kitchen sink. The fact that the univariate equally weighted specification is the best might imply that the sample is too small for proper estimation and evaluation. When considering the random walk again the main conclusion seems to be that the elasticities can be predicted and the only underperformer is the kitchen sink. After looking at Table 6.23 again we fail to see a specification which outperforms the long AR though all outperform the Random Walk.

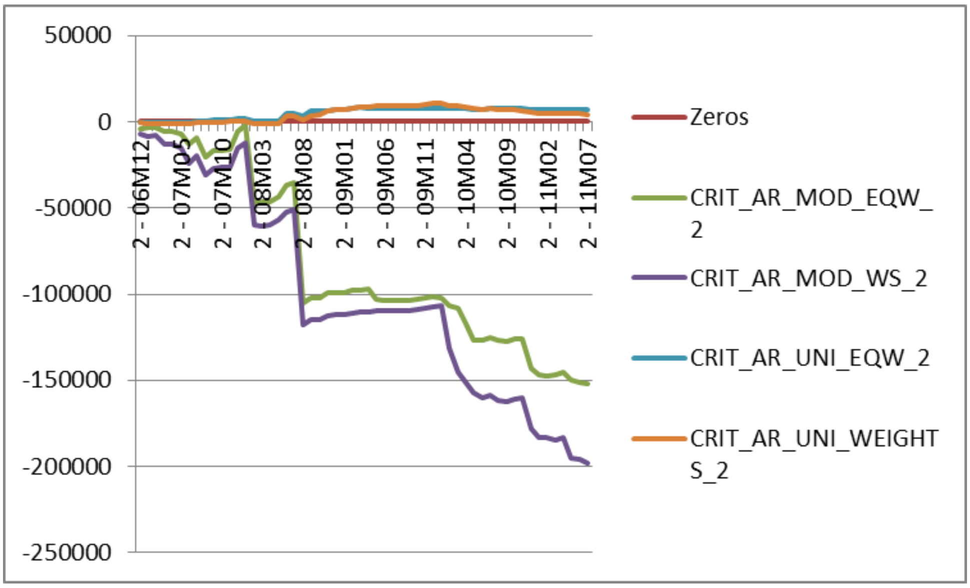


Fig 6.6 Cumulative squared errors Second Scenario with benchmark the long AR. Kitchen sink is omitted.

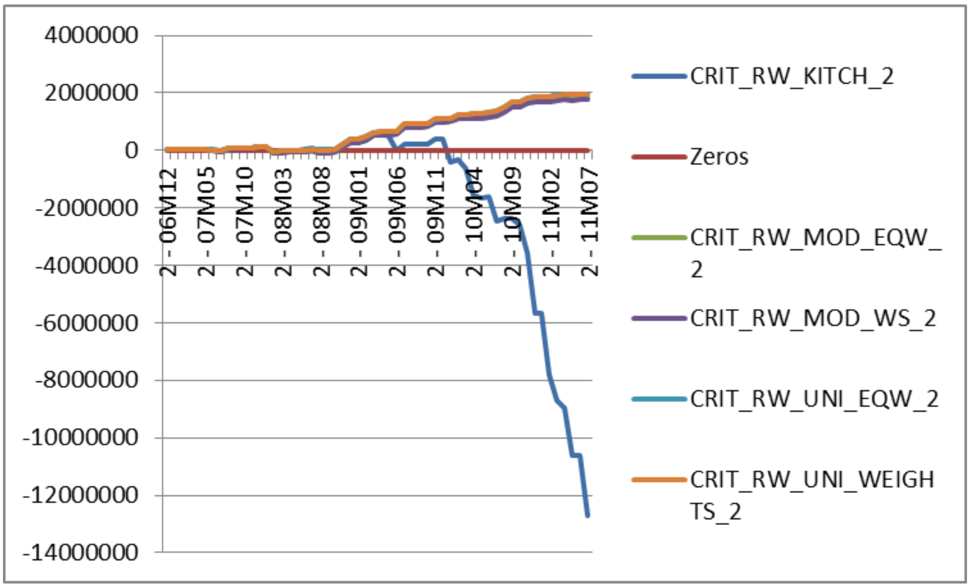


Fig 6.7Cumulative squared errors Second Scenario with benchmark the Random Walk.

specification	R	p_val
Kitchen, AR	-11.1846	0.11
Kitchen, RW	0.361388	**0.00**
Models Weights		
AR	-0.58749	0.28
Models Weights		
RW	0.916797	**0.00**
Models EQW AR	-0.28548	0.23
Models EQW RW	0.932627	**0.00**
Uni EQW AR	0.196897	0.69
Uni EQW RW	0.957908	**0.00**
Uni EQW AR	0.169068	0.63
Uni EQW RW	0.95645	**0.00**

Table 6.22 The forecast evaluation. Second scenario. The first column is the Rsquared os. The second column is the p value of MSPE adjusted. If the null is rejected then the specification is outperforming the benchmark

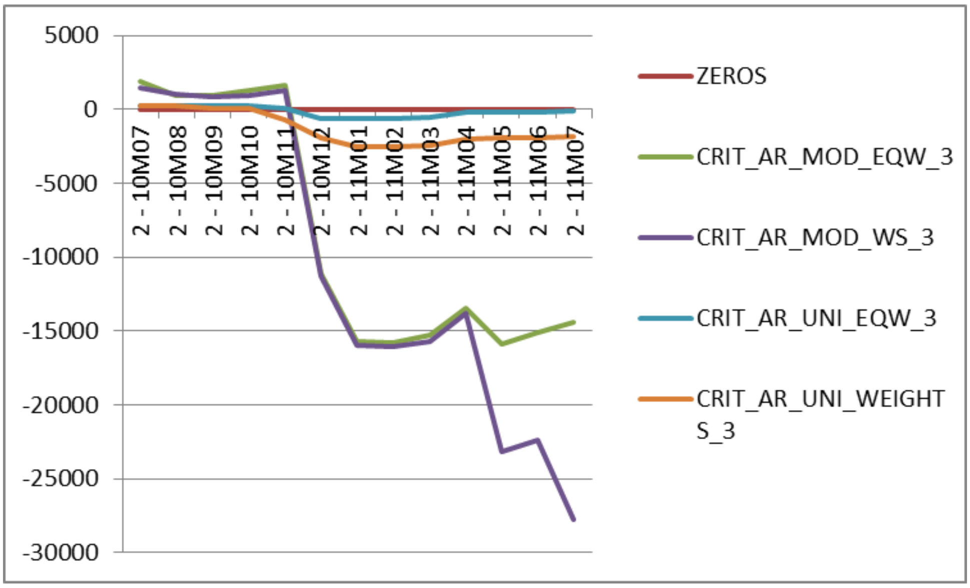


Fig 6.8 Cumulative squared errors Third Scenario with benchmark the long AR. Kitchen sink is omitted.

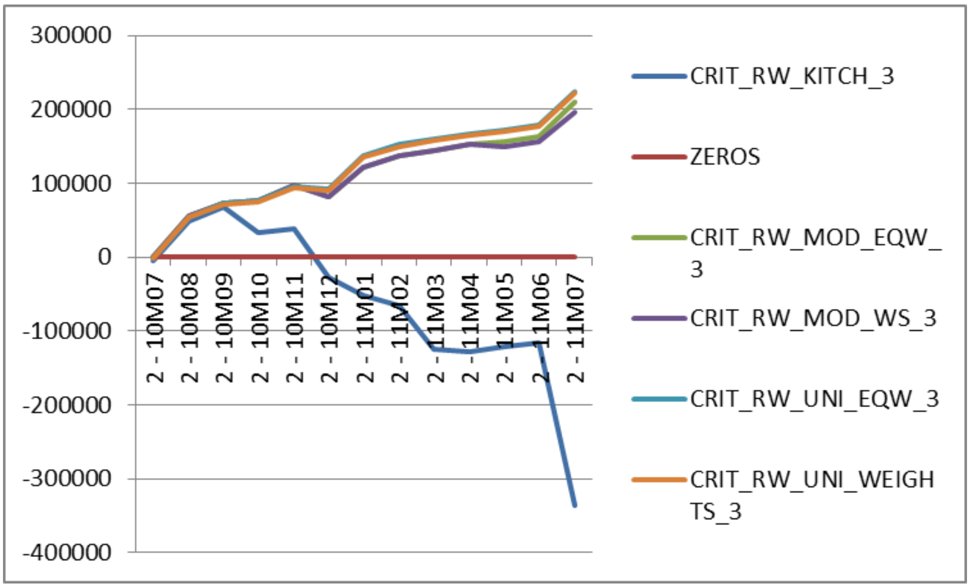


Fig 6.9Cumulative squared errors Third Scenario with benchmark the Random Walk.

specification		R	p_val
Kitchen, AR		-11.1846	0.46
Kitchen, RW		0.361388	**0.00**
Models	Weights		
AR		-0.58749	0.59
Models	Weights		
RW		0.916797	**0.00**
Models EQW AR		-0.28548	0.51
Models EQW RW		0.932627	**0.00**
Uni EQW AR		0.196897	0.46
Uni EQW RW		0.957908	**0.00**
Uni EQW AR		0.169068	0.95
Uni EQW RW		0.95645	**0.00**

Table 6.23 The forecast evaluation. Third scenario. The first column is the Rsquared os. The second column is the p value of MSPE adjusted. If the null is rejected then the specification is outperforming the benchmark

7 Conclusion and Discussion

In this work I used high frequency data from the Bloomberg forecast monitor to determine how 7 exchange rates react to macroeconomic surprises in monthly US announcements over the period 2003-11. My results suggest that the different elasticities were determined by a group of common factors irrespectively of the exchange rate considered. This suggests that US specific or global conditions affect the elasticities. Furthermore I determined that a strong break occurred around the time of the Global economic crisis which suggests that during that period the determinants of the elasticities changed.

Overall my results suggest that economic fundamentals influenced to some extent the elasticities but that in the period after the crisis their role decreased while that of sentiment increased. This is likely due to aftershocks from the crisis which has not ended as of 2011. Furthermore the out of sample section strongly suggests that elasticilies have autocorrelation and all of the specifications tested failed to perform better. This implies that overall the changing elasticities phenomenon is due to the crisis and that once set such elasticities will change only very gradually if at all but during crises they are unpredictable.

I recommend for future research that this analysis be conducted with the currencies of developing currencies as well as the use of non US macroeconomic surprises. Furthermore conducting research in a period that was not dominated by such a major crisis could also be beneficial.

Finally, this result might be of interest to traders and risk managers since it appears that the elasticities are relatively constant and only change after big crises. This implies that currency hedges might be even more important during crises than at times of business as usual.

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APPENDIX A

Appendix will be added in the final version of this master thesis including a list of variables, programming code and any other tables/graphs of interest.