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TITLE:
**“BRIDGING EMERGING MARKET MODELS AND
INVESTORS’ REALITIES: THE CASE OF CURRENCY AND
EXTERNAL DEBT MARKETS”**

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DEGREE:
PHD ECONOMICS

ABSTRACT

Our target is to objectively quantify important aspects of emerging economies' financial markets and deliver value adding actionable recommendations that can be used by a wide spectrum of end-users like academics, policy makers and real life investors. We create two quantitative models that capture the dynamics of global Emerging Market currencies and sovereign debt ratings. We build on the extensive literature on Emerging Market crises and introduce a number of methodological and conceptual innovations. A wide range of market stylized facts and practical and intuitive limitations dictate the way we progress with our research, from considering and selecting dependent and explanatory variables to the way we apply and interpret the model results. We first estimate a parsimonious panel specification that models and forecasts Emerging Market currency dynamics and produces trade signals for investing in one-month forward exchange rates. The second instrument models and forecasts credit ratings assigned by two of the leading rating agencies to Emerging Market sovereigns. The specifications we select are tested on the basis of their statistical and forecasting performance which is found to be solid and unbiased. The currency model is further tested based on its ability to generate profit making trading portfolios. The ratings model is also assessed based on its forecasts for forthcoming sovereign rating actions. We proceed to apply both models on real time data and compare the results from blindly following the model recommendations to a situation where an investor filters these results by superimposing his market awareness and subjective judgement. Our findings suggest that the tools developed here can reliably be integrated in an investor's decision process. The events of late 2010 suggest that many of the ideas presented in our work can be implemented to Developed Markets and be expected to produce interesting and usable results.

*Dedicated To My Father, Aristeidi Lekka,
Who Won Over Respect For His Rare Integrity And Wisdom
And Inspired Great Love For His Soul And Smiling Eyes.
Thank You For Everything.*

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As I submit the final version of my thesis I want to turn to each one of those who supported me in this journey. A PhD in Economics is expected to make a significant research contribution and requires strong commitment and long hours of work. Add to this the unpredictable hurdles presented by life and it took me more than a decade to fulfil this life-long dream. Still, had it not been for those extraordinary people who supported me in their own special ways, I would not have been able to achieve this precious closure.

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INTRODUCTION

The aim of this thesis is to develop quantitative tools that can be applied in different emerging market asset classes and produce actionable recommendations. The first tool we create is a Foreign Exchange (FX) Model that captures and forecasts significant moves of one month forward exchange rates for twenty one emerging markets globally. These forecasts are presented in the form of recommendations to buy or sell the underlying currencies on a one month horizon. The success of the model is gauged on the basis of its statistical consistency but more importantly on its ability to generate profit making trade recommendations. An important element of our work involves the overlay of market awareness and investors' intuition in creating but also using the FX model we create. The second model we created is an EM Ratings Model that describes and predicts the ratings that major rating agencies would assign to 30 emerging market sovereigns. Both products that we develop are global, in that they are applied on all emerging markets in a uniform manner. The aim is to build products that satisfy intuition and market stylized facts, remain statistically robust and produce results that are directly usable by investors.

We present our work on our FX model in the first four Chapters of the thesis. Chapter 1 outlines the relevant academic literature and our contribution, as well as our choice of dependent variable. Chapter 2 describes in detail the process via which we approached and selected the explanatory variables of our specifications. In Chapter 3 we present the methodology we adopted and the statistical performance of the different specifications we

tested and the ones we finally decided to select. Chapter 4 puts our FX model to the toughest test by translating the model generating signals to investment portfolios of EM currencies. The track record of these portfolios is assessed both in and out of sample as well as during a period of real time data. The latter forms the platform for one of the most interesting aspects of our work, that of presenting how real life EM investors could or would use a quantitative tool like our EM FX model.

Chapter 5 presents our work on building and applying our EM Ratings Model. We refer to the relevant literature and the ways in which our work differs from what was done previously. We describe the left and right hand side of our model specification, the accompanying statistical results and estimation methodology. We proceed to apply the selected model to real time data again and present specific examples and ways in which this product is both intellectually appealing and practically useful.

With the privilege of hindsight most market moves seem easy to explain. Currency moves are no exception. However translating this retrospective understanding to a clear, objective rule that models and forecasts currency moves is a very different exercise. Adding to this the complication of addressing emerging markets and doing so with a cross country and across time specification makes the target even more challenging. In the following Chapters we present our work in detail and provide guidance in ways that quantitative techniques and investment decisions can and should be linked to optimize returns in a systematic yet realistic fashion.

1 CHAPTER ONE: Modelling and Forecasting Currency Risks in Emerging Markets: Literature Review and Our Contribution

1.1 Introduction

Chapter 1 of the thesis is the first of four chapters that describe our work on our Emerging Markets FX model. In essence we develop a quantitative tool that builds on the widely published area of early warning signal mechanisms with regards to mounting exchange rate risks and the evolution of currency crises in emerging markets. Our work deviates from previous research in that we model high frequency, forward exchange rate dynamics, focus on both upside and downside risks and opt to generate actionable trade recommendations which are intuitive and profit-making. This chapter reviews the relevant research and puts our work in context.

In the last thirty years, vast amount of research has been carried out on the area of currency crises. The sequence of crises that shocked both developed and emerging markets in the 1990s triggered a renewed interest in the subject. The majority of currency crises, as defined in the literature, involved cases where pegged regimes were abandoned either following a successful attack from speculators or because the government chose to let the currency float. Literature both academic and empirical focused on a number of key issues, such as what constitutes a crisis, which variables best explain past currency crises or hopefully provide signals for forthcoming ones and what methodology would more appropriately describe the underlying

processes. With regards to the dependent variable, the near consensus view has been to focus on cases of substantial double digit depreciations of a bilateral nominal exchange rate.

The bulk of the relevant theoretical work has mainly focused on explaining past crises. However, the need to successfully predict future crises is inherently linked to the research on currency risks. An admittedly challenging task, as it is difficult to forecast an event that seems to adopt a different shape and form each time it occurs. Most have acknowledged the multifaceted feature of currency crises in emerging markets but support the notion that commonalities still exist and merit further research. This thesis builds on relevant research and significantly extends the work done previously in a number of ways. First of all we do not wish to assess currency crises or crashes per se. We opt to generate actionable trade recommendations on a monthly basis and therefore focus on high frequency exchange rate dynamics for a number of emerging market currencies globally. We assess both upside and downside currency risks as opposed to the almost unanimous tendency of previous work to only focus on risks of substantial devaluations or depreciations. We follow a parametric approach and create a very parsimonious, technically robust quantitative tool for gauging currency risks in emerging markets

The remaining of this chapter is structured as follows. Section 1.2 attempts a brief presentation of the relevant literature. Section 1.3 discusses the ways in which our work deviates from and extends previous research. In this section we present in more detail the rationale and key characteristics of our sample and dependent variable selection before we turn to the analysis of

the explanatory variables considered and selected in Chapter 2 of the thesis. Section 1.4 concludes.

1.2 Literature Review

The main objective of the current thesis is to produce quantitative tools, readily applicable in real life investment decision processes. As our aim is to model and forecast currency risks in emerging markets a natural starting point was to read, understand and exploit the substantial academic literature on the topics of currency and financial crises and crashes. Nevertheless, our work relates also to research carried out within financial institutions which share our goal for applicability of results and the limitations dictated by market stylised facts. This thesis is a sort of hybrid in that it explores both the relevant academic research, acknowledges the intellectual appeal of creating early warning signals for medium to long term mounting pressures, but also aims to account for market realities and create solutions that serve as high frequency investment tools. We tap on the vast supply of interesting material and make our own recommendations which hopefully others will find useful in the future.

This section does not aim to exhaust the list of important papers that have contributed to the understanding of emerging market crises over the years. Several other papers have masterfully presented a comprehensive review of relevant research. In what follows we provide a brief overview of the relevant research and present in more detail some of the most influential papers as well as a summary of the work which this thesis more closely relates to. As we proceed to present the key points of interest in the literature we also make a brief presentation of our views with regards to the different

lines of thinking. The majority of papers published on financial crises in recent years can broadly be classified with respect to two aspects: “What” each paper researches and “how” the authors chose to address the underlying issues. In turn, these broad criteria can be broken down to even more refined themes. A certain degree of over-lapping and complementarities between branches of work can reasonably be expected.

Let us first turn to the topics more often addressed by papers on crises. One thematic classification can be made depending on what sort of crises one is interested in. While a crisis will always constitute an out of the ordinary event, a distinction is made between currency crises, financial or banking crises and sovereign debt crises. In practice of course most incidents of economic disorder will involve many if not all of these types of crises simultaneously. Still, let us address the key characteristic of each of these aspects separately.

Debt crises refer to cases where a sovereign defaults on its debt obligations. The definition of default may vary somewhat but it will almost certainly involve the inability or unwillingness of a government to meet some or all of its principal and/or interest payment obligations for foreign currency or, less often, local currency denominated debt held by investors. Research on sovereign default became very topical with the Latin American “Debt crisis” in 1982. Renewed interest was attracted in the late nineties when a new wave of sovereign defaults hit global emerging market. This time it was a global issue with countries as far apart as Russia in 1998 and Argentina in 2001 defaulting on their debt obligations. In mid 2007 the developed world experienced the so-called Great Recession that initiated in the US and

effectively affected all major economies. As a result a new trend emerged whereby significant amount of debt was in one way or another transferred from the private sector (corporate, banking or household) to the sovereign level. This new trend unsurprisingly led to heated debates on the sustainability of the mounting sovereign debt levels. In early 2010 a number of European sovereigns attracted attention due to ballooning fiscal and debt burdens which were perceived by investors as unsustainable. In a domino effect that started with Greece, quickly involved other peripheral EU countries like Ireland and Portugal and touched even upon some of the key core European economies such as Italy and Spain, markets were swift to price in significant probabilities of possible default or restructuring. The spiralling market reaction led to a number of coordinated policy actions from the EU and the IMF in an attempt to minimize moral hazard and potential contagion. As this thesis is finalised the jury is still out on the outcome and success of these measures and the eventual response by markets. We shall return to the topic of sovereign credit-worthiness and default risk at the last chapter of the thesis where we review in more detail sovereign credit ratings and their links to fundamentals.

The other two types of crises, currency and banking ones have so often occurred sequentially or coincidentally that they are referred to as “twin crises” in the literature. Irrespective of the cause and trigger of a banking crisis, it usually manifests itself in mass withdrawals from the banking sector. This would in turn lead the banks to freeze deposits and refrain from servicing the withdrawal requests. Often the banks will lean to the government to intervene and bail-out the banking system from the liquidity shock. Currency crises often precede, coincide with, or follow liquidity squeezes or banking crises and

involve substantial weakness of the local currency. Hereafter in this chapter we shall focus on currency crises alone, although, as mentioned above, problems in most sectors of the economy can share common roots. The currency crises that occurred in the last thirty years are often broadly categorised in three “generations” depending on what is understood to be the cause of the crisis and what are the variables that would explain it best. Much of the research carried out in the field of currency crises has focused on one or more of these generations.

What is known as “first generation” models focused mainly on how pegged exchange rate regimes are bound to become pray for speculators who will likely attack the currency when they find it optimal to do so. This line of research follows the seminal work by Krugman⁽⁷⁵⁾ (1979) on “A model for balance of payments crises” which links excessive fiscal and monetary policies to currency crises. The key idea behind the “first generation” models was that it is weak fundamentals and unsustainable and incompatible policies that will lead to balance of payments deficits which will likely be financed by the a country’s foreign exchange reserves. This will, in turn, attract the interest of speculators, who monitor the level and depletion rate of foreign exchange reserves held by a central bank that tries to defend a pegged exchange rate regime. Once the reserves fall below a certain threshold level, investors will perceive the government as no longer able to defend the currency and believe that it may be forced to abandon the peg following what is called a “successful” speculative attack.

We too acknowledge the importance of macroeconomic fundamentals and the relevance of adopted macro policies. However we do not focus only

on cases of self fulfilling currency crises nor do we narrow our scope of interest in cases of transition from pegged to floating currency regimes. In fact we are particularly interested in the dynamics of currency markets in recent years which are first and foremost characterised by free or managed floating regimes in the majority of emerging markets that we monitor.

What is classified as “second generation” models acknowledged the fact that a peg may be abandoned not only because the government can no longer defend it, but also, as seemed to be the case in the collapse of the European Monetary System (EMS) in 1992 and 1993, because a government prefers to float the currency at a time that seems optimal to do so. Usually this is during a recession, a time at which abandoning the peg is expected to lead to a substantial weakening of the currency which in turn could help reinstate the country’s international competitiveness and support growth.

Again our work here deviates from the “second generation” models in that we define a crisis as a substantial change in the valuation of a currency, be it due to a peg being abandoned or during a floating exchange rate regime. Official intervention from the government to affect the exchange rate of its national currency is a very common scenario in emerging markets. However we are wary of how feasible it is to quantify, let alone model, such an intervention. We are also very much aware of the fact that central banks may need to, and indeed will tend to intervene to adjust an exchange rate higher or lower depending on the circumstances. As discussed our goal is to capture both upside and downside currency risks. Therefore it is fair to say that our work does not fall under the “second generation” group of research papers.

The “third generation” of models of currency crises includes work on

more recent events like the Mexican crisis in 1994 and the Asian crisis in 1997 were links are established between currency and banking crises. Factors seen as likely triggers for these crises include excessive money supply, significant capital inflows to unregulated economies which lead to bubbles in the domestic credit and often stock or housing markets. All this was often followed by unexpected capital flight as a sudden negative turnaround in the global economic environment made investors less complacent of stretched valuations within particular countries. This line of work brought the idea of contagion to the forefront of crises research. Colourful names like “Tequila Crisis” and “Asian Flu” have been used in the literature to describe the domino effects that followed respectively, the crisis in Mexico in December 1994, which affected the majority of the Latin America region and the crises in a number of East Asian currencies following the collapse of the Thai baht in July 1997.

We explore the literature on “third generation” currency crises to assess the event specific factors that mattered each time and, importantly, to select a group of explanatory variables that most have tested and many have found of some relevance. We do end up using the one variable that merits near consensus support, namely the real effective exchange rate. The other variables that we finally select though, have not, as far as we know, been presented in the literature. Furthermore our work is neither limited to one specific crisis nor limited to crises alone, at least not as defined by the relevant literature. In effect our research does not fall in the “third generation” of currency crises group of work either.

An interesting categorisation of most major crises was attempted by G.L.

Kaminsky⁽⁶³⁾ in late 2003. In her paper on “Varieties of Currency Crises”, Kaminsky suggests that the majority of currency crises that have preoccupied research work and devastated emerging and occasionally industrial countries can be categorised in six groups. Four out of six of these involve events that are a function of vulnerabilities in domestic fundamentals. One group links crises to the global market environment which could trigger a flight of international capital flows from certain countries and cause the countries in question to experience a crisis. The last group involves countries, which experienced a crisis despite strong fundamentals, though it is noted that these crises are inherent to developed rather than emerging markets. We only look at emerging markets and find that a global model would best describe currency risks in emerging markets if it includes both factors that are inherent in each country but also factors which reflect the dynamics and circumstances of global markets. It is therefore not possible to categorise our research in terms of one group alone as suggested by Kaminsky in the 2003 paper.

Besides deciding on what sort of crises to research, one also needs to address the question of what methodology to select. This issue brings us to the second way in which research papers on currency crises may be grouped. There are broadly two approaches to consider, the parametric and the non-parametric one. Those leaning towards the parametric approach will need to decide on the best modelling methodology, the most appropriate way to quantify the crises events they chose to research and the variables that will best help explain and hopefully forecast these events. The non-parametric approach will involve a similar selection process with regards to explanatory variables and definition of the crisis variable. The link between these two

though, will be typically assessed and established via graphical analysis. We adopt a clearly parametric approach in our analysis, and opt for an innovative, straightforward and parsimonious specification to fit all the countries in our sample.

A classic paper that set the standard for much of the parametric quantitative assessment of out-of-the-ordinary currency devaluations was published in 1996 by Frankel and Rose⁽⁴⁷⁾ (FR) on “Currency Crises in Emerging Markets: Empirical Indicators”. In their analysis, FR used annual data from 1971 to 1992 for a large group of 100 emerging markets. FR used graphical analysis as a starting point to gauge the way that different variables behave on the run-up to a currency crash but they noted that graphical analysis has its limitations. One of the biggest drawbacks of graphical analysis that they point out is that it is uni-variate and does not allow one to assess the way in which the selected explanatory variables interact.

FR proceeded to estimate a Probit model in their attempt to assess which variables are statistically significant indicators of forthcoming currency crashes. In a Probit model, a dummy variable is used to define a dichotomous dependent variable and the results are presented in terms of probability that the specified event will occur or not. In the case of currency crises, the dummy variable is, in most papers, set equal to one, at times when the definition of a currency crisis is satisfied and takes the value zero, at all other times. According to FR a currency crash occurs when the spot weakens by more than 25% in any given year and at the same time the weakening observed in that year is also at least 10% more than that observed in the previous year. The dependent variable will be zero at all other times.

According to the definition adopted by Frankel and Rose, fitting the estimated Probit model specification to the data will provide probabilities that a currency crash will occur within the following two years.

In our analysis we favour the choice of a Logit specification which falls in the same family of models as the Probit version. We try however, to estimate and forecast probabilities of currency crises occurring in the near future. We feel that a signal for the following 24 months, interesting as it may be, is not nearly as usable as expected from an investment tool. Our work differs from that advocated by FR and the majority of relevant research in a number of important aspects. First and foremost, we do not monitor changes in spot rates, but instead focus on forward exchange rates which we believe is really what investors are interested in. Moreover, we model cases of both exchange rate depreciation and appreciation as both provide investment opportunities and accordingly may conceal risks for those involved. Furthermore, we only condition our crisis variable on an exchange rate appreciating or depreciating by more than a certain rate at any given time period. In doing so, we do not rule out the moves which, significant as they may be, do not exceed the recent past. The main reason for us keeping a broader scope than what a purely academic or theoretical paper may do is our goal to create a tool that will be integrated in an investor's day to day decision making process.

A paper that promoted the use of graphical analysis and the creation of early warning signals mechanisms for currency crises was published by Kaminsky, Lizondo and Reinhart (KLR)⁽⁶⁸⁾ in 1997, and is titled: "Leading indicators of Currency Crises". In this classic paper, KLR employed uni-variate graphic analysis of monthly data to assess the likelihood of a crisis occurring

in the following 24 months. The definition of currency crises that KLR adopt is based on a weighted average of monthly percentage changes in both the nominal spot exchange rate and a country's foreign exchange reserves. This definition aims to capture not only the "successful" speculative attacks described earlier in this chapter, but also the "unsuccessful" speculative attacks against which a government managed to defend the currency. As KLR note this wider definition of what constitutes a crisis also allows them to deviate from the "first generation" models which assumed the existence of fixed exchange rate regimes which may or may not be abandoned following an attack. KLR's definition could pick up crises events even under floating exchange rate regimes.

Our research nears the KLR approach in that we too, do not limit ourselves on successful attacks and we too wish to account for currency moves under floating exchange rate regimes as well. We still deviate from the work that KLR did in that we focus on forwards and they still look at spot exchange rates. This is not merely a difference in the choice of the dependent variable. It manifests the difference in mandate and dictates the need for a possibly altogether different specification.

Others have adopted crises definitions similar to that suggested by KLR. In three seminal papers published by Eichengreen, Rose and Wyplosz (ERW)⁽⁴¹⁾ in 1994, 1995 and 1996, the authors advocate the use of an index for "exchange market pressure" which accounts for unsuccessful attacks as well as successful ones. For their currency crises variable ERW create an index which extends to include changes in the spot exchange rate, changes in foreign exchange reserves and changes in interest rates. They also look at

both the reserves and the interest rate as differential between each country and Germany, which they chose as reference point. Given the way their index of exchange rate pressure is defined ERW also account for revaluations and not only cases of devaluations following a successful speculative attack.

Incorporating interest rates in the measure of currency risks takes the crises literature on a whole new level. Spot rate changes are an important aspect to monitor but in high interest rate regimes, one needs to take into account what the interest rate implies for a currency's future valuation. One important point to make is that nowadays it seems more relevant to look at all currencies versus the USD which is the common reference point for most currency denominations. The other necessary adjustment would be to make the natural switch from using Germany as a reference point to using the euro-area interest rate. Another important contribution from ERW is the fact that their suggested index allows one to monitor both revaluations and devaluations. However this feature remains only a theoretical possibility as ERW really only focus their analysis in cases of downwards exchange rate pressures.

Moving on to the right hand side of the model specification we lean on papers such as FR mentioned above and others mentioned later in this part of the chapter, in order to assemble a group of variables which will best help us quantify, model and forecast currency risks in emerging markets. FR tested a number of different macro data as indicators of large spot exchange rate devaluations within the selected 24month horizon. FR looked at four groups of variables, including data on domestic macro economic fundamentals and data on "external variables" to quantify a country's vulnerability to shocks not

attributed to domestic factors. FR focused a lot on the importance of debt as an indicator of forthcoming crises and stressed the importance of the composition of debt in terms of maturity and interest rate variability. The last group of indicators that FR contemplated was “foreign variables” which aimed to account for the circumstances prevailing in the global financial arena. FR found that currency crises in emerging markets are closely linked to real exchange rate over-valuations, a rise in developed markets interest rates, high domestic credit growth and a depletion of foreign direct investment inflows. We discuss and assess the relevance of each of these, amongst other variables in a later section in this chapter.

A variable that attracted a lot of attention in the literature of currency crises and particularly the “third generation” models discussed earlier in this section is Contagion. The so-called “Tequila Effect” and the infamous “Asian Flu” are two prime examples of colourful names used to describe the spill-over of crises from one country to many others which were linked to the first one either due to geographic proximity or via other channels. In their 1996 paper on “Contagious Currency Crises” Eichengreen, Rose and Wyplosz, (ERW)⁽⁴¹⁾, review the work carried out by others on currency crises and contagion in particular and note that despite the wide selection of theoretical papers which tend to focus on a small sample or even a single event, only a handful of studies had attempted to systematically analyse contagion.

One paper which advocated the key role of contagion was a 1996 paper by Sachs, Tornell and Velasco (STV)⁽¹¹⁶⁾, on “Financial Crises in Emerging Markets: The lessons from 1995”. This work examined the way in which the 1994 Mexican crisis in particular had evolved and attempted to draw

conclusions applicable to other occasions. STV define crises as a combination of factors and carry out single year cross section regression analysis. STV point out the great relevance of contagion and suggest that the so-called “Tequila-effect” which led to a number of other emerging markets feeling similar pressures in the aftermath of the Mexican crisis, only hit previously weak countries that investors felt may be next. In their paper STV find factors like credit growth, over-valuation of the real exchange rate and depletion of reserves as the sort of weak fundamentals that characterised the countries hit by contagion in the Mexican crises.

In their own analysis of contagion ERW estimate a panel binary Probit model, using quarterly data from 1959 to 1993. They include both economic fundamentals and political factors in their model and they try to account for both successful and unsuccessful attacks. By including the explanatory variables both with and without a lag, ERW effectively tested which variables are leading and which are coincident indicators of exchange rate pressure. ERW first establish that there is clear evidence of contagion as they find that a speculative attack in one country, raises the probability that other countries will experience currency crises as well. Then they attempt to get a more clear sense of the channels via which contagion is transmitted. In particular they test the hypothesis of contagion transmitting a crisis from one country to its trading partners and from one country to others with similar economic policies and fundamentals. ERW find that both these channels are statistically important with trade links having a more dominant effect as a crisis transmission mechanism than common macro frameworks.

A key criterion that differentiates papers on currency crises is whether

the aim is to purely describe the past or to attempt to predict the future as well. In their 1997 paper mentioned above, KLR tried out a large group of candidates to assess whether these variables were good indicators of forthcoming currency crises. A threshold was adopted for each indicator and that indicator was assumed to give a signal once it crossed that pre-defined threshold. The selection of the parameters is based on the success of an indicator in signalling forthcoming crises. All indicators were expressed as year on year percentage changes of monthly data. Like FR, KLR looked to include domestic and international indicators and also tried to account for qualitative factors such as political stability via the inclusion of dummy variables. Again like FR, KLR found that real exchange rate deviations from trend are a key factor in currency crises. They also found that exports, some measure of output, equity prices and some ratio of money to gross international reserves are important early warning signals for forthcoming currency pressures.

As mentioned above, the majority of papers on currency crises, aspired to understand and explain past crises but did little in terms of testing the forecasting power of the suggested methodology, be it parametric or graphical. Berg and Pattillo, (BP)⁽¹²⁾ published in 1998-1999, their paper "Are currency crises Predictable? A Test" effectively put FR, STV and KLR to the test. BP assess the out-of-sample forecasting power of these models and in particular their ability to predict the Asian crises in 1997. BP's results are supportive of parametric multivariate probit models. They also suggest that further work could be carried out on the selection of explanatory variables and mention that contagion and qualitative factors like political stability are crucial.

BP conclude that although up to that point, research papers aimed and rather successfully managed to explain past crises, evidence suggested that research on forecasting future crises may also be expected to bear fruits.

We opt to generate a model that rather accurately describes the past but, equally, assists us in forecasting the near term currency risks in emerging markets in a consistent and intuitive manner. We also wish to apply our model on a monthly basis which is a frequency higher than what is adopted by the majority of similar papers. As far as the explanatory variables are concerned we assess many of the usual suspects presented in relevant literature but finally adopt a set of all but one new variables for our specification. In the sections that follow in this chapter we go through our selection criteria in detail. The issue of forecasting accuracy is nowhere a more central consideration than in financial institutions. As mentioned at the beginning of this section, our work shares the need for intuitive and usable results that is inherent in the creation of most modelling tools presented in the market. Below we briefly present some examples of models which were created within leading investment banks and which leveraged on the academic research work outlined above.

One example of empirical work that largely followed the relevant academic research was “GS-Watch”, by A.Ades, R.Masih and D. Tenengauzer⁽¹⁾, published by Goldman Sachs in December 1998. GS-Watch provides a combination of the econometric and non-parametric approaches presented in the literature. The outcome of GS-Watch was on the one hand a set of nine “early warning signals” of a forthcoming financial crisis and on the other hand a calculated probability that such a crisis will occur in the following

three months. The analysis was done and the logit-type panel model estimated on a sample of 27 emerging markets globally. The explanatory variables included a set of fundamentals consistent with relevant academic research and variables that attempted to account for political stability, global liquidity and contagion. GS-Watch incorporates most of the well established “schools” of thought on financial crises. However it still stops short of implementing the theory in a manner that will produce actionable trade recommendation. This already differentiates GS-Watch from our work here.

In their 2001 paper titled: “On Crisis models: An alternative crisis definition”⁽⁴²⁾, A.C. Eliasson and C. J. Kreuter,(EK), of Deutsche Bank Research point out a number of limitations enforced by the choice to model crises as a binary variable. EK suggest as an alternative the use of a “continuous” crisis definition which accounts for both exchange-rate and interest rate “extreme” events in emerging markets. Deutsche Bank also publishes “DESIX: Deutsche Bank Eurasia Group Stability Index”⁽³⁸⁾, an index that comprises of a combination of indicators that aim to capture both quantitative and qualitative factors that provide an assessment of a country’s ability to “withstand shocks and crises”. The usability of DESIX as a parameter in one’s investment decision is limited as no conclusion is driven with respect to the information content of the different index levels, nor are the index scores translated into trade suggestions.

R. Subbaraman, R. Jones and H Shiraishi published in September 2003 “Damocles: an Early Warning System Model”⁽¹²¹⁾ for Lehman Brothers. Damocles largely follows the literature of early warning systems and uses a combination of economic and financial variables as indicators that may

produce forward looking signals for future financial crises. Cases where the bilateral nominal exchange rate between a currency and the USD falls in any given month by more than three standard deviations from the sample mean are classified as crises. A set of 10 indicators including macroeconomic and market data are combined to construct an index measure. A reading above a certain index level is seen as an indication that a country's balance of payments is vulnerable to a financial crises and an index reading above an even higher threshold is interpreted as a signal that a financial crisis could be imminent.

Another example of empirical work which links academic background and the perspective of investment banks is "Credit Suisse First Boston's (hereafter mentioned as "CSFB") EMRI: Emerging Markets Risk Indicator"⁽⁷⁷⁾, first published by M.S. Kumar, W. Perraudin, V. Zinni in April 1998 and re-estimated in September 2000 by A. Roy and M.M Tudela, who published the renewed version in Dec 2000. In its 1998 version EMRI was a logit type panel model applied on 32 emerging markets globally, and producing risk scores for the probability of having significant country specific devaluations in the near term. Following the relevant academic literature a large number of economic, financial and qualitative variables were tested and 16 were selected for inclusion in the so called "parsimonious" version of the model. In EMRI an attempt was also made to capture the so called "unanticipated" depreciation and a second version of the model was estimated where the devaluation rate was adjusted for the interest rate differential between a country and the US.

In the version of EMRI as re-estimated and published by Roy and Tudela in 2000⁽¹¹³⁾, the general framework remains largely unchanged. Changes

include the extension of the sample to 36 countries. The 2000 EMRI version also calculated “raw” and “marginal” explanatory factor contributions to the likelihood of a forthcoming currency crisis. Regional models are also calculated besides the overall global model version. The model results are presented as monthly changes in annualised probabilities, aiming to best capture the dynamics of currency risks.

The attractiveness of products like Damocles, GS-Watch, DESIX and EMRI lays in the attempt to incorporate academic conclusions on the subject of financial crises, with the ability to update the results regularly and overlay market-oriented story telling. Nevertheless as long as all these products stop short of making trade recommendations to their clients they remain little more than technically robust exercises on academic crises research, carried out inside major investment houses.

A paper that builds on the conclusions driven by Berg and Pattillo mentioned earlier in this section and also on the work done in CSFB’s EMRI was published in January 2002 by M. Kumar, U. Moorthy and W. Perraudin, (KMP) titled, “ Predicting Emerging Market Crashes”⁽⁷⁶⁾. KMP estimated a logit type multivariate panel model to forecast what they call currency “crashes” instead of “crises” to emphasize that they wish to focus only on successful speculative attacks and in general cases where pressure on a currency does evolve to substantial currency depreciation. Consistent with the relevant literature KMP focused on downside currency risks. They attempted to quantify the forecasting performance of their findings via the application of a simple trading rule which makes “long” or “short” trade recommendations depending on whether the probability of a currency crash is above or below a

certain threshold. KMP define a “long” trade in a specific currency as a recommendation to buy and hold that currency against the US dollar and a “short” recommendation as a trade where investors are advised to sell a particular currency and buy US dollars instead. KMP’s findings support the idea that such models may be successfully used for the development of profit making trading rules.

Although KMP take the typical crises modelling exercises further, they do not address many issues which are crucial to a real life investor. In brief they do attempt to account for interest rate differentials but define crashes in a manner that does not completely depart from the shortcomings of modelling spot rather than forward exchange rates. KMP also admit to having no access to market determined data on interest rates which raises the obvious question of the applicability of their findings on real markets going forward. KMP, indeed attempt to quantify the performance of their model in making investment recommendations for both buying and selling an EM currency within a short period of time. However they base these recommendations on results from a specification that only models cases of substantial depreciations. Whether a weak buying signal can be reliably seen as a selling opportunity is highly debatable. In the remaining of this chapter we shall discuss in greater detail such practical aspects of the analysis carried out in papers like the one by KMP.

The research as presented in the first four chapters of the thesis replicates our work on “CREMM: CSFB’s Currency Risk in Emerging Markets Model”⁽⁸⁰⁾ (hereafter referred to as “CREMM”) which was developed, presented and maintained by the author of this thesis N.Lekka. An

introduction to CREMM was published by N. Lekka in July 2003. From July 2003 to May 2005 N. Lekka maintained, updated and applied the model to real life data on a calendar month basis. The results were published and shared with investors that were at the time clients of CSFB. CREMM was also presented to the ECB, IMF and a number of Universities and financial conferences globally. CREMM, which is in essence the model presented in great detail in this thesis builds on relevant research but was designed and implemented with a clear focus on the applicability and usability of the results. The focus was to provide an aid to investors that are interested in forward exchange rate returns and in model generated signals that are updated in a rigorous manner to produce high frequency trade recommendations for a whole group of emerging market currencies. The request for direct application dictated the need for the model input data to be leading indicators readily available in time for the model updates. As for the model output, the aim was to translate it into trade signals that are intuitive and, more importantly, profit making. To this date we have yet to come across a model developed within investment banking or in a more academic environment that addresses this constellation of issues. It is these considerations that we aim to present in detail in the next sections.

1.3 Our Contribution to Relevant Research

We tap on the wide research published on currency crises to underpin our understanding of emerging markets, understand the characteristics of each currency, develop a sense of what is the best way to capture currency risks, familiarise ourselves with the available methodologies and make a well

educated judgement on the selection of explanatory variables we consider or include in the model. The work presented in this chapter though, departs from the relevant literature on currency crises and crashes in a number of key aspects.

First, we adopt a different definition of our dependent variable as we wish to model forward exchange rate returns and not changes in the spot exchange rate. Second, we focus on both upside and downside currency risks and not limit our scope on cases of significant depreciation alone. Third, although we assess most of the variables that merit some sort of consensus in relevant research we chose to include in the selected model specification only a handful of variables, most of which are not discussed in previous research papers. A fourth important way in which this thesis differs from previous work is the manner in which we apply, present and test the model results. This section presents in greater detail all these aspects and considerations in the model development process.

1.3.1 Data Sample

We availed ourselves of monthly data on 21 emerging markets globally. In this section we present our data sample and outline some considerations, central in the data compilation process and key to gaining an insight to this modelling exercise. Compiling a data set for 21 emerging markets globally for any period is bound to be a major challenge. In this section we touch upon a number of practical limitations one is faced with when gathering economic or financial data for emerging markets, even from the most reliable of data sources. We shall return to many of these issues in a later section where we

discuss the variables that we considered and the reasons why we selected to include or exclude different data series in our analysis.

1.3.1.1 Data Sources

The majority of the data were downloaded from data providers such as Datastream and Bloomberg. We also utilised data sets publicly available by the IMF and the World Bank. For more specialised data series on credit ratings we turned to leading rating agencies like Moody's and Standard and Poor. A lot of the market determined data we use were provided by the economists, strategists and traders at CSFB.

1.3.1.2 Country Groups

We estimate one model for all 21 countries included in our sample. Admittedly no two emerging markets are alike and the one-size-fits-all model specification introduces a considerable degree of limitation in our ability to capture the characteristics inherent to each currency.

One way of grouping emerging markets advocated in the literature is in terms of geographic links. In line with market approach the countries included in our sample can be grouped in three geographical sub-samples. These regional groups are: "Latin America", "Emerging Europe, Middle East and Africa" and "non-Japan Asia", hereafter referred to as LATAM, EMEA and ASIA respectively.

Table 1 Regional Country Groups

LATIN AMERICA (LATAM)	EMERGING EUROPE MIDDLE EAST & AFRICA (EMEA)	NON-JAPAN ASIA (ASIA)
ARGENTINA	CZECH REPUBLIC	INDIA
BRAZIL	HUNGARY	INDONESIA
CHILE	POLAND	MALAYSIA
COLOMBIA	RUSSIA	PHILIPPINES
MEXICO	SLOVAKIA	SINGAPORE
VENEZUELA	SOUTH AFRICA	SOUTH KOREA
	TURKEY	TAIWAN
		THAILAND

1.3.1.3 Sample Starting Points

Data on emerging market series are rarely available for a considerably long period. When constructing our dependent variables we used data on bilateral spot exchange rates of each local currency versus the US dollar and one month market determined interest rates to calculate the forward points between each currency and the USD. For the US market we used the one month USD London inter-bank offered rate (LIBOR), which is the interest rate at which banks can borrow from other banks USD for one month. For the emerging market currencies included in our sample we use the market determined interests rates from the most liquid traded instrument as described in the following section. Table 2 below shows the earliest date for which we had data available on spot and forward exchange rates. The starting date for the forward exchange rates is conditional on the availability of interest rates. In all cases the forward exchange rates were available for a shorter period than the spot exchange rates.

Table 2 Data Sample Starting Dates

CURRENCY	SPOT EXCHANGE RATE SAMPLE START DATE	FORWARD EXCHANGE RATE SAMPLE START DATE
ARGENTINEAN PESO	OCTOBER 1994	MAY 1997
BRAZILEAN REAL	OCTOBER 1994	SEPTEMBER 1998
CHILE PESO	OCTOBER 1994	NOVEMBER 1998
COLOMBIAN PESO	FEBRUARY 1996	JANUARY 1998
CZECH KORUNA	OCTOBER 1994	MARCH 1995
HUNGARY FORINT	OCTOBER 1994	AUGUST 1997
INDIAN RUPEE	OCTOBER 1994	FEBRUARY 1998
INDONESIAN RUPIAH	FEBRUARY 1994	SEPTEMBER 1994
MALAYSIAN RINGGIT	FEBRUARY 1994	MARCH 1994
MEXICAN PESO	OCTOBER 1994	NOVEMBER 1998
PHILIPPINES PESO	OCTOBER 1994	NOVEMBER 1994
POLISH ZLOTY	APRIL 1999	JULY 1998
RUSSIAN RUBBLE	DECEMBER 1995	JULY 2000
SINGAPORE DOLLAR	JUNE 1995	JUNE 1995
SLOVAKIAN KORUNA	JULY 1996	JULY 1996
SOUTH AFRICAN RAND	OCTOBER 1994	DECEMBER 1995
SOUTH KOREA WON	AUGUST 1996	NOVEMBER 1997
TAIWAN DOLLAR	FEBRUARY 1997	OCTOBER 1997
THAILAND BAHT	FEBRUARY 1994	FEBRUARY 1994
TURKISH LIRA	FEBRUARY 1994	OCTOBER 1998
VENEZUELAN BOLIVAR	MAY 1996	NOVEMBER 1998

As will be explained in greater detail at a later section of this chapter, our dependent variable calculates the difference between the prevailing spot and forward exchange rate. Therefore we are limited to only include in our analysis the periods during which both spot and forward data are available. It follows that the last column of Table 2 below is the one that corresponds to the starting dates of the time series included in our analysis. One other major issue which is common in all data series but significantly more so in less transparent emerging markets, is the fact that even for the period during which data are available you are bound to either have gaps within the series

or a number of outliers which you need to amend. In our data we found only a small number of such discrepancies which rarely covered a period longer than one or two months. In these few cases we replaced the missing values with the average of the available data in the preceding and following month.

1.3.2 Choice of Dependent Variable

Our goal is to model and forecast returns from investing on the one month forward exchange rate of a number of emerging markets globally. Therefore, this work departs from the academic and empirical research published on currency crises which primarily focuses on one-off significant depreciations of the spot exchange rate. We too think that both investors and policy makers would benefit from a more rigorous understanding of the events that have devastated both emerging and developed markets in the past few decades. Our mandate nevertheless is different. We model one month forward exchange rate returns, generate monthly portfolios for a group of emerging market currencies globally and assess the model performance via tracking the profit and loss that would have been generated if one was to blindly follow the model recommended trading portfolios.

1.3.2.1 Exchange Rate Conventions Adopted

Before we proceed, let us outline some of the assumptions and certain basic rules we adopt in terms of notation and presentation of analysis. For matters of convenience, when referring to any currency pair we will use the notation adopted by Bloomberg and Reuters, the leading markets data providers. Table 3 below gives the names and codes for all the currencies we include in our model. In this thesis we will be quoting all emerging market

currencies versus the US dollar.

We will always quote an exchange rate in terms of units of local currency per one US dollar. That means that the local currency is our “quoted” currency and the USD is our “base” currency. An exchange rate of RUB28.5 means that you can exchange 28.5 Russian Rubbles for one USD in the market. A fall in the exchange rate from RUB28.5 to RUB28 indicates an appreciation of the RUB versus the USD as one can now buy one US dollar with less units of local currency, which in this case is the Russian rubble.

Table 3 Currency pairs and annotation

Currency	Bloomberg code vs the USD
ARGENTINE PESO	ARS
BRAZILEAN REAL	BRL
CHILEAN PESO	CLP
COLOMBIAN PESO	COP
CZECH KORUNA	CZK
HUNGARIAN FORINT	HUF
INDIAN RUPEE	INR
INDONESIAN RUPIAH	IDR
MALAYSIAN RINGGIT	MYR
MEXICAN PESO	MXN
PHILIPPINES PESO	PHP
POLISH ZLOTY	PLN
RUSSIAN RUBLE	RUB
SINGAPORE DOLLAR	SGD
SLOVAKIAN KORUNA	SKK
SOUTH AFRICAN RAND	ZAR
SOUTH KOREAN WON	KRW
TAIWAN DOLLAR	TWD
THAILAND BAHT	THB
TURKISH LIRA	TRL
NEW TURKISH LIRA ¹	TRY
VENEZUELAN BOLIVAR	VEB

¹ The Turkish lira was re-denominated on January 1st 2005. Until that date the currency code was TRL and it quoted in millions of liras per one USD. From that day onwards, the currency code was TRY to denote the New Turkish Lira which has dropped six zeros from the previous way it was quoted. Here we will use the TRL code and the old quote as our sample covers mostly the pre 2005 period.

In practice there is a difference between the exchange rate at which a bank will buy a currency and the exchange rate at which the same bank will be willing to sell the same currency at the same point in time. This price difference is called the “spread” between the “bid” and the “offer” levels. The “bid” is the exchange rate at which a bank is willing to buy the base currency, here USD, and sell the quoted currency. The “offer” is the exchange rate at which the bank is willing to sell the base currency and buy the quoted currency. So for our example above a currency trader within a bank will typically give a dual quote: USD/RUB: 28.55/28.58. This means that the bank is willing to pay 28.55 Russian rubbles for every US dollar it buys, but is willing to sell one USD for 28.58 Russian rubbles.

The bid/offer spread will vary and will tend to widen for less liquid currencies. Emerging Market currencies are typically less liquid than the developed market currencies. For the currencies considered here, the bid-offer spread represents the largest part of the transaction costs involved when dealing in emerging market currency markets. It is arguably the most quantifiable transaction cost. Even though the market liquidity has improved in the last decade and that in turn has brought down the bid/offer spreads considerably, they still represent some sort of entrance barriers for many market participants or could de-motivate investors from very frequently realigning their positions. In absence of objective and consistent data on transaction costs and for the sake of simplifying the presentation of our analysis we will not differentiate between bid and offer quotes in our analysis. We use the mid level of exchange rates which serves to split the cost evenly between purchase and sell recommendations made by the model. It also

helps us keep a neutral stand between a bank and its counterparties as our trade recommendations would equally apply to both target groups.

1.3.2.2 Forward Exchange Rate Mechanism

One of the key considerations in our work it that we chose to work with forward exchange rates, instead of spot, as this ultimately is what real life investors trade and effectively focus on. A forward exchange rate transaction involves an agreement by two parties to buy or sell a certain amount of currency at a pre-agreed exchange rate at a specific point in the future. We focus on the one month forward exchange rates and monitor the model results on a 12month calendar monthly basis. The mechanism involved in determining forward exchange rates is the same that applies to forward prices in all other financial markets as well, like commodities, interest rates or equities. In a forward rate transaction an agreement is made at time t for an action to take place at time T in the future. The one month forward exchange rate for the Russian ruble (RUB) versus the US dollar (USD) as quoted at the beginning of month t will be the exchange rate at which one investor agrees to buy from another investor Russian rubbles versus USD at the beginning of the next calendar month.

Technically the forward exchange rates will adjust the prevailing spot exchange rate at time t , for the cost involved in carrying out the forward transaction. At time t , investor A agrees to buy from investor B in one month, Russian rubbles at an exchange rate of F units of RUB per one unit of USD. By definition participant B agrees to sell to participant A the same amount of RUB in one month. We say that in this case investor A “goes long” the RUB

on a one month forward basis, while, investor B “goes short” the RUB on a one month forward basis. The one month forward exchange rate at which the transaction will be unwound in one month’s time is decided at time t by the market and is called the “outright forward exchange rate” which we denote with $F_{t,T}$. The outright forward $F_{t,T}$ is determined by adjusting the spot exchange rate prevailing in the market at time t for the so-called “cost of carry” applicable on a one month time horizon. The “cost of carry” is a term used to describe the cost born by investor B in order for him to be able to get hold of, keep and deliver the agreed amount of RUB in one month to investor A.

Below we present an example of a forward rate agreement in detail to graphically present the intermediate stages involved in the transaction and the way in which the cost of carry is calculated in practice.

Adopted notation:

$R_{q,t,T}$ The interest rate prevailing for holdings of the quoted currency (here RUB) at time t with maturity at time T

$R_{b,t,T}$ The interest rate prevailing for holdings of the base currency (here USD) at time t with maturity at time T

S_t The spot exchange rate for local currency (here RUB) versus one unit of foreign currency (here USD) prevailing at time t.

$F_{t,T}$ The market determined forward exchange rate for local currency (here RUB) versus one unit of foreign currency (here USD), set at time t, for delivery at time T.

K The amount of local currency (here RUB) versus foreign currency (here USD) that investor A agrees to buy from investor B at time T In the

future.

T The investment horizon, here assumed to be one month

Process Stage I: at time t :

Investor B buys K amount of RUB versus USD at the spot market at S_t .

In effect B is “locking in” his cost for delivering RUB in the future to investor A

If B did not hold any USD to settle the spot transaction he will borrow the necessary amount equal to $\frac{K}{S_t}$.

The K amount of RUB that B holds for the period of one month from time t to time T , will be invested in the local interest rate $R_{q,t,T}$.

Process Stage II: at time T

B delivers the K amount of RUB to A and gets USD.

B uses the USD proceeds from A to settle the loan he took at time t USD.

Investor B will need to repay the amount of dollars he borrowed at time t equal to $\frac{K}{S_t}$ plus any interest accruing on the loan.

The accrued interest will be calculated based on the one month USD interest rate $R_{b,t,T}$ prevailing at time t .

Overall, $F_{t,T}$, that is the one month forward exchange rate set at time t for time T , will be such that it accounts for the difference between the revenue B gets from investing the RUB in $R_{q,t,T}$ for one month and the money

B pays for borrowing USD at $R_{b,t,T}$ for one month. By definition, the forward exchange rates will imply that the currency with the highest local interest rate will tend to depreciate.

This fact is consistent with the interest rate parity condition which states that in the long run interest rate differentials cannot continue to exist without relevant changes in exchange rates. However in the short run, realised spot exchange rates tend to differ a lot from what the forward exchange rates had implied. Therefore, forward exchange rates need not necessarily be seen as unbiased forecasts for future spot exchange rates, particularly in the short run.

The term: “outright forward” is used to describe a market determined direct quote for the price at which one can buy or sell the local currency per unit of foreign currency at some future settlement date. In many emerging markets “outright forwards” are not or have not for a large part of our sample period been readily available. This is due to the lack of liquidity, the fact that many of these countries still impose capital controls or impose other constraints in market operations. Most of these aspects have been in a continuous improving trend as emerging markets become more transparent, less volatile and more market oriented. Following the currency crises in the 1990s most pegs were abandoned although many countries still implement a managed floating currency regime to this date, with the central bank intervention part of the everyday agenda. The fact remains, however that for most of the markets we are considering we can still not avail ourselves of outright forwards.

We therefore chose to construct the one month forward exchange rates for all the countries in our sample, in order to ensure that the data will be

comparable and consistent for all countries. In doing so we adopt the following definition for constructing our one month forward exchange rates: The forward exchange rate is equal to the spot exchange rate adjusted for the so-called forward points relevant to the time horizon we are interested in. In our case this will be the one calendar month period.

The forward points are practically the calculation for the cost of carry where one also accounts for the maturity of the forward exchange rate and the day count conventions adopted in each country and market. Note that in Equation 1 below we add the forward points to the spot exchange rate. The sign of the calculated Forward Points will depend on two factors. First, which is the base currency in the currency pair in question. As discussed earlier all the currency pairs we consider in our model are quoted versus the USD, making the latter the “base” currency in all cases. Second what matters is which currency in the pair is characterized by higher interest rates. In particular, if the USD interest rates, i.e. the Base currency interest rates are higher than the interest rates of the Quoted Currency then the Fwd Points will come with a negative sign. If the Base currency interest rates, in this case the USD rates, are lower than the interest rates of the Quoted currency, then the calculated Fwd Points will have a positive sign.

Equation 1 : Definition of Outright Forward Exchange Rate

$$F_{t,T} = S_t + FP_{t,T}$$

Where:

$FP_{t,T}$ Denotes the one month forward points set at time t for settlement at t+1

The forward points are constructed as shown in Equation 2 below.

Equation 2: Definition of Forward Points

$$FP_{t,T} = S_t \times \left[\frac{((100 \times D_b) + (R_{q,t,T} \times M)) \times D_q}{((100 \times D_q) + (R_{b,t,T} \times M)) \times D_q} - 1 \right]$$

Where we assume the following notation:

D_b Day count convention for the base currency (here the USD)

D_q Day count convention for the quoted currency (here each EM currency)

M Maturity of the forward in days (assumed 30days for one month forwards)

1.3.2.3 Market Determined Forward Exchange Rates

One very important feature of our work here is that in constructing the one month forward points we availed ourselves of interest rates as implied by the instrument actively traded in each country's currency market. This includes outright forward exchange rates or non-deliverable forwards (NDFs) or deliverable off-shore or on-shore interest rates. We now turn to review in greater detail a number of considerations central to an EM investor's market approach.

The non deliverable forwards are forwards where there is no physical settlement at time T . This means that in our example above B would not physically deliver RUB to A for exchange of USD at time T . Instead the transaction will be settled by payment between the two participants of the difference between S_T , the realised spot exchange rate which is also referred

to as the Fixing Rate at time T , and $F_{t,T}$, the forward exchange rate prevailing at the time the transaction was agreed upon. The NDF market has developed a lot in recent years and has been particularly popular in emerging markets where liquidity considerations or capital controls may not allow for a fully functioning forwards market. The NDF market enables an investor to take a position or cover his currency risk against a potential move in the underlying exchange rate and also allows one to express his views on the valuation of a currency. Deliverable Forwards would be the vehicle of choice for an investor who wishes to hedge a committed exposure in a certain currency. Such investors who need to have physical delivery of a certain currency at maturity of the forward transaction will typically not invest in NDFs.

In EM we also often see a differentiation between on-shore and off-shore forward exchange rates. This comes as a result of many emerging markets still imposing capital controls and all sorts of limitations to the capital that is allowed to be invested at local rates. Though the two rates theoretically cannot deviate too much or for long periods of time, market access limitations allow for significant discrepancies. Often investors with physical presence in the country can have access to the on-shore rates.

Table 4 below gives a brief description of the exchange rate regime and market stylized facts prevailing in each one of the currency markets we include in our model. It is important to note that the majority of emerging markets have seen at some point in time a change in the policy, the currency regime or market regulations that apply domestically. Although our sample of countries is no exception to this rule of transition and change in regimes, we manage to sustain some degree of homogeneity in our sample. This we

achieve by constructing the outright forwards based on market determined interest rates. Therefore under any regime one could either invest in forward rates directly if these are available, or replicate the model trade recommendation by investing in the spot exchange rate and the market determined interest rate and unwind the transaction at some point in the future, again at the prevailing spot. So our sample is homogeneous in that all the model signals refer to actionable currency trade recommendations.

Table 4 Currency Regimes as of 2005

CURRENCY	REGIME	MARKET IMPLIED INTEREST RATE USED IN CALCULATING FORWARD EXCHANGE RATES WAS DERIVED FROM THE FOLLOWING INSTRUMENT	COMMENT
ARGENTINE PESO	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	NON DELIVERABLE FORWARDS	Not freely convertible/ restrictions apply/ CB * intervenes regularly / ARS was fixed at ARS1.4 to one USD from Jan.1, 1992 to Jan. 6 2002
BRAZILIAN REAL	INDEPENDENTALLY FLOATING	NON DELIVERABLE FORWARDS	Non convertible/ CB* intervenes on ad hoc basis
CHILEAN PESO	INDEPENDENTALLY FLOATING	NON DELIVERABLE FORWARDS	Not freely convertible/ restrictions apply/ Free-Floating Currency/ CB* may intervene occasionally
COLOMBIAN PESO	INDEPENDENTALLY FLOATING	NON DELIVERABLE FORWARDS	Not freely convertible/ restrictions apply/Free-Floating Currency/ CB* intervenes regularly
CZECH KORUNA	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	DELIVERABLE FORWARDS	Fully convertible/ free floating/ CB* may intervene regularly particularly in the EUR/CZK bilateral exchange rate

HUNGARY FORINT	PEGGED EXCHANGE RATE WITHIN HORIZONTAL BANDS	DELIVERABLE FORWARDS	Fully convertible/CB* intervenes to ensure the EUR/HUF trades within the +/-15% band around a central parity as required by ERM-II prior to joining the EMU
INDIAN RUPEE	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	NON DELIVERABLE FORWARDS	Restrictions apply/ Reserve Bank of India intervenes to maintain a Real effective exchange rate stability
INDONESIAN RUPIAH	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	NON DELIVERABLE FORWARDS	Restrictions apply/ free floating/ CB intervenes occasionally to maintain stability
MALAYSIAN RINGGIT	VARYING FROM MANAGED FLOATING TO FIXED	NON DELIVERABLE FORWARDS	DURING OUR REAL LIFE APPLICATION MYR WAS FIXED AND THUS WE REMOVED IT FROM THE TESTING
MEXICAN PESO	INDEPENDENTALLY FLOATING	DELIVERABLE FORWARDS	Fully convertible/ free floating/ CB intervenes occasionally
PHILIPPINES PESO	INDEPENDENTALLY FLOATING	NON DELIVERABLE FORWARDS	Restrictions apply/ CB* intervenes to limit sharp fluctuations in the exchange rate
POLISH ZLOTY	INDEPENDENTALLY FLOATING	DELIVERABLE FORWARDS	Free floating/ fully convertible/CB rarely intervenes
RUSSIAN RUBLE	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	NON DELIVERABLE FORWARDS	Restrictions applied pre-june 2004/ fully convertible since 2006/Central Bank of Russia intervenes to maintain a stable ruble exchange rate
SINGAPORE DOLLAR	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	DELIVERABLE FORWARDS	Restrictions apply/ fully convertible/ Monetary Authority of Singapore (MAS) manages the SGD against an undisclosed trade weighted index
SLOVAKIAN KORUNA	MANAGED FLOATING WITH NO PRE-ANNOUNCED PATH FOR THE EXCHANGE RATE	DELIVERABLE FORWARDS	During our sample period the CB would intervene regularly/ Slovakia adopted the EUR and the SKK seized to exist in Jan 2009
SOUTH AFRICAN RAND	INDEPENDENTALLY FLOATING	DELIVERABLE FORWARDS	Not fully convertible/restrictions apply/CB intervenes heavily

SOUTH KOREA WON	INDEPENDENTALLY FLOATING	NON DELIVERABLE FORWARDS	Restrictions apply / both the CB* and the Ministry of finance and economy intervene occasionally
TAIWAN DOLLAR	INDEPENDENTALLY FLOATING	NON DELIVERABLE FORWARDS	Managed floating/ Restrictions apply / CB* intervenes heavily
THAILAND BAHT	MANAGED FLOATING WITH NO PRE- ANNOUNCED PATH FOR THE EXCHANGE RATE	DELIVERABLE FORWARDS	Managed floating since 2001/ restrictions apply / Authorities intervene and have imposed capital controls occasionally
TURKISH LIRA	INDEPENDENTALLY FLOATING	DELIVERABLE FORWARDS	Fully convertible and deliverable/ floating from 1998 to 1999, crawling peg from 1999 to 2001, fully floating since 2001/Central Bank intervenes occasionally
VENEZUELAN BOLIVAR	VARYING FROM MANAGED FLOATING TO FIXED	NON DELIVERABLE FORWARDS	DURING OUR REAL LIFE APPLICATION VEB WAS FIXED AND THUS WE REMOVED IT FROM THE TESTING

Note: (*) CB stands for Central Bank

1.3.2.4 Returns Defined on a Forward Exchange Rate Basis

Our goal is to model and forecast returns from investing on the one month forward exchange rate of a number of emerging markets globally. In practice our definition of returns for any given calendar month, measures the extent to which, the one-month-forward exchange rate available in the market at time t will deviate from what the spot exchange rate ends up being one month later at time T . Effectively we wish to capture the out-performance and under-performance of the realized nominal spot exchange rate from what the market had priced in, when adjusting the spot exchange rate prevailing one month earlier for the one month cost of carry.

Equation 3: Forward Exchange Rate Return below gives the expression we use to calculate the returns on a forward rate basis.

Equation 3: Forward Exchange Rate Return

$$R_{t,T} = \frac{S_T - F_{t,T}}{F_{t,T}}$$

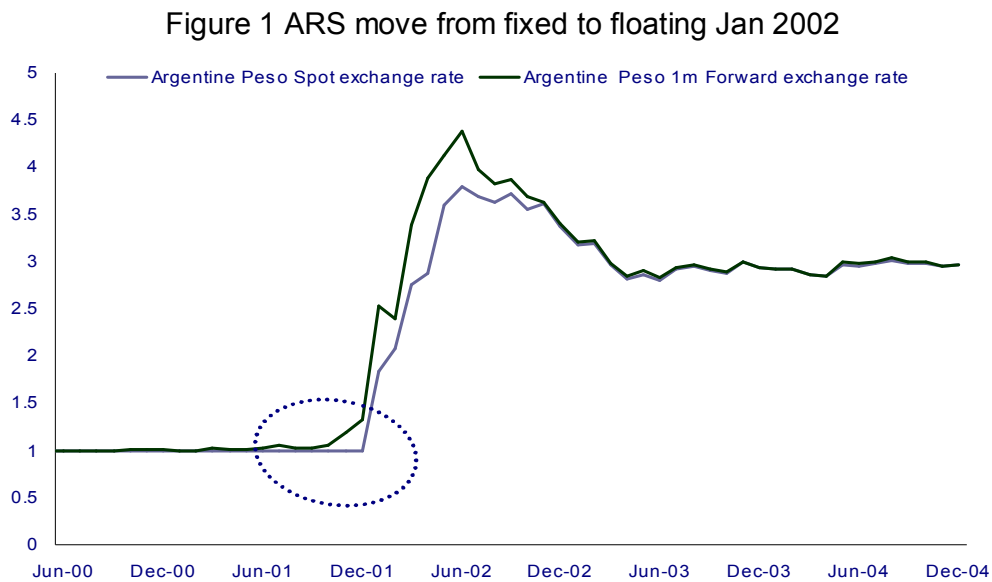
Where:

$R_{t,T}$ denotes the return from investing at time t , in the forward exchange rate maturing at time T

S_T denotes the spot exchange rate prevailing at the maturity of the forward exchange rate transaction

Modelling returns on a forward rate basis relates to investor's interest but is also an approach that allows us to maximise the number of observations available and get a better sense of the underlying currency dynamics during periods of floating exchange rate regimes but also during currency pegs and in particular at the point of transition from fixed to floating regimes. Below we present the arguments that support our thinking. Most of the exchange rates we include in our sample have been fixed for some part of their recent history. Following the majority of literature on currency crises and focusing on changes of the nominal spot exchange rate alone, would significantly reduce the number of observations available, simply because, during periods of fixed exchange rate regimes the spot, by definition, does not move. Arguably the focus of the academic literature has been on the time of transition from fixed to floating regimes, which is exactly what constitutes a crisis for most. However, we find that the forward rates will tend to provide signals long before the peg is abandoned. Therefore most papers that try to forecast when a peg will be abandoned may be missing out on significant amount of information by not accounting for market implied pressures on a fixed spot

exchange rate on the run up to a currency crisis. As Figure 1 below shows, the market implied forwards were reflecting the build up of exchange rate pressure at least six months before Argentina decided to move from a regime where the Argentine peso was pegged to the dollar, to a floating regime. The ARS peg was abandoned on January 6th 2002 while the first signs of weakening were priced in the forward rates as early as June 2001.



During periods of floating exchange rate regimes, forward exchange rates suggest themselves as the most appropriate variable to model as they account for interest rate differentials and determine the real return to investors. If the interest rate parity condition was to hold at all time horizons, the returns based on our definition above would have to be invariably zero, or only slightly different from zero to account for potential transaction costs. However, deviations from what the interest rate parity would imply are the rule rather than the exception in the short run and we find that indeed the forward exchange rate is rarely an accurate predictor of the realized future exchange

spot rate. This in turn means that by focusing on returns as defined in Equation 3 above, one can reasonably expect to indeed forecast cases where investors gain profits, after accounting for the cost of carry.

We are not the first to attempt to model returns above the cost of carry. KMP follow on the steps of CSFB's EMRI and besides modelling pure spot exchange rate depreciation they continue to model what they call "unanticipated" depreciation which they define as follows in Equation 4:

Equation 4: KMP definition

$$100 \times \underbrace{\left(\frac{S_T - S_t}{S_t} \right)}_{\text{Part a}} \times \underbrace{\left(\frac{1 + R_{b,t,T}}{1 + R_{q,t,T}} \right)}_{\text{Part b}}$$

In Equation 4 above we have replaced the notation in KMP with our notation adopted here to facilitate comparison. The difference between Equation 4 and the expression in Equation 3 that we use in our work is twofold. First of all at times of fixed exchange rate regimes, during which the spot does not change from one month to the next, what we note as "part a" in Equation 4, will be zero. As "part a" is multiplied by "part b", during periods of fixed exchange rate regimes the whole expression in Equation 4 will become zero. Therefore the above mentioned merit of our analysis in that we can have extra observation points during periods of fixed exchange rate regimes, is lost in the KPM approach. The second important difference has less to do with the mathematical calculation and more to do with the practicalities of data availability and the consequences this has for the model results. As noted by both KMP and the authors of EMRI the interest rates available to them were often not market determined, thus making the "unanticipated" depreciation a poor proxy for market determined forward exchange rates that we construct

and use in our work hereafter.

1.3.2.5 Selection of Returns' Threshold to Model

The aim of this exercise is to model cases where investors would have made substantial returns from investing in local currency versus the USD on a one month forward rate basis. What constitutes “substantial” returns is, clearly debatable. Most of the papers on currency crises focus on double digit, one-off depreciations of the spot exchange rate. Some have opted to account for momentum as well and have incorporated in their definition of a crisis an acceleration factor which assumes that the currency weakening at any time is significant but also exceeds the depreciation of that currency in the recent past. Depending on the data frequency and chosen horizon, the focus is on spot depreciation in any given month or year and the “recent past” is, in turn, defined as the previous month or the previous year for example.

In our analysis we model the cases where an investor gained in any given month, more than 5% above the cost of carry, when buying or selling any one of 21 emerging market currencies globally on a one month forward exchange rate basis. The choice of the 5% threshold is indeed subjective but we felt it accommodates a number of key considerations. First of all as we focus on returns on a forward rate basis we have already taken into account any currency moves due to interest rate differentials. In a way any non-zero deviation of the spot from what the market implied forward rates were pricing in, translates into net profit for an investor. In that sense, 5% profit above carry should compensate the risk appetite of most investors.

By definition, choosing a lower threshold would give us a greater number

of points to model. However, selecting the cases where returns were above 5%, gives us a sufficiently large number of observations for our dependent variable while filtering out a substantial amount of noise, which in volatile currencies like the emerging market ones, is bound to be even higher.

As discussed earlier in this chapter, we do not explicitly account for transaction costs in our analysis. Although transaction costs have been on a decreasing trend for most emerging market currencies, they are still an important consideration which can create entrance barriers for a number of investors. Occasions where investment in emerging market currencies would have generated more than 5% profit above carry, can reasonably be expected to have generated a net profit after transaction costs as well. What is more the transaction costs involved in forward rate transactions are significantly less than the cost involved in spot transactions, making the case for focusing on forward rate returns even stronger.

Last but not least it is worth pointing out that the returns refer to gains on a one month period and not on an annualised basis. EM currencies are indeed volatile and likely to move by high percentages at short periods of time. Still, making a 5% gain on a single currency month from investing in a single currency pair is an option worth pursuing.

1.3.2.6 Symmetric Assessment of Upside and Downside Risks

Another important way in which our work here extends on previous research is that we assess both upside and downside currency risks in emerging markets. As discussed earlier in this chapter, the near consensus view in the literature of currency crises is to focus on the risks of potential

depreciation. It is quite reasonable that most of the literature on currency crises primarily focuses on downside risks as their prime objective is to foresee the point in time when a currency is likely to be devalued or significantly depreciate after a pegged exchange rate regime is abandoned either under the pressure of a successful speculative attack or due to inconsistent policy targets. From an investor's point of view, information on both forthcoming significant appreciations and depreciations is equally interesting and profitable trades can be implemented in both cases on the back of early warning signals.

In fact the trend has been for emerging market currency to appreciate in recent years. So much so that the idea that when you buy and hold emerging market currencies you are bound to make a profit sooner or later, merits a near consensus status. Indeed it seems that we have entered an era that hardly resembles at all that of fixed exchange rates which were under the risk of substantial weakening should the peg be abandoned. If we focus on the years since 2002, which is the period of time which we use to test our model's forecasting power, we see that all the emerging market currencies included in our model have been under a floating exchange rate regime. Arguably the degree of independence that this floating regime enjoys varies significantly between countries, as Table 4 above shows. Nevertheless recent years have also seen improving emerging market fundamentals, greater degree of transparency and more liquidity for most emerging markets. This constellation of EM supportive factors attracted more capital from new or existing EM-dedicated investors which under-pinned a trend for most emerging market currencies to appreciate.

At the same time investors' rising risk appetite fuelled the search for yield-bearing investment instruments. Decreasing but still substantial interest rate differentials in favour of emerging market compared to developed markets triggered significant capital inflows to emerging market currencies. The demand for these so-called "carry trades" was a function of the interest rate spread that each currency offered over the relevant holding of US dollars. This trend may be unsustainable in the long run especially as the interest differential between emerging and developed markets is gradually depleted and valuations of emerging market currencies remain stretched prompting official intervention on behalf of local Central Banks aiming to smooth currency fluctuations or even target specific valuation levels. In the mean time, however, the currencies that would be expected to depreciate according to the interest rate parity are exactly the ones that tend to appreciate. The rationale is that an investor that agrees to buy a "high-carry" currency on a forward rate basis expects to at least earn some or all of the carry when he unwinds the trade given that the underlying currency, supported by capital inflows, is unlikely to have depreciated as much as the forwards had priced in. However, as economic theory and empirical evidence suggests, when these market exuberances correct, the trend reversal is usually very harsh and fast. It is such pressures that make it necessary to continue monitoring the downside risks even at times when trade recommendation for selling emerging market currencies are not very popular.

One approach that incorporates both revaluations and devaluations is that advocated by Eichengreen, Rose and Wyplosz (ERW) in their mid nineties papers. As mentioned earlier, ERW construct an index for exchange

rate pressure which comprises of a combination of changes in the exchange rate, the official foreign exchange reserves and the interest rates differentials. This index may rise or fall capturing spot appreciation or depreciation respectively. Even in these studies however, the focus is to gauge the downside risks as ERW define crises as the times when the created index exceeds the sample mean by more than 1.5 standard deviations. Cases where the index level is below the sample mean are not accounted for.

In our attempt to assess both upside and downside risks we estimate two separate parsimonious models one to capture the “appreciation” probabilities and one to capture the “depreciation” probabilities. It is important to keep the notion of “appreciation” and “depreciation” in the context of forward exchange rate returns as defined earlier. Our definition of “appreciation”, as shown in Equation 5 involves the cases where the local currency is, based on the end of month realised spot exchange rate, more than 5% stronger versus the USD than what the one month forward had implied one month earlier.

Equation 5 Definition of “Appreciation”

$$R_{t,T} = \left(\frac{S_T - F_{t,T}}{F_{t,T}} \right) < -5\%$$

Accordingly, Equation 6 below describes our definition of “depreciation” which includes the cases where the local currency is, based on the end of month realised spot, more than 5% weaker versus the USD than what the one month forward had implied one month earlier.

Equation 6: Definition of “Depreciation”

$$R_{t,T} = \left(\frac{S_T - F_{t,T}}{F_{t,T}} \right) > 5\%$$

The two models are estimated separately and in their final specification they have all but one common input variables. The use of two separate models allows us to also affect a second level test on the robustness of the model performance when translating the model results into trading signals. This aspect is discussed in greater detail in a later chapter of this thesis.

1.3.2.7 High Frequency Dependent Variable

Given that our goal was to create an investment tool to generate high frequency trade recommendations, we chose the period of one calendar month as our investment horizon. Effectively the model generated signals for any given month are implemented at the first day of the month and closed out, in the absence of any risk management, at the last day of that month. This point is essential in the tracking of the performance of the model generated portfolios. Our choice of the one month framework was also dictated by data availability. Admittedly, the use of very high frequency forward exchange data means that you may end up picking up a lot of short-term noise. Moreover the model results will be largely driven by the moves in the spot exchange rate which is bound to be more volatile than interest rates and particularly in the short run.

1.4 Conclusion

In the first Chapter of the thesis we presented in detail the research framework that relates to our analysis. We proceeded to outline the significant ways in which our work differs from what was done previously. Both academics and practitioners have understandably attempted to assess and model the dynamics that determine out of the ordinary moves and events in financial markets. Events deemed as crises in the banking, debt and currency spheres have been in the lime light of Emerging Market economic research for decades. The events of the late 2010's proved that the same risks can easily apply to developed markets and, if anything, Emerging Economies have learnt from their previous misfortunes and are now leading by example in terms of financial and macroeconomic stability. Even before the recent events, we opted to analyse currency risks in ways that distinguish us from most of the approaches adopted previously. The research that is relevant to our work primarily analysed extreme events in currency markets. Such events typically involved the case of Central Banks that were either forced to or willingly abandoned a fixed exchange rate regime and allowed a currency to float. They also involved currencies that were typically devalued or depreciated by double digit rates in a repeated fashion. The incidents analysed the behaviour of the spot exchange rate. Macro-fundamental or qualitative variables were used to explain these incidents via graphical analysis or modelling exercises.

Our work differs in all the aspects mentioned above. We do not wish to solely explain extreme currency moves and we do not focus on the spot exchange rate. We model significant moves of the forward exchange rate

which is relevant to investors. We have a one month horizon and construct forwards that replicate what investors would be able to practically trade in each emerging market. We do not solely rely on country macro-fundamentals but we do only use quantitative variables in our analysis. We adopt a parametric approach and apply the same model to all countries and throughout the whole sample of data. We aim for a specification that is tested on the basis of two aspects. First its ability to fit past history but also its ability to produce forecasts that can be translated into actionable trade recommendations. This allows us to generate signals that are directly comparable. Finally we look at both upside and downside currency pressures as both are equally relevant to an investor's agenda. In the following Chapter of our thesis we provide a thorough analysis of the considerations that dictated our choice of explanatory variables.

2 CHAPTER TWO: Modelling and Forecasting Currency Risks in Emerging Markets: Explanatory Variables Considered and Selected

2.1 Introduction

Data is a very precious commodity in research and it is rightly stated that the results you get from a model are only as good as the data you plug in to the model to begin with. When compiling the list of possible explanatory variables for our model we relied a lot on the usual suspects presented in relevant research literature. Academic papers like the ones published by FR, KLR, STV, BP and KMP and market products like Damocles, GS Watch or EMRI that were presented in greater detail in Chapter 1 of the thesis, provided useful insight with regards to which variables may best capture currency crises dynamics. Though there is a lot of common ground in terms of adopted methodology and variables considered, there is no consensus regarding the variables that work. Variables considered in the relevant literature include some form of real effective exchange rates, domestic credit growth, US interest rates, exports, money supply often measured as a ratio to foreign exchange reserves, output growth, equity prices and a host of other variables.

We assessed a number of variables and included them in several formats and lag structures in various versions of our model. Section 2.2 outlines the qualitative and quantitative characteristics considered when assessing the candidate explanatory variables. These considerations, often supported by statistical results from our estimations, allowed us to filter the

initially large sample of potential explanatory variables down to a handful of time series which we include in our selected parsimonious specification.

An issue of particular importance in our research here which also differentiates ours from previous work is the accuracy with which we approach the definition and format of each and every variable we used. Take oil prices for example, a data series that has been used as an explanatory variable by others. As far as we are concerned no paper would specify whether the data used were prices of crude or some other type of oil, let alone specify whether it is a region specific crude oil like the Urals crude Russians trade or Brent crude. We could not find a paper that would even specify if the data used refer to spot prices or prices of futures contracts. We strongly feel that one needs to be very explicit about the definition of the selected data as most versions are rather irrelevant to what we try to model.

We also find very few examples where the format of the data is explained or supported in detail. In our work we consider every variable in a number of formats such as level form, percentage change on a monthly, yearly or three month basis and other formats in which a variable is usually monitored by market participants. We try to assess as many versions as possible guided by intuition and common practice. However we remain wary of the effect that even the simplest mathematical transformation can have on the information content of data series. At the same time we remain conscious of the fact that no quantitative technique can capture all the factors that matter. We prefer to stick to a minimum common denominator approach which, although misses out on a number of country specific and crises specific attributes, serves well in providing a snapshot of global currency risks

in a form that allows for comparison between countries and throughout time.

In Section 2.3 we present the different variables we considered, the various versions that were reviewed and why we find that they may or may not be of relevance to a modelling exercise like ours. Section 2.4 proceeds to present in greater detail the handful of variables that were consistent from a statistical performance point of view and compatible with our rationale and market understanding. It is these variables we include in our selected specifications that we apply and review in Chapter 3 and 4 of the thesis.

2.2 Data Considerations

We proceed to briefly outline the key conditions that we expected our candidate variables to meet in order to even consider including them in the estimated model specifications. The criteria are driven by economic theory linked to market practicalities, limitations and realities we have found to be of extreme importance and relevance.

2.2.1 Data Consistency

A rather unobvious data consideration we had to be aware of is that even the most straightforward data series need not have the same definition for all the countries in our sample. Take the data on “Central Bank net non-gold foreign exchange reserves” for example, one of the key variables in the currency crises literature. The data title seems self explanatory, in practice though the composition of the data that market participants use may vary significantly across countries. For example, South Africa market analysts focus on non-gold FX reserves minus foreign loans and net forward position.

For Turkey the same data series most likely includes non-gold FX reserves net of outstanding obligations to the IMF. For Colombia the data include non-gold FX reserves net of Central bank's liabilities. Opting to get the data for all countries from a single source such as the IMF or a single data provider such as Bloomberg or Datastream did not resolve the issue of different compositions under the same data title. In cases where the title of the data did not correspond to the same definition across our sample of countries we first tried to minimize the differences and finally opted to use the data that market economists found to be more relevant for each country.

2.2.2 Frequency of Explanatory Variables

As discussed in Chapter 1, our dependent variable is a high frequency series of monthly returns on a forward exchange rate basis. The obvious choice for the variables that explain these returns would be to use monthly data series as well. Many papers use quarterly or even annual data but these papers tend to focus on medium to longer term horizons than we do and adopt quarterly or more often annual data for their dependent variable as well. Importantly, most of these papers remain theoretical in their focus and are not concerned with the applicability of their recommended model specification in forecasting the immediate future. We have different considerations to address than those faced by theoretical research papers as our work focuses on the usability of the results and the forecasting power of the selected specification.

The papers that, like us, adopt a high frequency dependent variable again use quarterly or annual data but affect some sort of interpolation to these series in an attempt to make the left and right hand side of the equation

consistent in terms of time frequency. One paper which as mentioned earlier, answers questions similar to ours is the 2002 paper by KMP. KMP used annual and quarterly data in their work and interpolated these series via fitting cubic splines to the data. We strongly feel that any method of interpolation, and cubic splines are no exception, introduces a bias in the model for a number of reasons listed hereafter.

To begin with, some of the macro data one may wish to incorporate in an exercise like ours are stock data. Take for example the use of GDP data as an explanatory variable which has been advocated by many relevant papers. GDP data are at best available on a quarterly basis. Assuming any particular way or accumulation of GDP from the first to the last month of any given quarter seems arbitrary and of little use, as the reality which we try to model is most certainly different from our assumptions. Such data manipulations may be more relevant for the research on early warning systems where the forecasting horizon is one or two years ahead and the use of low frequency data is less problematic if not desirable.

KMP do not discuss the problem presented when dealing with stock data, but they do mention that in order to account for flow data they first cumulate the series, then effect the interpolation and finally difference the resulting monthly series. Take current account data for example which is a series of flow data in that the quarterly data reflect the current account of that quarter alone. We feel that cumulating or interpolating such a series to higher frequency data, leads to a specification that models a different reality than the one we wish to forecast in the future. It seems to us that one would need to first carry out extended research on what is the seasonality and modelling

behaviour of each of these series separately and for each country in turn before moving to the next level of actually modelling currency moves using these series as input. This exercise is very laborious but, more importantly, it is by definition futile, as it would not conclude to results that could be usable in a modelling exercise like ours.

Another problem that arises when one uses monthly data which have been interpolated from annual data, is that going forward, he will need to use annual or quarterly data as well. Fitting a model on data that were interpolated from past available annual data is straightforward. Going forward though, if your explanatory variables are only available on a low frequency, you will need to use either extrapolations of past data or forecasts. Even if one unrealistically assumes constant availability of reliable forecasts in the future, you need to revise these forecasts periodically. Therefore your results will be updated accordingly based on the newly available estimates at any given time. Most importantly though, you will have estimated a model based on real facts and you will be applying it on assumptions. This was simply not an option in our exercise.

The explanatory variables considered and included in our model were all available on a monthly basis. This limits our selection somewhat but we felt very strongly against the use of any methods of interpolation of lower frequency data such as annual or quarterly, to monthly. We also see little use in finding a relationship that works with data from real historic time series and then attempt to implement the relationship on forecasts and estimates on variables that almost never come up close to even consensus expectations. Most macro economic data estimates are released with a considerable lag,

and even then are subsequently revised upwards or downwards for quite some time until a more accurate actual measurement is available. We believe that adding to that an extra degree of subjectivity by interpolating forecasts which are likely to be inaccurate would render the results even more spurious.

Ultimately the matter at hand here is whether one wants to model the link between fundamentals and currency moves or the way in which markets are bound to react to every release and adjustment. We do wish to capture the links between macro data and currency moves. However, to the extent that such links are either coincident and not possible to capture by our model, or to the extent that macro indicators can act as a low frequency indicator of pressure in the medium run, which again is not consistent with our high frequency analysis we chose to exclude these variables.

2.2.3 Standardization of Explanatory Variables

An issue that relates to and expands on both previous sections on data availability and consistency is the process of standardisation of the explanatory variables. There are two sorts of data standardisation that one sees more often. Filtering out extreme data points from a data series and standardising a data series with regards to the sample mean and deviation. We do not apply any of these types of standardisation to the data as we aim to extract from the series as much information as possible. Information that we feel is lost or at best distorted when crude methods of standardisation are introduced.

Often extreme points are deleted from a series in the name of facilitating the model estimation and getting results that will not be biased because of a

few extreme values present in the sample. Our way of thinking is again somewhat different. We are very wary of generally smoothing out irregular data points. First of all the definition of “irregularity” tends to be either very sample specific or at best subject to the researcher’s interpretation. More often than not what may seem irregular on a graph plot is in fact a very real event which occurred for any number of reasons and may or may not have led to a structural break in the series.

We are aware of the limitations that any quantitative instrument has in capturing all real world incidents going forward. But as long as we aim to model the constantly changing environment of emerging markets, we should make every effort to ensure that our model either captures these breaks and outliers or that we have at least a very clear idea of the model limitations in each case. The only outliers we wish to “clean” our data from are those introduced in the sample by human error. As there is by definition no consensus on which values have been distorted by human error, we once again recall the market awareness of specialists and discuss each point in turn before deleting only a handful of data points and replacing them by the simple arithmetic average of the previous and following points.

We now address the other standardisation often affected by researchers, that of expressing a data series as a function of a sample specific mean and deviation. In our analysis we use different starting points in almost every country which means that we would be standardising each series based on a different horizon. Moreover even if our country samples had common starting points there is no way of selecting the optimum sample length or even period. What is more, there is no way of deciding on the best way to implement the

model results going forward. There seems to be no clear answer on whether one should keep extending the sample constantly or adopt a rolling window keeping the sample size constant. In any case we object to the standardisation of the data in any manner that may result in the loss of information and remain apprehensive of using a methodology that renders our results sample specific.

2.2.4 Coincident versus Leading Indicators

Our aim is not only to model forward rate returns but also to forecast future returns on a monthly basis. Therefore, our explanatory variables need to be leading indicators of future exchange rate moves. There is little use for us to consider changes in variables that coincide with, let alone lag, forward exchange rates moves, much as this is intellectually interesting and theoretically solid. The focus in our analysis is the applicability of the model in forecasting future monthly returns. In any given calendar we can at best avail ourselves of data from the previous calendar month and calculate the model results with regards to the following month's forward exchange rate returns. Therefore, our preferred choice would be to work with indicators that perform well at two month lag from the forecast month. These data need to be available in a timely manner and on a regular monthly basis and, importantly, they should not be revised following their initial release.

2.2.5 Quantitative versus Qualitative Variables

Data availability in emerging markets can be a great challenge even regarding quantifiable data such as GDP, public accounts and financial markets. Most data are available with a few months lag and will most likely be

heavily revised for a number of months following their initial release. Discontinuities in data series, change in the data definition or in the construction and estimation methodology, outliers and differences between similar series from different countries are but a few of the hurdles that make filtering a sample of emerging market quantitative data a challenging task.

Qualitative factors such as political stability, market sentiment or contagion are equally if not even more important than fundamental or market data in emerging markets. Attempts have been made to quantify such elements in order to include them in a parametric model specification or a graphical approach, in order to render that analysis more accurate. We strongly feel that it is literally impossible to quantify such variables in any objective, consistent and meaningful manner.

Take political stability for example. Assigning a factor or a dummy variable to indicate the existence, lack of or degree of political stability at any point in the past is utterly subject to a researcher's assessment. This alone renders the results biased and defies the primary purpose of building a technical tool, which is to achieve objectivity. What is more, the same individual is more than likely to attribute a different degree of importance to any event, past, present or future as new pieces of information become available. This alone makes it impossible to assign a value to these factors and dictates the need to constantly reassess the estimation results which are based on past data, thus jeopardising the whole exercise of building a usable tool.

Importantly, even if one is to somewhat assign values to quantify past observations, it is practically impossible to forecast future observations, or at

least with any degree of accuracy and insight that would make sense to trust, let alone use. It is also unrealistic to expect such variables to have an effect which will not only be quantifiable but will also act as a leading indicator and a consistent one for a particular time horizon. Thus it is unlikely that any of these values would have an effect on monthly forward exchange rates with two month lag, which is the earliest that we can possibly calculate and the latest we are willing to use. This alone makes it futile to try and quantify the information content of such variables.

Contagion is a factor that has been cited as key for the “domino effect” that often characterises the aftermath of a crisis and its spill-over to other emerging markets. Contagion is a variable very heavily debated in the literature on currency and financial or banking crises in emerging markets. The rationale is that following a currency crisis in one country the probability that other countries will experience similar crises increases. Contagion however has taken a different shape and form every time it occurred. Common fundamental weaknesses, geographic or trade links have often provided the channels through which crises have spilled over from one country to the next. Such was the case for the Asian Flu crisis when a number of Asian currencies were affected after the initial events in Thailand which led to the collapse of the Thai baht in the summer of 1997. In other instances, the domino effect that followed a country specific crisis was triggered by international portfolio flows which may have been reversed for any number of reasons such as global recession. Sudden portfolio flows reversal was the main reason why Brazil followed Russia in crisis in 1998. After Russia defaulted in 1998 many emerging market investors sold profit making

Brazilian assets and used the proceeds to unwind their positions in Russia as fast as possible and cover part of their losses.

Many research papers, attempt to quantify the contagion effect but end up capturing only some of the forms mentioned above, if that. We feel that such qualitative factors are better assessed via their indirect effect on other quantifiable variables. We prefer to exclude such variables from our model altogether instead of doing a poor job describing them.

2.2.6 Macro Economic Fundamentals and Market Data

Country specific macroeconomic data are a credible indicator of currency pressures. Fiscal or trade account balances, growth rate, inflation, foreign exchange reserves, debt levels are but a few country variables that markets monitor in an attempt to assess a country's financial health. However, as mentioned earlier in this chapter as well, macroeconomic data in general, and even more so in emerging markets, are only available with a great delay and more often than not are heavily revised a number of times following their initial release. What is more, many economic data are either coincident or very early indicators of currency or other market moves. Importantly, there is no unique correct way to interpret or forecast the significance and effect of any given macroeconomic indicator on a currency's performance.

For example a rise in interest rates may trigger a weakening of the respective country currency as markets become wary of the effect of tighter monetary conditions on growth prospects. At the same time higher interest rates in many emerging markets often attract foreign capital from investors

seeking to capture the higher yield offered by these so-called “carry-currencies”. The FX market pricing will often reflect investors’ view on a central bank’s ability to stay “ahead of the curve”. That is the ability of policy makers to tackle monetary risks before they are perceived to get out of control. Most emerging market central banks have in recent years adopted official inflation targeting to appease such concerns. But the balance between inflation and growth is a battle that has yet to be decided. The effect of each macro variable is further conditioned on country specific factors such as the point in the business cycle that a country finds itself or overall economic fundamentals and political and social environment. It also almost invariably depends on external factors such as global economic circumstances and emerging market specific conditions. Given all these considerations it is therefore unsurprising that we find most macroeconomic data of little use in our forward looking research exercise.

Research has also often turned to market data for indicators that lead moves in exchange rate markets. Market data such as credit spreads, swap spreads or equity indices are assumed to discount all the information available to market participants. It seems appealing to try to use these data as packaged information on a number of different economic variables. Moreover, market data allow one to indirectly assess investors’ perception of qualitative factors, such as a country’s political stability.

Most EM financial markets have faced some type of distortion, such as access limitations or intervention policies at some point during our sample history. Even at times of reasonably free market dynamics liquidity is a key consideration. Pricing may only reflect a fairly insignificant change in light

positioning and not a change in perception from a well informed market group. These changes are attributed to the so-called “technical factors” and are closely monitored by investors as they may offer good entry or exit levels to otherwise “crowded” trades. It may not be reasonable to expect that any market can be used in a consistent manner across time and countries to encapsulate macro dynamics. In any case there is no good reason why one financial market such as debt or equities should consistently lead developments in another market such as foreign exchange. Our results amply confirm the hypothesis that different financial markets move in a more or less coincident manner. Therefore it is not possible to use financial market data as early indicators for future currency market returns.

2.2.7 Global versus Country Specific Data

Country specific data are variables that take different values for every country. Such country specific variables may be anything from macroeconomic data, like the real effective exchange rate, to financial data, like a country’s equity index. By definition they are specific to and reflective of each country’s economic and other conditions. Global factors on the other hand, are variables such as market risk appetite which are not conditioned on single country circumstances. Our research focuses on emerging markets. The consideration of global factors in our model specification enables us to capture elements which affect the emerging markets universe in a more or less homogeneous manner, as opposed to developed markets. For example, increasing risk appetite could be expected to coincide with or lead to greater interest in riskier investments such as emerging markets assets.

2.3 Candidate Explanatory Variables: Definition, rationale and formats considered

In our attempt to model and forecast exchange rate returns we tested all the usual suspects in terms of explanatory variables. The country specific data we considered include Real Effective Exchange Rates (REERs), trade balances, credit to the private sector, industrial production, foreign exchange reserves, money supply, country specific rating actions from S&P and the Morgan Stanley Composite Equity Indices (MSCI). Some of the global factors we tried out include the Institute of Supply Management (ISM) Purchasing Managers Index (PMI), the OECD leading indicator, oil prices and data provided by Moody's on world default rates. In the sections that follow we turn to each one of these variables separately and present and assess them in light of the considerations and criteria outlined in Section 2.2 above.

2.3.1 Global variables

We first review the so called Global Variables that we considered. The rationale, as presented earlier in Section 2.2.7 is that we treat the Emerging Markets Universe as a fairly homogeneous group which we expect to be affected by and react to global dynamics in a more or less synchronized manner. We fully acknowledge that emerging markets can differ significantly in more or less all aspects from politics and adopted policies to prevailing macro fundamentals and future prospects. However as these countries have come a long way in recent years they now present an asset class which has grown to be more transparent, more liquid and almost with no exception deliver higher returns than what is referred to as Developed Markets. It is this characteristic of higher returns that by definition comes with greater risks and

volatility. This may be one of the few common denominators that apply to most if not all emerging markets. It is this common feature that we believe is worth trying to capture with a Global Variable. A variable that will work as a proxy for global risk appetite. The expectation is that at times of euphoria it would translate into investment dynamics that are favourable towards EM and at times of risk aversion will likely trigger a generalised EM sell off. The latter could even describe the earlier mentioned contagion effect, which will affect negatively the bulk if not all emerging markets irrespective of country specific characteristics.

2.3.1.1 ISM Indices

The Institute of Supply Management (ISM) is a US non-for-profit organisation which since the 1920s has been publishing a number of indices on a regular basis which are closely monitored by market participants. ISM publishes indices on both the manufacturing and non-manufacturing sectors of the economy and on different sub-sections of these sectors. Both the ISM Manufacturing and the ISM non-Manufacturing are monthly reports, available on a timely manner as they are respectively published on the first and third business day of the month and refer to the previous calendar month.

The ISM indices are “diffusion indices” and compare the changes in each market on a month to month basis. The index readings capture the sector specific momentum with an index reading between 50 and 100 indicating growth in the relevant sector and an index reading between 0 and 50 indicating that the relevant sector is contracting. The ISM indices are not compiled based on market data. Instead they are constructed based on the

responses from thousands of market participants with regards to their understanding and perception of activity on different areas of their business. For example, a reading above 50 for the “current new orders” segment of the ISM manufacturing report indicates that the majority of market participants that responded to the survey placed more new orders in the current month compared to the previous one.

The ISM Purchasing Managers Index (PMI), which is part of the ISM report on the manufacturing sector, is one of the most representative and informative indicators for overall business activity. The PMI is constructed as a combination of sub-indices. In particular new orders form around 30% of the PMI, production covers 25%, delivery covers 15%, inventory 10% and employment 20%. According to the ISM a PMI reading above 50 indicates growth in the US manufacturing sector.

We tried out the ISM PMI index in our model estimations in level form and also in month on month and year on year changes (hereafter mom and yoy respectively) by taking differences of the index levels at the respective horizons. We felt that this series would be a good example of a global factor that we looked to include in our model. It is quantitative, market-related, available monthly on a regular and timely fashion and it provides an indication of the status of the US economy. Given that most often the US economy is the benchmark people use to judge the overall universe of developed economies and also given that in our model we look at all the emerging market currencies versus the US dollar the ISM PMI index seemed like a strong candidate for inclusion in our model.

Our statistical findings did not support our assumptions and we did not

include any version of the ISM PMI index in the final model specification. This does not suggest that the information content of the index is not as strong as previously thought. It is very difficult to find a variable that consistently explains currency risks, let alone on a monthly basis and in the same manner for a total of 21 countries.

2.3.1.2 Oil Prices

Commodity prices are often monitored by market participants as they may provide a credible signal for the phase of the cycle in which we are at any given point. They may also give a country specific signal for a market that heavily relies on that particular commodity either as a net importer or a net exporter. Oil is one commodity that every economy depends on albeit in different ways and to different degrees. It is therefore not clear how one would expect oil prices to affect the currencies of 21 emerging markets in a homogeneous manner. Even if we crudely assume some degree of homogeneity there is no unique clear cause and effect relationship to model. It is also not clear which exact data series it is best to use to capture what one expects from oil prices.

Starting from the first concern mentioned above, although the same oil prices will prevail for all countries it is debatable whether oil should be included as a global factor or as a country specific variable with separate estimated coefficients for each country or different country groups. For starters some of the largest oil producing and exporting countries are to be found within the emerging markets universe. Countries like Russia, Venezuela and Mexico stand to benefit from an increase in global oil prices. Some

analysts have included oil prices as a dummy variable that only affects net oil exporting emerging markets. We strongly feel that the effect of oil prices on oil importers is just as interesting for an investor, especially one that is betting on both the strengthening and the weakening of local currencies. In any case we are unwilling to use a dummy variable in order to capture a factor as versatile as oil prices.

Even if one distinguishes between oil importers and exporters there still remain a host of other differentiating factors un-addressed. An increase in oil prices may be driven by a number of reasons like increase of demand over winter or decrease of supply due to supply interactions or even following a change in international oil cartel policies. Oil prices may well increase during an economic expansion as increase in manufacturing and other sectors dictate the need for more and more oil supply which drives oil prices up globally. At the same time when oil prices increase for an extended period and rise to extreme levels for any number of reasons they put global growth at a risk as manufacturing costs increase significantly and expansion is stalled while it becomes only a matter of time before part of the costs are passed through to the consumer and inflation risks revive. Let's assume that weaker global growth and worsening growth prospects, in general coincide or trigger a more risk-averse environment which, in turn, is likely to adversely affect riskier assets like emerging markets. This argument suggests that one should include oil prices in a model as a global factor with an inverse relationship to local currency strength. Nevertheless it is far from clear how one would identify which levels of oil prices suggest the economy is overheating and which levels indicate economic growth.

To add to the complexity of the issue one has to decide which series to use. Relevant research papers typically provide a vague reference by stating that one of the variables considered or used is oil prices. As mentioned at the introduction of this Chapter, one may have used data on crude oil or other oil categories, they may have used region specific crude oil data and they may have used spot prices or futures. It follows from our research and discussions with market analysts that as far as oil is concerned the most relevant series would be the West Texas Intermediate (WTI) which is a crude oil traded on New York Mercantile Exchange (NYMEX). We look at the futures contracts which quote prices for the WTI that is nearer to delivery, and often by the end of the current month. As we look for a market indicator it makes sense to use the prices in the futures contracts as these are monitored by most market participants and also affected by all those who trade oil even if they are not looking to take or make physical delivery of the product.

We were interested in the role that oil prices, as described above, may have as a leading indicator of pressure in world markets. We thus included the relevant series in our model as a global factor expressed as an annualized percentage change over three month periods and we also looked at the monthly difference of that measure to try and potentially capture momentum. The statistical findings verified our concern that it is difficult to objectively capture the different effects that this variable may have under different scenarios. Effectively we did not include any measure of oil prices in our specification. One valid argument would be to try and incorporate the oil prices we tested above as a country specific variable with country specific estimated coefficients that may vary significantly from country to country. We

already capture this element however by the inclusion of the Real Effective Exchange Rates. The latter are calculated using headline inflation data, which is the measure of inflation that incorporates food and energy prices. Oil prices are the main element of the latter. We will return to the analysis of REERs in greater detail in section 2.4.1 below.

2.3.1.3 OECD Leading Indicator

One of the criteria based on which we selected explanatory variables was the ability of the data to serve as leading indicators, in that they consistently provide early warning signals for future emerging market currency risks. Therefore, the OECD Leading Indicator (LI) seemed an obvious candidate for explanatory variable. The OECD started publishing a list of leading indicators back in the 1980s, in an attempt to provide market participants with indicators that reliably precede and signal the turning points of the economic cycle. The OECD publishes composite leading indicators (CLIs) which are either country specific or cover the whole group of OECD countries. In our analysis we focus on the overall OECD CLI which can provide a useful indicator of global economic activity and predict the turning points and growth momentum of industrial production which may be seen as a proxy for output growth and economic activity in general. The OECD CLI approach is based on growth cycle methodology and therefore an upturn will correspond to an increase in growth while a downturn will correspond to a decline in growth rates, and not necessary a recession or decline in overall economic activity.

The OECD CLI is a weighted aggregate of country specific CLIs which,

in turn, are a sum of both quantitative data such as short term interest rates or equity prices, and qualitative factors such as consumer confidence and overall economic climate. The OECD publishes the data on its CLIs in two versions as a de-trended time series and as trend-restored series. The de-trended series makes it easier to identify turning points and assess the ability of the CLI to accurately provide leading signals for future turning points. The trend restored series allows for a more direct comparison between the CLI and the series which is used as a reference point when calculating the CLI. The reference series is in most cases the Index of Industrial Production (IIP) which covers almost all industry sectors and also proved to be a good proxy for overall economic activity as measured by GDP. In December 2002 the OECD updated the reference series, the component series and the methodology of composing the indices and for estimating the relevant trend of the reference series.

In our model estimations here we try out the trend restored version of the updated series of the OECD CLI. In particular we look at the 3month on 3 month percentage change of the CLI which we then annualise (3mo3mann). We also look at the momentum of this measure. OECD recommends the use of the trend restored CLIs and also suggests the use of the 6month percentage change on an annualised basis (6mo6mann). The 3month version that we adopted allows us to capture the dynamics of the index while keeping the reference horizon shorter than the 6month OECD formula and bringing it closer to our high frequency needs.

We found that the series had the expected sign in our estimations in that an increase in the OECD CLI on a 3mo3mann basis typically preceded a

month during which emerging market currencies tended to appreciate on a forward rate basis. The coefficient was also statistically significant and mostly so in the model that captured the local currency strengthening rather than the weakening. However we found that the OECD CLI only worked well as an indicator in absence of other global factors in the model and we also found that it was not the best performing global factor we considered.

The relatively poor performance of this series may be explained by the fact that the OECD CLIs need to be further updated in order to satisfy the criteria that we have set for our explanatory variables. For example although the criteria for updating the OECD CLIs in 2002 was to ensure that as many as possible from the input data were monthly series available on a timely fashion and not revised in the future, 12% of the component series were still quarterly data interpolated to monthly and 44% of the data were still not available on a timely manner. What is more the OECD itself suggests that the CLIs may serve as useful tools in capturing mostly the turning points in a business cycle and therefore the direction of the CLI is likely to be far more informative than the level, especially if we look at the trend restored series. The OECD notes that there is an asymmetry in the duration of different phases of a cycle, in that an average recovery phase lasts about 32 months while an average recessionary phase lasts about 25 months. The OECD also notes that this difference between how long recession and recovery last again varies, with European countries experiencing a smaller difference of about 6months and non-European countries experiencing almost double the difference at about 12 months although they find that the size of the average economic cycle is the same in European and non-European groups.

To summarise, the OECD CLI was a strong candidate for global variable. However it was not the variable most supported by our statistical findings and also worked well only in absence of other stronger global parameters. This together with the consideration of the limitations in the underlying workings of the series, led us to exclude this indicator from the final model specification

2.3.1.4 CSFB's Risk Appetite Measure

We availed ourselves of the Global Risk Appetite series developed and maintained in-house by the CSFB Global Strategy Group. As this is a data series developed internally at an investment house and is not an indicator people are expected to be familiar with, we will try to present the workings and the rationale of this variable in greater detail here. Realized 12month returns from a wide spectrum of markets are regressed on the realized 12 month rolling volatility from the respective markets. The slope of the regression is the Global Risk Appetite Index. The asset classes included in the sample span a spectrum from the typically less risky Developed Markets Fixed Income, to the riskier Developed Market Equities, to the Emerging Market Fixed Income and the riskiest of all Emerging Markets Equities. Risk Appetite will tend to rise during risk loving periods when riskier assets outperform safer ones and vice versa Risk Appetite will be contracting at times of risk aversion when investors will turn to safer asset classes where both returns and volatility are lower.

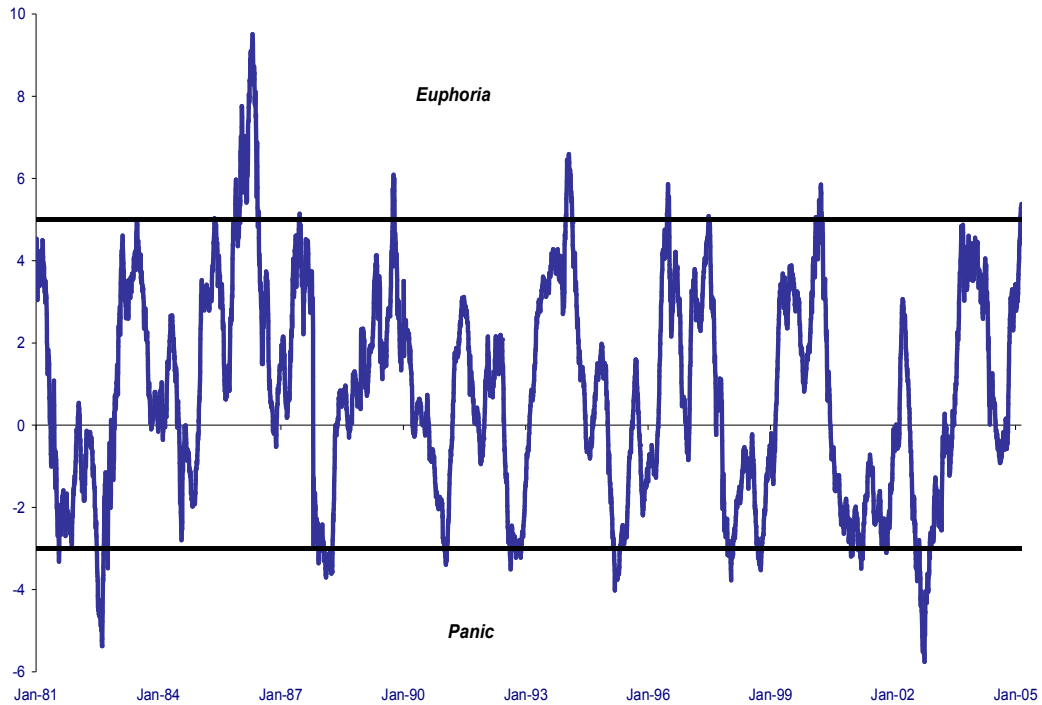
CSFB's Global Risk Appetite Index is a tool that describes market realities without trying to forecast the future. Trying to model and forecast the Index , CSFB's Global Strategy Team have found that it is highly correlated

with three indicators: First the slope of G3+ yield curve as expressed by the difference in the yield between 3m and 10year instruments. The G3+ yield curve will typically become steeper at times of higher growth expectations, when short terms rates have been reduced to inject liquidity in the economy and empower growth, while higher long term rates discount the market expectations of future rate hikes on the back of successful growth acceleration. Equally, flat or inverted curves will signal market fears of imminent growth corrections or the lack of any signs of correction for an existing slowdown. The second factor found to explain Risk Appetite well was the momentum of global Industrial Production, again an indicator of growth dynamics and potential. The third factor was the score produced by EMRI, the Emerging Markets Risk Indicator again produced in-house at CS which was expected to produce early warning signals for EM currency pressures.

In practice CSFB's Global Risk appetite index proved to be a highly mean reverting series which worked well in capturing market dynamics during periods of rising or falling risk aversion but proved a much stronger tool in capturing the extremes levels of markets exuberance on both the side of pessimism and optimism. It is these extreme levels which were called levels of Euphoria and Panic that we too found more informative of future market moves. Typically an extreme level would be followed by a correction which will be more or less consistent in its direction all the way to the opposite extreme of the chart, only to be followed by a new correction. Although it feels intuitive that extremes are more likely to be followed by corrections, one needs to remember that by definition extremes in market sentiment are driven by exceptional circumstances which make it significantly more difficult at the time

for investors to make the brave decision to go against the trend and re-allocate their portfolio against prevailing circumstances.

Figure 2 CSFB's GLOBAL RISK APPETITE INDEX



For example in Figure 2 above Risk Appetite reached Euphoria at periods when rallies looked like they could last forever but each time they were followed by a lasting correction. These corrections typically led the index all the way to the panic zone again on the back of risk incidents which seemed almost irreversible at the time. For example the significant fall in oil prices in mid-80s led to the longest euphoric period in the chart. Although the correction post this euphoric period was interrupted by another rise in risk appetite which peaked with the 1987 equity rally, this was in turn followed by a very fast and vicious correction which reached panic zone with the October 87 crash. In more recent years many of the 1990 events that dragged risk appetitive to its lows were triggered by EM – specific events like the Mexican

and the Asian or the Russian crises and euphoria levels were hit typically as risk appetite recovered after every crisis and led to equity bubbles and exurban behaviour. In the 2000's, September 11 in 2001 offered a new type of panic-trigger.

All in all it is very interesting to have a tool that can describe market sentiment and it would be a very powerful tool to have if indeed it had predictive power. However, as discussed, the index works well as contrarian indicator mostly at extreme levels. Our statistical results also confirmed this. We therefore opted to include the index in our model as a dummy variable that would capture the euphoric and panic points which can work as leading indicators of change in market sentiment. The definition of euphoria and panic zones therefore becomes one of great importance. The creators of the series have found that there is an asymmetry in describing these two opposite extremes in that they consider index levels with a measurement above 5 as euphoric, while panic is said to be reached when the index falls below a level of -3. Interestingly they also note how rebounds from panic zone tend to be faster than corrections from euphoric levels as short memory makes investors less willing to give up on their market optimism but typically more decisive to put the worst behind them at times of panic. We see the fact that we only used the Global Risk Appetite as a dummy variable for extreme levels which significantly reduces the number of data points available, the asymmetry between the euphoric and panic levels and the difference in expected market behaviour even following extreme levels, as factors that explain why statistically we did not find strong and consistent evidence to support the inclusion of this parameter in our model specification.

2.3.2 Country Specific Macroeconomic and Market Data.

We proceed to briefly present the country specific data that we have considered for our model. We tried out both macroeconomic data as well as certain market related data. Most of these data have been considered by other papers and their information content has been advocated in relevant research. Let us look at each variable separately and the reasons why we did not use any of these factors in our selected model specification.

2.3.2.1 Price Stability

Inflation is a major issue in emerging markets with periods of hyperinflation linked to eras of disarray in the overall economy. High interest rates linked to high inflation regimes and leading to a halt in overall growth as producers are burdened with higher costs which they sooner or later pass on to the consumer. This understandably triggers a decline in demand which in turn harms the economy. It is particularly hard to quantify this vicious cycle though. Looking at inflation rates per se does not help drive conclusive results as an inflation rate that may be alarming for a healthy developed country may be natural or even welcome in an emerging economy. This can be due to the fact the current high inflation rate may be really a significant improvement from even higher levels of inflation previously or that simply inflation goes hand in hand with a growing economy or that inflation merely reflects base effects. Accordingly disinflation or even deflation, a phenomenon that is dreaded as equally bad if not worse than high inflation in a developed economy, may be welcome in some emerging economies. Therefore it is both level and direction that are inconclusive when it comes to inflation.

The majority of the currencies included in our model are currently operating under a more or less free floating currency regime but they have, nevertheless, adopted a currency peg at some point in recent history. At times of fixed exchange rates, inflation will by definition lead to overvaluation of the pegged currency versus its trading partners via the purchasing parity condition. Given that this overvaluation will not be expressed via a change in the exchange rate, it is highly likely that the economy will eventually be led to a currency crisis where the peg will be abandoned following an overheating of the economy. Our sample comprises of periods of both fixed and floating exchange rates and inflation would therefore be expected to have a different currency effect in each of these cases in terms of direction and lag. Hence we cannot expect to have statistical results that apply to the whole sample period we wish to model.

Others have tried to capture the idea that only hyperinflation may be of interest in emerging markets, as high inflation is the norm and need not be indicative of forthcoming upside or downside pressures. Nevertheless we are very wary of introducing subjective views in our model and are cautious with selecting thresholds for any variable that is considered in the model. Let alone when there is no clear consensus as to what constitutes hyperinflation or whether those are the only times of interest to our analysis.

The issue of specific data series selection applies to inflation data as well. To mention one interesting dilemma one could use the Producer's Price Index (PPI) or the Consumer's Price index (CPI). Arguably the two cannot be or remain out of sync for long periods. Still, discrepancies may easily apply at times. Inflation pressures will by definition start building at the production level

and it will be the producer's pricing power and overall policies that will determine how and when these pressures will be passed on to the consumer. It is fair to suggest though that it is mainly when the heat reaches the average household that inflation is well entrenched and more of macro policy concern.

It is worth noting that even as we see many emerging markets moving to inflation targeting and being fairly honest about the statistical data they publish on macro data like inflation, the data manipulation and policy interventions are still very often a concern, thus raising the issue of data reliability. CPI data are available for most countries and they are published on a monthly basis. In our analysis we did look at the CPI and in particular at the month on month and year on year percentage change of the CPI series. However as expected, findings were inconclusive and we chose not to include the CPI in the final model specification. As in the case of oil prices though, we point out that the element of inflation has been captured in our model via the inclusion of REERs that we present in section 2.4.1 below. In the case of REERs we also capture directly the effect of inflation on exchange rates as REERs reflect the change in a currency's value whether this occurs via inflation or nominal appreciation or depreciation.

2.3.2.2 Domestic Credit Markets

As discussed earlier in the thesis, currency crises have most often occurred in tandem with banking and financial crises. A disorderly increase in credit that is offered to the private sector is one indicator of overheating which may, along with other symptoms in the overall economy, lead to a banking crisis. In our analysis here we use growth of credit to the private sector as a

potential explanatory variable. This however is not because it may trigger a banking crisis which in turn has often coincided with or preceded a currency crisis. We look at credit growth as an indicator that would monitor signals of an overheating economy. This would arguably test investors' confidence and may be expected to hurt the country's assets, alongside with its currency. At the same time however we are aware that growth in domestic credit may often signal a more advanced financial sector which facilitates the business initiatives of the private sector and the rising consumer needs which are typical of a growing economy. The worry however, remains that a disorderly increase in credit growth often comes hand in hand with poor risk management and precedes a rise in non-performing loans and overall disarray in the economy.

In our estimations we include the month on month percentage change of credit to the private sector. The variable is included at two months lag from the actual month we are forecasting. This allows the information time to feed into the system and affect investors' perspective while also satisfying our criterion for variables that work as leading indicators and are available on a timely fashion. When estimating the model for currency "appreciation" probabilities we find that the credit to the private sector indeed shows the expected sign in that an increase in domestic credit in general reduces the probability of a local currency appreciating in the near future. In fact this is the only one from the country specific variables that we try out in the so-called "Extended" model specification that returns the expected sign. Nevertheless we do not include this variable in the final specification as the estimated coefficient is very insignificant from a statistical point of view. This probably

reflects the fact that the variable may act in different ways as we discuss above and cannot be expected to act in a consistent manner as an indicator.

2.3.2.3 Output Measures

In our attempt to capture output dynamics in the countries we consider, we selected to work with measures of Industrial Production rather than the series of Gross Domestic Product. Interestingly, even the calculations of the OECD Leading Indicators that we discussed earlier in this chapter, consider industrial production as a proxy for GDP and a data series which is representative of the overall economy.

The main reason why we opted for IP data over GDP series is that although GDP data could be the obvious starting point in order to get some sense of a country's economic status, the data are at best available quarterly, are released with a considerable lag from the reference quarter and are subsequently revised for a number of times. Industrial production data have been found to provide a reliable proxy to overall economic activity and are available monthly.

We looked at the IP measure on a yoy% change and on a mom% change basis but found that the variable did not work well in forecasting near term currency pressures. In fact the sign of the estimated coefficient suggested that an annual rise in industrial production will tend to reduce the probabilities of a local currency appreciating in the near future. This finding may well reflect what we discussed earlier about the selection criteria for our explanatory variables. Macro economic data are often coincident rather than leading indicators of currency moves. Alternatively even when they point to

future currency risks, the signals refer to a horizon considerably longer than the one we are interested in here. All that considered we chose not to include industrial production data in our model.

2.3.2.4 Trade Data

Trade plays an important role in every open economy, even for the less transparent or less liquid emerging markets that we are considering. To best capture the external sector dynamics that prevail in an economy we gathered monthly data on trade balance for each one of the sample countries we look at. Current account data which are often suggested as an alternative are only available at the same or lower frequency as trade data but, importantly, will tend to be released with a greater lag than the trade data. This makes the use of current account data inconsistent with our criteria for data availability. However we have to point out that trade balance data miss out on external sector elements that are crucial for emerging market dynamics such as remittances from expats. We obviously also miss out on the bigger picture that Balance of Payment numbers draw. Foreign direct Investment or Portfolio flows play an increasing if not more important role for EM currencies than simple trade balance data.

What's more economists to this date have come to no consensus with regards to the information content of external imbalances. Deterioration in trade dynamics may be caused and sustained by strong domestic demand which has often been the driving force of growth empowering. This has been particularly the case in emerging markets in recent years when after long periods of dependency on developed market demand, analysts started

focusing on the decoupling of EM and their ability to fuel growth from intra-EM links or simply on the back of stronger domestic demand. In these cases a deteriorating trade surplus or even a trade deficit would not be a worrying factor at least in the medium run, and need not coincide or lead to a currency depreciation. If however trade deficits simply reveal underlying inability of an economy to produce enough to cover its domestic needs and a trade deficit or falling trade surplus ends up depleting the country's official foreign exchange reserves, then currency pressures will soon mount.

In our analysis we considered the 12month trailing trade balance. This allows us to keep a wider perspective and assess current circumstances in light of the recent past for each country. It also allows us to capture any continuous pressures in the trade account which may be more likely to trigger or lead to currency adjustments in the near future. Our analysis suggests that there is no clear evidence of the trade balance having a direct effect on currency pressures. The estimated coefficient is zero and also highly statistically insignificant. Again the arguments described above, the fact that we look at the data at two months lag from the actual currency move and the fact that even though the data are specific to each country, the estimated coefficient is common for all countries in our sample may well be good reasons why trade balance data did not prove worth including in our specification.

2.3.2.5 Liquidity Measures

Factors like the level or the rate of change of the international non-gold reserves held by the central bank have been at the forefront of research on currency crises. In fact the quick depletion of foreign exchange reserves was the number one factor behind the currency crises assessed by the so-called first generation models. The latter focused on cases where a currency peg was abandoned following a successful attack by speculators who monitored a country's FX reserves only to apply extra pressure the moment that reserves would fall below a threshold. Pressure that would render the peg non defensible by the government.

Data on FX reserves are not only available on a monthly basis but are actually published on an even higher frequency with weekly data releases. Effectively though too high a frequency of data releases makes it as difficult for us to use a variable at too low a frequency. It would make little sense to include in a model monthly data on a variable that has three intermediate releases to which the market is bound to react almost instantly. In an attempt to capture some notion of the market liquidity that prevails in the countries we monitor we express the monthly series of foreign exchange reserves as a ratio to M2, the most widely used measure of money supply. This measure captures capital flight pressures should fears of forthcoming crises rise and will in general allow us to monitor the degree of liquidity in the market.

Our findings did not support the use of this ratio in our specification. The near-zero estimated coefficient had a sign opposite to our expectations, which was also statistically insignificant. We therefore did not include FX reserves or money supply data in our selected model.

2.3.2.6 Financial Market Data

It is often argued that as financial market data and prices in particular discount all available information at any given point in time, it would make sense to expect such data to work well as indicators of condensed information and perceptions on different aspects of the economy. Nevertheless, in practice most financial markets absorb, adjust and react to new information not only fast but also in a more or less coincident manner. This alone makes it futile to expect that one financial market like equity and bond markets will lead and consistently so another market like currencies. We tried out one set of equity market data and one set of credit market data as potential explanatory variables that we could utilise in our model.

We considered using data on sovereign credit default swap spreads to test the hypothesis that credit markets may act as leading indicators of currency moves in emerging economies. Such data would typically reflect the risk that investors assign to a particular country defaulting on its sovereign debt at some point in the future, thus serving as a good proxy for the way investors view a particular market. Data gathering in this area is, however, particularly problematic as it is not feasible to get data on similar horizons for all countries let alone compiling a reliable history for such data. Moreover getting data on three or six month credit default swaps is not particularly informative because such instruments do not trade actively in the market as it is difficult to sell or buy protection for such short time horizon. The data that make more sense to look at are the five year default swap spreads which are the most liquid instruments in the default protection market. Such data though would have little relevance to our exercise here given that we are interested in

forecasting currency pressures in the following month.

With regards to equity markets data, we availed ourselves of the month on month percentage change of the Morgan Stanley Composite Index (MSCI), a well known and reliable country specific equity index. Counter intuitively our estimations suggested that a rise in the equities market reduces the chances of a currency appreciating. However this may be due to us using the data at a 2month lag. As discussed earlier a move in one financial market is swiftly priced in other financial markets. Two months later you may be more likely to see a correction rather than a continuation of a trend in prices. We therefore decided to exclude financial markets data from our model specifications.

2.4 Explanatory Variables Selected

A small selection of explanatory variables all of which were found to be both leading indicators of forward exchange rate returns and highly statistically significant indicators were chosen for inclusion in our selected model specification.

2.4.1 REER Deviations from Medium Term Trend

Consistent with relevant research, we find that the overvaluation and under-valuation of real effective exchange rates compared to near term trend is a very strong signal of forthcoming currency depreciation or appreciation respectively. The real effective exchange rate (REER) is an index form exchange rate between a base currency and the currencies of the country's major trading partners. The index is calculated as a geometrically weighted average of all the relevant exchange rate crosses each of which have been

adjusted for inflation differentials and terms of trade dynamics between the base country and each of its trading partners. REERs are calculated and updated by a host of data providers or institutions. We availed ourselves of the REER series calculated in-house by the Credit Suisse Global Strategy Team which is a series closely monitored by a large number of market participants. CS REERs use seasonally adjusted headline consumer price index (HCPI) data for the inflation adjustment of the exchange rates. The trade weights are derived from IMF's Direction of Trade Database.

Headline CPI is the broader measure of inflation that includes the more volatile components of the CPI basket such as food and energy prices. For poorer EM countries the food component merits possibly the highest weight in the basket at around 30% on average. Energy prices are also a very significant component in the EM HCPI basket and also play a key factor in driving markets. We therefore feel that the inclusion of food and energy prices is both informative and necessary in our analysis. The Terms of Trade Data as published by the IMF express the total value of exports from one country to each of its trading partners as a ratio to the total value of imports from each of these trading partners.

REERs are a simple measure of country competitiveness. Although a more elaborate analysis of what drives exchange rates is necessary, REERs provide some notion of exchange rate fair value, as they are a measure of nominal exchange rate that has already been adjusted for fundamentals such as inflation and trade links. Treating the medium trend of REERs as an equilibrium level, towards which REERs can be expected to revert, does seem like a fair assumption. In practice, substantial deviations of a currency's

real effective exchange rate from its recent trend tend to be followed by a correction through the nominal exchange rate. The concept of mis-valuations preceding corrections is intellectually appealing. Nevertheless it depends very much on what we consider “equilibrium” towards which a variable is expected to revert. In our analysis here we define over or under valuations as percentage deviations from a Hodrick-Prescott (HP) trend. The HP trend is a rather sophisticated version of a backwards and forwards looking moving average. More than just following the general move of the data series, an HP trend also follows rather closely the short-term data dynamics. We calculated HP trends using the relevant functionality of E-Views, a statistical and econometric software application.

The assumption behind the de-trending exercise is that a time series is a composition of two main elements: a trend and a cyclical component. The HP filter effectively extracts the trend component of the series, i.e. the underlying high frequency general movement of the data without the elements of lower frequency seasonalities. It does so by satisfying the following two conditions as per Equation 7 below:

Equation 7: Hodrick Prescott Filter

$$\min \left\{ \sum_{t=1}^T (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \right\}$$

Where:

y_t is the logarithmic version of the underlying time series we wish to de-trend

$t = 1, 2, \dots, T$ is the respective point in time that each data point refers to

λ is the smoothing parameter set equal to 14,400 for our analysis here

τ_t is the trend component at each point in time

$y_t - \tau_t = c_t$ is the cyclical component that remains after the trend is extracted from the time series.

The first part of Equation 7 denotes how the HP filter effectively minimizes the deviations between the underlying data and the estimated trend. The second part of the equation assigns a smoothing parameter that determines the growth rate of the trend itself. The smoothing parameter we use in our analysis is 14400 which is the default smoothing parameter used by E-views for monthly time series data. In practise the higher the smoothing parameter the less flexible the trend will be with the extreme case of λ tending to infinity which means the trend becomes linear. On the other extreme a λ equal to zero will create a trend identical to the underlying time series.

Trend extraction is not an exact science, nor a topic of consensus amongst analysts. We opted to use the HP filter which we feel is successful in capturing the dynamics of the whole underlying series. Starting from the centre of the series and working as a moving average, it assigns symmetrical weights on both backwards and forward points. We have some degree of control over the flexibility of the filter by the use of the smoothing parameter

although the latter is pre-determined by the statistical software we used. We find that the extracted trends do a good job in capturing the dynamics of the underlying series. We are aware of both statistical and practical limitations of our choice of trend filtering. Our sample of REERs is so wide and diverse that no single filter would accommodate the different characteristics that apply. We include exchange rates that are either free-floating or managed. Currencies that moved from a fixed to a floating regime or vice versa at some point during our sample. We have currencies that have followed a fairly smooth pattern and currencies which experienced a crisis in the form of significant one-off depreciation or devaluation. In light of all this we find the HP filter a much more appropriate technique than alternatives commonly adopted in the literature. An example of such alternatives defined the trend as a simple or moving average over a data sample. We find such approaches very subjective and crude in the way they treat the underlying time series.

Figure 3 to Figure 11 below show three representative examples of REERs in each of the three geographic regions we focus on: Latin America (LATAM), Emerging Europe Middle East and Africa (EMEA) and non Japan Asia (AXJ). All but one currency have had a significant break in the REER series at some point in the years that span our samples. This makes the applied filter biased towards accommodating the breaks and prone to over or underestimate valuations compared to the underlying trends in the months that precede or follow the series breaks. We are aware of this feature but still wish to include these breaks in our series and allow our estimated filters to accommodate them. The longer the time that has passed from the series break to the present the more the effect on the estimated trend will be

smoothed away. From the currencies below only CNY does not have an abrupt movement to bias the trend. However this is simply because the Chinese authorities have continuously managed the CNY very heavily, which was pegged to the USD from 1995 to 2005 i.e. practically for the whole period of our sample here. As the fluctuations and breaks in the REERs come mostly from the spot exchange rate moves, the CNY REER graph in Figure 3 simply captures the inflation and trade dynamics between China and its trading partners.

In Chapter 4 of the thesis when we look at the application of the model to real-time economic data and its use in producing actionable trade signals we discuss how limitations of the sort we are discussing here can somewhat be smoothed away when overlaying the real economy stylized facts and knowledge. For example in the case of the Argentine Peso which was devalued in November 2001 shortly before the end of the sample used in our model estimation, we are clearly aware that the HP trend will tend to give signals of currency undervaluation for a long part of our forecasting period. This will largely reflect the trend component which has adjusted to incorporate the structural break caused by the devaluation and have to be interpreted and used in light of this fact.

Figure 3 AXJ REERs and HP Trends: CNY

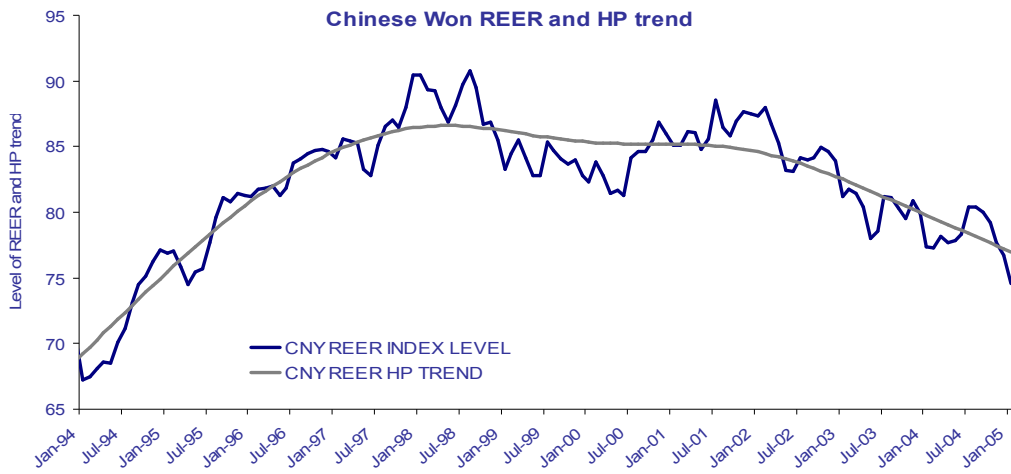


Figure 4 AXJ REERs and HP Trends: IDR

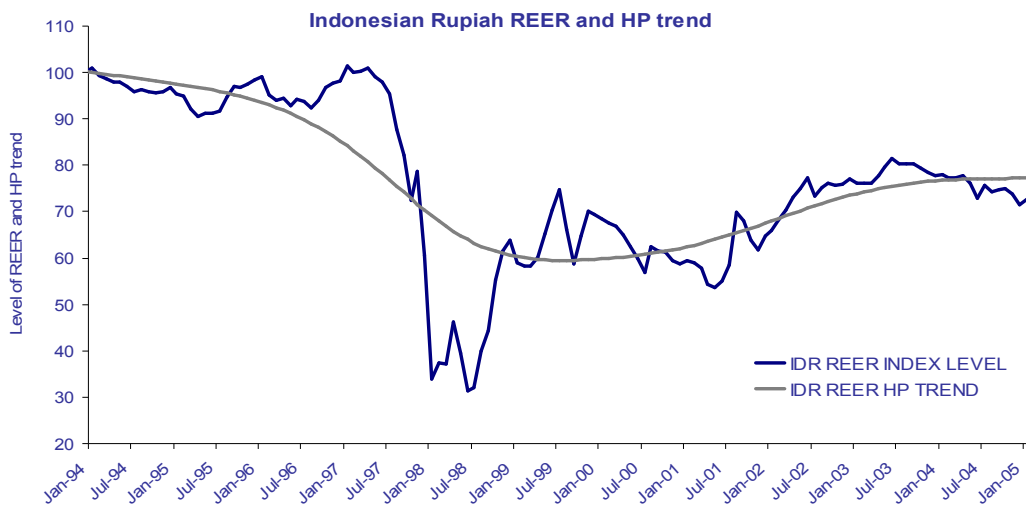


Figure 5 AXJ REERs and HP Trends: THB

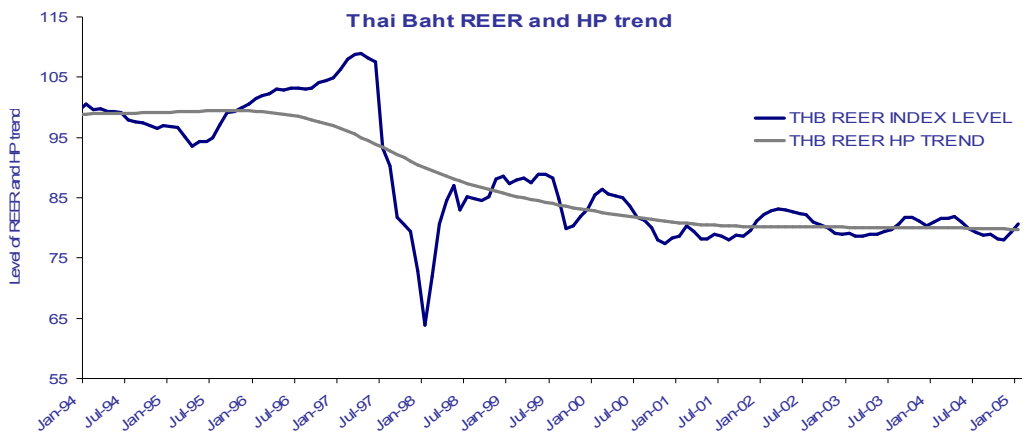


Figure 6 EMEA REERs and HP Trends: RUB

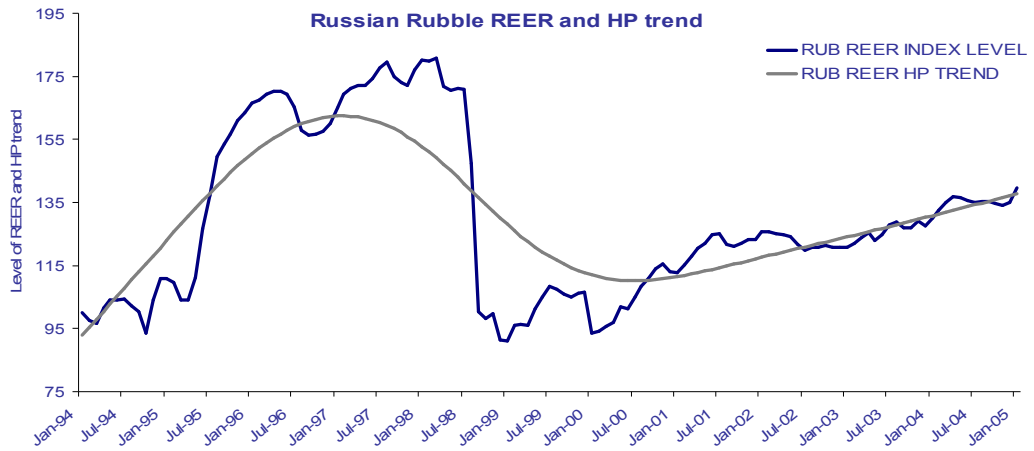


Figure 7 EMEA REERs and HP Trends: ZAR

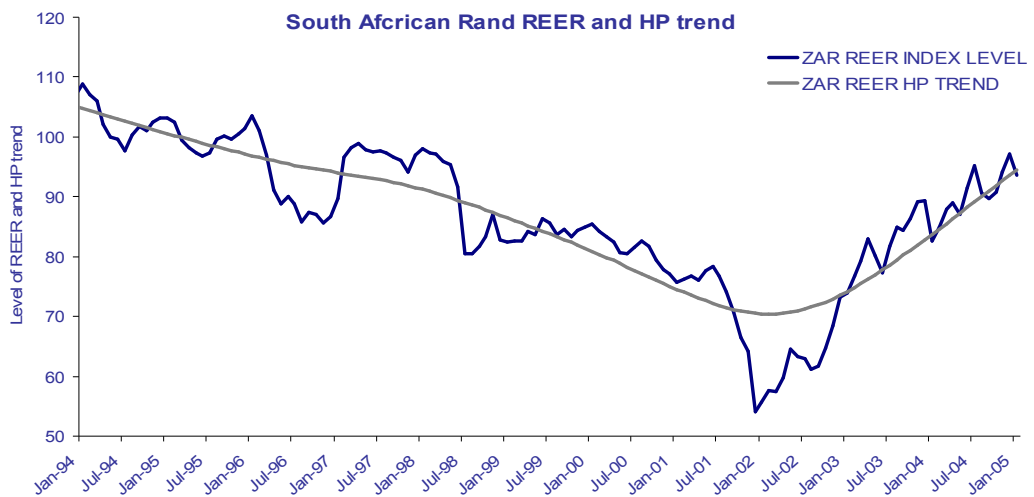


Figure 8 EMEA REERs and HP Trends: TRY

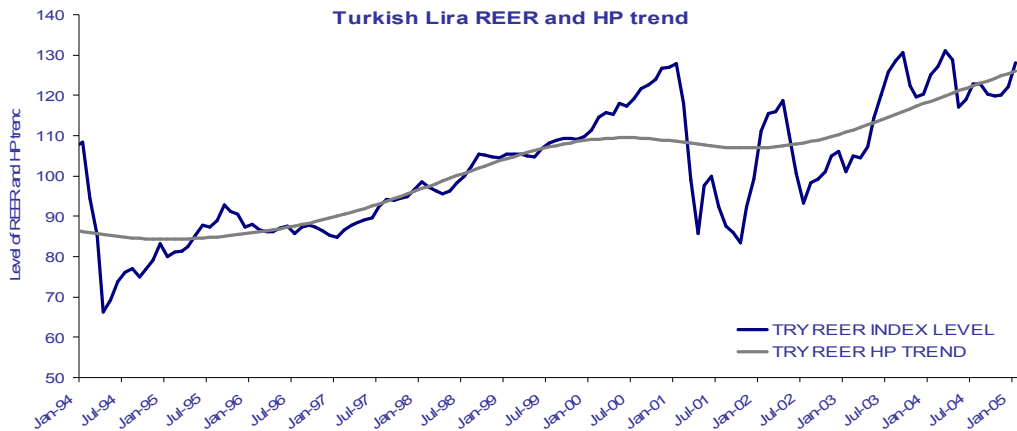


Figure 9 LATAM REERs and HP Trends: ARS

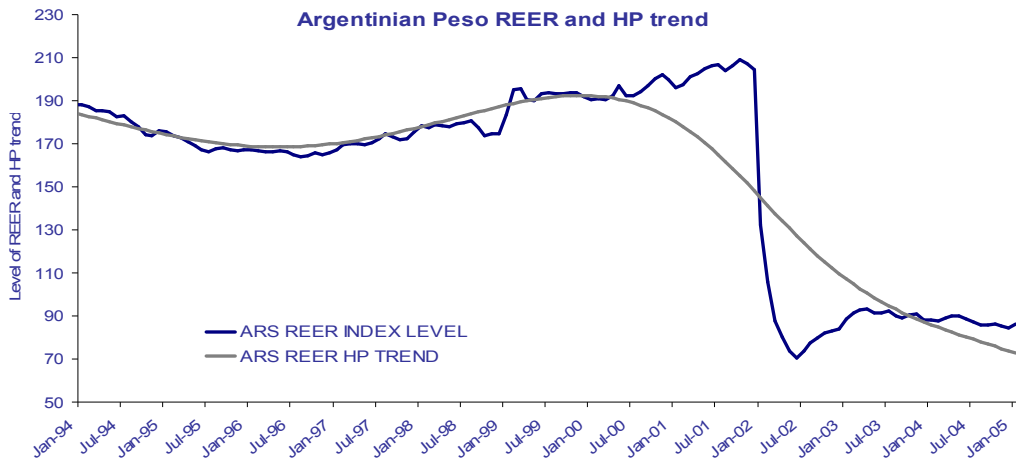


Figure 10 LATAM REERs and HP Trends: BRL

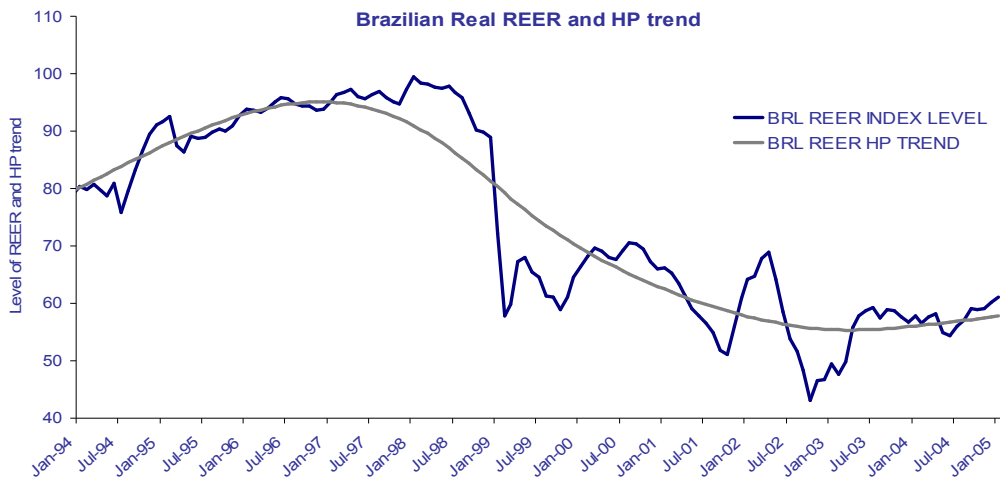
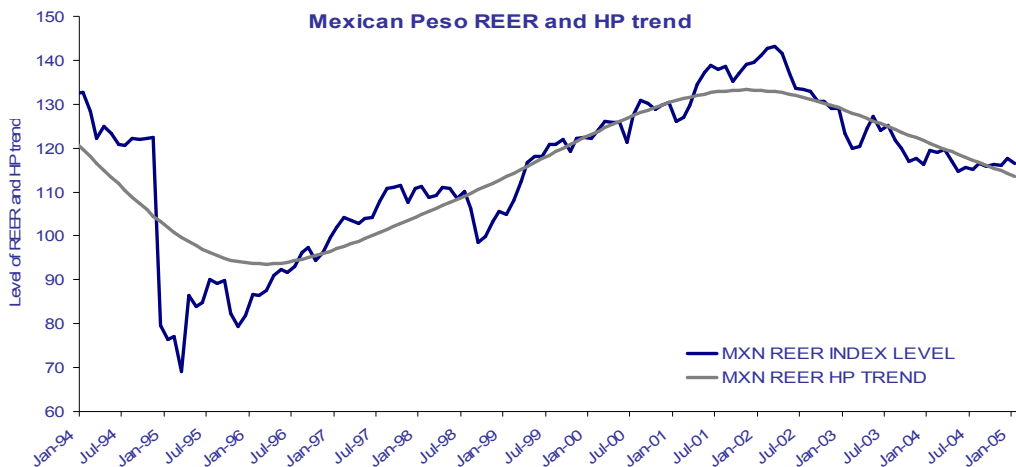


Figure 11 LATAM REERs and HP Trends: MXN



One point we found worth examining further with regards to the REER data was the use of average monthly spot exchange rates in the calculations. We went on to construct new REER indices using the end of month spot rates between a country and its trading partners. We found that the two series did differ and, as expected, the differences were amplified during periods when the exchange rates were not pegged or heavily managed. Still, as Figure 12 to Figure 14 below show in three representative examples of the three regions in our analysis the differences will typically not change the general movement of the series. Therefore the trends we would have calculated and in consequence the deviations from these trends would not have been expected to alter the results of our analysis. What is more we find the choice of calculating REER series based on a single data point of spot exchange rates arbitrary, even if the point is the last day of the underlying month. The latter would in a way incorporate the latest information with regards to the underlying exchange rates but this need not be the most relevant or informative. Especially at volatile times we find the smoothing effect of taking the average spot exchange rates from the whole calendar month a far more objective approach especially for the purposes of estimating and fitting the model to the historic data. As discussed in earlier sections of the thesis, moving to a monthly data horizon is already a much higher frequency than what is typically used in academic papers. We therefore feel comfortable avoiding any higher frequency data in our model estimation exercise.

Figure 12 THB REERs based on EoM and Avg monthly spot exchange rates

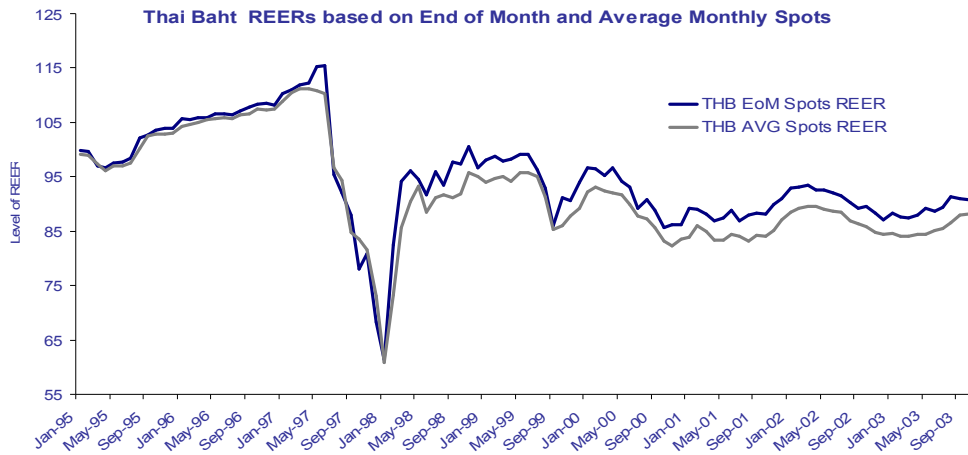


Figure 13 TRY REERs based on EoM and Avg monthly spot exchange rates

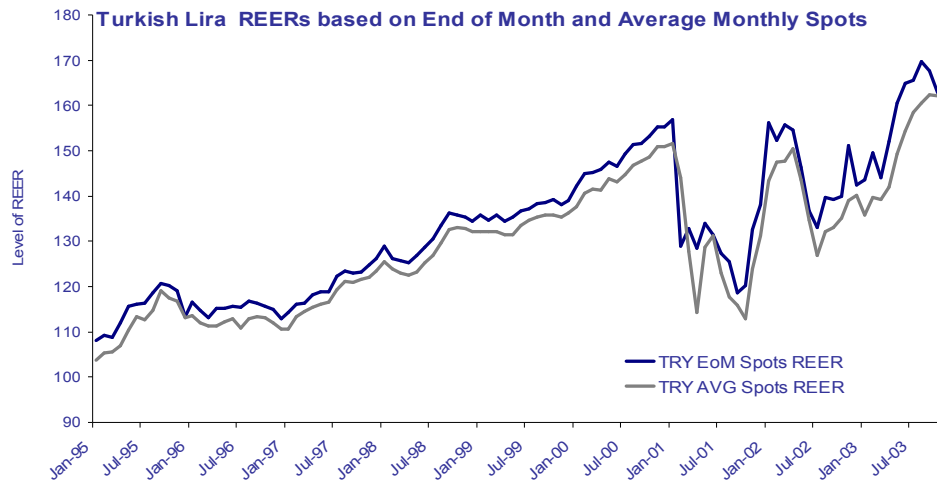
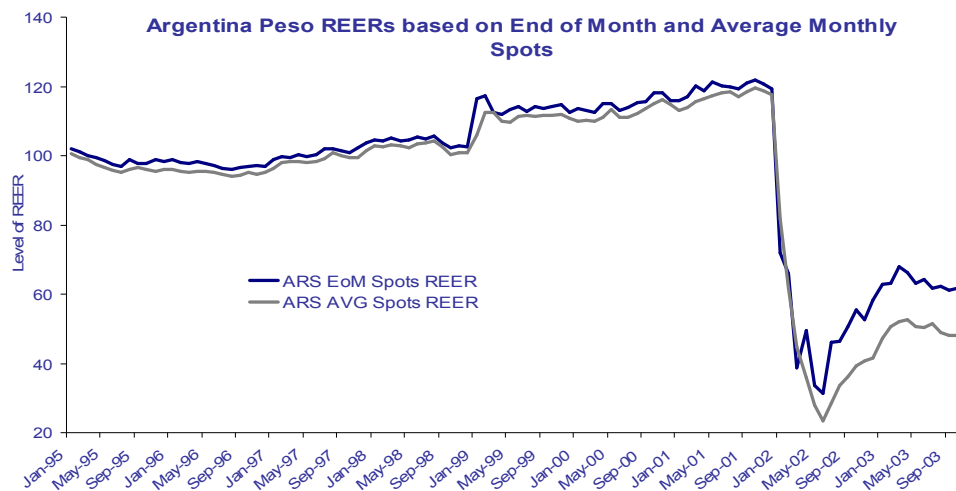


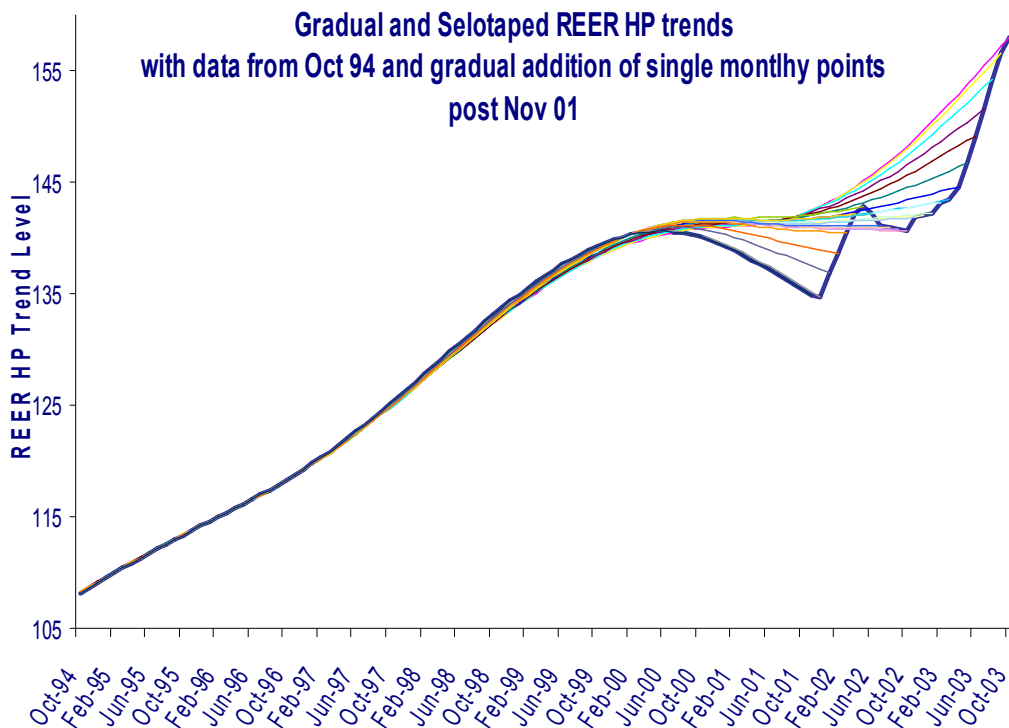
Figure 14 ARS REERs based on EoM and Avg monthly spot exchange rates



Let us further elaborate on how we further assessed the HP limitation mentioned above. When we fit the model to historical data, by definition we use the HP filter to extract the trend of the whole sample. All analysts would do the exact same thing almost by definition, as the way to model a sample is to use all the information available on that sample at the time of the estimation. However even if this approach is theoretically sound we were wary of having to fit a model on a trend that includes all the underlying data and then expect it to work equally well when applied to data outside the sample. Figure 15 below shows the case of the Turkish Lira. We calculated the HP Trend for the data from October 1994 to and including November 2001 and thereafter recalculated the HP trend for the REER series that included the data of one additional month each time. In Figure 15 we show both the individual HP trends updated to include one additional month each time and a so-called “selotaped” version. The latter is a cumulative trend generated from adding to the original trend that goes out to November 2001, one extra point each time which refers to the latest monthly observation. By definition the trends that only include data up to a certain point will defer from a trend applied to the whole sample, especially if the latter includes structural breaks not yet relevant at the time of estimation of the shorter trend versions. We know in practice we will be faced with this limitation when applying the estimated model to future data. Nevertheless structural breaks will not come in isolation and we believe that the model itself will point to mounting pressures on the run-up to such breaks. Second, when one estimates a model over a sample, they purposely benefit from the whole information content of that sample. This is why it is important to avail ourselves of as long

and as reliable data as possible. If this sample includes structural breaks, then we welcome the inclusion of these points as well, given that they are part of the reality we try to model in the first place. From a statistical point of view one aims to fit a model on enough information to make it reliably applicable to future data as well. In our case this aspect was tested by applying the models out of sample and on real time data as well. We will return to this issue in more detail in the next chapter of the thesis.

Figure 15 HP trends estimated based on gradually evolving time series post November 2001 (fine colour lines) and the cumulative “selotaped” HP trend (bold dark blue line)



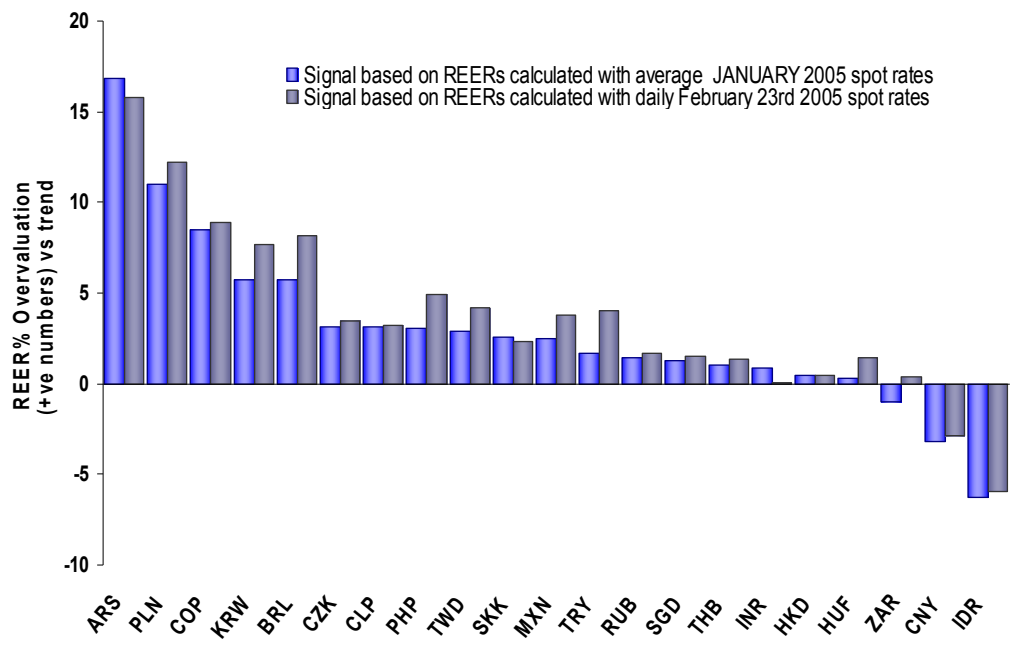
When we implemented the model out of sample but most importantly when we applied it on a monthly real time basis, we found it useful to practically account for the more recent changes in spot in the following

manner: While the model estimates for time t are calculated using REER and HP data at 2months lag, we also estimated the REERs based on the daily spot rate prevailing close to the end of the month at lag 1 of our estimated period. Effectively this provided us with an up to date picture of market sentiment which we found useful taking into account mostly when it served to cancel a model signal. This included cases where the market had already corrected in the direction suggested by the model and thus left little room for further moves. Figure 16 below gives an example of such an approach. In particular it shows the case of us applying the model to forecast March 2005 currency pressures. In this case we used input data of two months lag and in particular the deviation of the January 2005 REERs from the trend calculated with data up to and including January 2005. However as we were actually applying the model to forecast March 2005 signals when we were already towards the end of February 2005 we also calculated the HP trend which included the data up to and included the data on February 23rd and we show in the chart the deviation from these trends of the REERs based on the daily spots of that date.

Most signals, especially the strongest ones are still valid in terms of direction. Some are weaker but still suggest the same direction. Only one has actually reversed. This is the signal for the South African Rand (ZAR) which suggested that the currency was undervalued based on the REERs as of end of January 2005. However by the end of February because of market moves that took place in the mean time the signal was suggesting a marginal overvaluation. The signal that was generated based on the January REERs was a very weak one and would have probably been ignored by the model

anyway, without generating a trade recommendation to begin with. But if there was a recommendation, we would have suggested that investors ignore it as more recent market data suggest the information had already been priced in. Again, we will return to this type of qualitative analysis of the model applicability and features in Chapter 4 of the thesis.

Figure 16 REER deviations from trend at lag2 and intra-month at lag 1



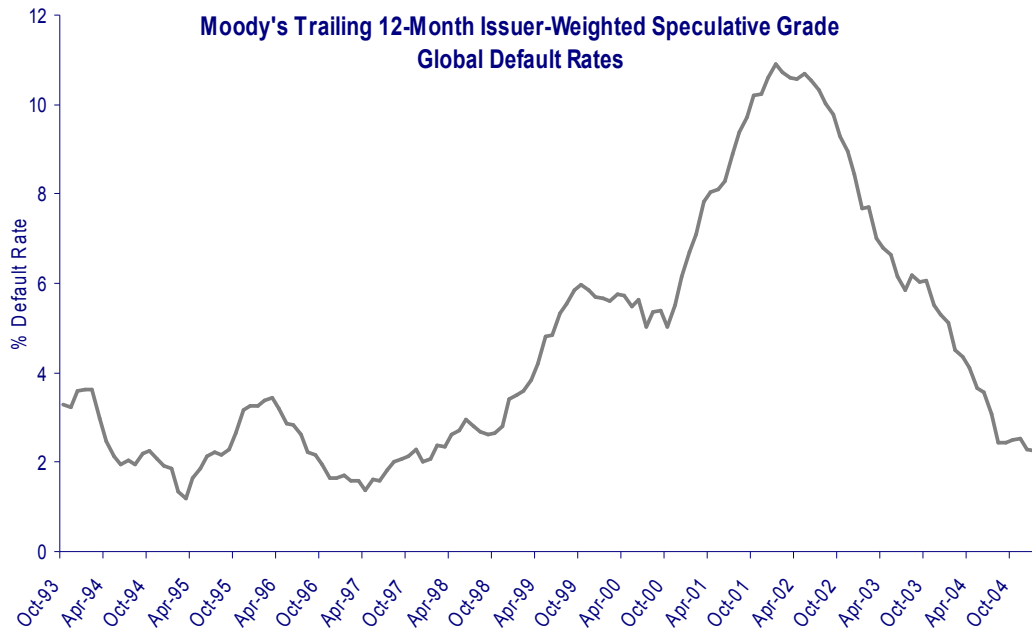
In our model estimation we used monthly REER series which were calculated using the average spot exchange rates of that particular month and the HCPI and Terms of Trade data applicable to the same calendar month. All data were used at 2months lag from the month we wish to explain or forecast in terms of currency moves. Our statistical results amply confirm that REER deviations from HP trend are an extremely significant and consistent leading indicator of forward rate returns.

2.4.2 Moody's World Default Rate

The second variable found to be extremely and consistently significant in explaining future forward exchange rate returns is Moody's speculative grade world default rate. This is the only global variable that we include in our selected model specification and the one we found to work well and better than all alternatives presented earlier in this chapter. The series is compiled by one of the leading rating agencies, Moody's, to include the cases where corporations that are rated as speculative grade, default on their debt obligations. Ratings are assigned to debt issuers by ratings agencies such as Moody's, S&P and Fitch. The assigned rating can take any value within a specific range and reflects the credit worthiness that the agency ascribes to each issuer. The ratings assigned by Moody's to a corporate issuer range from "triple A" to "single C" with twenty one main rating categories in between. A "triple A" rating corresponds to bonds and preferred stock that are judged by Moody's to be of the highest quality and the smallest investment risk, The lowest eleven ratings, namely from Ba1 to single C form the speculative-grade universe.

The measure that we are interested in is the 12-month trailing average of the rate at which such speculative grade corporations globally, defaulted in their obligations in the last 12 calendar months. So for example if the figure for January 2003 was 7.65%, it means that, over the 12 months to January 2003, 7.65% of speculative grade corporations defaulted on their obligations globally. In our selected specification we included the month on month percentage change (mom%) of this trailing 12-month speculative- grade default rate.

Figure 17 Moody's Global Default Rate

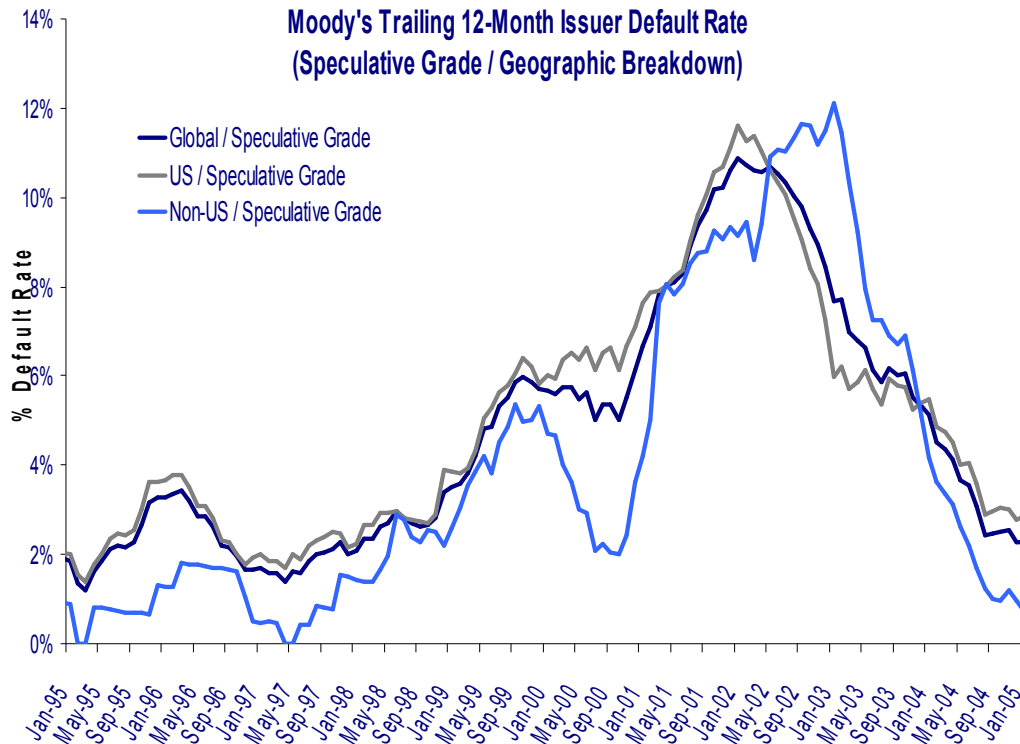


The success of this data series as a leading indicator of currency pressures could be attributed to it acting as a proxy for global risk appetite. Defaults are arguably more of a lagging rather than a leading indicator, given that the signs of distress are present long before a company defaults. Nevertheless, the momentum of default rates may well serve as a leading indicator of the direction that the economic cycle is heading towards. Evidence of deterioration in default rates can provide a credible signal that the recovery is yet far ahead or that the downturn has yet to trough. In that respect, further market sell offs of risky assets such as emerging market currencies may be expected to follow. Again because default rates are a lagging indicator, an improvement in the world default rate would signal that recovery is well underway and could reasonably be expected to precede further increases in investors' risk appetite. The latter often coincides with increased interest in emerging market assets, of which currencies are one

example. Our findings amply confirm the hypothesis that the monthly growth rate of Moody's global 12month trailing default rate for speculative grade corporates provides a proxy for risk appetite and market sentiment.

Default statistics are interesting indicators of underlying fundamentals but there are many aspects that one needs to consider when looking at such empirical data. We focus on global default rates as we are looking for an indicator to use as a global variable in our model. Traditionally default rates have been massively dominated by the US compared to the rest of the world. This is consistent with the fact that the US is also by far the leading geographic region in terms of corporate bond issuance. According to Moody's historical default rates the US issuers that defaulted represented around 90% of global defaults for the periods from 1920 to 2002. In 2002 and 2003 the data suggest that the US issuer default dynamics slightly improved and they now accounted for about 80% of total default issuers. Year 2002 was an atypically negative year for markets and credit dynamics were no exception, bringing default rate statistics to new territory pretty much on every metric. Figure 18 below provides a snapshot of a geographical breakdown for our preferred series of Trailing 12-month issuer default rates. Capturing primarily US dynamics is something we welcome in our analysis as this has been the market that typically leads developed world conditions and also acts as the barometer of global markets. Importantly we model all emerging currencies as exchange rates versus the US dollar. Therefore the fact that our global indicator has a clear bias towards capturing US specific characteristic is a very welcome parameter.

Figure 18 Geographic breakdown of Moody's Default Rates Statistics



As stated earlier we select the default rate series for the speculative grade corporate universe. We believe that the lower rated and more prone to default corporates will work better as risk indicators as they will tend to adopt a more knee-jerk reaction to a shift in global fundamentals. Indeed Moody's statistics in Figure 19 and Figure 20 below show the huge divergence between Speculative and Investment Grade corporates with the latter exhibiting an almost default-free history compared to the former at least until the end of 2004.

Figure 19 Moody's Default Rates: IG and SG: Default Rates

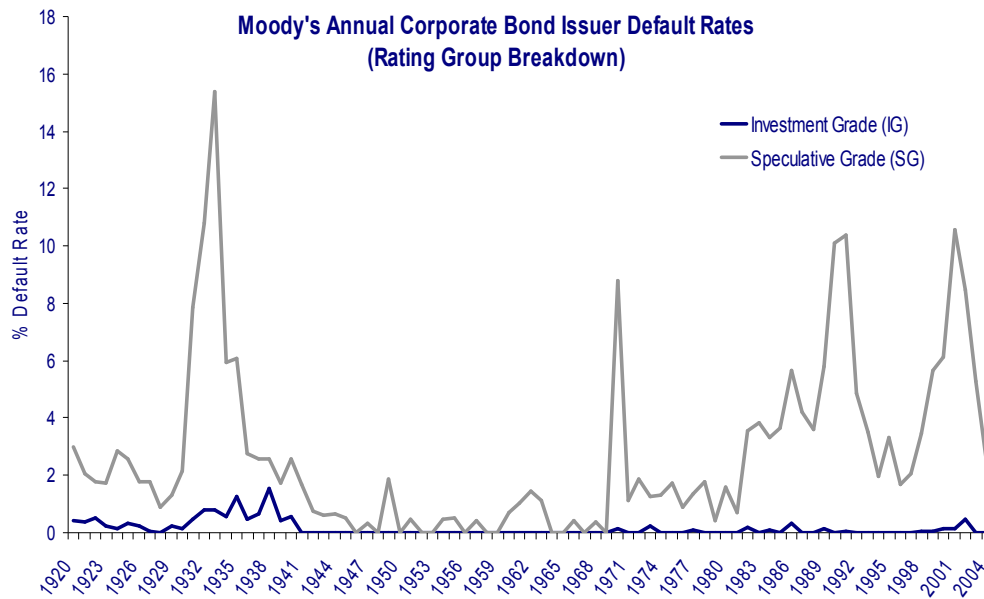
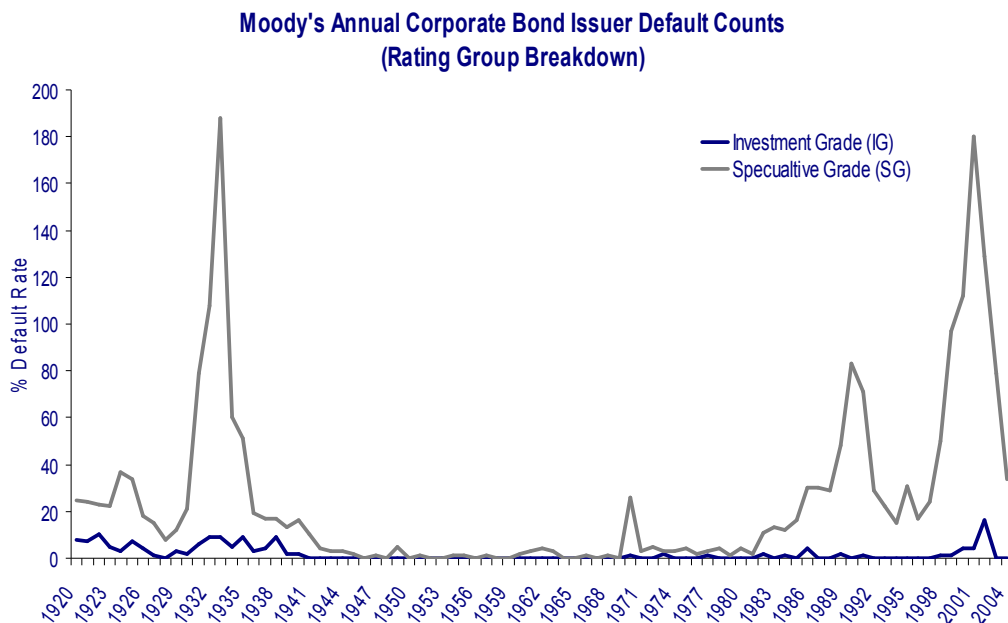


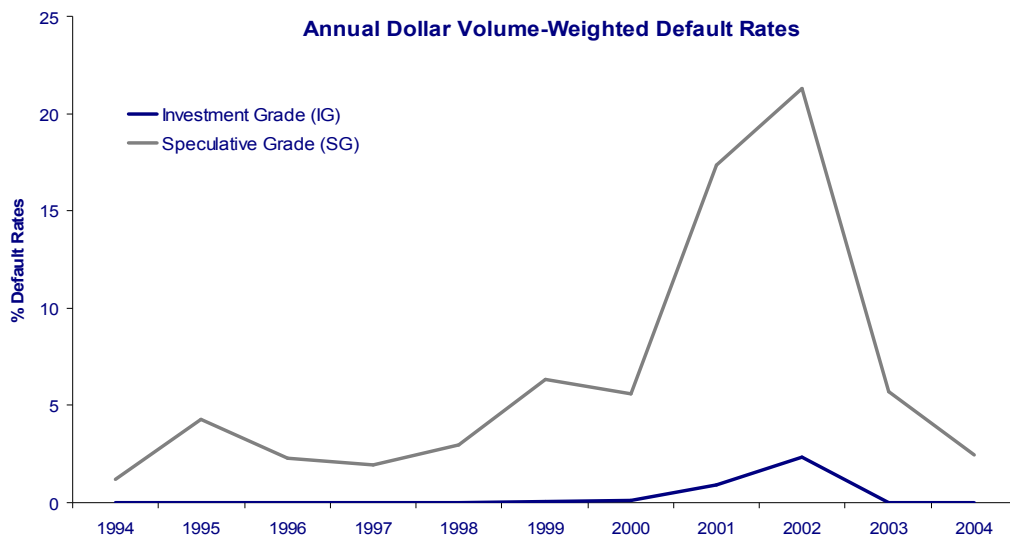
Figure 20 Moody's Default Counts: IG and SG: Default Counts



The difference between the two charts above is that Figure 19 shows global annual default rates as a percentage of total issuers in each one of the two rating groups, while Figure 20 shows the annual number of defaults occurring globally in each one of the two rating groups. Figure 21 below tells

again the same story but focuses on the market collapse of 2002 which was to be compared only to the 1930's crises levels. Figure 21 shows annual default rates weighted by volume instead of issuers. Again speculative grade corporates are on a league of their own with their deviation from the investment grade universe rising significantly at times of crises. It is worth looking at volume weighted statistics as well as issuer weighted because not only the number of defaults but their size is significantly increased. This is particularly relevant at times of market deterioration.

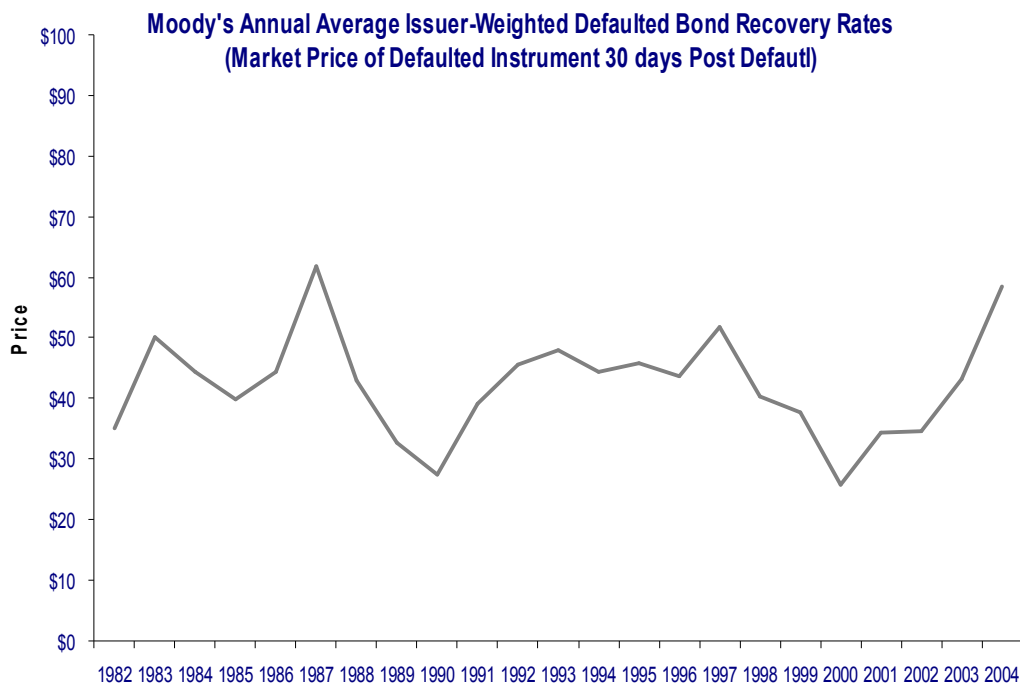
Figure 21 Moody's Default Rates Statistics: IG and SG: Volume Weighted Default Rates



If we look at Default Statistics as a risk indicator we need to accept that they tell only half the story. Recovery rates, i.e. what an investor will likely get as a percentage of the face value of his original investment is an equally important consideration if this is above zero. Indeed as Figure 22 below shows recovery rates have tended to be to around 30% and 60% of the original face value. These numbers are based on the market price at which

the defaulted debt trades 30days post default. Arguably the distribution around this average can be expected to be very wide but on the other hand these recovery rates may well be expected to increase significantly as we move further away from the default event. It matters to specify what the default event was in the first place, as that can range from a simple delay in interest payment to a full blown bankruptcy. Again speculative grade corporates can be expected to lead the pack in most default events of more permanent nature and to have a lower recovery rate altogether. Still the fact remains that recovery rates have been on an improving trend in recent years and have also been fairly stable in the last decades, leaving little room for surprises.

Figure 22 Moody's Default Rates Statistics: Issuer Weighted Recovery Rates



Qualitative factors like the ones mentioned in this section matter in our

analysis but we find that most of them tell the same story from a different angle. Overall US corporates dominate both issuance and default rates be it weighted by number of issuers or USD volume. This picture is somewhat more balanced in recent years as corporate debt market becomes deeper and more liquid outside the US. Speculative Grade defaults almost by definition outweigh Investment Grade defaults. Recovery rates are just as important as the default rates and they have been in a range bound mode in the last decades which means that investors have a more or less expected recovery rate they can incorporate in their investment decisions. All this considered we feel confident that our choice of the monthly percentage change of the trailing 12-month speculative-grade global default rate is very representative of the risk dynamics we wish to capture. Our statistical results amply confirm our expectation that this factor is strongly and negatively correlated with moves in risky asset classes like emerging market currencies. It works like a good proxy for global risk appetite and directly reflects corporate sector dynamics which one needs to accommodate when trying to assess investment dynamics.

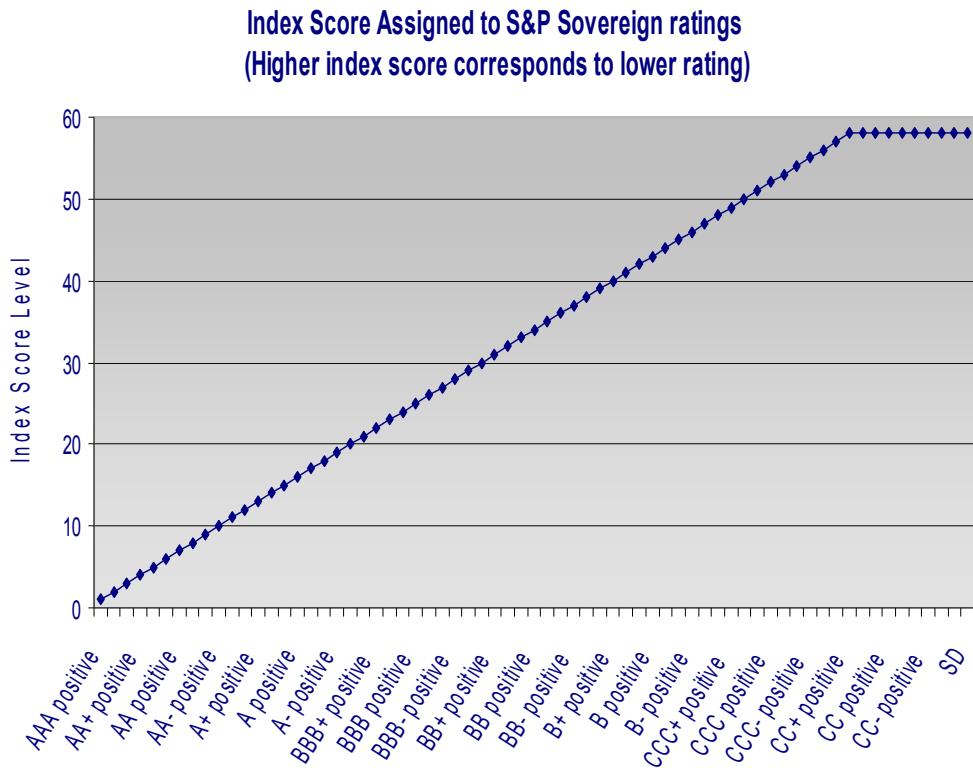
2.4.3 Sovereign Debt Ratings downgrades by Standard & Poor

The third variable that we used captures the downgrades of long term sovereign credit ratings by S&P. Downgrades are found to be extremely significant leading indicators for further EM currency weakness. This is why we only include them as explanatory variable in the version of the model which predicts probabilities of forthcoming “depreciations” of emerging market currencies. We only account for downgrades by one of the leading rating

agencies, namely Standard and Poor because at the time of the research we could not avail ourselves of historic data on rating outlooks from Moody's, the other leading rating agency.

As discussed in more detail in Section 2.4.2 above, ratings can take any value within a spectrum ranging from AAA for the best rated issuers, to Selective Default (SD) for the issuers which have not honoured at least one of their credit obligations. Within each rating category above the level of Selective Default, rating agencies differentiate their assessment of the credit-worthiness of the issuer via the use of a rating outlook which can be positive, stable or negative. Figure 23 below shows the whole spectrum of ratings and rating outlooks applicable and how we have transformed them into the form of a numerical index in order to quantify the rating changes and include them in our model analysis. The index is composed in such way that higher index scores correspond to lower ratings. The worse index score is that of level 58 which we assigned to any rating equal to or the worse than CC- with a positive outlook. In Figure 23 the horizontal axis only displays the sequential rating levels with a positive outlook. This is done merely for presentation purposes as the chart would not be readable if we were to include in the axis labels all the rating outlook categories. However as described above, the underlying index does comprise of different levels for each ranking of outlook within each rating level.

Figure 23 S&P Hard Currency Sovereign Ratings Spectrum



Rating actions apply to all countries of our model and should capture a common rationale on behalf of rating agencies. Arguably factors like the stability, the history and possibly the size and political power of different sovereigns often merit somewhat different treatment by the agencies. We welcome the fact that this variable also captures such subjective elements as they surely matter in the minds of investors as well. At the same time as rating agencies act independently and are judged for the credibility of their own analysis it is fair to assume that the information content of ratings will be rather standardised for different rating categories. As rating agencies monitor and assess a large sample of factors, both quantitative and qualitative that affect the credit worthiness of an issuer, it is fair to say that both rating levels and rating actions act as a good proxy of the perception of a country's

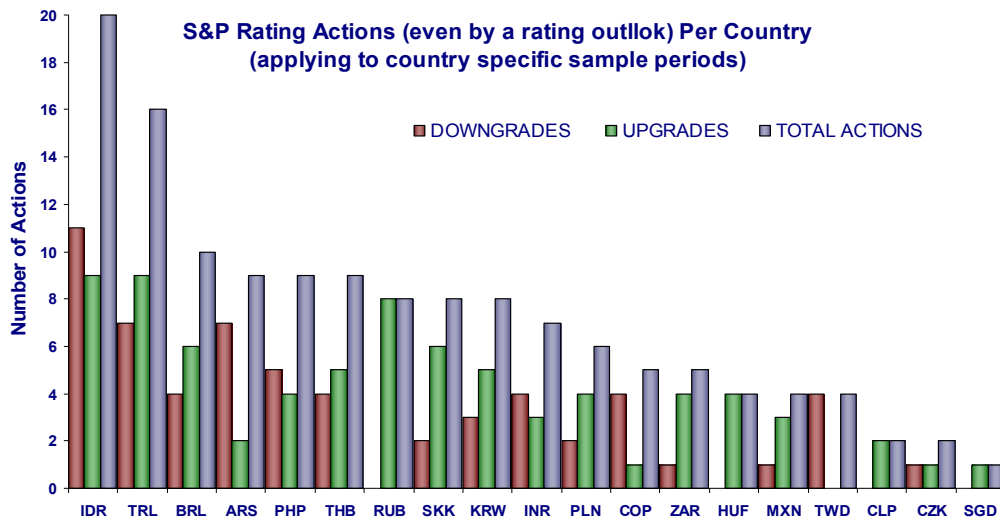
overall position and circumstances at any given time. It is this type of reliable “all encompassing” information we would typically look for in the indicators we include in our model.

In our analysis we use ratings assigned to a Sovereign’s Hard Currency Debt. This typically refers to USD denominated debt as opposed to local currency denominated debt. The idea is that a country will be more at risk of defaulting in the obligations denominated in a currency on which the country has little power to affect via intervention or other policies. Local currency denominated debt can easily be reduced in value and therefore become easier to service via inflationary policies. In practice nowadays hard currency debt also corresponds to the bulk of the outstanding EM sovereign debt. What is more, there may be credit accelerating terms that will consider a credit event to have been triggered in both the hard and local currency obligations once a sovereign defaults in its hard currency debt. Of course there are always exceptions to the rules. Russia in 1998 defaulted on and effectively restructured only its local currency debt. However Russian debt assets of all currencies and Russian assets in general came under significant selling pressure at the time.

Figure 24 below provides a summary of the S&P rating actions that applied to the sovereigns we include in our model sample. These actions refer to the years for which we have exchange rate data. As a reminder these time series are not homogeneous across the different countries but it is safe to say that most series refer to the years from 1998 to 2004. There is clearly no common pattern with regards to how S&P treated the different sovereigns in these years, both in terms of frequency and direction of actions. On the one

end we have the example of Indonesia which saw its rating or its rating outlook change a total of 20 times in these years, almost equally split between positive and negative rating actions. Indonesia was downgraded gradually from BBB-positive in 1994 all the way to SD in March 2000, bounced out of SD status briefly in October 2000 only to start being downgraded again in March 2001 and end up defaulting again in April 2002. It exited the SD status in September 2002 when it was assigned a CCC+ rating with a stable outlook and really got out of default status in May 2003 when it was assigned a B- with a stable outlook which was later further revised upwards. At the other end of the spectrum of sovereign credit worthiness we have Singapore which has enjoyed an almost unquestionable credit stability and only saw one positive rating action in recent years and that was back in 1994 when it was upgraded from AA+ stable to AAA stable, the second highest rating available. Notwithstanding significant differences in the rating history of EM sovereigns, the fact remains that rating actions will apply to all countries and will convey a more or less uniform message in terms of information and perception of the country's fundamentals.

Figure 24 S&P Sovereign Rating Actions



In recent history ratings agencies have often been accused of acting as a lagging rather than a leading indicator. Rating actions would typically confirm rather than drive market sentiment. In the case of rating Sovereigns the element of political relationship and reputation at risk was understandably significantly more pressing than when rating corporates. This meant that often upgrades came too many too early while downgrades came too little too late. As rating agencies were faced with actual defaults in emerging markets and tried to recapitulate their credibility one could note a change in their approach to sovereign rating actions. Agencies started to expect a consistently improving track record before reversing past penalties or rewarding a country for solid policies and fundamentals via upgrades of their sovereign rating or outlook. So upgrades were now coming a bit too late as a reward rather than an early indicator. This again reduced their information content for investors. Consistent with these market stylised facts we found that upgrades did not work well as a leading indicator of future “appreciations” and are thus not included in the “appreciation” version of our model.

However, we did find that downgrades work well as leading indicators of negative currency pressures in emerging markets. This asymmetry in the significance of the rating actions as signals of forthcoming upward or downward pressures does not come as a total surprise. As discussed above, markets will typically require much more information than a rating upgrade to be convinced to increase their buying interest. Especially in the case of a positive rating action by as little as a rating outlook the information content of the action itself is unlikely to drive significant market action. However the average risk-averse investor will look for indicators of stress to incorporate in his investment decision and rating downgrades are one such indicator. Having been accused of delayed response in a number of negative credit events, rating agencies became much more pro-active in downgrading a sovereign at signs of stress. Especially downgrades by only one or more rating outlooks can help deliver the message of the agency's assessment while not jeopardising their relationship with the rated sovereigns, which can be at risk in case of serious negative rating actions. This stylised fact served well to explain why rating actions are likely to be more informative on the downside and importantly why even a negative change in outlook will most likely drive a market reaction.

In our analysis we take into account downgrades by a rating notch or even by a rating outlook. In our selected model specification we define "downgrades" in terms of downwards rating actions as a function of direction and independent of the size of these actions. We use a "dummy" variable to capture rating downgrades. When a sovereign is downgraded by even a rating outlook the "dummy" variable is assigned the value 1 for that specific

sovereign and month. The variables take the value zero in all other cases, i.e. if there is no action at all or if there is positive rating action. By including the occasions when the value takes the value of 1 we capture the increased probability of forthcoming “depreciation” in the country that was downgraded that month. In the absence of downgrades, the variable has zero effect on the model results. It is important to stress that by including downgrades of even one rating outlook we have a much wider and finer spectrum of observations that significantly increase the sample of rating actions. Downgrades of outlooks are also much more likely to have a more immediate and direct market effect.

A sovereign, whose rating history shows the willingness of rating agencies to be forward looking and pro-active in times of stress, is Argentina. Before the infamous default in late 2001, S&P had already downgraded Argentina’s sovereign a total of 6 times in a period of one and a half years from February 2000 to July 2001.

Figure 25 S&P Argentina Sovereign Rating Actions

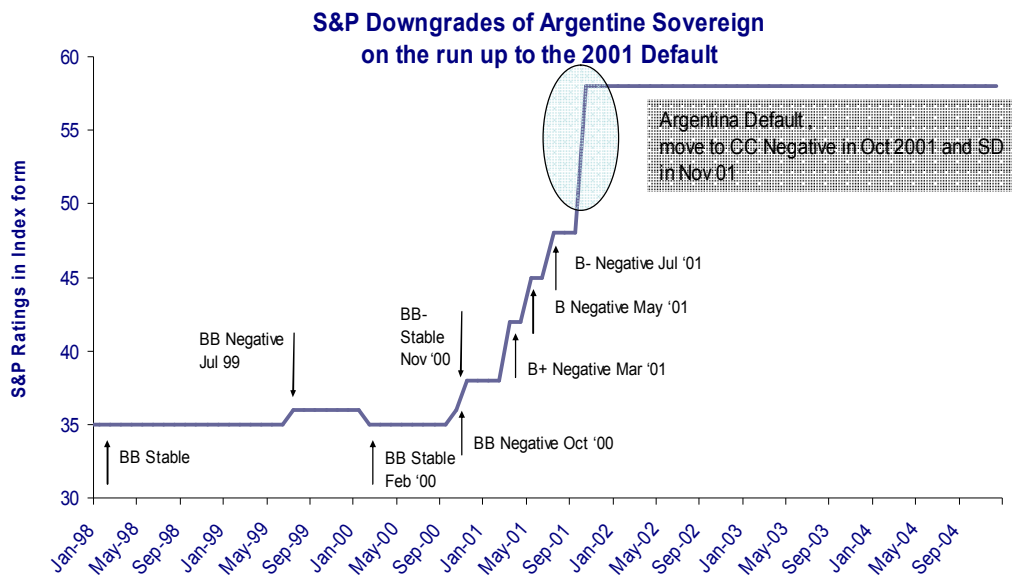
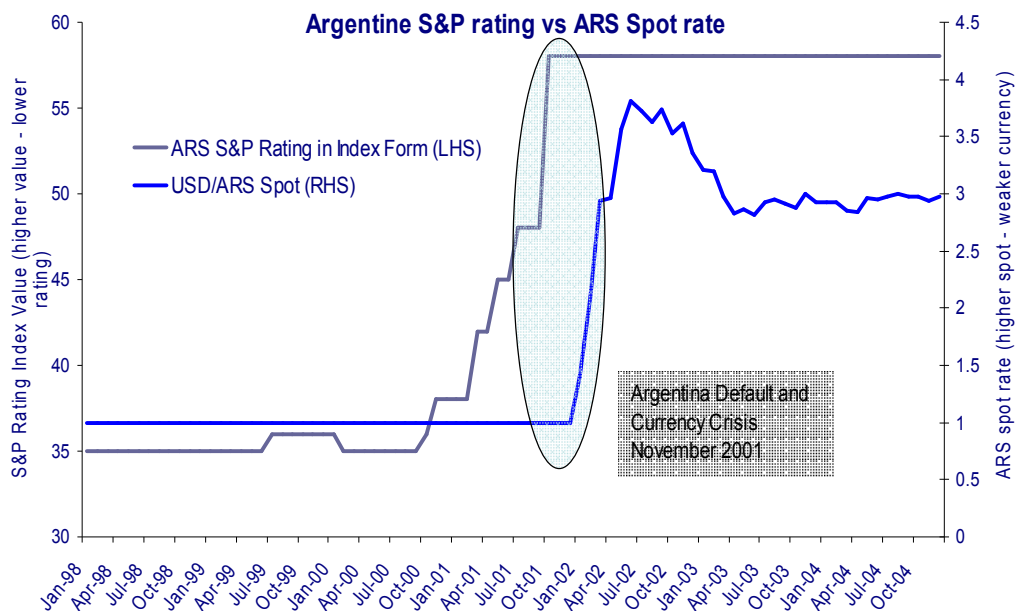


Figure 26 below tells the same story but magnifies one point of particular interest in our case here. As discussed in Chapter 1 of the thesis forward exchange rates led the market reaction to deteriorating fundamentals in Argentina long before the spot was actually devalued in 2001. The Argentine peso devaluation came together with the Argentine sovereign default in November 2001. As Figure 26 suggests the leading rating agencies had been proactive long before the actual default took place. Rating downgrades had started more than a year before the actual default took place. This is an extreme case of a country that actually defaults on its obligations and at the same time abandons its previous currency regime and devalues its currency as a reaction to a multi-faceted crisis that explodes.

Figure 26 S&P Argentina Sovereign Rating Actions & Argentine Peso Spot Exchange Rate



We will return to the subject of Sovereign Ratings in the last Chapter of the thesis where we set out to model and forecast rating actions by both Moody's

and S&P in a number of emerging markets globally. Our findings support the idea that credit ratings can be explained to a significant degree by macro fundamentals prevailing in the underlying countries. Thus we feel that the inclusion of rating downgrades in our model of currency depreciation serves well to capture a number of macro-parameters in a condensed proxy manner and also incorporates the assessment of these macro dynamics by an independent agent. Such information is highly likely to be of interest to market agents. Our currency model findings support these notions.

2.5 Conclusion

In Chapter 2 of the thesis we outlined the criteria behind our choice of explanatory variables and described the many data series we considered and in greater detail the few factors we selected. We aim to create a model that applies in a homogeneous manner to all the emerging markets included in our sample. This choice is driven by the need to produce a specification that is as simple as possible, intuitive and practical. We want the model results to be comparable across different countries and this can be done best by applying the same coefficients to all countries. The only differentiation we are happy to accommodate is that between what we call global variables whereby the exact same data are applied to all countries and the so called country series whereby we adopt data that are specific to each country but again estimate one common coefficient for all countries. Both global and country specific data need to be thoroughly assessed to ensure they are comparable, consistent and meaningful. The consistency of the data is ensured with the very detailed analysis and understanding of what each series represents. Where

differences applied between countries we made sure we adopted the data commonly used by market participants and market economists. We also made a point of including all series in the most informative and relevant format, avoiding all types of sample specific or other standardisations, commonly adopted in academic research.

The next big hurdle in our data selection is derived from the purpose of the models themselves. We wish to model and forecast forward exchange rate moves on a monthly basis. That means that our data will typically have to be available on a monthly basis so that we will not need to apply any type of manipulation like interpolation or extrapolation which we believe destroys a significant part of the information content of the data. This makes a number of usual suspect macro data irrelevant to our exercise especially for stock data like a country's GDP. The data also have to be released before the month that we wish to forecast and thus be leading indicators of currency moves. This is the only information that we will be able to use going forward in forecasting currency dynamics. We thus had to exclude a number of market data like equity or credit market data which may well be very relevant to investors but will typically coincide rather than lead moves in exchange rate markets. Our explanatory variables also need to not be heavily revised after their initial release. We also want to find variables that work in a fairly homogeneous manner for all the countries we incorporate in our sample. A host of macro data are excluded on the basis of these criteria. Data like oil prices, inflation, money supply and credit growth data, output measures like industrial production, external sector variables such as trade data and data on foreign exchange reserves have been in the forefront of academic literature on

currency crises. In our case however they were all filtered out of our explanatory variable selection process as they failed to meet one or more of the criteria outlined above. Many of these data were available at a lower or higher frequency than one month, almost all were released with a significant delay and were revised more than once following initial release. Many would have a radically different effect depending on which country we focus and a common coefficient would not be representative.

In order to keep our variables as objective as possible we excluded all qualitative factors which may be extremely relevant but is practically impossible to properly capture let alone forecast. Therefore factors such as contagion or political stability or corruption were not even tested in the models. Indices that incorporate qualitative information but are available in a quantitative format were tested though. Leading Indicators calculated by the OECD and diffusion indices like the ISM PMIs were tested but failed to meet the statistical criteria and were therefore excluded from the final specifications. Market measures like CSFB's Risk Appetite which incorporates data on different asset classes from equities to fixed income and from developed to emerging markets were also tested as global variables that may prove good proxies for market sentiment. Again statistical results did not support the inclusion of such data.

Our thorough filtering exercises resulted in merely three explanatory variables that met all the practical, intuitive and statistical criteria in a consistent manner and that were included in our models. Over and under valuations of Real Effective Exchange Rates (REERs) from HP trends, the growth rate of Moody's speculative grade default rate and Sovereign

downgrades by S&P. The first two were included in both versions of our models, the one that captures appreciation and the one that captures depreciation. The last variable was only included in the depreciation model. From the three variables that we used, one is global and two are country specific. Importantly they all provide packaged information on market elements that are significantly wider than the measure they describe in the first place. Real Effective Exchange Rates are the single variable that merits universal approval from all relevant research. REERs capture trade dynamics and inflation dynamics as well as exchange rate dynamics. They effectively are a proxy of currency fair value and this explains why any significant deviations from their medium term trends will typically be restored via market moves. We use the HP trend as an anchor and find that indeed over and under-valuations of REERs from their HP trend lead reverse currency moves by about two months.

The other two data we eventually use are both from the universe of Rating Agencies. The latter have become an integral part of the financial system and the crisis of the end of 2010 brought renewed attention to their role, functionality and importance. We find that the default rate that Moody's publishes on speculative grade corporates works as a valid proxy for global risk appetite and tends to precede in a timely fashion currency moves on both directions. The S&P downgrades of sovereign credit ratings is a variable we only found working in the depreciation model. This is understandable given the asymmetry inherent in the way rating agencies rate sovereigns. One factor that is very important and determinant of this variable's importance in our model is the inclusion of rating outlooks as well, a much higher frequency

indicator that understandably bears significant weight in investors' perception and reaction.

In the first two chapters of the thesis we presented in detail the rationale behind our research agenda and the dependent and independent variables we have selected. In the following two chapters we proceed to present the statistical and empirical findings from our attempt to model and forecast exchange rate dynamics in emerging markets.

3 CHAPTER THREE: Modelling and Forecasting

Currency Risks in Emerging Markets: Specification

Selection

3.1 Introduction

In the third chapter of the thesis we present the process of selecting the final model specification from a statistical point of view. In Section 3.2 we present our choice of methodology. We estimate a Logit type of model where the left hand side is a dummy variable that captures the binary nature of our explanatory variable. We estimate two model specifications to separately capture upside and downside currency risks. In Section 3.3 we present the findings from fitting our models both in-sample and out of sample. We select the specification we find to be consistent with our criteria for a parsimonious, technically robust model which also delivers the expected results. We then proceed to Chapter 4 where we apply the chosen specifications to real life economic data that span about a year and a half of data. Chapter 4 concludes the presentation and analysis of our emerging markets currency risk model. Chapter 5 of the thesis finally attempts a comprehensive presentation and application of our emerging markets sovereign credit ratings model.

3.2 Adopted Methodology: LOGIT Models, Symmetric Assessment of Currency Risks, Panel Data

The modelling methodology we adopt is straightforward, intuitive and consistent with the relevant academic literature on currency and banking crises. At the same time we introduce several new elements in our

methodology as we aim to model and forecast returns on a forward rate basis and we also wish to apply and utilize our model as a trading tool. This difference in mandate between our work here and previous research dictates and justifies the need to focus and address different issues. In this section we present the methodology we adopted and the thought process behind the selection of our final specification.

In our attempt to model and forecast some measure of exchange rate returns on a monthly forward exchange rate basis we adopted a Logit type methodology. Logit models are used to model and forecast a dichotomous event where the focus is on the occurrence or not of a particular assumption or event. In our case we focus on the cases of making more than 5% profit from investing on one month forward exchange rates. Therefore our dependent variable is a dummy variable which takes a value equal to one when the above mentioned condition is satisfied and a value of zero at all the times in our sample when the condition was not satisfied.

As discussed in the previous Chapters of the thesis, the near consensus view in crises literature has been to focus on downside risks and try and model the cases of substantial local currency depreciations. However, the focus of our research is far more market oriented and the main goal is to produce a model than serves as a high frequency trading tool to a real life investor. Therefore it is essential that we try and address the needs and constraints of market participants. A key consideration is that one may profit from either the weakening or the strengthening of a particular currency as long as he is positioned accordingly. We tried to capture this reality by estimating two separate model specifications. As outlined in Section 1.3.2.6 of

Chapter 1 we define local currency “appreciation” as the situation where a local currency turns out at the end of a calendar month stronger, in terms of its spot exchange rate versus the USD, than what the one month forward exchange rate had priced in a month earlier. Accordingly we define “depreciation” as the case where a local currency is actually weaker in spot exchange rate terms at the end of a calendar month, compared to what the one month forward had priced in a month earlier. Both the spot and forward exchange rates are expressed versus the USD.

In practice we estimate two different Logit models in order to describe two separate “either /or” scenarios. Our first specification which we shall refer to as the PROBAPP specification, models and forecasts the probabilities of “either having more than 5% “appreciation” in any given calendar month on a forward exchange rate basis or not”. Equation 8 below describes the way the dependent variable is defined in our PROBAPP specification.

Equation 8: PROBAPP model Dependent Variable

$$R_{t,T} = \left(\frac{S_T - F_{t,T}}{F_{t,T}} \right) \begin{matrix} <-5\% \Rightarrow \text{PROBAPPRDU} & \text{MMY} = 1 \\ >-5\% \Rightarrow \text{PROBAPPDUM} & \text{MY} = 0 \end{matrix}$$

The second specification that we estimate forecasts the probabilities of “either having more than 5% “depreciation” in any given calendar month on a forward exchange rate basis, or not”. We shall refer to this specification as the PROBDEP model and the relevant dependent variable is described in Equation 9 below.

Equation 9: PROBDEP model Dependent Variable

$$R_{t,T} = \left(\frac{S_T - F_{t,T}}{F_{t,T}} \right) \begin{matrix} > 5\% \Rightarrow \text{PROBDEPDUM} & \text{MY} = 1 \\ < 5\% \Rightarrow \text{PROBDEPDUM} & \text{MY} = 0 \end{matrix}$$

The result from a Logit type model is translated in the form of probabilities of the assumed “either/or” scenario occurring as shown in Equation 10 below.

Equation 10: Logit model resulting probabilities

$$\Pr[(R_t > 5\%) \text{ or } (R_t < -5\%)] = \frac{\exp(\beta'X)}{1 + \exp(\beta'X)}$$

Where

X denotes the independent variables included in the model and

β' denotes the matrix of estimated coefficients for each one of the independent variables.

In our analysis we use the outcome of the models in probability format exactly as they are generated by Equation 10 above. Others, like A. Roy in his paper on CSFB’s EMRI, chose to annualise the model generated probabilities in order to transform them in more sizable numbers which users may find easier to digest. We strongly feel that any such mathematical transformation is highly debatable. When you annualise the probability of an event occurring in any given month, it is no longer clear whether the resulting probability has more or even the same relevance to the initial time horizon of one month. Even if the annualised probabilities proved to be the relevant measure to describe the chances of the modelled event occurring in the next year, we would still see no use in calculating such measures as we intend to focus on

forecasting currency moves within the next calendar month.

In A. Roy's paper on CSFB's EMRI we find another aspect which mostly involves the way in which the results are presented rather than calculated. The monthly EMRI publication, presented the model results in terms of change in the monthly probability scores rather than publishing the monthly probability scores directly. We feel that presenting the results as monthly changes deprives the reader of the possibility to directly compare the scores between countries and time periods. Moreover even if the change in the scores gives us some sense of momentum in currency pressures, base effects are likely to strongly bias the interpretation of the results. For example a 10% increase in the probability of appreciation clearly has a different meaning for a currency which is correcting from previous pressure to depreciate than it would for a currency which was already in an appreciation trend.

In our analysis we assess the model results in terms of monthly probabilities, as those are calculated by the model directly. We carry out any second level analysis when interpreting the results and overlaying our market sense and experience. Probabilities, as a measure of the estimated model outcome are intuitive and straightforward. Importantly, probabilities are comparable across countries and through time. Moreover the monthly probabilities that we focus on provide information about both the magnitude and the timing of expected future forward exchange rate moves.

From the two models we develop and estimate here, it is the PROBDEP model which mimics more the work on "currency crises" which only focuses on the downside currency risks. Our two models are symmetrical in their

structure except from one explanatory variable. This is the dummy variable that we include in the PROBDEP model to capture the effect of any negative rating action suffered by a country in our sample. In doing so we effectively suggest that all other things being equal, this additional factor further increases the chances that the currency will weaken in the near future. We chose to work with a “one-size fits all” model specification in that we estimate one specification which is common for all the countries included in our sample and covers the observations from all the years for which we have data available. In particular we estimate two separate panel models, namely the PROBAPP and PROBDEP versions described in the previous section. For the explanatory variables included in our model we estimate a coefficient which is common for all countries and all periods, one for the PROBAPP model and one for the PROBDEP model. These sets of coefficients are then plugged in Equation 10 above to produce the probabilities of having more than 5% “appreciation” or “depreciation” in any given month.

As discussed in detail in Chapter 2 of the thesis, we used two types of explanatory variables, those described as “global” explanatory variables and the “country specific” variables. For the “global” explanatory variables we use the same time series for each of the countries in our sample and estimate a single coefficient common for all countries across time. We thus expect “global” variables to affect all emerging market countries in a uniform way. For the “country specific” variables we again estimate one common coefficient for all countries and across time, but avail ourselves of time series data applicable to each country. We therefore assume that these variables are expected to affect different countries in a similar manner but the country

specific circumstances will determine the final outcome.

We acknowledge the limitations that a panel model imposes, given that currencies move for any number of reasons, in any possible direction, in any given country or period. We also share the concern voiced by many researchers in the currency crises literature that a number of non-linearities may not be captured when the “one-size fits all” specification is adopted. We felt however that such characteristics and single currency valuations are best captured by fair value and enhanced purchasing power parity (PPP) models. However, this thesis aims to find a set of variables that serve as a minimum common denominator in describing currency risks for a whole group of countries over their recent history. A set that will effectively provide leading indicators of short term currency risks going forward. We find that a panel model serves well in addressing this objective.

In this section we outline the main steps in the thorough filtering process we underwent in order to make an educated judgement with regards to which is the most appropriate model specification for us to select. Throughout this process we tried out the list of potential explanatory variables in a variety of formats. These formats include level form at any given month, differences from month to month (Δmom) or year to year (Δyoy), or growth rates on a month on month ($\text{mom}\%$), or year on year basis ($\text{yoy}\%$). We also tried to capture momentum by looking at the change in the growth rate from one period to the next ($\Delta\text{mom}\%$ or $\Delta\text{yoy}\%$). At times we assessed the effect of extreme levels using dummy variables which would only turn non-zero when the variable in question would exceed a predefined threshold. We tried out but eventually opted not to include sample specific definitions of thresholds, like a

number of standard deviations away from the sample mean. We also considered at times certain fixed criteria such as a time series exceeding at any point in time a value we had independently selected. Importantly we also tried out versions for our explanatory variables in which markets tend to look at different data even if the particular format does not come across as a very obvious candidate. This alone differentiates our work from an uneducated data mining exercise. Take the OECD leading indicator for example. This measure of global growth momentum may be considered in a number of formats. However many market analysts tend to focus on the three months over three months annualised percentage change of the series and this is the way we tested this variable in our modelling exercise here.

Below we list a number of aspects that we considered in our specification selection process. We present a selection of results from several versions which we decided against and present in greater detail the rationale for keeping the final model specification. The first stage of the analysis outlines the criteria applied in gauging the statistical power of the specifications. Having selected the specifications that perform consistently well statistically and also make sense to us as end users we proceed in the following Chapter to apply the models in real time and judge their ability to perform well as trade generation mechanisms.

3.3 Selection of Final Specifications based on Statistical Performance

As discussed in Chapter 1 of the thesis, the dependent variable of our modelling exercise captures the cases when the end of month spot outperforms or underperforms by more than 5%, the 1month forward that was available a month earlier. This we call “excess returns” higher than 5%. As discussed, we estimate two separate models. What we call the “PROBAPP” model captures the probabilities that the local currency is likely to “appreciate” by more than 5% on a one month forward return basis. Our definition of “appreciation” as described in Equation 11 below describes the occasions when the local currency ends up being, based on the end of month realised spot exchange rate versus the USD, more than 5% stronger than what the one month forward versus the USD had implied a month earlier. In the PROBAPP model our dependent variable is a dummy variable that takes the value of 1 when the above condition is satisfied and the value of zero at all other instances.

Equation 11 Definition of Returns in PROBAPP model

$$R_{t,T} = \left(\frac{S_T - F_{t,T}}{F_{t,T}} \right) \langle -5\% \rangle$$

What we call the “PROBDEP” model captures the probabilities that the local currency is likely to “depreciate” by more than 5% on a one month forward return basis. Our definition of “depreciation” as described in Equation 12 below describes the occasions when the local currency ends up being,

based on the end of month realised spot exchange rate versus the USD, more than 5% weaker than what the one month forward versus the USD had implied a month earlier. In the PROBDEP model the dependent variable is a dummy variable that takes the value of 1 when the above condition is satisfied and the value of zero in all other instances.

Equation 12 Definition of Returns in PROBDEP model

$$R_{t,T} = \left(\frac{S_T - F_{t,T}}{F_{t,T}} \right) > 5\%$$

Having selected the definition of our dependent variables we turn to the laborious task of selecting the explanatory variables that best help model and forecast one month forward exchange rate return. In doing so we begin by estimating various model specifications on the period from as early as January 1994 to June 2002 which is the sample for which we had data on all the candidate variables. In reviewing here our findings from this first phase we will present a number of representative specifications that we tested, the signs of the estimated coefficients and the probabilities that these coefficients are statistically significant. The criteria applied in narrowing down the explanatory variables to a small set of acceptable candidates were also presented in detail in Chapter 2. We reject variables that have either poor or inconsistent statistical performance or those that are not available at the frequency and time frame we need them. We also reject variables that are statistically significant but their estimated signs contradict our understanding of how these variables should work in practice. In Table 5 and Table 6 below we present in a compressed format the statistical results from a selection of variations we

tried out for our PROBDEP and PROBAPP models which we feel tell the story of how we narrowed down the number of variables considered.

All variables are data available on a monthly basis and no interpolation or standardization has been performed. All the variables are included in the estimation at two months lag from the referenced dependent variable, unless otherwise indicated in the table details above. In all the tables we shall present in this section we use the following notation to allow us to present a number of pieces of information in a compact yet comprehensible manner: If we do not include a specific variable in a certain specification we make the relevant cells grey. For the variables we include in each model we show the resulting estimated sign and probability. In terms of the estimated sign, we use a light blue colour to denote that this is consistent with what is dictated by intuition and economic theory. If the sign contradicts our understanding of how the variable is expected to work we show it in a dark blue font. This typically points to formats or variables that were eventually excluded from the specification. We then show for each of the variables considered the resulting probability of this variable been statistically significant. Again we use a light blue font for the cases where probabilities are lower than 10%, thus suggesting that the variable is fairly statistically significant and a good candidate to possibly consider. We use a dark blue font to denote that a variable is statistically insignificant and thus not worth including in our selected specification in the particular format.

A variable may be statistically significant or insignificant irrespective of whether its estimated sign is intuitive or not. And vice versa, we may have a correct sign which is highly insignificant or a wrong sign which is highly

significant. In our selection process we kept only the variables that come up with the expected sign and were also found to be statistically significant. The global variables in particular are expected to satisfy both these conditions equally in the PROBAPP and PROBDEP models. We also expect the variables to have consistently good performance irrespective of the specification and to continue to perform as well when we later prolong or alter the estimation sample period. What we describe as “PART I” of our presentation of results includes the specifications that were run on the initially available sample that runs from January 1994 to June 2002.

3.3.1 Definition of In and Out of Sample Testing

The data used in this thesis start at different points in time for the various countries included in our sample, with some going as far back as January 1994. In terms of the ending points of the sample, the data can be divided in two types. The first group includes the data available to us when we first set out to model currency risks. This includes data up to June 2002 and this is the sample used to filter the initial number of alternative specifications and keep only those that satisfied our statistical criteria. By the time we finished this first phase of the selection process we could avail ourselves of more data and this made our sample longer, ending on March 2003. We thus re-estimated our selected specifications in this longer sample which provided a second level of proof that our specifications worked. We also used this longer sample to apply the updated estimated models which provided the in-sample testing of our selected models. These specifications we present here with the actual estimated coefficients and the relevant probability of statistical significance.

Having tested the model performance in-sample we then re-estimated the same specification on a shorter sample that ended in January 2002. It is these specifications that we then fit to the data from February 2002 to the end of our longer sample in March 2003 and test the model's performance out-of-sample. The reason why we applied our out-of sample tests on a sample starting on January was that we wanted the starting point to be an objective date that would not create any concerns to readers of our research. We felt that the beginning of a calendar year would provide such an objective starting point. We ended the-out-of sample testing period on March 2003 because we wanted to benefit from the longest available data sample, which at the time included March 2003. Both the in-sample and out-of-sample tests involve the rigorous analysis of the model's results and their translation to trade recommendations.

3.3.2 Part I: Excess returns greater than 5%, in sample testing

In Table 5 and Table 6 below we present the models that include the dependent variable defined as returns that are higher than 5% in each given month, either on the depreciation or the appreciation side. As discussed in detail in Chapter 2 of the thesis we have included in the various specifications a selection of global and country specific variables. The global variables that we consider in Table 5 and Table 6 below are the month on month difference of the ISM index and in some cases the year on year change of the ISM, the annualized 3month on 3month percentage change in the OECD Leading Indicator and in some cases the momentum of this growth rate, the momentum of and the month on month percentage change of the 12 months

trailing measure of Moody's speculative grade world default rate. One key global variable we include is CSFB's measure of Risk Appetite which we typically consider as a dummy variable that captures the times that the index indicates Euphoria and in one specification we include this variable in the form of index level.

The first country specific variable that we consider in Table 5 and Table 6 is the country specific Real Effective Exchange Rate as deviation from its HP trend. The HP trend has been calculated using only data of the estimation sample each time. We also consider the CPI monthly percentage change as a measure of price stability, the yearly percentage change of Industrial Production as a proxy of output growth, the MSCI index on a yearly percentage change as a measure of domestic financial markets, the momentum of the monthly percentage change of the credit to the private sector as an indication of domestic credit markets, the ratio of FX reserves to Money Supply and the 12months trailing measure of the country's trade balance to gauge external market dynamics.

Table 5 PART I: Variations of PROBDEP model with 5% returns threshold

PART I PROBDEP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROB ABILI TY	SIGN	PROB ABILI TY	SIGN	PROB ABILI TY	SIGN	PROB ABILI TY	SIGN	PROB ABILI TY
ISM INDEX mom change	-	0.64	-	0.68	-	0.67	-	0.65	-	0.68					-	0.64
RISK APETITE euphoria dummy	+	0.03	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+ *	0.00	+	0.03
OECD LI 3m/3m ann% momentum	-	0.87	+	0.96											-	0.87
MOODY's DEFAULT RATE mom%	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00
REER deviation from HP trend	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00	+	0.00
CPI mom%	+	0.09	+	0.44	+	0.43	+	0.43							+ **	0.00
IP yoy%	-	0.22	+	0.83	+	0.83									- **	0.06
MSCI yoy%			-	0.00	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00		
CREDIT TO THE PRIVATE SECTOR mom% momentum	+	0.34	+	0.35	+	0.35	+	0.35							+ **	0.00
FX RESERVES ratio to MONEY SUPPLY	-	0.43	-	0.43	-	0.43	-	0.43							- **	0.52
TRADE BALANCE 12m trailing moving avg	-	0.49	-	0.47	-	0.47	-	0.47							- **	0.46

* indicates that the Risk Appetite is included in the specification in index level form

** indicates that the explanatory variable is included in the specification in lag1 instead of the default assumption of lag 2

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign

The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant

Estimations are run on sample from Jan 1994 to June 2002

Table 6 PART I: Variations of PROBAPP model with 5% returns threshold

PART I PROBAPP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY
ISM INDEX mom change	-	0.49					+ **	0.99	- **	0.29		
RISK APETITE euphoria dummy	-	0.13	-	0.07	-	0.05	-	0.16	-	0.08	-	0.07
OECD LI 3m/3m ann% momentum	+	0.52	+ *	0.41	+ *	0.54	+	0.77	+ *	0.18		
MOODY's DEFAULT RATE mom%	-	0.00	-	0.00	-	0.00					-	0.00
REER deviation from HP trend	-	0.00	-	0.00	-	0.00					-	0.00
CPI mom%	+	0.02	+	0.02								
IP yoy%	-	0.01	-	0.01	+	0.25						
MSCI yoy%												
CREDIT TO THE PRIVATE SECTOR mom% momentum	+	0.82	+	0.77	-	0.20						
FX RESERVES ratio to MONEY SUPPLY	-	0.42	-	0.39	+	0.20						
TRADE BALANCE 12m trailing moving avg	-	0.52	-	0.56								

* indicates that the OECD LI is included in the specification as a 3m/3m ann%

** indicates that the ISM index is included in the specification as yoy change

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign

The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant

Estimations are run on sample from Jan 1994 to June 2002

Let us first turn to the global variables considered and the way we selected the ones to keep in our final specifications. As discussed in Chapter 2 we considered including oil prices as a candidate explanatory variable but decided against it as there was no strong evidence that this variable should exhibit a specific sign in either specification. From the variables we did test in our estimations our statistical findings suggest that the ISM index and the OECD leading indicator come out consistently insignificant as explanatory variables. In our analysis we tried out alternative formats for these two variables other than what is included in Table 5 and Table 6 although these are the most intuitive formats. Nevertheless the results again confirmed that these global indicators are not fit candidates for modelling high frequency currency moves in emerging markets. We also tried including in our estimations only one of the two variables in case the spurious statistics were the result of over-lapping information included in each one of them. The variable that we left in the specification in each case was still insignificant.

A global variable that suggested itself as a possible candidate for inclusion in our models was CSFB's Risk Appetite Index. It proved to be a significant explanatory variable for the PROBDEP model both when we included the measure in index level form and as a Euphoria dummy. It is worth noting that the definition of Euphoria we adopted requires the index to be higher than its sample average value by more than 1 standard deviation. As discussed in Chapter 2 the definition that CSFB tends to adopt in practice is somewhat different, defining euphoria as the cases when risk appetite takes a value higher than +5. As this definition is not statistically supported and rather arbitrary we opted to create a definition that is more systematic. The

PROBDEP model results suggest that when risk appetite rises to extreme levels and the euphoria dummy becomes one, the probabilities of near term local currency weakness are increasing. When we include the risk appetite index in level form our findings suggest that the higher the risk appetite the higher the chances that a downwards correction in emerging market currencies is imminent. However the Risk Appetite variable somewhat loses its significance in the PROBAPP model. Here we tried to include the risk appetite index in dummy form to capture the times when the index enters the Panic zone. Like with the Euphoria dummy the definition of Panic we used in our estimations captures the points when the index level in any given month is lower than its sample average value by more than 1 standard deviation. Again as discussed in Chapter 2 CSFB defines panic as the cases when risk appetite takes a value lower than minus three. Again we feel that the use of an arbitrary, let alone asymmetric, definition of extreme zones is not appropriate for a modelling exercise like ours. We would expect the Euphoria dummy to work in the PROBDEP model and the Panic dummy in the PROBAPP model as indicator that the local currency rally or sell-off respectively has peaked or troughed and is likely to be reversed soon. However we found that only the Euphoria dummy performed as expected, and in both models. This together with the fact that risk appetite reached euphoria only a handful of months during our long sample and the lack of access to the risk appetite index data outside of CSFB led us to exclude the variable from the final specification.

Moody's world default rate is the only global variable that comes up with the expected sign in both the PROBDEP and PROBAPP models. It is also

statistically significant at near zero probability level and its performance is consistent irrespective of what other explanatory variables are included in the estimation. The results suggest that indeed a rise in the default rate of the global speculative grade corporate universe is a reliable early indicator of forthcoming weakness in riskier assets like emerging market currencies. Accordingly, an improvement in global default rates of high yielding corporates is a good indication that risky assets will perform well in the near future. These findings amply confirm our decision to include Moody's default rate as the only global variable in both the PROBAPP and PROBDEP model specifications that we finally selected.

Moving on to the selection process of the country specific variables, it is apparent from Table 5 and Table 6 that macroeconomic fundamentals are not statistically significant explanatory variables when included at 2 months lag in the model estimation. Some macro series like our measure of Industrial Production when included both in the PROBDEP and PROBAPP produced erratic results in terms of the sign of the estimated coefficient. Others, like the measure of Credit to the Private Sector or the ratio of FX reserves to Money Supply and the Trade Balance figures exhibit the sign expected based on macroeconomic theory in the PROBDEP model but still come out as insignificant. In the PROBAPP version these variables remain insignificant but also exhibit erratic signs depending on the selected specification. Interestingly when we include these variables in the PROBDEP model at zero lags, two out of four, namely IP and Credit to the Private Sector become significant and also hold the correct sign. However even if these data are statistically significant coincident indicators of currency pressures we cannot, in practice,

avail ourselves of these data in a timely fashion to use in our model application. The other two variables, namely the Ratio of FX Reserves to Money Supply and the Trade Balance data continue to show the correct sign but remain insignificant even when tested at zero lag. Inflation is another macro variable we considered which again held the correct sign when included in the PROBDEP model although statistically insignificant depending on which specification we estimated. However inflation did not work as expected when included in the PROBAPP model. This finding might be supported by practical experience which suggests that markets are likely to react more aggressively at periods of hyperinflation that lead currency weakness than periods of slower inflation growth which may lead to a rise in risky assets valuations. However the definition of hyperinflation and its causes differ from time to time and from country to country, making it difficult for us to conclude on a robust relationship between inflation and near future currency moves.

In summary the above findings support our understanding that macroeconomic fundamentals may well be linked to exchange rate dynamics but the former need not be leading indicators of the latter in any systematic quantifiable manner. This is even more so in our analysis here, as our definition of exchange rate dynamics does not involve spot exchange rates but returns on a high frequency forward rate basis. The slow moving nature of macro fundamentals together with their delayed availability and the fact that they are often revised for quite some time after their initial release led us to exclude these variables from our high frequency trade signal generating model. From the country specific variables that we include in the

specifications above only the Real Effective Exchange Rate of each country and its deviations from the respective Hodrick Prescott trend comes out as a consistently very significant early indicator of both currency strength and weakness.

3.3.3 Part I: Excess returns greater than 2.5%, in sample testing: to June 2002

As discussed earlier in this section we have decided that we wish to model the 1month forward excess returns that are higher than 5% in any given month. One of the alternatives we tried out was the same definition of returns on a forward rate basis but capturing the cases when these exceed 2.5% in any given month. This threshold has been suggested by the literature but we do not feel it provides the necessary buffer for unquantifiable transaction costs or more importantly for error absorbance. The latter factor inevitably becomes very relevant when you try to model moves that are more frequent in nature and may be explained by a host of different ways. Our results as shown in Table 7 and Table 8 below suggest that lowering the bar for the currency moves we model does not improve the results in the specifications we chose to dismiss already.

Macro fundamentals exhibit similar patterns as in the models that capture returns higher than 5%. They either exhibit the correct sign but are found to be highly insignificant or, they have statistically significant coefficients that bear the counter-intuitive sign, or as both insignificant and with the erroneous sign. These findings are also consistent in both the PROBAPP and the PROBDEP models that capture returns higher than 2.5%. From the global variables we tested, the ISM index again has the correct sign but remains

insignificant. The only variable that improved its statistical performance when the threshold for returns falls to 2.5% is the OECD Leading Indicator which now bears the correct sign and is statistically significant in both the PROBAPP and the PROBDOWN model. This exception does not suffice for us to change our assessment. Especially as the variables we had already selected still meet all the criteria we have set.

Table 7 Variations of PROBDEP model with 2.5% returns threshold

PART I PROBDEP 2.5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY
ISM INDEX mom change	-	0.32	-	0.39	-	0.05
RISK APETITE euphoria dummy	+	0.01	+	0.00	+	0.00
OECD LI 3m/3m ann% momentum	-	0.06	-	0.06		
MOODY's DEFAULT RATE mom%	+	0.00	+	0.00	+	0.00
OIL PRICE 3m/3m%						
REER deviation from HP trend	+	0.01	+	0.00	+	0.00
CPI mom%	-	0.81	-	0.51		
IP yoy%	-	0.20	-	0.99		
MSCI yoy%			-	0.00	-	0.00
CREDIT TO THE PRIVATE SECTOR mom% momentum	+	0.45	+	0.44	+	0.42
FX RESERVES ratio to MONEY SUPPLY	-	0.36	-	0.36	-	0.36
TRADE BALANCE 12m trailing moving avg	-	0.16	-	0.15	-	0.17

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign
The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant
Estimations are run on sample from Jan 1994 to June 2002

Table 8 Variations of PROBAPP model with 2.5% returns threshold

PART I PROBAPP 2.5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY
ISM INDEX mom change	+	0.47	+	0.50
RISK APETITE euphoria dummy	-	0.19	+	0.30
OECD LI 3m/3m ann% momentum	+	0.08	+	0.02
MOODY's DEFAULT RATE mom%	-	0.00	-	0.00
OIL PRICE 3m/3m%				
REER deviation from HP trend	-	0.00	-	0.00
CPI mom%	+	0.00		
IP yoy%	-	0.01		
MSCI yoy%				
CREDIT TO THE PRIVATE SECTOR mom% momentum	-	0.96	-	0.01
FX RESERVES ratio to MONEY SUPPLY	+	0.29	+	0.34
TRADE BALANCE 12m trailing moving avg	-	0.08		

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign
The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant
Estimations are run on sample from Jan 1994 to June 2002

3.3.4 Part II and III: Excess returns greater than 5%, in sample testing: to March 2003

Based on the above analysis and findings we decided that we will indeed proceed to model one-month forward exchange rate returns that exceed 5%. As far as the explanatory variables are concerned we concluded that from all candidates considered above the ones we will include in our specifications are the Real Effective Exchange Rates expressed as deviations from the respective Hodrick-Prescott trends and the monthly percentage change in the trailing 12-month global corporate speculative grade Default Rate as published by Moody's.

By the time we finished the work that produced the results shown in

Table 7 and Table 8 above we could avail ourselves of a somewhat larger sample, starting again from as early as January 1994 and ending in March 2003. We thus proceeded with what we call here Part II of our specification selection process and re-estimated our selected specifications on this longer sample. The results are summarized in Table 9 and

Table 10 below. Some of the models summarized in Table 9 and Table 10 below include the Risk Appetite dummies we found to be a close candidate in previous model tests. The results again support our choice to exclude this factor as the risk appetite dummies we include in our PROBAPP model estimations exhibit most of the times a wrong sign or are statistically insignificant. The euphoria dummy works well in the PROBDEP model version. Nevertheless as described above we are wary of the lack of consistency in the statistical behaviour of this variable. We thus re-affirmed our conclusion that we will exclude the Risk Appetite index from our final model specification.

One variable we only considered towards the end of our initial filtering stage was the Rating Actions by S&P on hard currency sovereign debt. We therefore chose to present our findings with regards to this variable based on this second stage of the selection process. This indeed proved to be one variable we used in our final PROBDEP specification and also is the only variable that is not symmetrical in both models we estimate. Below we present the reasons why we opted to keep this variable in one of our specifications. In Table 9 we present our testing of the rating actions as an indicator of forthcoming currency appreciation. As discussed in more detail in Chapter 2 of the thesis, the market effect of a positive rating action on the country's

assets classes is likely to be imminent or may at times precede the rating action itself. Our understanding is that this is exactly the reason why rating upgrades did not work as an early indicator of higher currency appreciation pressures when included in the PROBAPP model. Often rating agencies wait in the sidelines before praising a sovereign with an upgrade while markets tend to discount good news faster than agencies. Often a rating upgrade may even lead to a weakening of the currency as markets take profits from their previous positioning. On the other hand, as per the results in Table 9, rating downgrades come up as marginally significant but always with the wrong sign when included in the PROBAPP model.

Besides the arguments presented above, which still apply, it is worth adding one more factor in our interpretation of why downgrades do not work well in the PROBAPP model. In our modelling exercise we do not capture all possible movements of currencies, but rather focus on a sample of extreme events where significant excess returns are to be made. Hence it is only the clearest and strongest links between these returns and a handful of dependent variables that will show up in our statistical tests results. Moreover as our model results come in the form of probabilities and not hard indications of specific currency moves there is clearly more room for ambiguity. In the case of rating actions these concerns apply in the following manner. The most direct link between rating actions and currency moves is the link from upgrades to appreciation and downgrades to depreciation. Saying that an upgrade will reduce the probabilities of a depreciation or that a downgrade makes an appreciation less likely is too convoluted and need not be supported by the data. Indeed Table 9 suggests that downgrades are a

significant variable but bear wrong sign. We thus exclude them from our analysis.

In the PROBDEP model we only tested the relevance of downgrades in signalling forthcoming depreciations. As shown in Table 10, downgrades are a highly significant variable which also exhibits the sign supported by intuition in that they increase the probability of depreciation. The model results suggest that when a specific country experiences a negative rating action even by a rating outlook by S&P, on the country's hard currency long term debt obligations, that country's currency is likely to feel significant downwards pressures in its currency in the months to come. Negative actions contain more information for market participants than positive ones. Investors will have typically already acted on their own positive views for a country but would still be wary of additional penalties that could trigger or justify further sell offs. This becomes even more relevant as we capture actions even by a rating outlook which makes rating events greater in number and frequency. Moreover, a negative rating action may have an immediate market effect but may also be expected to have a more lasting effect that remains relevant in the months following the rating action.

Table 9 PART II: Variations of PROBAPP model with 5% returns threshold

PART II PROBAPP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY
RISK APETITE euphoria dummy	-	0.26	-	0.19						
RISK APETITE panic dummy							-	0.04	-	0.06
MOODY's DEFAULT RATE mom%	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00
REER deviation from HP trend	-	0.00	-	0.00	-	0.00	-	0.00	-	0.00
S&P RATING ACTION upgrades									-	0.44
S&P RATING ACTION downgrades			+	0.12	+	0.10	+	0.07		

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign
 The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant
 Estimations are run on sample from Jan 1994 to March 2003

Table 10 PART II: Variations of PROBDEP model with 5% returns threshold

PART II PROBDEP 5% model variations	SIGN	PROBA BILITY
RISK APETITE euphoria dummy	+	0.04
RISK APETITE panic dummy		
MOODY's DEFAULT RATE mom%	+	0.00
REER deviation from HP trend	+	0.02
S&P RATING ACTION upgrades		
S&P RATING ACTION downgrades	+	0.00

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign
 The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant
 Estimations are run on sample from Jan 1994 to March 2003

We now move to what we describe as Part III of our model selection process. Having selected the specifications we wish to work with, we tested one last variable that was often suggested by investors at the time. The corporate credit market spreads which many felt would capture information we could use. Credit spreads are the price markets put on the debt issued by

corporates to quantify the credit risk element that each corporate represents compared to the theoretically risk-free debt issued by a sovereign. Indices exist that capture the average credit spread of a basket of corporates which are deemed to be representative of a specific category of risk. Risk profiles are ranked by the rating assigned to each corporate. A number of investors we consulted at the time felt that credit spreads would replace Moody's world default rate as a global risk indicator. We set out to test this hypothesis by including different credit spread metrics in the place of Moody's world default rate in the PROBDEP model.

As our Moody's variable refers to the defaults of the speculative grade corporate universe we also considered credit spreads from the same ratings universe. In particular we tested the High Yield Credit Spread index in level form, as monthly change in index levels and as a monthly percentage change of the index levels. We also tested the more specific Indices for BB, B and C rated corporates, again in levels, monthly changes and monthly percentage changes form. All variations were included in the model at two months lag. As suggested by the results in Table 11 below all spread variables exhibited the wrong sign, suggesting that an increase in credit spread, which occurs at times of weakening corporate fundamentals or increase of general risk aversion, reduce the probabilities of forthcoming currency sell-offs. In terms of statistical significance of results, only when the variables were included in level form were their coefficients found to be significant. In all other cases both the signs were wrong and the coefficients highly insignificant.

Table 11 PART III: Variations of PROBDEP model with 5% returns threshold

PART III: PROBDEP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	PART III: PROBDEP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY
CREDIT SPREAD INDEX HIGHYIELD level	-	0.00					CREDIT SPREAD INDEX BB level	-	0.00				
CREDIT SPREAD INDEX HIGHYIELD mom change			-	0.27			CREDIT SPREAD INDEX BB mom change			-	0.72		
CREDIT SPREAD INDEX HIGHYIELD mom %change					-	0.50	CREDIT SPREAD INDEX BB mom %change					-	0.92
FEER deviation from HP trend	+	0.00	+	0.00	+	0.00	FEER deviation from HP trend	+	0.00	+	0.00	+	0.00
S&P RATING ACTION downgrades	+	0.00	+	0.00	+	0.00	S&P RATING ACTION downgrades	+	0.00	+	0.00	+	0.00

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign

The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant

Estimations are run on sample from Jan 1994 to March 2003

Table 12 PART III: Variations of PROBDEP model with 5% returns threshold

PART III: PROBDEP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY	PART III: PROBDEP 5% model variations	SIGN	PROBA BILITY	SIGN	PROBA BILITY	SIGN	PROBA BILITY
CREDIT SPREAD INDEX B level	-	0.00					CREDIT SPREAD INDEX C level	-	0.00				
CREDIT SPREAD INDEX B mom change			-	0.25			CREDIT SPREAD INDEX C mom change			-	0.17		
CREDIT SPREAD INDEX B mom %change					-	0.41	CREDIT SPREAD INDEX C mom %change					-	0.29
FEER deviation from HP trend	+	0.00	+	0.00	+	0.00	FEER deviation from HP trend	+	0.00	+	0.00	+	0.00
S&P RATING ACTION downgrades	+	0.00	+	0.00	+	0.00	S&P RATING ACTION downgrades	+	0.00	+	0.00	+	0.00

The (dark) light blue sign indicates that the estimated coefficient displays the (reverse from the) expected sign

The (dark) light blue probability measure indicates that the estimated coefficient is statistically (in)significant

Estimations are run on sample from Jan 1994 to March 2003

The lack of compelling evidence in support of this variable does not necessarily contradict the investors' perception of the information content of credit spreads. As discussed in Chapter 2 in more detail market prices of one asset class cannot be expected to work as leading and consistent indicators of another asset class. The same applied when we tried including the MSCI equity indices in our models. Equity, credit and currency markets are likely to

contain the same information at the same time, rather than with a lead-lag relationship to each other. In the case of credit prices in particular it is understandable that the move of an index as a whole need not correspond to the same type of market reaction for each and every emerging market from a diverse sample or across time. In summary we felt this evidence supports our decision to exclude the Credit Spread variables from our model specifications and continue with the inclusion of our Moody's world default rate as a proxy of global risk appetite.

3.3.5 Selection of Final Specifications

At the end of this selection process we conclude that we wish to keep the PROBAPP and PRODEP model specifications as shown in Table 13 and Table 14 below. The final PROBDEP specification as presented in Table 13 below includes the monthly percentage change of the 12month trailing Moody's Global Corporate Speculative Grade Default Rate, the deviations of every country's Real Effective Exchange Rate from its respective Hodrick Prescott trend expressed as the logarithmic ratio of the REER over the HP trend and a dummy variable that takes a value of one every time S&P downgrades the long term hard currency sovereign credit rating or rating outlook of each country. The final PROBAPP specification as presented in Table 14 below includes the two of the three variables included in the PROBDEP version, namely the Moody's world default rate measure and the REER over and under valuations from their HP trends. All variables exhibit the signs that are consistent with our intuition, economic theory and market stylized facts. All estimated coefficients are also extremely statistical

significant. What's more these supportive statistical characteristics have been consistent in all specifications we have tested so far irrespective of the sample used or the other variables included in or excluded from our specifications. We also note that the overall McFadden R-squared of the selected specifications are at the 10% level which outperforms similar models in the literature. These specifications have been estimated in the sample that starts from as early as January 1994 and ends in March 2003. It is on the basis of this specification that we present all the findings in Chapter 4 where we apply the models and test their practical usability and performance.

Table 13 Selected specification for PROBDEP model with 5% returns threshold. Version applied to perform in sample testing from Jan '94-Mar '03

PROBDEP (5% depr) MODEL ESTIMATION on Jan '94 - Mar '03 Specification applied for in sample fitting (Jan'94-Mar'03)				
Explanatory Variable	Estimated Coefficient	Std. Error	z-Statistic	Probability*
Constant	-3.4151	0.16	-21.39	0.0000
MOODY's DEFAULT RATE mom%	0.0686	0.02	4.10	0.0000
REER deviation from HP trend	0.0747	0.02	4.31	0.0000
S&P DOWNGRADES dummy	1.8842	0.35	5.40	0.0000
Mean dependent var	0.05	S.D. dependent var	0.22	
S.E. of regression	0.21	Akaike info criterion	0.36	
Sum squared resid	67.56	Schwarz criterion	0.38	
Log likelihood	-272.65	Hannan-Quinn criter.	0.37	
Restr. log likelihood	-301.95	Avg. log likelihood	-0.18	
LR statistic (3 df)	58.59	McFadden R-squared	0.10	
Probability(LR stat)	0.00			

* Probability that the estimated coefficient is insignificant

Model estimated on dependent variable sample from Jan '94 to Mar '03

All explanatory variables are included at 2 months lag from the dependent variable

REER deviation from HP trend is calculated as the logarithmic ratio of REER over the HP trend

HP trend based on input data from Nov '93 to Jan '03 to be compatible with the estimation sample

This specification was fitted to the output data from Jan '94 to Mar '03 to produce the in-sample results for the trading rule

Table 14 Selected specification for PROBDEP model with 5% returns threshold. Version applied to perform in sample testing from Jan '94-Mar '03

PROBAPP (5% appr) MODEL ESTIMATION on Jan '94 - Mar '03 Specification applied for in sample fitting (Jan'94-Mar'03)				
Explanatory Variable	Estimated Coefficient	Std. Error	z-Statistic	Probability*
Constant	-2.9455	0.12	-23.80	0.0000
MOODY's DEFAULT RATE mom%	-0.0601	0.01	-4.21	0.0000
REER deviation from HP trend	-0.0933	0.01	-8.46	0.0000
Mean dependent var	0.06	S.D. dependent var	0.25	
S.E. of regression	0.23	Akaike info criterion	0.41	
Sum squared resid	78.12	Schwarz criterion	0.42	
Log likelihood	-312.11	Hannan-Quinn criter.	0.42	
Restr. log likelihood	-366.38	Avg. log likelihood	-0.20	
LR statistic (2 df)	108.54	McFadden R-squared	0.15	
Probability(LR stat)	0.00			

* Probability that the estimated coefficient is insignificant

Model estimated on dependent variable sample from Jan '94 to Mar '03

All explanatory variables are included at 2 months lag from the dependent variable

REER deviation from HP trend is calculated as the logarithmic ratio of REER over the HP trend

HP trend based on input data from Nov '93 to Jan '03 to be compatible with the estimation sample

This specification was fitted to the output data from Jan '94 to Mar '03 to produce the in-sample results for the trading rule

We proceed to re-estimate these final specifications at a somewhat shorter sample that ends in January 2002. The resulting models are then fitted to the remaining sample available from February 2002 to March 2003. This provides the basis for what we call our "OUT-OF-SAMPLE" results of the models performance. The model versions estimated in the shorter period as presented in detail in Table 15 and Table 16 below. This again forms part of our analysis in Chapter 4.

Table 15 Selected specification for PROBDEP model with 5% returns threshold. Version applied to perform out-of-sample testing from Feb '02-Mar '03

PROBDEP (5% depr) MODEL ESTIMATION on Jan '94 - Jan '02 Specification applied in out-of-sample forecasting (Feb '02 - Mar '03)				
Explanatory Variable	Estimated Coefficient	Std. Error	z-Statistic	Probability*
Constant	-3.4793	0.19	-18.52	0.0000
MOODY's DEFAULT RATE mom%	0.0716	0.02	3.93	0.0001
REER deviation from HP trend	0.0739	0.02	3.24	0.0012
S&P DOWNGRADES dummy	2.0939	0.36	5.75	0.0000
Descriptive Statistics				
Mean dependent var	0.05	S.D. dependent var	0.22	
S.E. of regression	0.21	Akaike info criterion	0.37	
Sum squared resid	55.04	Schwarz criterion	0.39	
Log likelihood	-224.32	Hannan-Quinn criter.	0.38	
Restr. log likelihood	-248.57	Avg. log likelihood	-0.18	
LR statistic (3 df)	48.50	McFadden R-squared	0.10	
Probability(LR stat)	0.00			

* Probability that the estimated coefficient is insignificant
 Model estimated on dependednt variable sample from Jan '94 to Jan '02
 This specifaicon was subsequently applied to produce out of sample forecasting from Feb '02 to Mar '03
 All explanatory variables are included at 2months lag from the dependent variable
 REER deviation from HP trend is calculated as the logarithmic ratio of REER over the HP trend
 HP trend based on input data from Nov '93 to Nov '01 to be compatible with the estimation sample

Table 16 Selected specification for PROBAPP model with 5% returns threshold. Version applied to perform out-of-sample testing from Feb '02-Mar '03

PROBAPP (5% appr) MODEL ESTIMATION on Jan '94 - Jan '02 Specification applied in out-of-sample forecasting (Feb '02 - Mar '03)				
Explanatory Variable	Estimated Coefficient	Std. Error	z-Statistic	Probability*
Constant	-3.2188	0.16	-20.47	0.0000
MOODY's DEFAULT RATE mom%	-0.0581	0.02	-3.60	0.0003
REER deviation from HP trend	-0.1160	0.02	-7.27	0.0000
Descriptive Statistics				
Mean dependent var	0.05	S.D. dependent var	0.22	
S.E. of regression	0.20	Akaike info criterion	0.34	
Sum squared resid	50.51	Schwarz criterion	0.35	
Log likelihood	-203.39	Hannan-Quinn criter.	0.34	
Restr. log likelihood	1.00	Avg. log likelihood	-0.17	
LR statistic (2 df)	90.37	McFadden R-squared	0.18	
Probability(LR stat)	0.00			

* Probability that the estimated coefficient is insignificant
 Model estimated on dependednt variable sample from Jan '94 to Jan '02
 This specifaicon was subsequently applied to produce out of sample forecasting from Feb '02 to Mar '03
 All explanatory variables are included at 2months lag from the dependent variable
 REER deviation from HP trend is calculated as the logarithmic ratio of REER over the HP trend
 HP trend based on input data from Nov '93 to Nov '01 to be compatible with the estimation sample

In Chapter 4 that follows, we establish the ability of our two models to perform well as trading tools both in and out of sample and we proceed to apply the models in real time and forecast the period from January to December 2004 on a monthly basis. By that time Moody's had published a slightly updated version of their World Default rate series and we felt it was appropriate to incorporate this new series in our estimation. This change made only marginal difference in the resulting specification as presented in Table 13 and Table 14. The newly estimated versions are presented in Table 17 and Table 18 below.

Table 17 Final specification for PROBDEP model with 5% returns threshold. Version applied to real time testing from January 2004 to December 2004

PROBDEP (5% depr) MODEL ESTIMATION on Jan '94 - Mar '03 Specification applied in real time forecasting from May 2003 to Jan 2005				
Explanatory Variable	Estimated Coefficient	Std. Error	z-Statistic	Probability*
Constant	-3.4091	0.16	-21.43	0.0000
MOODY's DEFAULT RATE mom%	0.0668	0.02	4.05	0.0001
REER deviation from HP trend	0.0747	0.02	4.32	0.0000
S&P DOWNGRADES dummy	1.8861	0.35	5.41	0.0000
<hr/>				
Mean dependent var	0.05	S.D. dependent var	0.22	
S.E. of regression	0.21	Akaike info criterion	0.36	
Sum squared resid	67.59	Schwarz criterion	0.38	
Log likelihood	-272.88	Hannan-Quinn criter.	0.37	
Restr. log likelihood	-301.95	Avg. log likelihood	-0.18	
LR statistic (3 df)	58.14	McFadden R-squared	0.10	
Probability(LR stat)	0.00			

* Probability that the estimated coefficient is insignificant

Model estimated on dependent variable sample from Jan '94 to Mar '03

All explanatory variables are included at 2 months lag from the dependent variable

REER deviation from HP trend is calculated as the logarithmic ratio of REER over the HP trend

HP trend based on input data from Nov '93 to Jan '03 to be compatible with the estimation sample

This specification was fitted to the output data from Jan '94 to Mar '03 to produce the in-sample results for the trading rule and was also used in forecasting each month post March 2003 until December 2004.

Table 18 Final specification for PROBAPP model with 5% returns threshold. Version applied to real time testing from January 2004 to December 2004

PROBAPP (5% appr) MODEL ESTIMATION on Jan '94 - Mar '03 Specification applied in real time forecasting from May 2003 to Jan 2005				
Explanatory Variable	Estimated Coefficient	Std. Error	z-Statistic	Probability*
Constant	-2.9478	0.12	-23.79	0.0000
MOODY's DEFAULT RATE mom%	-0.0607	0.01	-4.25	0.0000
REER deviation from HP trend	-0.0933	0.01	-8.46	0.0000
<hr/>				
Mean dependent var	0.06	S.D. dependent var	0.25	
S.E. of regression	0.23	Akaike info criterion	0.41	
Sum squared resid	78.10	Schwarz criterion	0.42	
Log likelihood	-311.91	Hannan-Quinn criter.	0.42	
Restr. log likelihood	-366.38	Avg. log likelihood	-0.20	
LR statistic (2 df)	108.94	McFadden R-squared	0.15	
Probability(LR stat)	0.00			

* Probability that the estimated coefficient is insignificant

Model estimated on dependent variable sample from Jan '94 to Mar '03

All explanatory variables are included at 2 months lag from the dependent variable

REER deviation from HP trend is calculated as the logarithmic ratio of REER over the HP trend

HP trend based on input data from Nov '93 to Jan '03 to be compatible with the estimation sample

This specification was fitted to the output data from Jan '94 to Mar '03 to produce the in-sample results for the trading rule and was also used in forecasting each month post March 2003 until December 2004.

3.4 Conclusion

In Chapter 3 we presented the model methodology we adopted and the process involved in selecting the final specifications. We apply a Logit type regression on two separate models and the results are translated in the form of probabilities of specific events occurring within the following calendar month. In both cases the findings refer to the performance of the local exchange rate versus the USD. The first version is called the PROBAPP model and estimates the probabilities of the end of month spot outperforming the one month forward that prevailed at the beginning of that calendar month. The second specification is called the PROBDEP model and is used to explain and forecast the probabilities of the end of month spot underperforming the one month forward that prevailed one month earlier.

After thorough assessment of statistical findings we excluded a host of both global and country specific explanatory variables. The exclusion was done on the basis of wrong signs and statistical insignificance of the estimated coefficients. We opted to include only three variables which came out with the correct signs, were extremely statistically significant, were supported by market intuition and applicable or theoretical economics and had a performance that was consistent for all countries and irrespective of data sample. These specifications were estimated and fitted on a sample that offered the basis for our in-sample analysis. They were however also re-estimated on a shorter sample and re-applied on the remaining data to form the basis of our out-of sample analysis. Finally we updated the selected specifications with all the up to date data series that applied and used them to forecast currency dynamics in real life for a whole calendar year. In Chapter 4 below, we conclude our work on the EM Currency risks by applying the models in and out of sample as well as on real life data and testing their forecasting and profit generation power.

4 CHAPTER FOUR: Modelling and Forecasting Currency Risks in Emerging Markets: Model Application and Performance Review

4.1 Introduction

A key consideration in our modelling exercise was to decide on a specification that would work well in providing trustworthy trade recommendations on a consistent basis. As discussed earlier in the thesis the model results are transformed into probabilities of appreciation or depreciation events occurring. We need to translate these probabilities into a usable format that would constitute a recommendation to either trade or not in any given month. It is important to decide on this aspect at an early stage as we apply this criterion both when looking at the in sample goodness of fit of the models and later when we assess the models' out of sample and real life forecasting power and profit generating ability.

As discussed in Chapter 3 we estimate two separate model specifications. One, which we refer to as the PROBDEP version, models and forecasts the risks of local currencies underperforming the 1month forward exchange rate versus the US dollar. The second, to which we refer to as the PROBAPP version, aims to model and forecast the probabilities of a local currency appreciating in forward rate terms. One could argue that we would get an equivalent result if we only estimated one specification modelling both appreciation and depreciation on a one month forward basis. Our findings do not support this notion. In practice we ended up using two specifications that

are largely symmetric but with the PROBDEP version including one additional explanatory variable. Moreover we model cases where the spot significantly out or underperforms the forward by more than 5%. Therefore the two models describe opposing but not complementary events given that we have the range between 5% appreciation and 5% depreciation that is not covered by either model.

Having selected our two model specifications we need to decide on a probability level above which we will classify the model result as a recommendation for buying or selling the local currency against the US dollar on a one month forward basis. We classify as a model generated recommendation to “sell” the local currency on a one-month forward rate basis the cases when the PROBDEP model generates a probability equal to or higher than $k\%$. We classify as a model generated recommendation to “buy” an emerging market currency on a one-month forward exchange rate basis, the occasions when the PROBAPP model generates a probability equal to or higher than $g\%$. We first apply these two rules separately as we assess the ability of each model in turn to fit in-sample what it was supposed to model. Later, when we move to the application of the models and build a trading rule to evaluate the model as a trading tool we consider the option of applying each model separately or combining the signals from both specifications in suggesting a trade for either direction. In the sections that follow we shall present results from both alternatives. We finally proceed to combine both models and translate their trade recommendations into actionable portfolios whose monthly performance we scrutinize.

4.2 Assessing Model Predictive Performance In and Out of Sample

In this section we provide an overview of the models' performance in successfully signalling significant currency moves at different probability cut-off points. The rationale is the following: In any given calendar month we will either have more than 5% local currency "Depreciation" on a 1month forward basis or not. And in the same calendar month the PROBDEP model would have generated a probability that such "Depreciation" will occur. We select a certain level of $k\%$ for these probabilities and consider the instances when the model generates a probability higher than " k " as a "sell" trade recommendation. We test a number of different levels for " k ", assess in each case the success of the model in correctly classifying that month's currency moves and decide which probability cut-off point works best for our purposes. We carry out the same exercise for the PROBAPP model. In any given calendar month we will either have more than 5% local currency "Appreciation" on a 1month forward basis or not. And in the same calendar month if the PROBAPP model generates more than $g\%$ probability we consider this a "buy" recommendation from the model. Again we test a number of different levels of " g " and select which probability cut-off point works best in capturing the significant real life appreciations as defined in our analysis.

By definition, the lower the probability level we select as our event cut-off point the more successful our model will be in capturing incidents of actual currency moves by more than 5%. In fact the models would effectively be over-predicting significant moves in either direction in that they will typically generate erroneous signals for forthcoming sizeable currency moves when in

reality such moves do not materialize. We need to find a level of probability that balances the performance of the models in these two aspects. The trade-off we are describing here is captured by the Type I and Type II statistical errors described in summary in Table 19 and Table 20 below. Type I error quantifies how many times the models gave a signal for an event that did not materialize. Type I error thus, penalizes the model for over-predicting significant currency moves in any given month. Type II error penalizes the model for missing real events. It quantifies the number of times when the model did not predict an event that actually occurred. Obviously we are interested in minimizing the two errors in order to maximize the times when the model provides a signal for an event that really occurs and the times when the model correctly predicts that we will not have an event in any given month. The trade-off between these two error types and the respective success ratios is a direct function of the probability selected for classifying signals. The lower the k% and g% probabilities we select the more cases we will have where the models will be giving event signals which will not happen in reality and therefore decreasing Type I error in the expense of Type II error. Vice versa the higher the probability levels the more likely that the model will be missing actual events and thus missing out on actionable and profitable trade recommendations but it will also be more successful in avoiding the false event signals thus reducing the risk of over-investing for the wrong reasons.

Type I and II errors are traditional metrics adopted to quantify and assess a model's goodness of fit. That is the ability of the estimated specification to really capture the reality it is supposed to describe in the first place. In our analysis we also introduce the notion of what we call Type III

error, which again is described in Table 19 and Table 20. Type III error is driven by the fact that our two models describe events that are opposing but not complementary. Between the incidents where we have more than 5% appreciation or more than 5% depreciation in any given month, we have the significant gap of currency moves of 10% in magnitude. We have explained that the choice of modelling returns of more than 5% in any given month was an arguably arbitrary decision which we felt provides a safety net for capturing events that are common enough to provide a sufficiently large sample and significant enough to cover transaction costs and accommodate the risk appetite of the majority of investors. However we look to apply our model in producing actionable trade signals and thereafter gauge the success of our trading rule in generating profits. Therefore we cannot ignore the reality that for any given month when the models produce a trade signal even if the returns are not more than 5% in reality, the investor still stands to profit as long as the actual currency move that month was in the direction suggested by the models. What really constitutes a failure for our exercise are the cases when the models produced a trade signal for currencies moving in one direction and in reality the currency in question moved in the opposite direction. This is the statistic we wish to capture with the Type III error. Effectively Type III error is what remains from Type I error when we extract the cases where the model got the direction correct even if the size of the profits was not more than 5%. From our point of interest the cases where the models predict the correct direction even though they miss the size of the move, can be considered an enhancement to the overall success ratio of the models in correctly predicting currency moves.

Table 19 Type I, II and III errors in the case of the PROBDEP model

		ACTUAL		ACTUAL	
Prob cut off = k%		DEPR > 5%	DEPR < 5%	0% < DEPR < 5%	DEPR < 0% (APPR)
PROBDEP SIGNAL	DEPR > 5%	Getting Events Right = 1-b	Missing Non-Events = a = Type I error	Getting At Least Direction Right = a-c	Missing Direction Altogether = c = Type III error
	DEPR < 5%	Missing Events = b = Type II error	Getting Non-Events Right = 1-a		

Table 20 Type I, II and III errors in the case of the PROBAPP model

		ACTUAL		ACTUAL	
Prob cut off = g%		APPR > 5%	APPR < 5%	0% < APPR < 5%	APPR < 0% (DEPR)
PROBAPP SIGNAL	APPR > 5%	Getting Events Right = 1-b	Missing Non-Events = a = Type I error	Getting At Least Direction Right = a-c	Missing Direction Altogether = c = Type III error
	APPR < 5%	Missing Events = b = Type II error	Getting Non-Events Right = 1-a		

In what follows we present the results from testing our models goodness of fit both in and out of sample. In-sample testing constitutes of us fitting the model that was estimated in the sample that starts as early as January 1994 and ends in March 2003, on the same period. Out-of-sample testing involves the re-estimation of the model in the sample that starts again from as early as January 1994 but ends in December 2001 and subsequently fitting the model on fourteen months of out-of-sample data from January 2002 to March 2003.

Table 21 PROBAPP model: Type I, II and III errors: in-sample Jan 1994 – Mar 2003

PROBAPP MODEL SUCCESS RATIOS INSAMPLE Jan 1994- Mar 2003										
g%Probability cut-off level for classifying trading signals	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
MODEL SUCCESS IN SIGNALING APPRECIATION >5%	78%	72%	65%	59%	55%	51%	45%	40%	37%	29%
TYPE II ERROR	22%	28%	35%	41%	45%	49%	55%	60%	63%	71%
MODEL SUCCESS IN SIGNALING LACK OF APPRECIATION >5%	8%	39%	56%	68%	75%	79%	83%	85%	87%	90%
TYPE I ERROR	92%	61%	44%	32%	25%	21%	17%	15%	13%	10%
MODEL SUCCESS IN SIGNALING APPRECIATION ALBET <5%	47%	32%	23%	15%	11%	8%	6%	5%	4%	2%
TYPE III ERROR	45%	29%	22%	17%	14%	13%	11%	10%	10%	8%

Table 22 PROBDEP model: Type I, II and III errors: in-sample Jan 1994 – Mar 2003

PROBDEP MODEL SUCCESS RATIOS INSAMPLE Jan 1994- Mar 2003										
k%Probability cut-off level for classifying trading signals	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
MODEL SUCCESS IN SIGNALING DEPRECIATION >5%	84%	64%	55%	53%	47%	41%	39%	33%	32%	25%
TYPE II ERROR	16%	36%	45%	47%	53%	59%	61%	67%	68%	75%
MODEL SUCCESS IN SIGNALING LACK OF DEPRECIATION >5%	15%	53%	67%	76%	81%	84%	86%	87%	88%	90%
TYPE I ERROR	85%	47%	33%	24%	19%	16%	14%	13%	12%	10%
MODEL SUCCESS IN SIGNALING DEPRECIATIONALBET <5%	31%	18%	12%	7%	5%	3%	2%	2%	1%	1%
TYPE III ERROR	53%	28%	21%	17%	15%	13%	12%	11%	11%	10%

Table 23 PROBAPP model: Type I,II and III errors: out-of-sample Feb2002–Mar2003

PROBAPP MODEL SUCCESS RATIOS OUT OF SAMPLE Feb 2002- Mar 2003										
g%Probability cut-off level for classifying trading signals	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
MODEL SUCCESS IN SIGNALING APPRECIATION >5%	86%	67%	53%	50%	47%	47%	44%	42%	42%	39%
TYPE II ERROR	14%	33%	47%	50%	53%	53%	56%	58%	58%	61%
MODEL SUCCESS IN SIGNALING LACK OF APPRECIATION >5%	11%	44%	57%	71%	78%	82%	87%	88%	90%	95%
TYPE I ERROR	89%	56%	43%	29%	22%	18%	13%	12%	10%	5%
MODEL SUCCESS IN SIGNALING APPRECIATION ALBET <5%	57%	36%	29%	19%	14%	11%	8%	7%	6%	3%
TYPE III ERROR	32%	19%	14%	10%	9%	7%	5%	5%	4%	3%

Table 24 PROBDEP model: Type I,II and III errors:out-of-sample Feb2002–Mar 2003

PROBDEP MODEL SUCCESS RATIOS OUT OF SAMPLE Feb 2002- Mar 2003										
k%Probability cut-off level for classifying trading signals	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
MODEL SUCCESS IN SIGNALING DEPRECIATION >5%	69%	46%	38%	38%	31%	23%	23%	8%	8%	0%
TYPE II ERROR	31%	54%	62%	62%	69%	77%	77%	92%	92%	100%
MODEL SUCCESS IN SIGNALING LACK OF DEPRECIATION >5%	29%	80%	89%	93%	96%	97%	98%	99%	99%	100%
TYPE I ERROR	71%	20%	11%	7%	4%	3%	2%	1%	1%	0%
MODEL SUCCESS IN SIGNALING DEPRECIATION ALBET <5%	22%	6%	3%	2%	1%	0%	0%	0%	0%	0%
TYPE III ERROR	49%	14%	9%	5%	3%	2%	2%	1%	1%	0%

The results in Table 21 to Table 24 above suggest that selecting a probability level above 10% for either model would have resulted in a significant loss of power in predicting significant currency moves in favour of an almost perfect ability of the models to avoid giving a trade signal in cases where we did not have a substantial currency move. Such a trade-off is not consistent with our mandate as we will end up with only a handful of trade recommendations to follow. These findings are consistent both for the PROBAPP and the PROBDEP models, and in both the in and out of sample tests. We therefore conclude that we need to select a probability lower than 10% for both models. On the other end of the spectrum as expected when selecting very low probabilities like 2% we get a very high success ratio in capturing significant currency moves above 5% but we end up with two trigger happy models that consistently over-predict big moves and will probably not benefit a real investor who needs to know both when to invest and when to stay in the sidelines. Again these results are consistent in and out of sample for both models. We therefore decide to select a probability level that will be higher than 2% for both models.

Looking at the probability levels between 2% and 10% one could easily select a number of different levels as the trade-off between the success ratios and types of errors are both acceptable and consistent across different specifications. Our aim is to select a probability cut-off point that will generate fairly balanced error types and will only sacrifice the ratio of capturing significant moves to the extent that is necessary to avoid pointless over-prediction of events that do not occur. Probability levels above 6% demonstrate a success ratio in avoiding over-prediction that starts from

around 70% and in most cases lays in the mid80% to mid90%. We are uninterested in such high success ratios if the ability of the model to predict actual big moves falls well below the 50% threshold.

Taking all this into consideration and accepting that given how many parameters are relevant, the selection of the probability cut-off point to use is not an exact science, we selected a 5% probability as the cut-off point above which each model will be considered as generating a trade recommendation for us to follow in any given month. Arguably the choice between 4% and 5% was not a clear cut selection. If anything the PROPDEP model seems to perform better with the 4% probability level. Still we felt that we gave up little success, that could also be sample specific, to gain in terms of consistency of having the same cut-off level in both models. In sample results suggest that 5% probability is a reliable cut-off point that captures 55% or 65% of depreciations or appreciations of more than 5% respectively. At the same time the models have 67% and 57% success ratio in not providing a sell or buy trade signal respectively when there is no need for one. These statistics are further enhanced by the third metric we follow according to which in about 12% and 23% of the times that the models gave a trade signal to respectively sell or buy a currency, the latter indeed depreciated or appreciated respectively, be it by less than 5%.

Arguably the in-sample results are important for the assessment of the goodness of fit of the model. However the toughest test for any model and the real criterion by which we need to decide on the models' ability to generate reliable trade recommendations are the out-of sample results. As long as the latter do not contradict or cancel the in-sample findings we believe we have a

solid foundation for trusting the model's performance in real life. Our results in Table 23 and Table 24 support this notion. Although the out of sample period is fairly short consisting of only fourteen monthly observations, the results are by and large consistent with the in-sample findings. The two models have roughly a 40% to 50% success ratio in predicting actual moves of over 5%, and this with what seems to be a very cautious prediction pattern as they also manage to avoid generating a trade signal in around 60% to 90% of the cases. The results from the PROBAPP model are more consistent with our previously outlined selection criteria as success in both metrics is above 50%. In the PROBDEP model we find that the out-of-sample performance is a bit biased to the cautious side but at the same time we see that the trade-off could only be improved significantly if we opt for a probability level of 2%. A level of 4% seems like a good compromise in the case of the PROBDEP model but again we prefer to keep this characteristic in mind when we proceed to apply the models in real life monthly samples but stick to a single common probability cut-off point of 5% probability for both models.

4.3 Assessing Model Trading Performance In and Out of Sample: Individual Trade Review

We proceed with the current section where we set out to quantify the profit making ability of the model. Describing how many times a model gets the currency moves right tells only half the story from an investor's point of view. The key consideration is how much profit would the model recommended trades generate. This is where we turn our focus to here. Again we look at the results in-sample and out of sample as defined in the previous section. We relate actual currency moves to the model signals that were

generated in any given month. We do so in two different ways. We first consider the two models separately and quantify the gain and loss generated if an investor were to go short or long a currency every time the PROBDEP or PROBAPP models respectively generated more than 5% probability of a significant depreciation or appreciation. The investor would have remained sidelined and un-invested at all times during which each model generated probabilities lower than 5% for either side.

Having assessed the ability of each model on its own to generate profitable recommendations we then proceed to combine the results from the two models together in the following manner. In order for an investor to go long a specific currency we need the PROBAPP model to give a probability of significant appreciation equal to or more than 5% and at the same time we need the PROBDEP model to generate a probability of significant depreciation lower than 5%. In this way we cancel out conflicting signals that could at times be generated if one was to look at the two models separately as we apply one additional layer in our investment selection approach. All the results we present in this section are based on the assumption that investors blindly follow the model generated trade recommendations and implemented trades are not in any way biased or filtered by views or other subjective factors. Note also that in our analysis of the models' profit generating ability we consider gains and losses higher than zero, and not necessarily higher than 5% in any given month. In Table 25 and Table 26 below we review the in-sample results from investing on the model trade recommendations when these are generated based on one of the two models or, in turn, when we have a signal that is based on the combined results from both models.

Table 25 P&L of short recommendations as generated from PROBDEP model alone and from the combination of both models. In sample Jan '94 – Mar '03:

P&L PERFORMANCE OF SHORT RECOMMENDATIONS BASED ON PROBDEP MODEL SIGNALS IN SAMPLE: JAN '94 TO MAR '03										
PROBABILITY CUT-OFF LEVEL K%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF SHORT TRADE RECOMMENDATIONS	1279	677	450	313	227	174	134	106	92	59
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS	557	338	228	155	110	85	66	51	43	31
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS (% OF TOTAL SHORT TRADE RECOMMENDATIONS)	44%	50%	51%	50%	48%	49%	49%	48%	47%	53%
AVERAGE NET P&L PER SHORT TRADE RECOMMENDATION	0.27%	0.91%	1.24%	1.67%	2.32%	2.84%	3.13%	2.79%	3.19%	4.73%
P&L PERFORMANCE OF SHORT RECOMMENDATIONS BASED ON COMBINED MODELS' SIGNALS IN SAMPLE: JAN '94 TO MAR '03										
PROBABILITY CUT-OFF LEVELS K%=G%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF SHORT TRADE RECOMMENDATIONS	143	601	422	290	213	162	129	103	92	59
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS	73	309	219	149	105	80	64	49	43	31
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS (% OF TOTAL SHORT TRADE RECOMMENDATIONS)	51%	51%	52%	51%	49%	49%	50%	48%	47%	53%
AVERAGE NET P&L PER SHORT TRADE RECOMMENDATION	3.28%	0.97%	1.44%	2.02%	2.59%	3.16%	3.35%	2.93%	3.19%	4.73%

Table 26 P&L of long recommendations as generated from PROBAPP model alone and from the combination of both models. In sample Jan '94 – Mar '03

P&L PERFORMANCE OF LONG RECOMMENDATIONS BASED ON PROBAPP MODEL SIGNALS IN SAMPLE: JAN '94 TO MAR '03										
PROBABILITY CUT-OFF LEVEL G%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF LONG TRADE RECOMMENDATIONS	1381	897	634	442	335	263	204	168	135	79
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS	812	574	417	292	226	181	140	120	99	57
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS (% OF TOTAL LONG TRADE RECOMMENDATIONS)	59%	64%	66%	66%	67%	69%	69%	71%	73%	75%
AVERAGE P&L PER LONG TRADE RECOMMENDATION	0.35%	0.66%	0.99%	1.31%	1.51%	1.78%	2.01%	2.31%	2.62%	4.05%
P&L PERFORMANCE OF LONG RECOMMENDATIONS BASED ON COMBINED MODELS' SIGNALS IN SAMPLE: JAN '94 TO MAR '03										
PROBABILITY CUT-OFF LEVELS K%=G%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF LONG TRADE RECOMMENDATIONS	145	821	606	419	321	251	199	165	135	76
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS	160	527	398	275	217	174	137	119	99	57
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS (% OF TOTAL LONG TRADE RECOMMENDATIONS)	65%	64%	66%	66%	68%	69%	69%	72%	73%	75%
AVERAGE P&L PER LONG TRADE RECOMMENDATION	1.46%	0.76%	0.96%	1.23%	1.50%	1.79%	2.00%	2.31%	2.62%	4.05%

In Table 25 we look at the times when either the PROBDEP model alone or both models combined generated signals for an investor to sell a local currency versus the USD on a one month forward basis. In Table 26 we summarize the results from all the times when either the PROBAPP model on its own or in combination with the PROBDEP model, generated signals for investors to buy an emerging market currency versus the USD in any given month, again on a one month forward basis. A number of conclusions can be driven from these two tables. First it is important that the models' buy and sell recommendations, whether these are the result of each model separately or from their combination, are largely symmetrical. This supports the notion that both models perform in a consistent manner. Secondly the profit making recommendations are in almost all cases above 50% of total recommendation with many cases well above 70% of the total generated signals. Arguably the profit making percentages are higher in almost all probability cut-off points for the long recommendations. This could be well explained from the stylized fact that when one goes long emerging market currencies they stand to also benefit from what we described as the "carry" which results from high interest rate differentials in favour of the local currencies in most emerging markets. However it is worth remembering that besides higher returns on average, emerging currencies also display significant volatility and even though one is on average likely to benefit more times than not when buying the local currencies, it is also the case that once-off significant corrections can easily wipe out the gradual gains from these long positions. This reality is captured by the model results in Table 25 and Table 26 when we look at the average net gain and loss per long or short trade recommendation. It is worth

mentioning that in line with the argument presented above, short recommendations, although profit making less often than long recommendations, actually generate a higher profit per trade when one takes into account the size of all profits and losses generated. In any case, the models' recommendations consistently generate profits for both long and short trades. This is a significant evidence of their goodness of fit, practical applicability and usability.

Results remain largely unchanged when we move from using each model separately to using both models combined in the manner defined earlier in this section. Long recommendations are again more than short ones, have higher percentage success ratios, but generate lower net profit on average per trade when losses are also considered for the total of trade recommendations. One may also note that when combining the two models we get in most cases fewer trade signals than when taking our cue from each model separately. This though is not always the case. For example when we take the 2% as a probability cut-off point we basically consider as trade recommendations all the cases when one model generates a probability higher than 2% which can easily happen, but at the same we need the opposite model to have generated a probability lower than 2%, which is a fairly difficult condition to meet. Thus we see that in this case the long or short recommendations that result from the combination of the models are far fewer that when one looks at each model separately for trade signals. Similarly when we go to the other end of the spectrum combining the model or taking them separately makes little difference. Because in practice conditioning one model to generate more than 10% or 15% probability and the opposing model

to generate a probability of less than 10% or 15% is fairly easy to achieve as a combination. The rare event here would be for the first model to generate such high probabilities. Once this is achieved it is fairly unlikely that the opposite model would have also generated equally large probabilities. The fact that our results in Table 25 and Table 26 confirm this argument again supports the reliability of the two models.

We now turn to Table 27 and Table 28 below and review the same results as above but for our out-of-sample period. The out-of-sample period covers 14 months of data which is fairly long to allow us to confirm or cancel the in-sample findings. However any period of around one year can reasonably be expected to generate results which will capture very specific characteristics of that period, and our models are no exception. At this point what we were primarily testing is whether the out-of-sample results would contradict our in-sample findings in any significant way. It is fair to say that the results in Table 27 and Table 28 confirm our findings above.

Table 27 P&L of short recommendations as generated from PROBDEP model alone and from the combination of both models. Out of sample Feb '02 – Mar '03:

P&L PERFORMANCE OF SHORT RECOMMENDATIONS BASED ON PROBDEP MODEL SIGNALS										
OUT OF SAMPLE: FEB '02 TO MAR '03										
PROBABILITY CUT-OFF LEVEL K%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF SHORT TRADE RECOMMENDATIONS	208	62	37	25	16	11	10	5	5	1
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS	71	23	13	11	7	4	4	2	2	0
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS (% OF TOTAL SHORT TRADE RECOMMENDATIONS)	34%	37%	35%	44%	44%	36%	40%	40%	40%	0%
AVERAGE P&L PER SHORT TRADE RECOMMENDATION	-0.73%	-0.29%	-0.27%	0.42%	0.14%	1.01%	1.52%	3.99%	3.99%	-0.97%
P&L PERFORMANCE OF SHORT RECOMMENDATIONS BASED ON COMBINED MODELS' SIGNALS										
OUT OF SAMPLE: FEB '02 TO MAR '03										
PROBABILITY CUT-OFF LEVELS K%=G%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF SHORT TRADE RECOMMENDATIONS	34	55	30	19	11	8	8	5	5	1
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS	14	21	11	9	5	3	4	2	2	0
NUMBER OF PROFITABLE SHORT TRADE RECOMMENDATIONS (% OF TOTAL SHORT TRADE RECOMMENDATIONS)	41%	38%	37%	47%	45%	38%	50%	40%	40%	0%
AVERAGE P&L PER SHORT TRADE RECOMMENDATION	-0.14%	-0.15%	-0.02%	0.99%	0.27%	-0.05%	4.15%	3.99%	3.99%	-0.97%

Table 28 P&L of long recommendations as generated from PROBAPP model alone and from the combination of both models. Out of sample Feb '02 – Mar '03

P&L PERFORMANCE OF LONG RECOMMENDATIONS BASED ON PROBAPP MODEL SIGNALS										
OUT OF SAMPLE: FEB '02 TO MAR '03										
PROBABILITY CUT-OFF LEVEL G%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF LONG TRADE RECOMMENDATIONS	260	168	129	92	75	63	50	45	41	28
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS	177	118	93	66	52	45	36	32	31	21
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS (% OF TOTAL LONG TRADE RECOMMENDATIONS)	68%	70%	72%	72%	69%	71%	72%	71%	76%	75%
AVERAGE P&L PER LONG TRADE RECOMMENDATION	0.73%	0.78%	0.65%	0.73%	0.79%	1.05%	1.59%	1.40%	1.70%	2.81%
P&L PERFORMANCE OF LONG RECOMMENDATIONS BASED ON COMBINED MODELS' SIGNALS										
OUT OF SAMPLE: FEB '02 TO MAR '03										
PROBABILITY CUT-OFF LEVELS K%=G%	2%	4%	5%	6%	7%	8%	9%	10%	11%	15%
NUMBER OF LONG TRADE RECOMMENDATIONS	86	161	122	86	70	60	48	45	41	28
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS	60	113	88	62	49	43	34	32	31	21
NUMBER OF PROFITABLE LONG TRADE RECOMMENDATIONS (% OF TOTAL LONG TRADE RECOMMENDATIONS)	70%	70%	72%	72%	70%	72%	71%	71%	76%	75%
AVERAGE P&L PER LONG TRADE RECOMMENDATION	0.51%	0.75%	0.60%	0.69%	0.84%	1.29%	1.28%	1.40%	1.70%	2.81%

Consistent with our in-sample results when we look at each model on its own trade recommendations become, as expected, less frequent as we raise the bar of probabilities. Like in the case of our in-sample results, we get more buy than sell signals, and the success ratios for the buy signals are by and large very high and superior to the sell trade recommendations statistics. In general profitable sell recommendations are around 35% to 50% of total sell signals, which is somewhat lower than the relevant in-sample statistics. Our out-of-sample statistics support the profit making ability of the model but although this is true for all probability cut-off points for the buy recommendations it is not true in all cases for the short trade signals. In fact we notice that net gain is superior in almost all the cases for long trade signals compared to short ones. This is true irrespective of whether we look at signals generated by one of both models together. These last two results are the two cases where the out-of sample results differ from our in-sample findings. However at the same time these findings can easily be biased due to the specific sample we are applying our models on. Year 2003 was in general a period of increased risk appetite during which risky assets outperformed. In particular high carry emerging market currencies were a very strong candidate for profitable long investments. What we prefer to focus on from the results in Table 27 and Table 28 is the fact that our models maintained their profit making ability even when applied in a fairly short sample which need not be very representative of the average circumstances that applied in-sample. Importantly the models displayed a bias towards generating more long recommendations which in our out-of-sample period were indeed the trades that made more profits on average.

4.4 Assessing Model Trading Performance In and Out of Sample: Portfolio review

Satisfied with the models' performance and the consistency of this performance we proceed to look at the model recommendations on a monthly portfolio basis. Again we review results in and out of sample but now we do not separate between long and short recommendations. Having reviewed the results in Table 21 to Table 28 above we now opt to look at the trade signals which are the result of combining both models and both directions together. In almost all cases this combination improved the average profit and loss per trade. In Table 29 and Table 30 below we review signals generated from such a combination on a monthly basis. Each country we included in our analysis has data that span on average 75 months. This is the basis on which we standardize our in-sample findings in Table 29 below. Importantly in Table 29 and Table 30 we look at both portfolio returns and volatility. We also calculate the annualized Sharpe Ratio which is the ratio of the returns over their volatility times the square root of 12. Sharpe ratios standardize returns for their volatility. The higher the Sharpe ratio the stronger the performance of a portfolio as investors endure less volatility for making a certain amount of profit. These statistics matter to a real life investors as they reflect in a nutshell the overall model performance. Sharpe ratios allow us to drive safer conclusions even for out-of-sample periods. We mainly focus on the results for the 5% probability cut-off point that we have selected, but in Table 29 and Table 30 we also present the relevant figures for a handful of other probability levels as well, as a reference.

Results in Table 29 and Table 30 suggest that the models perform

consistently well in and out of sample on a monthly portfolio basis. The same results hold both when one looks at returns alone, which are invariably positive, and when one measures the Sharpe ratio of these results which again are consistent and satisfactory. Both in and out-of-sample the models on average generate portfolios that consist of around 60% to 70% profit making trade signals.

Table 29 P&L of portfolios recommended by the combination of both models: In sample Jan '04 – Mar '03

P&L PERFORMANCE OF COMBINED MODELS** RECCOMENDATIONS IN SAMPLE: JAN '94 TO MAR '03				
PROBABILITY CUT-OFF LEVELS** K%=G%	5%	7%	10%	15%
AVERAGE NUMBER OF TRADE RECCOMENDATIONS PER MONTH	14	7	4	2
PROFIT MAKING TRADE RECCOMENDATIONS (% OF TOTAL TRADE RECCOMENDATIONS)	60%	60%	63%	65%
AVERAGE MONTHLY RETURNS ON RECCOMENDED PORTFOLIO	1.20%	2.37%	2.58%	4.69%
STANDARD DEVIATION OF AVERAGE MONTHLY RETURNS	2.25%	4.67%	5.94%	9.93%
SHARPE RATIO OF AVERAGE MONTHLY RETURNS (ANNUALISED BASIS)	1.850	1.760	1.420	1.640

* the trading signals are based on the combination of a strong signal from both PROBAPP and PROBDEP

** This is the probability cut-off for clasifying trading signals. Here the same probability level is applied to both the PROBDEP (k%) and PROBAPP (g%)

Table 30 P&L of portfolios recommended by the combination of both models: Out of sample Feb '02 – Mar '03:

P&L PERFORMANCE OF COMBINED MODELS** RECCOMENDATIONS OUT OF SAMPLE: FEB '02 TO MAR '03				
PROBABILITY CUT-OFF LEVELS** K%=G%	5%	7%	10%	15%
AVERAGE NUMBER OF TRADE RECCOMENDATIONS PER MONTH	11	6	4	2
PROFIT MAKING TRADE RECCOMENDATIONS (% OF TOTAL TRADE RECCOMENDATIONS)	65%	67%	68%	72%
AVERAGE MONTHLY RETURNS ON RECCOMENDED PORTFOLIO	0.53%	0.82%	1.69%	2.19%
STANDARD DEVIATION OF AVERAGE MONTHLY RETURNS	2.30%	3.84%	5.48%	5.90%
SHARPE RATIO OF AVERAGE MONTHLY RETURNS (ANNUALISED BASIS)	0.793	0.738	1.068	1.342

* the trading signals are based on the combination of a strong signal from both PROBAPP and PROBDEP

** This is the probability cut-off for clasifying trading signals. Here the same probability level is applied to both the PROBDEP (k%) and PROBAPP (g%)

The resulting portfolios are invariably profit making whether we look at the in or out of sample results for any of the probability cut-off levels that we consider. The in-sample results suggest that a 5% probability cut off point will not only generate by far more trades on average every month, but these will also come at the best trade off between profit and volatility, thus giving the highest Sharpe ratio of all probability cut-off levels. A probability level of 15% for example would improve the average in sample portfolio monthly profits to a high 4.69% but this will come at a cost of significantly higher volatility which deteriorates the overall Sharpe ratio to 1.64 compared to 1.85 for the portfolios generated when we select 5% probability as a cut-off point.

Looking at the out-of sample results in Table 30 we again see higher probabilities generating portfolios with fewer trades per month. Profit making trades as a percentage of total signals are consistently high and roughly the same at all probability levels. Like our in-sample results, the higher the probability cut-off point we select the higher the average monthly return our portfolios will generate. Interestingly the out of sample results suggest that Sharpe ratios actually improve as we move to higher probabilities but this could easily be a sample specific characteristic. As long as the 5% probability cut-off point generates profits and at a fairly low volatility cost even in our out-of-sample tests we are happy to stick with this choice of cut –off point.

We proceed to also test the consistency of the models' performance across the different countries we include in our sample. As mentioned in Chapter 1 of the thesis our sample consists of and our estimations are run, fitted and tested on a total of 21 currencies. However when we continue to implement the models on real life data as presented in the following section

we only do so on 19 of these currencies. In particular we omit the Venezuelan Bolivar and the Malaysian Ringgit which were practically fixed during our real life testing period. We therefore decided that applying our models in these two countries would not be of any use and would unnecessarily bias our results. Consistent with this rationale starting from Figure 27 below we exclude these two currencies. Figure 27 shows the number of profit and loss making trades generated by the models for each of the 19 countries we focus on during the in-sample period, while Figure 28 shows the average net P&L per country in the same period. The numbers in Figure 27 and Figure 28 are based on the trading rule we selected above, that is the trade signals are based on portfolios generated when combining the results from both the PROBAPP and the PROBDEP models and selecting 5% probability as the cut-off level above which to classify trade signals. Both figures support the fact that the models are not biased towards a sub-sample of countries as most countries display similar mix of profit and loss making trades. As shown in Figure 27 the models generated more profit than loss making trades for fifteen out of the nineteen countries included in our analysis. On average the models generated anything between 20 and 30 profit making recommendations for the majority of countries. There are of course outliers like Indonesia, South Africa or Thailand for which the models seems to have generated more than 40 profitable trades in the 75 available monthly observations per country on average. It is also worth mentioning that as Figure 28 shows, with the exception of Mexico, the models' trade signals have in total been profitable for all the countries in our sample. The results are consistent through all three geographic regions we include in our analysis.

Figure 27 Total number of profit and loss making trades per country: In sample Jan '94 – Mar '03

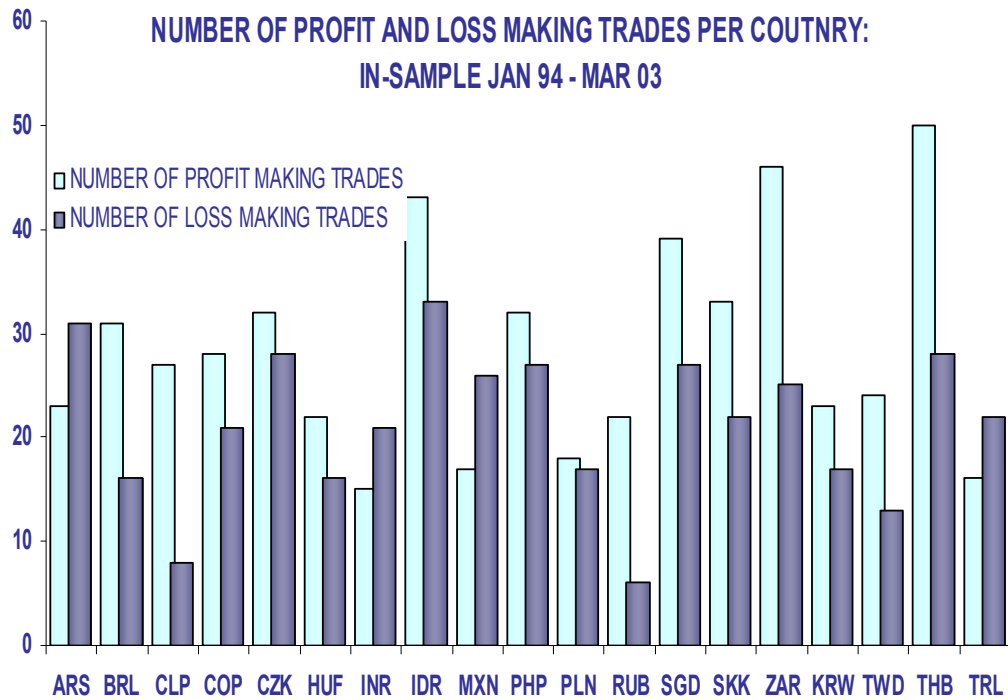
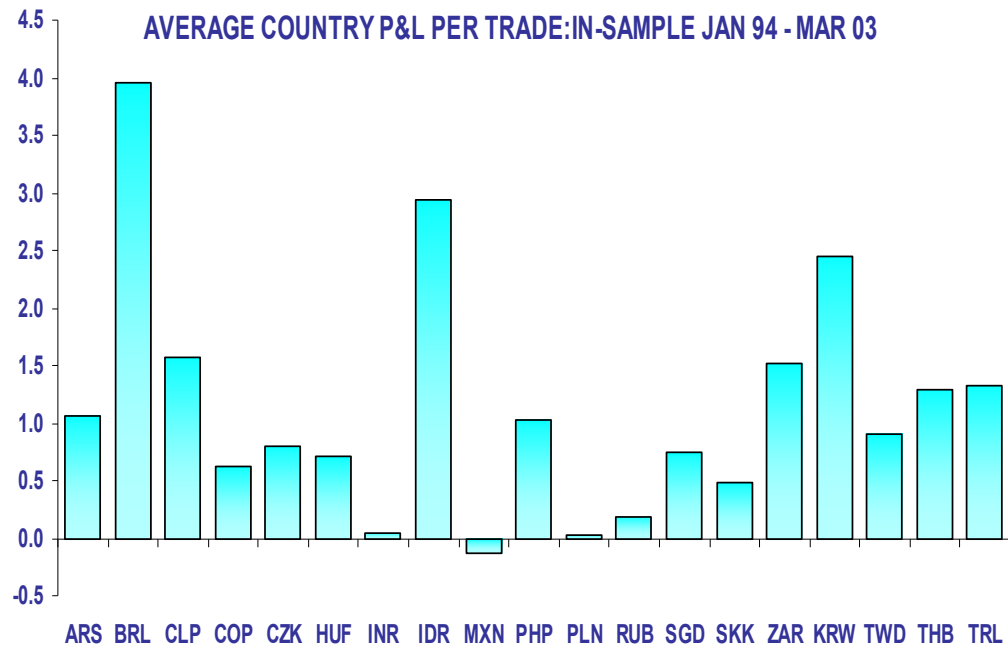


Figure 28 Average country P&L per trade: In sample Jan '94 – Mar '03



Combining the results from Figure 27 and Figure 28 it is difficult to find a pattern between quantity and quality of signals. The only example of consistency in this sense is the exception of IDR for which the model generates the highest number of trades, amongst the greatest number of profitable trades and also the second highest profit on an overall portfolio basis. Brazil is one interesting case where the models generate only 30 profit making trades but still merits the highest portfolio profit in our sample of countries. What matters to us most is the fact that the model recommended portfolios are by and large profitable, generate a fairly large number of signals and are not biased towards a sub sample of countries in any significant manner.

Moving on to the out-of sample period of observations we find that the results although not identical, remain largely in line with our in-sample findings. Figure 29 shows how the models again generated more profitable than loss making trade signals for 15 out of the 19 countries we monitor. Again some countries will have more trades in total apply to them than others, but interestingly these are not the same countries as in our in-sample results. Figure 30 demonstrates how the model signals generated a profit for the majority of countries while the results were pretty neutral for another 5 countries leaving only four of the countries having generating a loss in the specific data period we consider for our out of sample analysis. Again these results can easily be biased and sample specific but the important aspect to consider is that they do not cancel the in-sample results and remain consistent with our overall findings. These support the notion that the models work well in generating trade recommendations that can be expected to

generate profits for emerging market investors.

Figure 29 Total number of profit and loss making trades per country: Out of sample Feb '02 – Mar '03

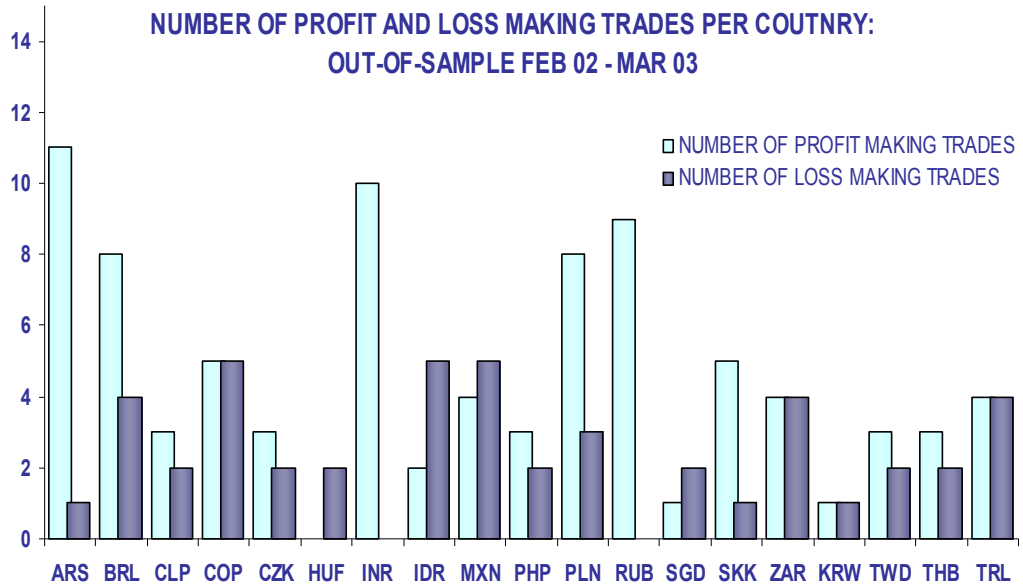
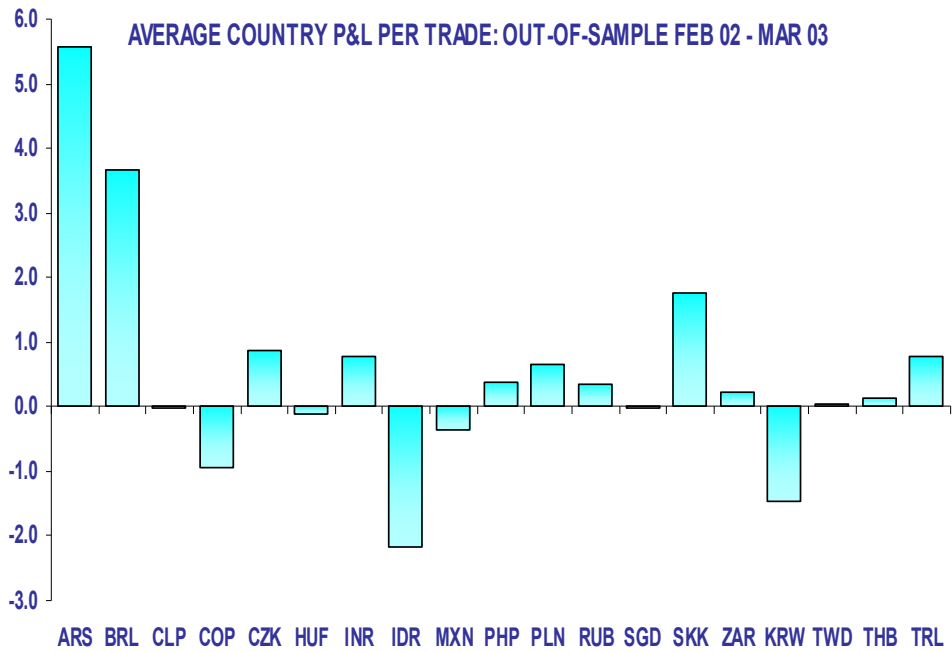


Figure 30 Average country P&L per trade: Out of sample Feb '02 – Mar '03



4.5 Assessing Model Trading Performance On Real Time Data

In the fifth section of this Chapter we put our models to the toughest test with regards to their applicability and usability in investment decisions. What we refer to as “real life” exercise covers a whole calendar year from January 2004 to December 2004. We select a whole calendar year to apply our models to eliminate any concern that an arbitrary choice of sample may raise. During this period we applied the two models as described in Table 17 and Table 18 and applied the combined rule that produces country specific portfolios as described and applied in Section 4.4 above. Every time the PROBAPP (PROBDEP) model generates a probability equal to or higher than 5% and for the same month and the same currency the PROBDEP (PROBAPP) model generates a probability lower than 5% we buy (sell) one unit of local currency against the USD on a one month forward basis at the beginning of the month and close the position at the last calendar day of the month against the prevailing spot. As we were doing this exercise in real life we also had the opportunity to scrutinize the model results and have a view on whether we would actually follow the model recommendation or ignore it. This is an essential element to this part of our analysis. However we wish to first review this year of results to further support the legitimacy of our models as objective investment tools. We present how the results can be altered by intuition and investors’ subjective judgment through a number of selected examples in the following and last section of this Chapter. What we will focus on here is the presentation of the 2004 model performance if one was to blindly follow the model generated portfolios.

As it follows by the data in Table 31 and Figure 31 and Figure 32 below, the model generated trade signals in 2004, remain largely in line with our in sample and out of sample findings as reviewed in the previous sections. The model generated trade signals in all calendar months and these signals were fairly evenly distributed across different months. In the large majority of cases the models generated signals for most of the underlying currencies. In particular as per Table 31, in seven months the models generated a trade recommendation for 16 to 19 currencies from a total of 19 currencies on which we apply the models. In other three months the models generated a high number of total trades, ranging from 11 to 13 and on the remaining 2 quieter months the models generated signals for 7 or 8 currencies.

Continuing the 2003 theme, high risk appetite remained the main element theme in 2004 with assets such as emerging market currencies rallying. This was successfully captured by the models which displayed a clear bias towards generating significantly more buy than sell recommendations throughout the year. As Figure 32 below shows, from a total of 174 trade signals generated by the models in 2004, 68% were recommendations for investors to go long the local currency versus the USD. Only 9% of the model signals were a suggestion for investors to sell the local currencies. In 23% of the cases the combined model findings resulted in a neutral signal. Importantly, the models were in general successful in both their long and short recommendations. As shown in Figure 31 the models' long signals turned out to be profitable in 67% of cases. Although the success ratio for the short signals was lower, still 38% of the models' short recommendations turned out to be profitable. In general 61% of the trade

signals generated in 2004 would have been profitable if one was to simply follow all recommendations. April 2004 was a particularly bad month for the model performance as out of 19 generated signals only 11% was profit making, a result that drags down the average performance of the whole year. At the same time September 2004 was a month with a portfolio of 18 trades, 94% of which were profit making, an astonishing result for a quantitative model.

Table 31 Overview of trade recommendations in 2004:

	SIGNALS TO SELL LOCAL CURRENCY vs USD		SIGNALS TO BUY LOCAL CURRENCY vs USD		TOTAL SIGNALS	
	TOTAL SHORT TRADE SIGNALS	PROFIT MAKING SHORT TRADE SIGNALS (% OF TOTAL SHORT TRADE SIGNALS)	TOTAL LONG TRADE SIGNALS	PROFIT MAKING LONG TRADE SIGNALS (% OF TOTAL LONG TRADE SIGNALS)	TOTAL TRADE SIGNALS	PROFIT MAKING TRADE SIGNALS (% OF TOTAL TRADE SIGNALS)
JANUARY 2004	2	50%	14	71%	16	69%
FEBRUARY 2004	4	25%	12	67%	16	56%
MARCH 2004	2	50%	14	71%	16	69%
APRIL 2004	1	0%	18	11%	19	11%
MAY 2004	1	100%	12	67%	13	69%
JUNE 2004	1	0%	10	40%	11	36%
JULY 2004	1	100%	18	61%	19	63%
AUGUST 2004	1	100%	12	67%	13	69%
SEPTEMBER 2004	0	0%	18	94%	18	94%
OCTOBER 2004	0	0%	18	89%	18	89%
NOVEMBER 2004	3	0%	5	100%	8	63%
DECEMBER 2004	4	25%	3	67%	7	43%

Figure 31 Profitable trade signals as % of total model recommendations in 2004

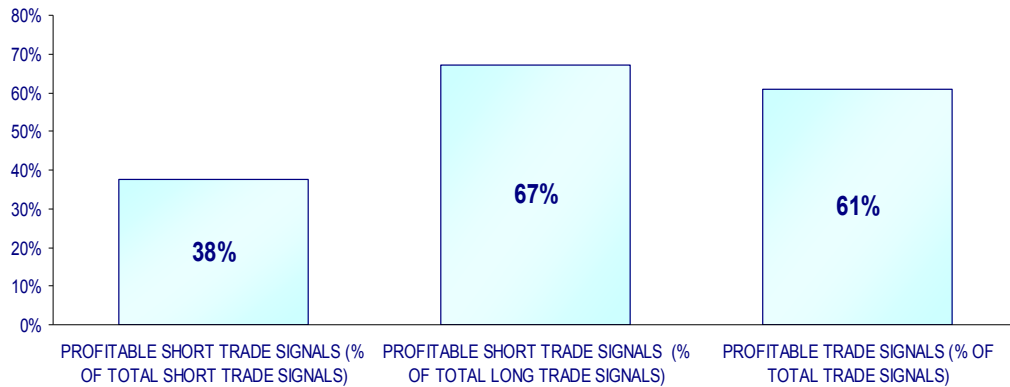
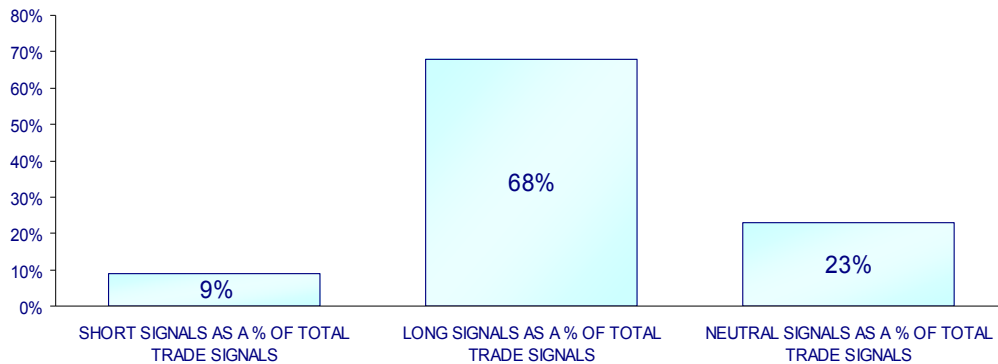


Figure 32 Breakdown of total 2004 model signals.



From the 12 monthly portfolios that the model generated in 2004, seven were profitable, three were loss making and two were neutral. Both the profitable and the loss-making months yielded roughly 1% profit or loss respectively on average. On a cumulative annual basis the model monthly portfolios generated a total profit of 4.06% per trade for the whole of 2004. Interestingly the cumulative P&L only turned negative in one month of the whole year but subsequently recovered to profit making mode. The reliability of the models' consistent profit making ability is further supported by the return to volatility ratio of the 2004 portfolio results. As Table 32 below shows the model annualized return of 4.06% profit came with an annualized volatility

of 3.5%. Together these two give an annualized Sharpe ratio of return to volatility of 1.16. This level comes as a clear improvement of the out-of-sample Sharpe ratio for 5% probability cut off, which stood at 0.79% and outperforms all but one of the other out-of-sample Sharpe ratios.

Figure 33 Monthly & cumulative P&L of model recommended portfolios in 2004

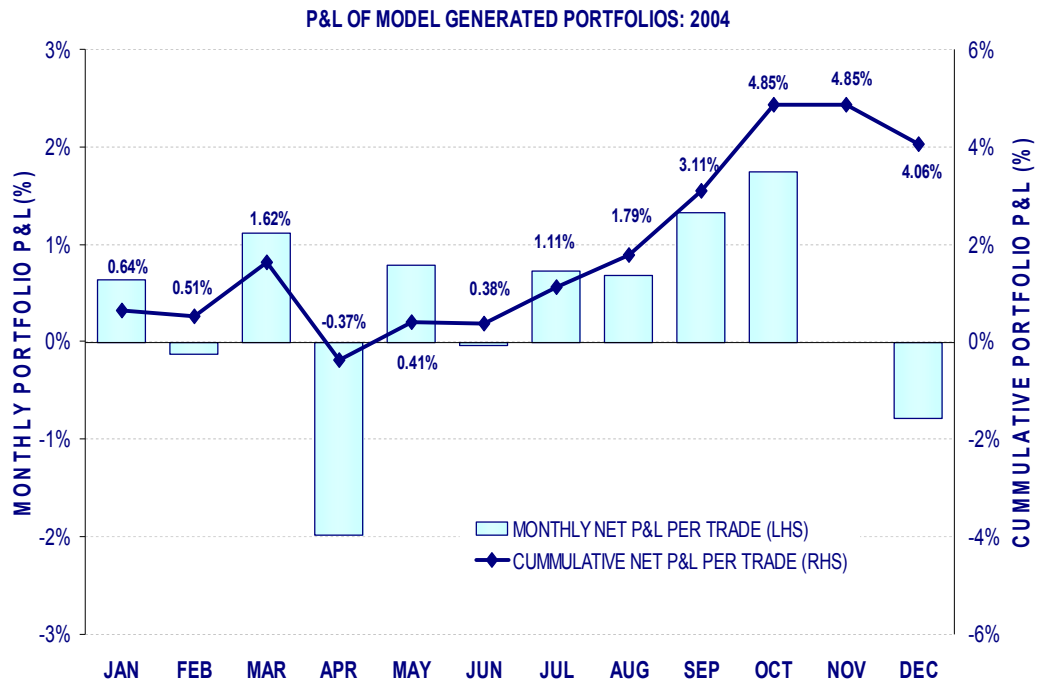


Table 32 Statistical performance of model portfolios in 2004:

2004 MODEL RECOMMENDED PORTFOLIOS	
RETURN OF AVERAGE MONTHLY RETURNS PER TRADE (ANNUALISED)	4.06%
VOLATILITY OF AVERAGE MONTHLY RETURNS PER TRADE (ANNUALISED)	3.50%
SHARPE RATIO OF AVERAGE MONTHLY RETURNS PER TRADE (ANNUALISED BASIS)	1.16

To summarize we find that one whole calendar year of results from applying our models and blindly following the resulting trade recommendations support our belief that the PROBAPP and PROBDEP models provide a set of quantitative tools that tick the boxes that are important to real life investors. They are parsimonious and straightforward, intuitive in their structure, robust in their statistical performance both in and out of sample and most importantly consistent in their ability to generate profitable trade recommendations one can trust to blindly follow. At times the models are likely to display a bias in the recommendations they generate like in the case of our out-of-sample and 2004 exercises where most of the trade signals were for investors to buy the local currencies against the USD. However, this bias was well justified by market conditions of improved risk appetite during these periods, thus proving the models ability to capture the underlying market dynamics. Equally important is the fact that even when the type of trade signals was biased towards buy recommendations the resulting portfolios still turned out to be profitable. All in all one can safely conclude that the models developed herein meet the criteria of quantitative tools that investors can trust to include in their box of reliable tools. As investors go about making their final investment decisions by combining a number of different factors and considerations they stand to benefit from an intuitive and objective tool like the PROBAPP and PROBDEP models. These can assist in removing any degree of subjectivity which is often difficult to achieve in the absence of quantitative models. Of course the manner in which these tools will be ultimately used relies completely on an investor's mandate and approach. It is this aspect that we discuss in greater detail in the following last section of this Chapter.

4.6 Bridging Quantitative Tools with Investors' Realities

Different types of investors adopt fundamentally different investment styles. Specialization has evolved so much that investment firms raise capital with the mandate to invest it based on only one of many approaches, on one of many asset classes and target to satisfy one of many investor profiles. There is enough diversity to accommodate different risk appetites, different geographic regions, implement different risk management systems, introduce different degrees of technical expertise, apply different investment criteria altogether. The only common denominator in every fund raising exercise is the ability to convince about the profit generating ability of the chosen agenda. Products like the models developed and presented here fit well with a number of different investment profiles and mandates albeit with varying degrees of compatibility. On the one end of the spectrum a quantitative fund that invests in emerging markets or EM currencies in particular, would be a natural target for such products. Quantitative Funds opt to follow trade recommendations generated by models without any implementation of subjective judgment. Tools that are robust technically and have been proved to generate profits are exactly what such funds would typically look for.

Investors with different risk appetites can adapt the model results by applying a higher or lower probability cut-off point when classifying the model probabilities as trade signals. Global emerging market investors would benefit from the fact that our models cover all three major emerging market geographic regions. However, even local investors can utilize the trade signals that apply to their mandate and simply use the rest of the model results as a barometer for global emerging markets. The same can apply to

investors who do not typically or at all invest in emerging markets but still need to keep them in their radar given the degree of linkages between emerging and non emerging markets and the constant possibility of contagion between the two. Equally, investors that do not directly invest in currencies but have a prime or sole focus on other asset classes from equities to credit to real estate stand to benefit from monitoring the results of the models developed here as these can serve as one additional indicator of general EM or country specific trends. Academics or policy centres such as the OECD, the ECB, the FED or the IMF would also merit from reviewing and monitoring tools adopted by investors especially if these incorporate elements of macroeconomic theory and generate signals that consistently lead currency moves in emerging markets.

We will now look at what we consider as a representative investor who could use the trade signals generated by the PROBAPP and PROBDEP models. An investor that would review and possibly filter the model results based on his own personal views but more importantly on a number of stylized facts and market considerations which are well known at the time of publication of the model results. Such information would have possibly served to ignore some of the generated recommendations. In our analysis we will attempt to be as specific as possible and present a number of clear rules that would apply rather than base our views on instinctive and subjective judgment. In doing so we will scrutinize the model recommended portfolio for March 2004 which we feel offers a representative example of results.

As shown in Figure 34 and Figure 35 below the probabilities generated by the PROBAPP and PROBDEP models in March 2004 were quite

representative of the models' results as presented so far in this Chapter. The models generated trade signals for sixteen out of the nineteen countries included in the analysis. None of the "buy" recommendations generated by the PROBAPP model were cancelled by the PROBDEP results and vice versa none of the "short" trade signals that the PROBDEP model generated were cancelled based on the PROBAPP probabilities. We end up with a typical mix of more long than short recommendations. In particular the combined models' results suggest that an investor should buy one unit of each of the COP, ZAR, THB, RUB, TWD, SGD, INR, MXN, HUF, PHP, CZK, KRW, PLN, IDR all against the USD on a one month forward basis at the beginning of March and close the positions at the prevailing spot at the end of March. From these fourteen buy signals about half are substantially stronger in terms of probabilities but at this point we do not filter model recommendations on the back of the signal strength. The combined model results also suggest that investors should in March sell two emerging market currencies, the ARS and CLP versus the USD.

Figure 34 Monthly Probabilities of local currencies appreciating in March 2004

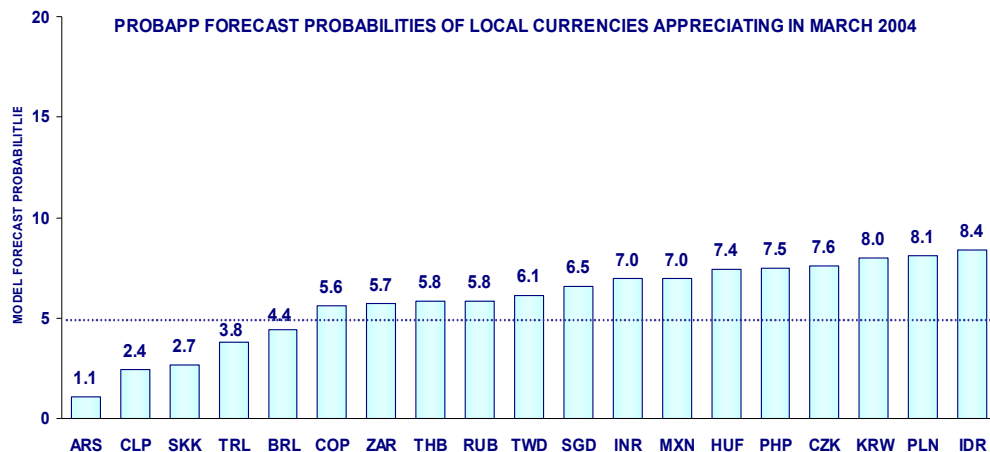
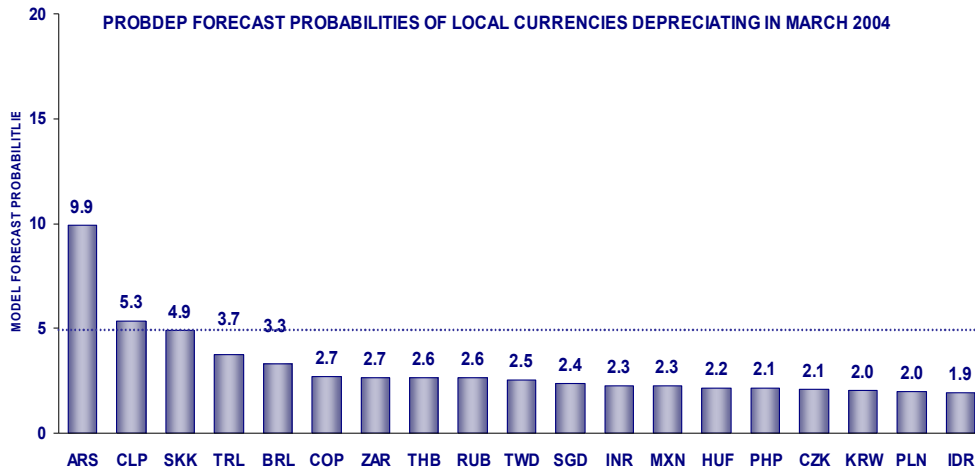


Figure 35 Monthly Probabilities of local currencies depreciating in March 2004



Blindly following the model portfolio as presented above would have generated a net profit of 1.11%. One of the two short recommendations and ten out of the fourteen long recommendations were profitable.

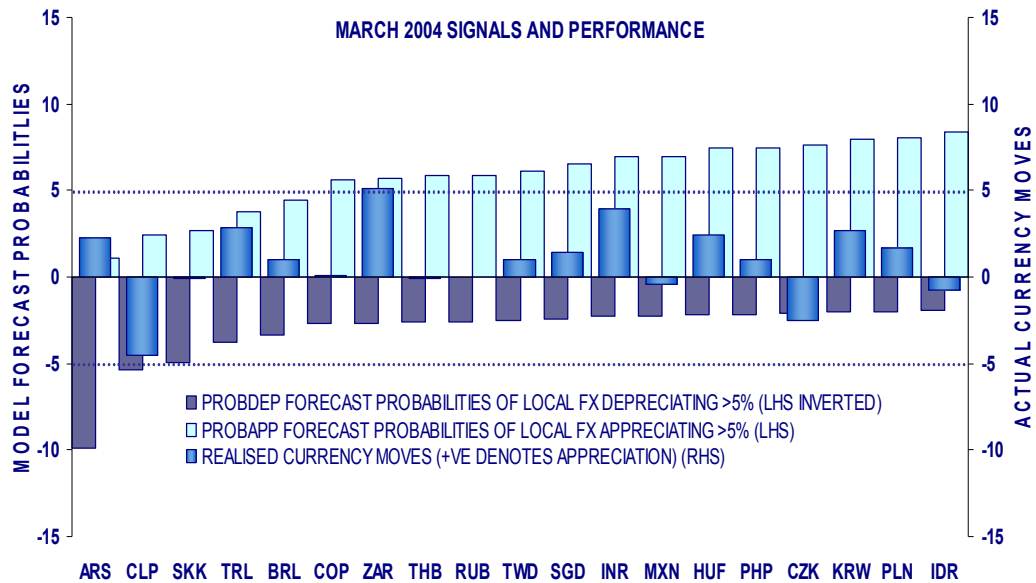
Table 33 Performance of model portfolio in March 2004:

MARCH 2004 PORTFOLIO BASED ON BLINDLY FOLLOWING THE MODEL TRADE SIGNALS			
	SHORT TRADE SIGNALS	LONG TRADE SIGNALS	TOTAL TRADE SIGNALS
NUMBER OF TRADES	2	14	16
PROFIT MAKING TRADES	1	10	11
PROFIT MAKING TRADES (% OF TOTAL TRADES)	50%	71%	69%
	NET MARCH PORTFOLIO P&L		1.11

Figure 36 below shows the following information: On the left hand axis one can see the PROBAPP and PROBDEP probabilities for March 2004. On the right hand axis on an inverted scale we show the actual realized performance of each currency on a forward basis in March 2004. The “long” model recommendations that coincide with positive monthly returns and the “short” model recommendations that coincide with currency depreciations are

the trades that generated a profit in March. The “buy” model signals that coincide with weakening currencies and the “sell” model recommendations that coincide with currencies appreciating are the loss making trades from the March portfolio.

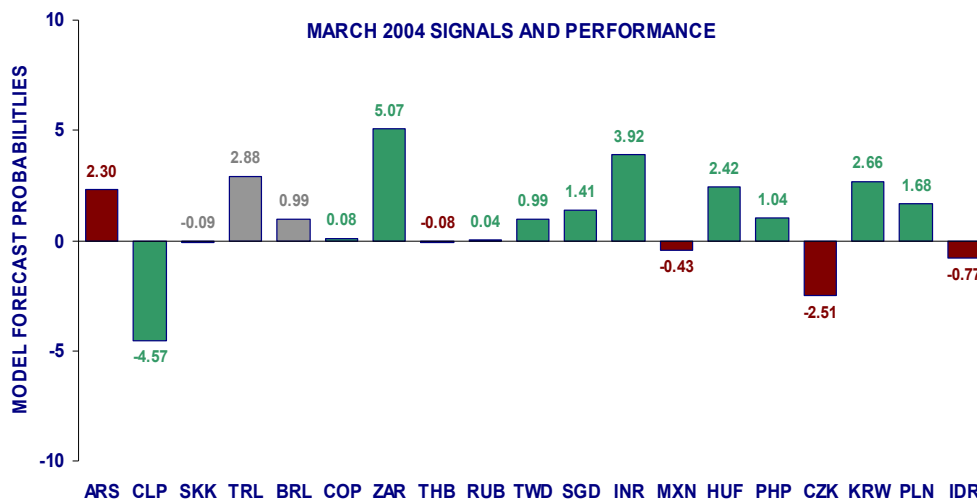
Figure 36 Monthly probabilities of local currencies appreciating or depreciating and actual realized returns in March 2004



To make these results more clear we show, in Figure 37 below, the currency specific gain and loss for March 2004. The grey bars refer to currencies for which the models did not generate a signal and in which we did not invest. The green bars are the buy or sell signals that were profitable and the red bars are the model buy or sell signals that made a loss. Interestingly some of the weaker signals were the ones that made the least or no profit at all. Such examples include the signals to buy COP, THB or RUB. Some of the stronger signals indeed made significant gains like the PLN and the KRW on the buy side or the CLP on the sell side. However one can see that we also have strong signals that generated losses like the two extremes of sell ARS or

buy IDR and we actually have the higher profit coming from one of the weaker signals, that for buying ZAR. These results alone suggest there is no safe rule in ignoring or accepting the model results simply on the back of their strength and one would do well to stick to the objective probability cut-off points adopted in our analysis so far.

Figure 37 March 2004 signals generated by the models and relevant performance



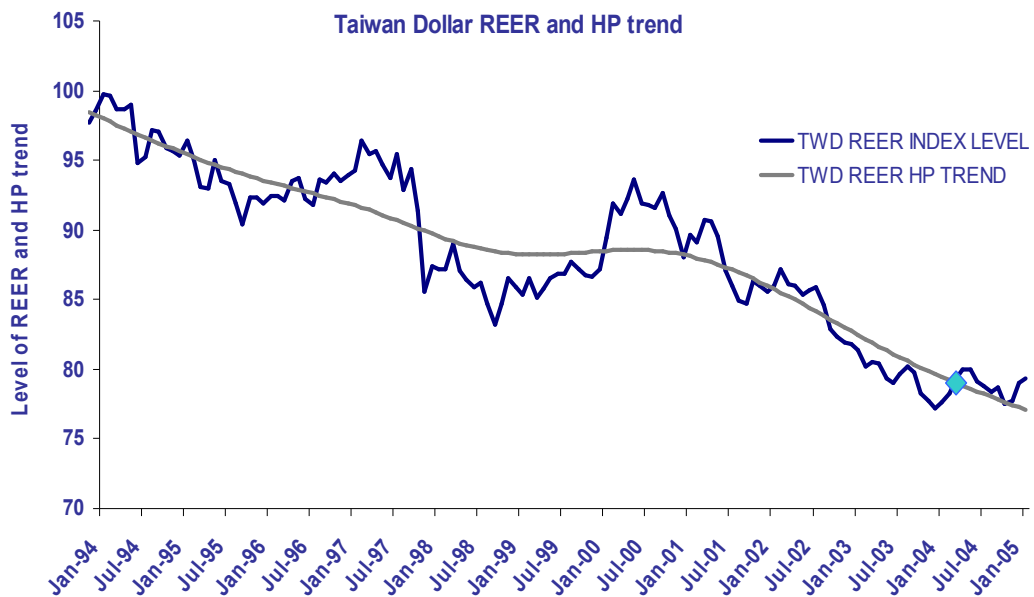
Below we present a number of suggestions that we personally found to work as safe guide-sticks that one could adopt when filtering the model results. In the absence of a country specific negative rating action, the driving force behind the model results are the deviations of each country's real effective exchange rate (REER) from its Hodrick Prescott medium term trend (HP). The deviations are based on REERs that are calculated using the average realized spot exchange rates between each currency and its major trading partners two months prior to the month we are forecasting. Accordingly the HP trends cover the period from January 1994 to and including the relevant REER month. As we are forecasting March 2004 here

both the REERs and the HPs used span the period up to and including January 2004. In reality we will only be producing the model March forecasts when we are at the end of February and there is a good chance that currencies will have moved significantly in the time from the end of January till our update. This is a type of information we would have incorporated in our investment decision and we would like to somewhat quantify in the way we review the model results. Thus we decided to also monitor the deviations of each currency's REER from its HP trend based on the daily spot of the day when we run the model to forecast March, which was the 26th of February. Besides spot exchange rates, REERs also incorporate inflation and trade weight data which would still be largely, if not solely, reflecting the January releases. However the factor that affects REERs intra-monthly is indeed by far the spot exchange rate. The latest spot rates are likely to incorporate the latest market information available, be it positioning, fundamentals or investors' appetite. And we could stand to benefit from such information.

The way one uses this information is not an exact science. We find it is worth ignoring signals that are reversed in the time that passed from the end of January till the time we update the model near the end of February. For example if a currency comes up as undervalued in REER terms at the end of January but the spot has moved so significantly that by the 26th of February the currency seems overvalued, then we could consider ignoring the buy recommendation. In our example below only TWD fits this profile but only marginally so as it went from being mildly undervalued by 0.7% based on the deviation of the January REER and HP trend to being around 2% overvalued when comparing the February 26th REERs to the respective trend. This is

arguably not a very strong signal though. The light blue dot in Figure 38 below shows how in March 2004 the TWD REER was crossing the long term HP trend moving from slightly undervalued levels to slightly overvalued ones. Still these are all relevant to a trend that is overall downwards sloping and a REER which is not terribly volatile in the post 2001 years. This is compatible with the significant degree of market intervention that Asian central banks have displayed in recent years in an attempt to slow down significant currency appreciation and also manage exchange rates with the aim of avoiding the repetition of the crises they experienced in the 1990s. One could chose to ignore the buy TWD signal on the back of our rule suggested above. However we would in general suggest one looks for stronger signs of valuation reversals before ignoring trade signals purely on that basis.

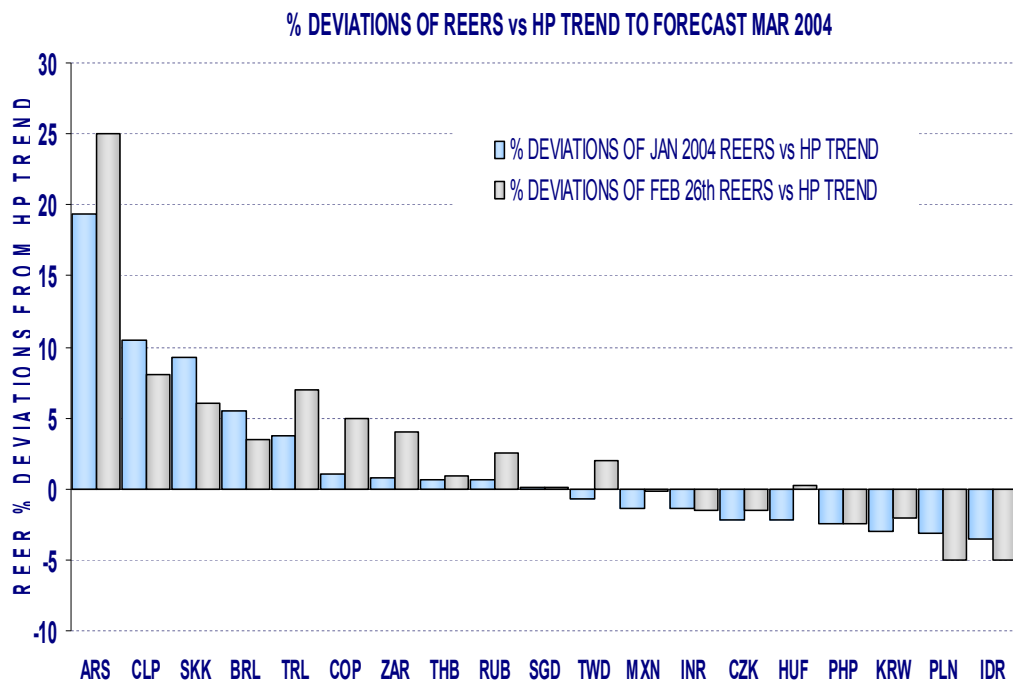
Figure 38 TWD REER and relevant HP trend



We would also gauge the strength of the signals that did not reverse in the period from the end of January to the 26th of February. Most signals are

still supportive of REER valuations as of the end of January and many of them now seem even stronger than before. Such examples include the ARS which came with a sell recommendation and some of the strongest buy signals like the ones for IDR and PLN. We would not ignore any of the model March signals on the basis of the REER dynamics as per February 26th. This rule served well in successfully filtering out a number of signals in other months and we think it can serve as a valid safety net for those wishing to evaluate the model results in any given month.

Figure 39 REER %deviations from HP trends (+ve denotes REER overvaluation)



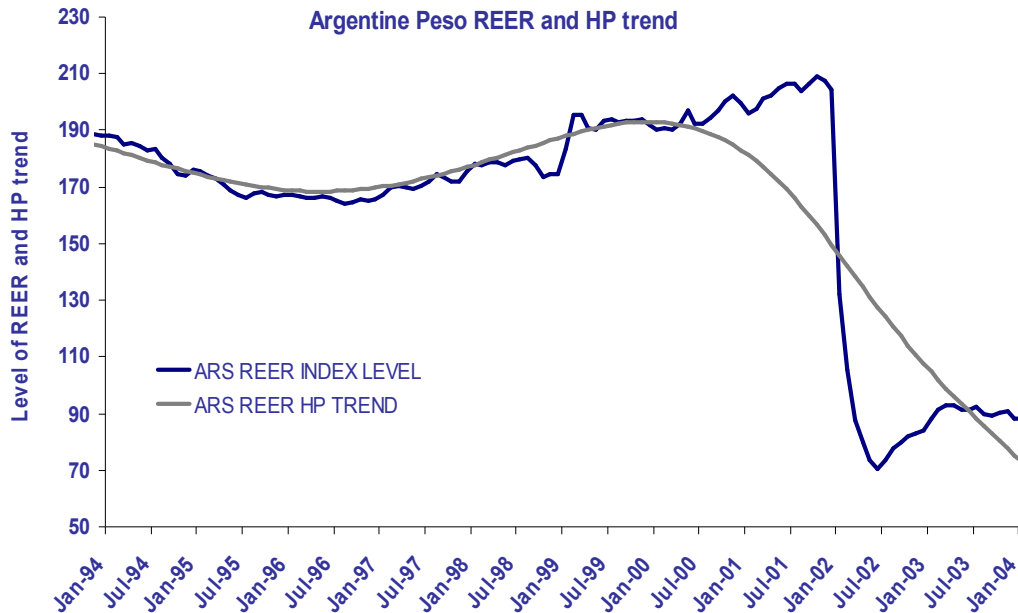
There are limitations in using any long term trend as a fair value against which we measure currency over and under valuations. Still we have discussed in detail the benefits of using the HP trend and our findings strongly support the use of the HP trend and the deviations of REERs from this trend.

However the educated investor will look for exceptions to the general rule of trend dynamics working efficiently. The Argentine Peso offers such an example. In March 2004 like in many months before that, the models generated a sell recommendation for the ARS which is often, like in the case of our March portfolio, the strongest sell trade signal. This signal come in the absence of a negative rating action for Argentina and despite the overall bullish environment which, as discussed, tended to bias the model results towards generating significantly larger number of buy than sell recommendations. The sell ARS signal comes on the back of the estimated overvaluation of the currency when compared to its HP trend. The ARS REER is around 20% stronger than the HP trend would have suggested at the end of January, the month we use as input for our March signals. This however is the result of a technical limitation of backwards and forwards looking trends like the HP. As shown in Figure 40 below the ARS HP trend is strongly downwards sloping in an attempt to adjust for the structural break that occurred with the January 2002 devaluation. Two sided trends that include structural breaks as abrupt as in the case of the ARS will typically depict the following characteristic. The retrospective trend will typically suggest the underlying series is overvalued before the event and undervalued for a number of months following the big event. However this type of information would have not been evident at the time if one looked at the trend ending before January 2002.

This trend would have only gradually adjusted to the devaluation in the months that followed. One would typically expect structural breaks to gradually return to some notion of pre-break balance and the trend to

accordingly smoothen as it adjusts to more regular REER valuations. However in the case of Argentina the devaluation was followed by constant policy intervention to avoid currency strength. This successful intervention was seen as the only solution to the country's macro imbalances by protecting the competitive advantage of the country's external sector and supporting its exporters. Most economists were openly against this type of policies, especially as they came hand in hand with manipulation of economic statistics. The country's inflation data in particular were regularly fudged, with official figures only a fraction of real numbers. In the case of Argentina the weak currency coincided with a period of extremely beneficial terms of trade effects from international commodities tripling in the decade following the Argentine default and devaluation. This effect allowed the country to generate greater fiscal revenues and balance its fiscal dynamics faster and grow even without tapping international capital markets or restructuring the defaulted debt for a considerable amount of time. The highly interventionist policies kept the ARS and the REER artificially weak and the HP trend reflected this reality. Therefore what we have in our March model results is a fundamentally weak currency showing as overvalued only because it is compared to a technically biased trend. This is a good example of the type of model signals we would ignore as misleading due to the way the models are set up.

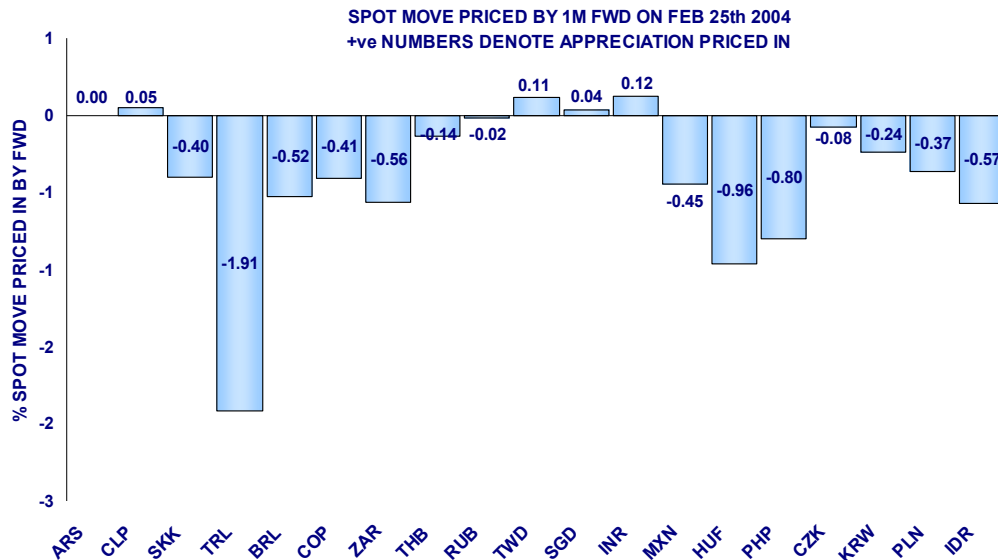
Figure 40 Argentine Peso REER vs HP trend



Another element important for emerging market investors that again aims to capture the most up to date market information is the carry that is priced in already by forward exchange rates at the time of updating the model results. Figure 41 below shows how much carry was priced in the one month forward exchange rate as of February 25th 2004. Negative carry works as a supportive factor for all the buy recommendations and would only really deter an investor from buying an emerging market currency if it was significantly positive. Most emerging market forward exchange rates will benefit from the higher local interest rates compared to the USD and price in a local currency depreciation for the coming month, which is how we define the negative carry. At times of high risk appetite this is like a free lunch for investors who buy the local currencies and benefit from the overall market interest that effectively supports these currencies. At the end of the month, investors that went long these currencies stand to benefit at a minimum from the depreciation that was

priced in, in the form of carry. Any actual appreciation will provide additional gains. At the same time the negative carry offers a buffer, should the currencies indeed weaken in spot terms and provides some comfort until the positions start making losses. This is exactly the argument that deters investors from shorting high yielding currencies at times of rising risk appetite and lack of significant country specific negative views. For example if the models generated a sell signal for the TRL one would have to have a very strong conviction that the currency will indeed weaken in March and significantly more than the almost 2% move priced in already, before actually selling the TRL on a one month forward basis against the USD. However this is not a relevant dilemma here as the models generated a neutral signal for TRL in March.

Figure 41 Spot moves priced in by 1month Forward exchange rates on February 25th 2005



For the rest of the portfolio recommended for March 2004 we have no hard rules to suggest. We can however give examples of the thinking process

we underwent when assessing each of the model signals. Starting from the fewer sell recommendations we first turn to the Chilean Peso. The CLP appreciated versus the USD by as much as 26% in 2003 largely on the back of generalized US dollar weakness, global positive growth momentum and thriving commodities prices and in particular copper. A USD rebound which led to a CLP downwards correction by almost 6% from January 9th to February 27th 2004 brought the CLP at levels almost flat to the beginning of the year. If the dollar was expected to continue on its strengthening trend it would mean the CLP could be expected to weaken further. However, the CLP's recent move described above meant valuations were less supportive of significant further CLP weakening in the immediate future. Taking into account that there is no carry cost in shorting the CLP we decide to abide by the sell CLP model signal but also decide to apply a 1% stop loss trigger in case our fears for dollar re-pricing turn out to be correct. The other trade signal that referred to a Latin American currency was the buy MXN recommendation. This signal came at a time when investor appetite had lost its momentum for MXN as a number of good news failed to provide the expected peso support. Although this could be seen as a technical feature that was bound to correct, by mid February 2004 rising uncertainty on Mexican inflation was adding to the currency downside risks. In light of these factors we decided to ignore the model buy MXN signals. We also had no strong reasons to object the weak COP buy signal.

Continuing on to the buy side of the model portfolio we see a theme that is consistent in many previous months, that of a general bullish trend for Asian currencies. The models generate a buy recommendation for the Indonesian

rupiah (IDR), the Korean won (KRW), the Philippines peso (PHP), the Indian rupee (INR), the Singapore dollar (SGD) the Taiwan dollar (TWD) and the Thai baht (THB). Overall Asian currencies were allowed to strengthen more than usual in 2003 but this change of policy was largely enabled by the weakening US dollar. Most Asian authorities remained very wary of allowing their currencies to appreciate versus their major trading partners. This was justified by the reality that growth in Asia was largely driven by trade dynamics and external demand. However as a large portion of the Asian trade was intra-regional and often between each country and Japan the Asian governments could afford to allow the USD crosses to somehow appreciate. This also relieved an amount of pressure they were incurring from international organizations asking for free floating currencies and less policy intervention. The overall Asian bullish trend was indeed uninterrupted in 2004 but as mentioned above by mid February the understanding was that the USD had recovered a lot of its lost ground and could well continue to do so.

On a more country specific mode we would have traded on the IDR buy signal as the positive carry was still a significant driver of positioning for the IDR. The PHP was the Asian currency offering the highest carry at the time. However in the case of Philippines, political concerns relating to the run-up to the highly emotional elections of May 10th 2004, were keeping many investors side-lined. On these grounds we too would have decided not to follow the model buy PHP signal in March 2004. We decided to trade the buy SGD signal but with a stop loss of 1% because the authorities of Singapore followed at the time an undisclosed REER and NEER target for the SGD and in REER terms we see that the SGD had been very stable and does not seem

undervalued. At the time we also decided to ignore the buy TWD signal as the REER signal had reversed by the end of February as discussed earlier, but also because of ongoing political tensions on the run up to the December 2004 election in Taiwan. In the months that preceded the elections conflict between major parties with regards to how the Taiwan-China interstate relations should be handled were creating a lot of heat which, like in the case of the Philippines, was enough to de-motivate international investors. We had no reason to dispute the models' buy INR recommendation. We also followed the models' buy recommendation for the Korean won (KRW) which we felt had room to further appreciate. A possible USD rebound was a concern and we felt that if this materialized it would be worth switching our long KRW position against the JPY instead of the USD. Last on the Asian model signals we decided to follow the buy THB recommendation on the back of strong fundamentals that supported further currency appreciation. We remained wary though that the Bank of Thailand was likely to intervene to cap substantial currency strength.

Turning to the EMEA trade signals we have a buy recommendation for three out of the four central European currencies, The Polish zloty (PLN), the Czech koruna (CZK) and the Hungarian forint (HUF). The model signals came at a time of interest rate decisions in all three countries. Interestingly, although all three decided to leave their interest rates unchanged their decisions triggered different market reactions for each one of them. In Poland the Monetary Policy Committee left interest rates unchanged and signalled a possible move to a tightening bias in coming months. Together with expectations for progress in structural reforms and in particular fiscal reform

based on a vote expected in March, we felt markets would support the zloty in the near future. We therefore traded on the models' buy PLN recommendation but with a stop loss of 1% to avoid sudden market reactions to nasty political surprises. Following the decision not to change interest rates the Hungarian forint became the highest carry currency in the EMEA region leading us to endorse the models' buy signal on expectations for further HUF strength. We also followed the buy CZK recommendation as we had no strong reasons to oppose the signal. We also abided by the models' long recommendation for the Russian ruble which had been pretty resilient to event risk from a recent cabinet reshuffle. We felt the RUB was running little downside risk from the upcoming presidential elections in mid March and had fundamentals and high oil prices supporting it. One buy signal we ignore in the EMEA region is that for the South African rand. The models were correctly capturing the significant ZAR weakness in January 2004 which saw the ZAR drop by as much as 17% vs the USD in a matter of ten days. However the rand had recovered most of its losses and rose by about 10% by the end of February. This volatility together with unsupportive country fundamentals and the fears of possible US dollar continuing rebound led us to ignore the buy ZAR signal.

From applying our subjective approach to the model generated trade signals we ended up trading fewer currencies and marginally improving our overall portfolio performance. However the results were mixed in that our filtering meant that at times we avoided losses but at times we also missed out on profits. In general as shown in Table 34 below we ignored a total of five signals, of which one was a sell and four were buy recommendations. We also implemented a stop loss when trading three of the model generated trade

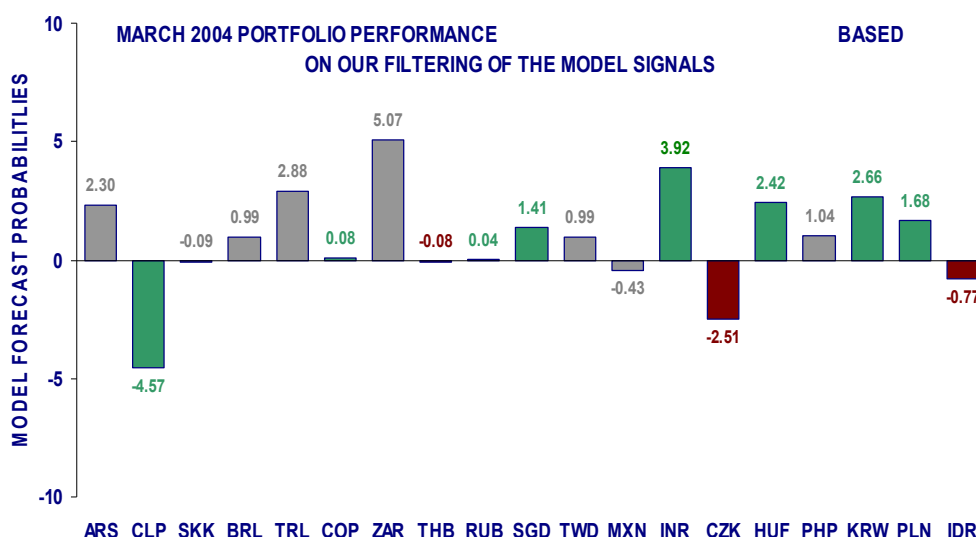
signals. None of the stop losses were actually triggered as all three positions on short CLP, long SGD and long PLN were profitable. From the signals we ignored we avoided a loss of -2.3% in the case of the ARS and a loss of -0.43% in the case of the MXN. The two Asian currency buy recommendations we ignored meant we actually missed out on profits. Both the PHP and the TWD appreciated in March on one month forward rate terms but we feel our judgment to not invest on the back of political concerns was well funded. Of course other investors with higher appetite of risk would have probably not ignored these signals. The other signal we ignored was the long ZAR trade which cost us the highest profit as the rand appreciated by 5.07% in March. Still the arguments we presented against this position would have been enough to deter most investors who trade on the back of macro and other fundamentals and not purely on a speculative basis.

Table 34 Recommendations of model portfolio in March 2004

LOCAL CURRENCY	MODEL RECOMMENDED PORTFOLIO MAR 2004	MODEL RECOMMENDED PORTFOLIO MAR 2004 ADJUSTED FOR SUBJECTIVE VIEWS
ARS	SHORT	NEUTRAL
CLP	SHORT	SHORT*
SKK	NEUTRAL	NEUTRAL
TRL	NEUTRAL	NEUTRAL
BRL	NEUTRAL	NEUTRAL
COP	LONG	LONG
ZAR	LONG	NEUTRAL
THB	LONG	LONG
RUB	LONG	LONG
TWD	LONG	NEUTRAL
SGD	LONG	LONG*
INR	LONG	LONG
MXN	LONG	NEUTRAL
HUF	LONG	LONG
PHP	LONG	NEUTRAL
CZK	LONG	LONG
KRW	LONG	LONG
PLN	LONG	LONG*
IDR	LONG	LONG

* INDICATES WE IMPLEMENTED A STOP LOSS OF 1%

Figure 42 Performance of model recommended portfolio in March 2004



As per Table 35 below overlaying our subjective judgment on the model results meant that overall we scored a slightly higher portfolio P&L of 1.22% compared to the 1.11% if we were to simply follow all the models' recommendations for March. We improved the success ratios for our short trades as we only sold one currency and this trade was profitable. Our long success ratios were slightly worse as we bought ten instead of fourteen currencies and 70% of these trades were profitable compared to 71% success ratio if we had not implemented any judgment. Overall our hit ratio improved to 73% of all trades we implemented compared to 69% before.

Table 35 Performance of model portfolio in March 2004:

MARCH 2004 PORTFOLIO BASED ON OUR FILTERING OF THE MODEL TRADE SIGNALS			
	SHORT TRADE SIGNALS	LONG TRADE SIGNALS	TOTAL TRADE SIGNALS
NUMBER OF TRADES	1	10	11
PROFIT MAKING TRADES	1	7	8
PROFIT MAKING TRADES (% OF TOTAL TRADES)	100%	70%	73%
	NET MARCH PORTFOLIO P&L		1.22

Arguably March is only one month of observations and it is hard to drive solid conclusions based only on this exercise of how subjective views alter the P&L of a portfolio. However March was a very representative month in terms of the model results and more importantly the criteria we opted to apply when filtering the model recommendations. It was also very balanced in terms of how subjective views even the ones that are funded on very sound arguments are not necessarily going to improve overall performance. This is why it is of extreme importance from an investors' point of view to know that his starting point is a robust tool like the PROBAPP and PROBDEP models which when left to perform their objective mandate can be trusted to consistently generate signals that are intuitive and also generate profits.

4.7 Conclusion

Chapter 4 concludes the detailed presentation of our work on building an emerging markets currency model that can be an addition to the toolbox of a wide spectrum of users from academics and members of policy setting centres to and foremost real life investors. In the previous chapters we presented the literature that relates most to our line of work, the ways in which we extended previous research and the steps we followed in selecting the specifications that met the intuitive and statistical criteria we set. In Chapter 4 we proceeded to scrutinise the applicability of our model in a number of ways. We estimate two separate models applying a Logit type of regression analysis on each one in order to model and forecast two different binary outcomes. We transform the model results into probabilities of having or not more than 5% returns from investing in the one month forward exchange rate of 19 emerging

market currencies. What we call the PROBAPP model captures and forecasts the probability of having more than 5% appreciation in any given calendar month, while the model we call PROBDEP estimates the probabilities of local currency depreciating in one month forward rate terms by more than 5%.

The primary task was to decide on the level of model generated probability that we would consider as the cut-off level above which we would categorise model results as trade signals. In doing so we reviewed the model performance when implementing a range of probabilities from as low as 2% to as high as 15%. We applied three different approaches. First we considered each model separately and reviewed the signals each one would have generated at any given probability level. Every time the PROBAPP or the PROBDEP model produced a probability higher than $g\%$ or $k\%$ respectively, we would classify that point as a buy or sell signal accordingly. The second step was to combine the two models when generating and reviewing individual buy or sell trades. For us to classify a point as a buy recommendation two conditions had to be satisfied. The PROBAPP model should have generated a probability higher than $g\%$ and, at the same time, the PROBDEP model should have generated a probability lower than $k\%$. All other signals would have been ignored. The third step was to assess the model results on a portfolio basis whereby we considered the overall group of trades recommended in any given month, both buy and sell recommendations, and quantify the performance of those model generated portfolios.

We first reviewed the Type I, II and III errors to test our models' ability to successfully generate trading signals when fitted to our long in-sample data

series or forecast the shorter out of sample data. Type I error penalises the models for “over-predicting” and generating too many signals for returns higher than 5% while realised returns do not meet this threshold. Type II error penalises the models for “under-predicting” and missing points when realised returns were indeed above 5% in either direction. We also introduced what we called Type III error which filters the Type I errors and captures the cases when the models predicted excessive returns in a certain direction but not only did returns not reach such levels but actual direction was opposite to what the models forecasted. We proceeded to review in a number of formats the profit generating ability of the model. This was applied to the individual and combined results but also, and in greater detail, to the model results that were reviewed on a portfolio basis.

From a sample point of view our tests were performed on three different levels. The first involves what we call the in sample analysis where we estimate and fit the models on a large sample from as early as January 1994 to March 2003. The second involves what we call the out-of-sample analysis, where we first estimate the model on a sample that ends in January 2002 and we then test the model performance on a period of fourteen months from February 2002 to March 2003. The third involves our real time analysis where we apply the models that were estimated on the long in sample period on monthly data that span a whole calendar year, from January to December 2004. The real time data are first reviewed solely on the basis of the objective tests and criteria we set out. We then apply our market awareness and subjective judgement and assess how such elements that are inherent in a typical investor’s decision process would alter the model performance.

Turning first to the selection of the cut-off probability level we applied we found, unsurprisingly, that applying higher probability cut-off points meant the models avoided false trade calls but also missed actual trades. The lower probabilities produced a model that over-predicted moves and ended up with lower success ratios. After considering all the results, we selected the 5% probability for both models as the threshold that provided trust-worthy, actionable trade recommendations while balancing in a satisfactory manner several performance trade-offs such as the three types of errors we mentioned above. The PROBDEP model would have benefited from a slightly lower probability cut-off level but for the sake of consistency we opted for a common threshold of 5%. In-sample and at the 5% probability threshold, the PROBAPP and PROBDEP models were successful in fitting 65% and 55% of actual cases of more than 5% appreciation and depreciation respectively thus missing about 35% and 45% of events. These PROBAPP and PROBDEP success ratios in capturing the currency moves they aim to model, were further enhanced by about 23% and 12% respectively due to the residual from the Type I and Type III errors. These residuals cover the cases where the models predicted the correct direction but not the correct size of returns. In-sample the models were also successful in not signalling non-trades. The PROBAPP and PRBDEP models correctly did not signal a trade in 56% and 67%, respectively, of the times when indeed we did not see returns in the desired direction and of more than 5%. Out-of- sample the PROBAPP model had a small deterioration in its performance capturing a total of 82% of cases of appreciation while the PROBDEP model had a poorer performance with a success ratio of capturing a total of 41% of depreciations.

We proceeded to apply the 5% probability threshold at the individual or combined buy and sell signals and also when looking at the model generated portfolios and assessed the success of the models in generating profitable trades. The PROBAPP signals were profitable in 66% of the cases in-sample and 72% of the cases out-of-sample. The PROBDEP model had a success ratio of profitable trades of around 52% in-sample, which dropped to about 37% out-of-sample. The results were consistent irrespective of whether we looked at single model signals or combined both models. With the exception of the out-of-sample PROBDEP signals we had consistently profit making trades with very high success ratios. The PROBDEP performance could be justified by the higher than optimal probability level we applied to it. Our out-of-sample period covered a risk loving era which meant the models were rightly biased in generating significantly more buy than sell recommendations. Importantly the bulk of the buy signals were profit-making.

Analysing the models on a monthly portfolio basis helps smooth away any minor biases we have mentioned so far and also provides a more rounded overview of the model performance. The 5% probability threshold generated portfolios that involve a significant number of trades each month of which about 60% and 65% were profit making, when looking at the in and out-of-sample periods respectively. Importantly, the portfolios generated an average monthly return of about 1.2% and 0.53% in and out-of-sample and at a Sharpe ratio of 1.85 and 0.8 respectively. With an acceptable degree of variation and only a few exceptions, these results were not biased towards a sub-sample of countries or any specific period that we analysed. The above mentioned results amply confirm our view that the models developed are

indeed reliable quantitative tools that one can trust to consistently generate profit making trade recommendations. Importantly these trade recommendations can be followed blindly without overlaying any type of subjective judgment or even stylized facts evident to investors which may invariably be expected to improve the overall investment performance.

We finally carried out our exercise in real time throughout 2004 and proceeded to overlay our sense of market stylized facts prevailing at the time and our understanding of the technical limitations of our quantitative model. The 2004 model generated portfolios are very much in line with our previous results and, if anything, improve our out of sample statistics. We still have a bias towards more buy than sell recommendations due to the continuation of high risk appetite globally in 2004. Throughout the year we only had one month of loss making model signals. On average per month we had the same number of trades and the same high percentages of profit making signals as in our previous analysis. The annual returns per trade stood at a 4.06% with a Sharpe ratio of 1.16. We concluded our analysis by focusing on the March 2004 results and applying our knowledge of market realities and model limitations. We introduced a number of criteria that suggested we ignore certain model generated signals. For example, we ignored signals that had been reversed by more recent market price actions or signals that went against the intervention policies adopted by country authorities. We also ignored signals that were the result of the model bias to structural breaks. Finally we ignored signals that we felt were too sensitive to follow due to political and other qualitative risks that applied to certain countries at the time. Following the implementation of these guidelines we saw a small

improvement in the March 2004 model results.

Our analysis and findings confirm that our Emerging Markets Currency Models are the sort of quantitative products that can be applied in real life and produce reliable recommendations. Blindly following the model signals results in profitable trade portfolios, while intuition and market awareness assist the deeper understanding and often the better implementation of such signals. In the following final chapter of the thesis we present our work on another quantitative product, the Emerging Markets Ratings Model. The latter is yet one more attempt to quantify one aspect of emerging market dynamics, albeit at a lower frequency and with a more macroeconomic orientation than our currency model. The two products combined help support or cancel signals that can be translated into investment decisions on a number of asset classes in the unquantifiable emerging markets universe.

5 CHAPTER FIVE: Modelling and Forecasting Emerging Market Sovereign Rating Dynamics

5.1 Introduction

The current Chapter describes our work on developing an Emerging Markets Ratings Model. The model forecasts ratings assigned by S&P and Moody's to long-term, hard currency denominated sovereign debt. It provides information about both the ratings and the rating outlooks of 30 emerging markets sovereigns. Tests on historical data indicate that the model performs consistently well in capturing the dynamics of sovereign credit ratings. Our selected specification is a linear description of the linkage between the values of a few key macroeconomic variables and the assigned sovereign ratings. We have not attempted to capture the impact of non-quantifiable variables such as political stability, on sovereign credit ratings. This arguably constraints the forecasting accuracy of the model but it also helps keep the interpretation of its results "clean" of subjective judgments. The model presented here introduces a number of innovative improvements, over what has been attempted and presented in relevant literature in terms of focus, estimation methodology and applicability of results.

In the first four chapters of the thesis we presented in detail the rationale, structure and application of a quantitative model used to model and forecast currency dynamics in emerging markets. The aim of the specifications we called PROBAPP and PROBDEP models was to generate actionable trading signals with regards to near term direction of an emerging country's forward

exchange rate versus the US dollar. The time horizon involved was one calendar month and the key input of the models was the deviation of a country's Real Effective Exchange Rate from a medium term trend which we calculated with the use of Hodrick Prescott filters. The other two variables we included in our currency models were both related to rating agencies. In particular we used the 12 month trailing moving average of the global speculative grade corporate default rate as calculated by Moody's and the downgrades of long term hard currency sovereign ratings by S&P. The former was the only "Global" variable we incorporated in the models and a variable we felt provided a measure of global risk appetite as perceived by markets. The latter was only included in the model of currency depreciations and was seen as a barometer that would weigh on investors' balance of risks as an early warning signal for forthcoming country malaise.

Our findings of strong links between currency risks and rating agencies' data, support the notion that financial market actions and sovereign ratings are often the two sides of the same coin. Rating actions were described in Chapter 2 as a data series that provides packaged information on a country's fundamentals and captures both, quantifiable macro data and qualitative elements of sovereign risk. In this last chapter of the thesis we present our attempts to explicitly model and forecast this variable and prove in greater detail that ratings and rating actions can indeed be explained largely by hard economic data and provide the assumed and desired proxy for a country's macroeconomic outlook.

In Section 5.2 below we present an overview of the mandate and evolution of major rating agencies. Section 5.3 reviews a selection of the most

prominent and relevant academic papers that attempted to model sovereign rating dynamics before us and provide an update of the topics relevant to our findings with regards to more recent research. We proceed to outline how our work compares to previous work and what are the new elements that we introduce in the modelling of ratings and rating actions. Section 5.4 presents in more detail the considerations we underwent when building the model specification we eventually adopted. Section 5.5 presents our findings from applying the selected specification on real time data in 2003 and 2004 and provides a number of examples of how the results of such a model could be incorporated in the agenda of an emerging markets investor. Finally Section 5.6 Concludes.

5.2 Rating Agencies and the Evolution of their Mandate

Rating Agencies are private corporations that assign credit rating scores to a number of entities, corporate or sovereign. The two major rating agencies that we also focus our analysis on are Moody's and Standard and Poor (hereafter referred to as S&P). Both these agencies were set up in the 20th century and were primarily involved in rating corporates. Agencies started assigning developed markets sovereign ratings in recent decades and only expanded to the emerging markets universe in the 1980's. The details of how rating agencies were first set up and how they go about deciding which entities to rate is of little relevance to this thesis. We do however wish to outline a number of characteristics that describe their increasing role in capital markets and highlight the effect of their decision. This in turn helps explain why we think it is worth modelling ratings and rating actions and why we

considered them valid candidates for inclusion in our currency risk models.

As mentioned above in our analysis we focus on the two major rating agencies namely Moody's and Standard and Poor. Both are well established agencies whose ratings are essential elements of market practices. Rating agencies act as independent agents that assess all information publicly or privately available to them with regards to the credit quality of an entity they rate. After combining a number of quantitative analytics and qualitative assessments they conclude with a credit rating relevant to that entity. The fact, however, that agencies are hired by the rated entities themselves has attracted a lot of criticism in terms of their ability to remain objective and independent. We will review the criticism and defence of rating agencies in the next section of this chapter. Once a rating has been decided by the agencies, they promptly inform both the rated entity and the market participants of their decision and thinking process. Ratings are supposed to reflect medium term credit dynamics and capture the overall ability of an entity to repay its current and future credit obligations in full and on a timely manner. The universe of ratings covers a spectrum of scores that is crudely divided into two sub groups. The higher quality ratings form the sub-group that is called Investment Grade (hereafter referred to as IG) and the lower quality ratings form the group that is called Speculative Grade (hereafter referred to as SG). Within each one of these subgroups credit quality will obviously vary. In the IG group the highest rating one can assign is the so called triple A (hereafter referred to as AAA) which describes the best possible credit quality with the minimum, if any, associated risks of default. The SG sub group includes ratings that can range from poor credit quality to what is described as

default or selective default and describes a credit event that has already taken place according to the agencies.

Rating agencies provide scores for a vast number of entities that can be generally grouped to two categories: Sovereigns and Corporates. In our thesis here we are focusing on the sovereign credit ratings that agencies assign to a number of emerging countries. The definition of “sovereignty” incorporates the ability of the entity to act independently of external control and merit political autonomy. Country or central government ratings which are the type we analyse in this thesis, will typically assign a very significant weight on that country’s macro fundamentals and will also attempt to capture elements of political and social pressure that are implicit in all governments’ political framework. When rating Sovereigns, agencies have an even greater incentive to look beyond short term factors and incorporate all possible elements that matter to a nation’s debt repayment plans. Most importantly in the case of a sovereign, agencies attribute a very significant weight not only to the nation’s ability but also to its willingness to service its debt obligations fully and on time. Every nation’s central government is assumed to be able to mobilize enough resources to meet its obligations. However the social and political implications of what are often very tough decisions could affect a government’s willingness to implement all necessary measures. The lack of willingness becomes more relevant for lower rated entities, where the possibility of a credit event and the loss in case of default increase.

A sovereign will not face the same sanctions that a corporate would in case of default. This could at a first reading reduce the willingness of a sovereign to meet its debt obligations. In practice though there are many key

considerations that motivate central governments to service their debt properly and fully. First and foremost history has shown that countries that do select to restructure or default on all or part of their debt face significant difficulties in returning to capital markets. Hence their ability to raise further debt and finance their operations is heavily hindered. This together with the fact that sovereign defaults are almost invariably linked with banking and currency crises results in a significant hit to a country's growth prospects for the near and medium run. Sovereigns are seen as most likely to default on their foreign currency obligations as, in theory at least, they have unlimited ability to print the local currency amounts they need to service local currency obligations. Even before or without actually defaulting, sovereigns may find a number of ways to alleviate their debt burden, like causing an inflation spiral domestically that effectively "eats in" their debt obligations. Sovereign ratings are central to the considerations of all investors considering the specific country. This is also because rating agencies consider the sovereign's foreign currency rating as a ceiling for all other ratings assigned to any entity corporate or other within that country.

The ratings spectrum we described earlier in this section carries a somewhat more specific interpretation in the case of sovereigns. For example S&P describes the "AAA" universe of sovereigns as those that amongst other characteristics "typically have strong political institutions and adaptable political systems, are open to trade and finance and their macroeconomic stability precludes the development of destabilising imbalances and provides an environment conducive to investment." The middle of the spectrum "BBB" sovereigns are described as those for which "the cushion supporting timely

debt service is not as large as at higher rating levels. Political factors play a larger role than at higher levels but orthodox market –oriented economic programs are generally well established.” According to S&P median per capita GDP is far below for these countries compared the median A rating category and “there is likely to be greater reliance upon short term debt and debt denominated in a foreign currency”. At the low end of credit quality below the single B rating S&P finds that “there is a clear and present danger of default. There is considerable economic and perhaps political turmoil. The currency is weakening, inflation is rising and the short term debt service burden is a huge challenge.”

Default is obviously the most important incident in any entity’s history of credit servicing. Agencies define default in a very narrow and rigid fashion as missing or delaying even a single interest payment in part. Sovereign defaults are the most serious of all in terms of their serious and lasting implications. Often people feel that these are only rare occurrences but reality is very different. For example according to rating agencies in the twenty two years from 1960 to 1982, at least 22 countries had defaulted in some shape, form and size towards their creditors. All of these countries were part of the emerging markets universe. In our analysis here we do not care solely about actual default events because with the evolution of markets and the improving growth prospects of most major emerging markets this risk has been diminishing substantially. Even if actual defaults are still a possibility, they are rare and not what we solely aim to model. An entity may exhibit financial stress long before or even without defaulting. Equally an entity may avoid default and recover solidly. Our focus lies on the more high frequency

dynamics captured by all rating actions and their possible implications for markets. The majority of what is described as Emerging Market sovereigns have typically been rated lower than developed market nations. The very nature of emerging markets and their evolving character explains why rating actions are far more common in the case of emerging sovereigns. For our purposes these characteristics mean that we have a far greater number of data points to model, making our exercise more promising.

The assigned ratings also differ with regards to a number of other factors. For example agencies distinguish between ratings with different time horizon, namely short term and long term. They also assign different ratings for different currency risks, namely local or foreign currency. Different rating categories will typically reflect different credit considerations. Nevertheless rating agencies have always been conscious of the market need to use ratings in a way that is as uniform as possible. Therefore the attempt has been to increase the common denominator behind the different rating categories and assign a lesser weight in the idiosyncratic factors. Ratings are in general expected to reflect a view on a number of elements: namely financial stability of the rated entity, probability of default and expected loss in the case of credit event. All these factors are interlinked and also affected by external elements like third party support or the point in the business cycle. Agencies make a point of smoothing through the business cycle and expressing a view that looks beyond the current snapshot of the credit fundamentals of an entity.

In an attempt to create a finer way to convey their views to investors , which would allow them to reflect and adjust their short term views while

standing to their long term convictions, agencies have introduced a number of elements like reviews and outlooks. To be exact S&P refers to the medium run signals as Outlooks and Moody's as Credit-watches. Notwithstanding the possible fine differences in definition or practice we shall consider the two as equivalent and refer to both as "outlooks" in the remaining part of the chapter. Both, reviews and outlooks have a shorter time frame than official ratings and serve to signal the most up to date direction of the agency's assessment. Reviews are more official processes that have a defined timeframe of about three months and indicate the direction towards which an agency is thinking of proceeding. An entity can be placed on review for possible upgrade or downgrade and can subsequently be upgraded, downgraded or confirmed at its current rating. Outlooks were introduced in the 1980's and reflect a less rigid part of the rating process than reviews. Outlooks are not expected to result in a specific decision within a specific timeframe and are supposed to reflect a prospect that could trigger a rating action within the following six to eighteen months. As agencies assigned outlooks for a growing number of years and cases, they improved the way that these instruments are used by them to convey the necessary information to markets, and the way market participants feel comfortable to use such indicators as signals of forthcoming actions.

Rating agencies aim to provide market participants with independent, in depth analysis of the credit dynamics that apply to the rated entities. Market participants tend to use the resulting credit scores as a comparable score they can trust to incorporate in their investment process. The investment mandate of most investors, especially those that solely invest in bond markets, dictates

that they can only invest in securities that have obtained a minimum rating from major rating agencies. Most investable bond indices are designed to incorporate entities of specific rating categories. These indices are often the benchmark against which many investors link their performance. Rating agencies are in practice seen by many official institutions and market participants as quasi-regulators of bond markets but ironically lack any regulation themselves. Agencies have often been accused of a number of limitations that do not serve the interests of investors. The agencies' slow reaction to change of fundamentals, the need to decrease subjective judgement, increase the uniform interpretation of ratings or improve the clarity with which agencies disclose the information available to them are but a few of the issues that are part of an almost constant open dialogue between agencies and investors.

The crisis of late 2010 brought many of these issues again in the limelight. Debates, credit considerations and rating action processes that till then only applied to the riskier emerging markets, became relevant for developed markets. In the aftermath of the great recession that hit markets globally in the middle of 2007, the focus turned to the structural vulnerabilities of a number of countries. In recovering from the 2008 recession, the trend was for governments to step in and take over the debt burden of the private sector and at the same time try to support growth with spending that was largely financed by low cost financing. In Europe sovereign debt accumulation and fiscal loosening led to a number of EU countries breaching the fundamental criteria outlined in the Maastricht Treaty. The implicit or explicit support by the EU became a matter of debate and the ability and willingness

of these governments to service their debt came under market scrutiny. With first the case of Greece that was downgraded a number of times in the space of two years and a number of other EU countries following suit as possible candidates for debt restructuring, the unthinkable had become very likely or, according to many market participants, unavoidable. As we type, these events are still unfolding but they have at a very minimum brought renewed interest on the role of agencies in global markets.

Rating agencies have been trying to normalise their decision making procedures and have been trying to stay as objective as possible. Introducing quantitative processes and tools in the process is one way of proving their commitment to objectivity. It also serves well to assess the historic performance and consistency of these agencies. Historic evidence of their ability to assign proper ratings, inherent default probabilities and resulting loss and recovery values are a very clear cut way to quantify their success ratio. Ratings unavoidably incorporate the element of subjective judgement as agencies avoid using solely quantitative tools in their decision process. In that sense it is futile to attempt to create a quantitative tool to replicate their decisions. It is however very useful to try and model that part of their rating process which is attributable to measurable factors. This is indeed the scope of our modelling exercise here.

5.3 Academic Literature and our Contribution to Sovereign Rating Models Research

Most analysts that have addressed the topic of sovereign debt dynamics have by and far focused on debt crises. The latter typically describes the cases of a sovereign that has defaulted in some shape, form and size on their debt obligations. Similarly, as discussed in the first Chapter of the thesis, most analysts focused on currency crises when researching currency dynamics. Currency and debt crises are events that have been linked in theory or in practice and are often analyzed together. The definition of a debt crisis unavoidably brings the rating agencies in the picture as most consider a sovereign being in default once it has been assigned the Selective Default (hereafter referred to as SD) rating by a leading agency. Unsurprisingly, a significant amount of research has focused on explaining the decision process and actions of these agencies. The motivation is usually the wish to defend or criticise the agencies' responses. Some have found that rating agencies indeed provide early signals ahead of debt crises but others have claimed that agencies react too slowly and too inconsistently to events and more often than not aggravate existing situations instead of helping guide markets and rated entities.

A number of papers have flagged the need for practically usable results and have attempted to link rating actions to market moves. The most obvious and common link attempted is that between rating changes and some measure of spreads of investable securities like bonds, issued by the rated entity. Our take on the analysis of ratings dynamics shares a number of concerns of these papers but extends on previous work in a number of

methodological, conceptual and practical manners which we shall outline throughout this section. This section does not by any means aim to provide an exhaustive overview of research on rating dynamics. We will merely attempt a brief summary of trends in the relevant research and findings in the years that preceded our own exercise which was carried out in 2002 and mention a number of key papers that were published in recent years and relate to our line of work.

The authors that set the base for the analysis of Rating Agencies and their work are R. Cantor and F. Packer who produced two seminal papers in mid 1990's. In 1994 they set out the basics in a paper titled: "The Credit Rating Industry"⁽²⁰⁾ and in 1996 they published the most closely followed piece on the field with the title "Determinants and Impact of Sovereign Credit Ratings"⁽²¹⁾ (hereafter we shall refer to the latter piece as "CP"). In this paper Cantor and Packer use data from 49 rated countries which include both emerging markets (hereafter referred to as EM) and developed markets (hereafter referred to as DM). CP estimate a cross section model where the dependent variable is an average of the ratings assigned by Moody's and S&P and subsequently they run the same regressions for each one of the two agencies separately. Interestingly they find that their results hold in a very similar manner for both agencies individually as well as for the resulting average rating. These ratings are transformed into an index ranging from 1, for the weakest rating they consider which is the lowest in the single B universe, to 16 for the highest AAA rating. The model is estimated with the use of the Ordinary Least Squares method (hereafter referred to as OLS). They use a small group of quantitative variables some of which describe

macroeconomic variables, dummy variables that distinguish between EM and DM and one dummy variable to indicate if a country had a default history or not. The macro variables they test are: the GNP per capita, the real GDP growth, some measure of fiscal and external balance both as ratios to GDP, some measure of external debt again as a ratio to GDP and inflation. CP find that macro data indeed explain ratings by a significant amount and that surprisingly measures of fiscal and external balance do not seem to work as expected. CP also proceed to test the link between ratings and bond yields and find that there is indeed a relationship between the two and that, especially for lower rated entities, rating announcements do seem to have an effect on bond yields and markets.

Again in 1996, N.U.Haque, M.S.Kumar, N. Mark and D.J.Mathieson (hereby referred to as "Haque et al '96") published an equally prominent paper titled: "The Economic Content of Indicators of Developing Country Creditworthiness"⁽⁵²⁾. In their work they focused on panel data for over 60 emerging markets and review their creditworthiness by analyzing the ratings assigned to them by Institutional Investor, Euromoney and The Economist Intelligence Unit. They too find that economic data explain 80 to 97% of the variation of ratings. The variables they find of greater importance are non-gold FX reserves as a ratio to imports, like CP, GDP growth and inflation, and unlike CP current account balance to GDP. "Haque et al '96" also find that events in global financial markets affect EM ratings in a uniform manner, similarly to how we described global risk appetite affects EM currencies in the earlier chapters of the thesis. "Haque et al '96" were also interested in suggesting ways that could, in theory, speed up the process of a country being rated

again or being upgraded following an economic stabilization program. In 1998 N.U.Haque, N. Mark and D.J.Mathieson (hereby referred to as “Haque et al ‘98”) published a paper on “The relative importance of political and economic variables in creditworthiness ratings”⁽⁵³⁾ complementing their 1996 findings by attempting to also capture and incorporate the political variables that determine a country’s rating. They tried to incorporate amongst other incidents events such as coups, assassinations, strikes or major government crises and concluded that although the inclusion of such factors may improve the results, the exclusion does not bias their estimates for economic variables. They conclude that indeed ratings of EM sovereigns’ creditworthiness are by and large determined by economic factors.

G.Larrain, H.Reisen and J.von Maltzan published in 1997 a paper (hereafter referred to as LRM) on “Emerging Market Risk and Sovereign Credit Ratings”⁽⁷⁸⁾ where again they look at a mix of 26 OECD and non-OECD countries throughout a number of years and also incorporate the change in rating outlooks when accounting for rating actions. They run Granger Causality tests between ratings and bond spreads and find that indeed rating actions affect financial markets. LRM also stress that interestingly negative rating actions have a significantly greater impact compared to positive ratings actions. In their paper LRM acknowledge that Rating Agencies were amongst the many that failed to predict the Mexican crisis of 1994-1995 but conclude that rating agencies could play a significant role in the future.

The advent of the Asian, Russian and Brazilian Crises in late 1990’s brought renewed criticism on the workings of Ratings Agencies and the possible bias they may have when rating sovereigns as these provide the bulk

of the rating agencies' fees income. Analysts re-estimated the CP models and found that the relationships failed to reflect what was considered a structural break in 1998. Others focused on re-calibrating the default and transition probability models, in an attempt to re-define the core of the Ratings Agencies mandate. In 1999 G.Ferri, L.-G. Liu and J.E.Stiglitz (hereafter referred as FLR) published a paper on "The pro-cyclical role of Rating Agencies: Evidence from the East Asian Crisis"⁽⁴⁵⁾ where they directly blamed the major rating agencies of multiple failure. They basically accused the rating agencies of both failing to predict but also exacerbating the Asian crisis. In 2001 C.M Reinhart (hereafter referred to as Reinhart) published her work on "Sovereign Credit Ratings Before and After Financial Crises"⁽¹¹¹⁾ and took the criticism one step further linking the debt crises to currency and banking crises as these all share very strong links in the EM universe. Reinhart made the point that ratings should be forward looking and downgrades should precede EM financial crises of the sort we described in more detail in the first chapter of the thesis. Reinhart concluded that practical evidence does not support the leading role of ratings and wondered whether one should question rating agencies for their overall ability to meet their mandate of assessing a sovereign's ability to service its debt. Reinhart makes the point that Rating Agencies' failure to capture forthcoming crises is largely due to the fact that they focus on the wrong set of fundamentals. The criticism in particular is that Agencies focus too much on debt to export ratios and play little notice on important factors such as liquidity, currency mis-valuations and asset prices. H. Reisen (hereafter referred as Reisen) raised similar concerns in the 2001 paper titled "Ratings Since the Asian Crisis"⁽¹¹²⁾ where the point is made that

Rating Agencies failed to learn from their mistakes both in the Mexican and Asian crises and remained lagging rather than leading indicators for the markets. Reisen went as far as predicting that the role of Rating Agencies would and should diminish as a result of their inability to adjust and improve.

In 2001 N.Mora ((hereafter referred as Mora) published a paper that seemed to come to the defence of Rating Agencies. In the paper titled: "Sovereign Credit Ratings: Guilty Beyond Reasonable Doubt?"⁽⁹¹⁾, Mora clarifies the definition of the Rating Agencies Mandate and what one can expect of ratings and ratings actions as leading variables of crises. Mora outlines a number of objections to the FLR paper against Rating Agencies and suggests that once a number of corrections are made to their specification, their results fail to condemn the Agencies. Mora makes the point that the relationship between ratings and spreads becomes more clear when one introduces lagged spreads as dependent variables, but this also reflects the reality that spread markets and ratings are inter-linked and capture similar dynamics. Mora argues that Ratings can indeed be forward looking and good predictors of forward crashes and in particular currency crashes. The Logit panel analysis Mora introduces includes both rating levels and actions or change in outlooks as explanatory variables of future currency crashes. Mora finds that different specifications yield different results but in general rating actions are an important factor in explaining currency crashes. Surprisingly Mora finds that rating levels per se come up with the wrong sign in most specifications. All in all Mora concludes that despite the failures of Rating Agencies, markets still use them as second best but necessary resource and they cannot be proven to be guilty beyond reasonable doubt.

In the relevant research in the years post 2001 the link between rating actions and markets, whether that is reflected in stock prices or bond spreads, was the focus of a number of studies many of which yielded contradicting results. Others continued trying to address the more general issue of debt crises, their causes and the ability of ratings to forecast such crises. Our analysis here does not exactly fall in any of the lines of thinking outlined above though there are more similarities with some and differences with others. We proceed to outline the main points where we have common and different approaches with previous work. Like in the case of our Emerging Markets Currency Model, we carried out our work on developing our Emerging Markets Ratings Model while working in the strategy departments of Credit Suisse. We thus leveraged from the wealth of market expertise and data available within a major financial institution and also worked to improve an existing version of a ratings model. Amlan Roy had re-estimated in September 2000 the previous version of CS's EM Ratings Model (hereafter referred to as Roy 2000) ⁽¹¹⁴⁾. Roy closely followed the work of CP in that he transformed the ratings in index form but chose to extend the index beyond the 16 ranks used by CP and assign the index rank of 20 to the four rating categories below the single B level. Roy focused only on emerging markets hard currency sovereign debt ratings and used only a handful of macro variables against which he regressed the rating levels. Roy performed annual cross-section regressions and found the ability of the macro data to explain ratings to be significant but varying throughout the years. The four variables Roy used were: the GNP per capita at PPP, Import cover defined as the ratio of FX Reserves to Imports, Total external Debt to Exports and Average

Inflation of 3 to 5 years.

In our attempt to model Sovereign Ratings we too focus on Emerging Markets and the ratings of their long term hard currency sovereign debt. We have already found that downgrades are a powerful variable in explaining forthcoming currency risks and we also have seen that default statistics are an important market consideration when assessing near term currency dynamics. In this part of the thesis we outline our work in building a model that uses a small selection of highly significant macro variables that would substantially and consistently explain the ratings and rating actions of the two major rating agencies Moody's and S&P. We cover a universe of 30 countries globally and run both single and multi year regressions of ratings on a number of macroeconomic variables. Our work differs from what has been carried out before in a number of ways which we outline hereafter.

Firstly we want to develop a medium frequency tool that we trust to update regularly and produce reliable indicators of forthcoming ratings and rating actions. Though the very definition and likelihood of default is of central consideration in credit markets we do not focus our analysis only on such incidents but rather aim to capture the whole palette of rating dynamics. Even though the dependent variables of the specifications we create are the rating levels per se, we test our models' performance not only in terms of fitting and describing such ratings but also in terms of their ability to forecast both ratings and rating actions. This element of forecasting success alone distinguishes our work from what was done previously. In our work we acknowledge that post 1998 Rating Agencies themselves have adapted to the request of markets for faster and better reaction by the agencies and the need for them

to be more leading rather than lagging indicators of credit dynamics. Thus we use data starting from 1998 onwards. We run both single year cross-section and multi-year panel models to test the stability of our findings and conclude that we can safely use single-year analysis.

A key consideration in our analysis is that we apply a very significant weight on rating outlooks and consider them as equivalent to ratings. This is a main point that differentiates us from the work done by analysts before us. Our empirical results provide strong support for the inclusion of “rating outlooks” in the model. S&P and Moody’s use changes in the “rating outlook” as the initial signal of a change of their credit-assessment in response to new macroeconomic or political developments. Changes in actual ratings happen less frequently and sometimes with a substantial time-lag from the time at which a change in the macro-environment occurs. It is therefore unsurprising that the explanatory power of our ratings model rises substantially when we use it for forecasting a combination of “ratings and outlooks” rather than when we use it for forecasting “ratings” on their own.

A number of more recent papers by the Agencies themselves but also from independent analysts support our findings with regards to the information content of rating outlooks. In a working paper by the IMF in late 2010 the role of Ratings Agencies is re-assessed in light of the great recession that started with the US crisis, had a domino effect throughout the world and also triggered the sovereign debt crisis of the EU in late 2010’s. In this paper titled: “The uses and abuses of Sovereign Credit Ratings”⁽⁵⁹⁾ the IMF (hereafter referred to as “IMF”) reaffirms that Rating Agencies indeed affect markets through their actions, that downgrades especially through the

Investment Grade threshold cause market reactions and that Agencies indeed convey new information in particular via their use of outlooks, reviews and watches.

A factor in which we differ from all other papers before or after our modelling exercise is that in modelling ratings and rating outlooks we use the rating agencies' own forecasts of macro-data both when building and when applying the models. For example, for the purpose of estimating the model parameters for 2001 we used Moody's own estimates for the 2001 macro variables. We aimed to maximize the likelihood that the data used in our estimations were the data used by the agencies when making their ratings decisions. The admittedly arbitrary choice of data provided by Moody's rather than S&P purely reflects the fact that Moody's data were readily available. Another parameter that distinguishes our work from that of the academic research on debt crises and default dynamics is that we wish to produce a product that will be usable and practical. The Ratings Model we select is the one that performs best when tested for its forecasting power. When forecasting the 2002 ratings for example, we applied forecasts for the 2002 macro-data to the estimated parameters from the 2002 model. These forecasts were produced by highly market sensitive economists of a major investment bank, CS. We present the model selection process in more detail in the following section. We then proceed by applying the selected specification to real time data for a number of years and suggest ways in which an investor could incorporate this type of quantitative product to their universe of decision making tools.

5.4 Model Selection Process

5.4.1 Selection and Transformation of Dependent Variable

Since the seminal paper of Cantor and Packer published in 1996, it has become commonplace to model sovereign ratings by transforming them into an index. Moody's and S&P's ratings range from triple-A (the rating that signals the lowest default risk) to "default" or in the case of many sovereigns "selective default" (the rating that describes that a credit event has taken place). In this thesis we use the terms default and selective default as equivalent and refer to both with the term SD. The method suggested by Cantor and Packer if applied to replicate the whole range of possible ratings assigned, involves transforming ratings into numerical scores ranging from 1 to 20 with higher index scores corresponding to higher default risk and therefore lower ratings. For the purpose of the estimation of the model described here, we chose to use a finer scale that takes into account both the ratings and the rating outlooks and treats the difference between any two points in the index as equivalent. We thus end up with an index that ranges from 1 to 58. For each of the 20 possible ratings-levels, except "SD", there are three possible outlook-levels, "positive", "stable", and "negative". Table 31 below shows the full spectrum of possible ratings, their respective outlooks and their mapping to index format. In our specification selection process outlined below in section 5.4.4 we explain how we tested both the models of ratings alone and those that explained ratings and rating outlooks. Our results strongly supported the inclusion of rating outlooks in the analysis.

Table 36 Ratings and Rating outlooks transformed into Index form

Moodys Rating & Outlook	Index Score Assigned	S&P Rating & Outlook
Aaa positive	1	AAA positive
Aaa stable	2	AAA stable
Aaa negative	3	AAA negative
Aa1 positive	4	AA+ positive
Aa1 stable	5	AA+ stable
Aa1 negative	6	AA+ negative
Aa2 positive	7	AA positive
Aa2 stable	8	AA stable
Aa2 negative	9	AA negative
Aa3 positive	10	AA- positive
Aa3 stable	11	AA- stable
Aa3 negative	12	AA- negative
A1 positive	13	A+ positive
A1 stable	14	A+ stable
A1 negative	15	A+ negative
A2 positive	16	A positive
A2 stable	17	A stable
A2 negative	18	A negative
A3 positive	19	A- positive
A3 stable	20	A- stable
A3 negative	21	A- negative
Baa1 positive	22	BBB+ positive
Baa1 stable	23	BBB+ stable
Baa1 negative	24	BBB+ negative
Baa2 positive	25	BBB positive
Baa2 stable	26	BBB stable
Baa2 negative	27	BBB negative
Baa3 positive	28	BBB- positive
Baa3 stable	29	BBB- stable
Baa3 negative	30	BBB- negative

Moodys Rating & Outlook	Index Score Assigned	S&P Rating & Outlook
Ba1 positive	31	BB+ positive
Ba1 stable	32	BB+ stable
Ba1 negative	33	BB+ negative
Ba2 positive	34	BB positive
Ba2 stable	35	BB stable
Ba2 negative	36	BB negative
Ba3 positive	37	BB- positive
Ba3 stable	38	BB- stable
Ba3 negative	39	BB- negative
B1 positive	40	B+ positive
B1 stable	41	B+ stable
B1 negative	42	B+ negative
B2 positive	43	B positive
B2 stable	44	B stable
B2 negative	45	B negative
B3 positive	46	B- positive
B3 stable	47	B- stable
B3 negative	48	B- negative
Caa1 positive	49	CCC+ positive
Caa1 stable	50	CCC+ stable
Caa1 negative	51	CCC+ negative
Caa2 positive	52	CCC positive
Caa2 stable	53	CCC stable
Caa2 negative	54	CCC negative
Caa3 positive	55	CCC- positive
Caa3 stable	56	CCC- stable
Caa3 negative	57	CCC- negative
SD	58	SD

The second important point with regards to our dependent variable is that despite the higher number of values with the inclusion of outlooks, we still model a bounded variable. Assigned ratings can only take any one from a total of 58 values from AAA with a positive outlook to SD. The explanatory variables we consider however are macro fundamentals like GDP per capita or inflation that are not bounded. This creates the inconsistency of mapping unbounded data series that can in theory at least, take any value, onto a limited range with only integral values. In an attempt to address this concern we effect a Logarithmic transformation to the ratings Index we have constructed as described in Equation 13 below, where:

I_t = the value of the Index of ratings and rating outlooks we described in Table 31 above at time t

L_t = the logarithmic version of the Index of ratings and rating outlooks at time t

Equation 13 Logarithmic transformation of Ratings and Outlooks Index

$$L_t = \ln\left(\frac{I_t}{59 - I_t}\right)$$

Once we regress this logarithmic transformation of the index on the selected macro variables we produce fitted and forecasted values. These we transform back in the more usable and intuitive measure of Index format as described in Equation 14 below.

Equation 14 Transformation of regression results to Index format

$$I_t = \frac{59 e^{I_t}}{1 + e^{I_t}}$$

Again in our specification filtering process we tested both, regressions where the index was used in its original format, which is also the way many others before us have used it, and regressions of the logarithmic version of the index. Our results strongly supported the use of the latter.

5.4.2 Explanatory Variables: Selection process and sources

After testing the explanatory power of a large number of variables, we selected the four that consistently provided for the best model performance. The selected variables are: real GDP per capita expressed in US dollars at a purchasing power parity exchange rate; year-end CPI inflation and two measures of the country's net indebtedness. The two debt-measures are both expressed as ratios of the level of indebtedness to a scale variable. The absolute level of indebtedness is computed as the difference between the whole country's foreign currency debt and the central bank's foreign exchange reserves. The two debt ratios differ only with respect to the scale variables. The first is the ratio of indebtedness to GDP, and the other is the ratio of indebtedness to exports of goods and services. Given the empirical results that other analysts have published, it is not surprising that these four variables (GDP per capita, inflation, and the two debt measures) performed best in our empirical tests, in terms of their ability to describe the rating-actions of S&P and Moody's. Our selection of variables is largely consistent with the findings in relevant academic literature. Let us review each of these variables separately and in more detail.

GDP per capita and inflation appear in our regression-analysis as important explanatory variables of rating actions. Arguably a country with high GDP can repay a given nominal amount of debt more easily than a country with low GDP. This argument fully justifies scaling the measure of a country's indebtedness by GDP. Such scaled debt measure is already included as a separate explanatory variable in our model. It is not necessarily clear why this argument also justifies the separate inclusion of GDP per capita as an explanatory variable in the model. According to our empirical results though, ratings agencies do assign a significant weight on GDP per capita especially when this is measured on a Purchasing Power Parity basis. One possible argument to the defence of this finding is that a particular country's GDP per capita, especially when it is measured at a purchasing power exchange rate, can be seen as a very broad measure of the cumulative success of the country's policies and systemic characteristics over many years. Another more practical reason why GDP per capita matters in the eyes of rating agencies is very simply because it quantifies the extent to which a government can tap into wealth resources and raise the funds necessary to service its debt. This can be done via additional taxation or other administrative or macro prudential measures. The effectiveness of such measures arguably has to be tested on a case by case basis as additional taxation does not always translate into higher fiscal revenues. Here like in the case of the sovereign default risk parameters the willingness of the individuals is of prime consideration, whilst the GDP per capita merely captures their ability to pay more.

Inflation also shows up in our empirical testing as a significant influence

on the sovereign ratings. Again this finding is consistent with the findings of many others before us. There is no direct theoretical link between the level of inflation in a country and the country's debt repayment capacity, except in cases where inflation becomes sufficiently high to be synonymous with chaos. Arguably though, many governments have tried to inflate their way out of their debt burden. Our empirical results indeed point to an inverse relationship between inflation and the ratings-agencies' perception of creditworthiness which we find intuitive. A country using higher inflation to evaporate the value of its foreign exchange debt cannot be praised by the agencies. Therefore it is understandable that agencies will react or will be expected to react with lower ratings in cases of higher inflation. Inflation also tends to be correlated with other variables that are important for a country's sovereign default risk. Thus, the level of inflation may in many cases be seen by the ratings agencies as an indicator that is inversely related to fiscal responsibility displayed over the years.

What we found interesting is that measures of the whole country's indebtedness perform better statistically, as drivers of the agencies assessment of sovereign credit risk than do measures of sovereign indebtedness alone. Our estimation results indicate that both measures have significant explanatory power but that the models work best if only the whole country's indebtedness is taken into account. A possible reason for this is that the ratings agencies may see a high risk that non-sovereign debt within a particular country ends up creating a serious problem for the sovereign in times of crisis. Government may easily face calls for government-sponsored bailouts of banks or systemically important corporates. This is particularly

relevant in Emerging Markets where state support is explicit or implicit in many cases. But as the global recession of the end of 2010s showed, government of developed markets are just as likely and might be even more direct in transferring risk from strained private agents to the government balance sheet, which in turn translates into higher sovereign credit risks.

5.4.3 Model Assessment Considerations

One important element when discussing the explanatory variables considered and selected, is our choice to use the Rating Agencies themselves as data sources. When running a regression on any period we used as model input the estimations that Moody's produced for that period. When we initially selected our specification we used data from 1998 to 2001. The older the data the more the Moody's estimation would have adapted to actual official data. But the more recent data for 2001 for example were indeed estimates. We also tried out both single year and panel estimations in an attempt to test the robustness of our model. In the case of panel data we started with a single year model for 1998 and expanded the time horizon by adding one more year of data each time and tested the consistency of our model. Our findings were largely unaffected by the choice of year or method. We thus concluded that we prefer to use single year specifications which will allow us to best capture the information content from the agencies' macro estimates for any given year. Even if these forecasts were not the best forecasts of released data, it would not matter as our aim is to model ratings in the first place. If these ratings are based on data that will be heavily revised, the ratings will also be revised.

We used annual data published by Moody's in their "Statistical Handbook for Country Credit". This is published quarterly by Moody's directly and includes data on a number of years for a long list of macro variables that Moody's claims to pay attention to in the rating process. The choice of Moody's over S&P reflects simply the availability of such comprehensive data from Moody's at the time of our work. Interestingly our findings suggest that these data work equally well in explaining both the decisions of Moody's and S&P, thus introducing no bias in the analysis. By selecting to use single year specifications, we effectively commit to re-estimate the models on an annual basis. This we feel adds to the ability of the specifications to capture any possible change in the agencies methodology.

When selecting our preferred specifications we fitted each estimated model on the data of the period it was estimated on and on the data of the next calendar year. In the first case we compared the model suggested results with actual results and quantified the models' success ratio. In the latter case we assessed the models' forecasting ability. In this last exercise we used forecasts produced by the emerging market economists of Credit Suisse. At the beginning of a calendar year, say 2003, we would model the previous year, in this example 2002, with Moody's 2002 macro estimates. We would then fit the 2002 Moody's data in the resulting estimation and calculate the 2002 theoretical ratings and outlooks. We would then apply the 2003 CS macro forecasts on the 2002 estimated values to estimate where we think ratings could be at the end of the year. We finally compare the 2003 forecasted values to the actual ratings and outlooks applying at the time of the update. This comparison allowed us to see how much room for upgrades or

downgrades was suggested by the models for every sovereign.

Our models capture levels of ratings and outlooks. However one is also interested in the dynamic aspect of rating agency decisions as depicted by rating actions. Due to the nature of the model workings the most appropriate way of quantifying its success in capturing rating actions is the following: In our example above we compare model generated rating forecasts for 2003 to the 2002 values that resulted from again fitting the models with CS estimates for 2002. This allows us to remain consistent in terms of macro data we compare from the one year to the next. The difference of the CS 2002 fitted model estimates and the 2003 CS forecasted values suggested a direction and size of the rating actions expected to apply to the underlying sovereign. We would then compare these to the actual direction and size of actions taking place in a calendar year. Throughout the real-life application of the models we re-estimated them annually at the beginning of the year and updated them with revised macro forecasts and realized actions quarterly. We review the success of our selected models in the sections that follow.

5.4.4 Specification Selection process

In this section we outline our criteria in selecting a model specification and the explanatory macro variables used as a basis for our ratings forecasts. A large number of different specifications were estimated and tested in terms of forecasting ability and statistical robustness. In particular we run regressions on single year cross-section data from 1998 to 2001 and subsequently we run panel regressions on data starting from 1998 and adding one extra year each time till we included 2001. We finally run a panel

regression that started from 1999, the year past what we described as structural break for the rating agencies methodology, and again included one additional year every time till we reached 2001. We run all these specifications on Moody's data alone, on S&P data alone and on the average rating between the two agencies. We defined the dependent variable as ratings alone and then as the combination of ratings and rating outlooks. We also tested both the regressions where the dependent variable was in index form and in logarithmic transformation. As dependent variables we considered in all the above model versions some measure of the following: Real GDP per capita, CPI inflation, External Debt, Government Debt, FX reserves as a ratio to money supply and an indicator of a government's overall financing requirements calculated as the current account deficit plus debt amortizations adjusted for Foreign Direct Investments and all this as a ratio to GDP.

We opted to select the specification that displayed the highest forecasting power. To choose between different model specifications we applied statistical criteria for the model's goodness of fit such as the R-square, the standard error, F-statistics and information criteria. We selected only variables for which the estimated coefficients displayed the signs (positive or negative) that would be expected on the basis of economic theory and intuition. We made the choice between different variables satisfying this criterion by comparing the statistical significance of their estimated coefficients. We expected our results to be consistent across time.

We chose the model specification that best complied with these selection criteria. This was the single year specification that included both ratings and rating outlooks and in which the dependent variable was included

in logarithmic format. The explanatory variables we included in our selected model were: the log of real GDP per capita on a PPP basis, the end-of-year annual percentage rate of consumer price inflation, foreign currency debt minus non-gold foreign currency reserves expressed as a percentage ratio to GDP and separately as a ratio to exports. The selected model displays a high R-square indicating a good explanatory power. This is true whether the model is used to forecast ratings from Moody's, ratings from S&P or the average rating between the two agencies. The high R-square is consistent across all years, signalling that the structure of the model is relatively stable and thus could be trusted for forecasting purposes. All four explanatory variables display the expected sign in all specifications. As we finally opted for the single year specification we find it of little use to show the actual estimated models because we would have to show the results for every year and each agency as the estimated coefficients change every year. Instead we prefer to tabulate below in a more concise manner the results from the resulting specifications for the four years from 1998 to 2001 which we used to forecast the years from 1999 to 2002 and on the basis of which we selected the single year version. We then proceed to show the results of the model estimated in real time that cover 2002 and 2003 and are used to forecast 2003 and 2004 respectively.

Table 37 Selected specification statistical performance

	1998 model (Used to forecast 1999)	1999 model (Used to forecast 2000)	2000 model (Used to forecast 2001)	2001 model (Used to forecast 2002)
R-squared				
Moody's	70.8	85.2	79.6	73.9
S&P	72.6	78.1	72.7	77.9
Average	73.2	85.6	76.3	76.9
Correct signs*				
Moody's	4 (3,0)	4 (4,0)	4 (4,0)	4 (2,1)
S&P	4 (3,1)	4 (3,1)	4 (3,0)	4 (3,0)
Average	4 (3,1)	4 (4,0)	4 (3,0)	4 (3,0)
Source: Credit Suisse First Boston				
*The numbers in parentheses show how many of the correctly signed coefficients were significant at up to 10% level and between 10% and 20% levels				

For the purpose of assessing the model's forecasting ability we focused on both levels and direction of ratings and rating outlooks. Let us first review the model performance in forecasting what it sets out to model in the first place, rating and rating outlook levels. As explained in more detail in the previous section when estimating the model for a certain year, say 2000, we used Moody's forecasts as input for that year's (2000) macro-data. We estimated the values of the model-coefficients on an annual basis – i.e. we estimated a separate set of coefficients for each year, based on cross-country data for only that year. We then fitted CS forecasts for the following year's macro data, say 2001, to the 2000 model-coefficients. This produced the model "forecasts" for ratings and rating outlooks for the year 2001. For the purpose of testing the forecasting ability of the model, we compare our 2001 model-generated forecasts with the actual ratings at the end of the same year (2001). As Table 38 below suggests, on average, 60% of the model's forecasts for the period 1999-2001 were within one notch of the actual rating,

whereas, on average, 18% of the model-forecasts were exactly right. The “forecast-errors” regarding the level of the ratings might in some cases reflect sluggishness on the part of the ratings agencies, or the inadequacies and simplicity of the model, such as the fact that that model fails to capture political developments.

Table 38 Selected specifications’ power to forecast ratings and outlook levels

Forecasted rating was:	1999			2000			2001			2002		
	Moody's	S&P	Average Rating	Moody's	S&P	Average Rating	Moody's	S&P	Average Rating	Moody's	S&P	Average Rating
Same as actual rating	17%	17%	13%	13%	17%	33%	10%	20%	20%	23%	10%	10%
Higher by one rating	20%	20%	23%	17%	17%	17%	20%	17%	20%	20%	37%	27%
Higher by more than one	13%	23%	30%	20%	23%	30%	23%	23%	33%	17%	17%	37%
Higher by more than two	10%	13%	23%	10%	13%	17%	10%	17%	20%	13%	10%	13%
Lower by one rating	33%	23%	30%	37%	17%	7%	20%	20%	20%	13%	13%	13%
Lower by more than one	17%	17%	3%	13%	27%	13%	27%	20%	7%	27%	23%	13%
Lower by more than two	0%	0%	0%	7%	10%	0%	7%	7%	0%	17%	10%	7%

Source: Credit Suisse First

When testing the directional forecasting ability of the model we compared, for each country, “actual ratings changes” to “changes that the model would suggest”. For example, the model-based forecasts for the direction of change for year 2000 was computed by comparing the model-generated rating-scores when fitting macro-data for 1999 and 2000 in the model that was estimated on 1999 data. The difference between these scores could be directly compared to the actual ratings changes occurring between

the end of 1999 and the end of 2000. The tables below suggest that our model does well in forecasting the direction of change of the ratings. The errors that the model generates are in many cases explained by easily identifiable factors that fit into the universe of non-quantifiable variables that we have deliberately kept out of our modelling exercise. We provide examples of this type of the model limitation later in this section. In other cases, our model produces erroneous model-forecasts because the model responds “too fast” to macro-changes compared to the relatively sluggish responses of the ratings agencies. For the historical period covered by our tests, there are many cases in which the model suggests a directional move in a particular year, but the move only occurs in the following year.

The model’s ability to forecast rating changes is measured below by the share of actual rating actions (changes in either the ratings-level or the ratings outlook) that moved in the direction that was suggested by the model. The model has impressive performance in capturing the dynamics of sovereign ratings. Arguably the model consistently performs best in forecasting Moody’s actions compared to the S&P. This bias however diminished in certain years. Importantly the success ratio in forecasting the S&P actions remains significantly high and above 60% in all cases. In the case of forecasting Moody’s actions the model successfully predicts, direction wise, on average 85% of actions. These success ratios become even more relevant in light of the fact that both rating agencies have been very active in the years of our analysis acting anything from 12 to 26 times in any single year.

Table 39 Selected specification's power to forecast ratings actions:
Share of actual rating actions moving in the direction suggested by the model

	1999		2000		2001		2002	
	number	%	number	%	number	%	number	%
Moody's	13 out of 15	87%	12 out of 14	86%	10 out of 12	83%	18 out of 21	86%
S&P	9 out of 15	60%	15 out of 19	79%	11 out of 16	69%	15 out of 17	88%
Average Rating	14 out of 20	70%	16 out of 21	76%	14 out of 18	78%	19 out of 26	78%

Source: Credit Suisse First Boston

The "forecasted direction of change for a particular year" was calculated as the difference between the model-estimate for the "ratings and rating outlooks" for the end of that year and the equivalent model-estimate for the end of the previous year.

5.5 Model real time application: 2003-2004

Having concluded our theoretical and analytical work, we carefully tested and selected the model specification that we felt best captured the dynamics involved in the decision process of two major ratings agencies when it came to scoring emerging market sovereigns. We tested the model on four consecutive calendar years of input data from 1998 to 2001 and accordingly four consecutive years of forecasts from 1999 to 2002. Like in the case of our currency model we then proceeded to put our ratings model to the hardest test by applying it on real time data to fit and forecast two calendar years 2003 and 2004. At the beginning of each year we re-estimated the model based on the Moody's data for the previous year. This meant that we really did use agency's estimates and not their replication of officially announced data. This is because most macro variables are only available with a significant lag and even then continue to be revised for some time after. Therefore using year-end Moody's data for any given year, does really suggest we are using Moody's forecasts. Over the 2 years during which we run our Ratings Model in this manner, the performance remained very impressive. The results repeat the success ratios of the previous testing period and if anything the bias in

favour of Moody's seems to almost disappear.

Table 40 Selected specification statistical performance in 2003-2004

	2003 model (Used to forecast 2004)	2004 model (Used to forecast 2005)
R-squared		
Moody's	81.7	83.3%
S&P	81.0	74.2%
Average	82.2	82.8%
Correct signs and significance levels*		
Moody's	4 (4,0)	4 (3,1)
S&P	4 (3,1)	4 (2,1)
Average	4 (4,0)	4 (4,0)

Source: Credit Suisse First Boston

* The numbers in parentheses show how many of the correctly signed coefficients were significant at up to 10% level (first number), and b/w 10% and 20% (second number)

Table 41 Selected specification performance in forecasting 2003-2004 ratings levels

Forecast Rating was:	2003			2004		
	Moody's	S&P	Average Rating	Moody's	S&P	Average Rating
Same as actual rating	33%	47%	43%	21%	32%	29%
Higher by one rating	10%	7%	7%	7%	0%	7%
Higher by more than one rating	13%	10%	13%	14%	25%	18%
Higher by more than two ratings	10%	7%	7%	11%	14%	14%
Lower by one rating	7%	10%	13%	21%	7%	11%
Lower by more than one rating	37%	27%	23%	36%	36%	36%
Lower by more than two ratings	13%	10%	10%	18%	18%	18%

Source: Credit Suisse First Boston

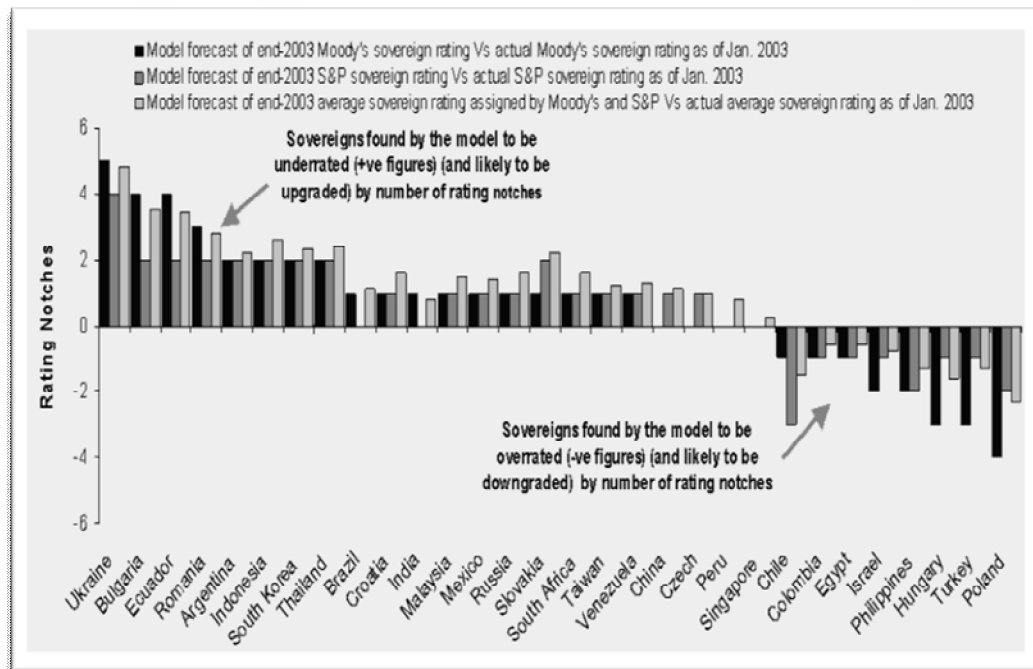
Table 42 Selected specification performance in forecasting 2003-2004 rating actions

Share of actual rating actions moving in the direction suggested by the model		
	2003	2004
Moody's	11/14 (79%)	11/13 (85%)
S&P	15/16 (94%)	13/14 (93%)

Source: Credit Suisse First Boston

At the beginning of each calendar year we would produce two different tabulations of the model forecasts for that coming year. Let's take 2003 for example. In January we would put together the data depicted Figure 43 and Table 43 below. Figure 43 below shows for each country whether our model suggests that the sovereign is "overrated" or "underrated". "Underrating" of a particular sovereign implies scope for upgrades. The sovereigns that appear on the left in the table are, according to the model, "underrated". This implies that there is a positive gap between (1) the model's forecasts for Moody's and S&P's end 2003 sovereign ratings and (2) the actual ratings assigned by these agencies as of January 7th 2003. As a reminder the model forecasts are the result from plugging the CSFB economists' 2003 macro forecasts as of January 2003 in the specification estimated with 2002 Moody's macro estimates.

Figure 43 Differences between Model-forecast for the appropriate level of ratings and/or rating outlooks in 2003 versus actual ratings and outlooks as of January 2003



Even in cases where the model may misjudge the appropriateness of a particular “ratings level” (because it is missing political and other non-quantifiable variables) it can be a useful tool for gauging the extent to which changes in the macro-fundamentals speak in favour of upgrades or downgrades. In Table 43, we show what the model tells us about this. This chart shows the direction of change (over time) in the model-estimate for each country’s sovereign rating and rating outlook.

Table 43 Model-forecast for the direction of change in ratings and/or rating outlooks during 2003: Update as of January 2003

COUNTRY	Argentina	Brazil	Bulgaria	Chile	China
Moody's	↑	↑	↔	↔	↔
S&P	↑	↑	↔	↔	↔
COUNTRY	Colombia	Croatia	Czech	Ecuador	Egypt
Moody's	↑	↔	↔	↑	↓
S&P	↑	↔	↔	↑	↓
COUNTRY	Hungary	India	Indonesia	Israel	Malaysia
Moody's	↑	↑	↑	↑	↔
S&P	↑	↑	↑	↑	↔
COUNTRY	Mexico	Peru	Philippines	Poland	Romania
Moody's	↑	↔	↔	↔	↑
S&P	↑	↔	↔	↔	↑
COUNTRY	Russia	Singapore	Slovakia	South Africa	South Korea
Moody's	↑	↑	↓	↑	↔
S&P	↑	↑	↓	↑	↔
COUNTRY	Taiwan	Thailand	Turkey	Ukraine	Venezuela
Moody's	↔	↑	↑	↓	↑
S&P	↔	↑	↑	↓	↑

Source: Credit Suisse First Boston

Interpretation of the individual arrow's orientation and color:

UP (DOWN) = Model results suggest a favorable (unfavorable) macro-change within 2003

Sideways = Model results suggest a macro-change within 2003 that is small enough to be considered insignificant (representing less than a change in rating- outlook)

The chart's measure of the "direction of change" is defined as the difference between (1) the models forecast for what the rating will be as of end-2003 (this forecast is based on CSFB's latest forecasts for the macro-data for 2003) and (2) the model estimates of what the ratings "should have been" at the end of 2002. The latter is the result of fitting the end of 2002 estimates by CSFB economist for the 2002 values of the macro-variables in the estimated 2002 model specification. At the end of a calendar year we would review the performance of our recommendations in Table 43. We show the results for 2003 in Table 44 below.

Table 44 Model-performance in forecasting for the direction of change in ratings and/or rating outlooks during 2003

COUNTRY	Argentina	Brazil	Bulgaria	Chile	China*
Moody's					
S&P					
COUNTRY	Colombia	Croatia	Czech	Ecuador	Egypt
Moody's					
S&P					
COUNTRY	Hungary	India	Indonesia	Israel	Malaysia
Moody's					
S&P					
COUNTRY	Mexico	Peru	Philippines*	Poland*	Romania
Moody's					
S&P					
COUNTRY	Russia	Singapore	Slovakia	South Africa	South Korea
Moody's					
S&P					
COUNTRY	Taiwan	Thailand	Turkey	Ukraine	Venezuela
Moody's					
S&P					

Source: Credit Suisse First Boston

Interpretation of the individual arrow's orientation and color:

UP (DOWN) = Model results suggest a favorable (unfavorable) macro-change within 2003

Sideways = Model results suggest a macro-change within 2003 that is small enough to be considered insignificant (representing less than a change in rating- outlook)

The way to read the results that are presented in Table 44 is the following: the direction of the arrows reflects the direction of a country's fundamentals when comparing the CS estimates for the previous (2002) and forecast (2003) year. The color of the arrow demonstrates whether there was a rating action in 2003 (grey arrows signal no action, white and black arrows signal a rating action) and whether the realized direction was consistent (white arrows) or opposite (black arrows) to what the evolution of macro fundamentals would suggest. The important point to make is that the rating actions that took place in 2003 and 2004 were widely spread to many of our sample countries and this applies to both rating agencies. In particular around 20 countries had their rating changed by at least a rating outlook in 2003 and 2004. This represents two thirds of our sample of countries. The vast majority of these ratings were upgrades with only three downgrades in each year.

In the remaining of this section we discuss in more detail the way in which we typically presented the results of our model. At the beginning of the year we would review the success of the model throughout the previous calendar year, re-estimate it and present the model signals for the coming calendar year. We would also interpret the results as a combination of the signals in the two formats we discussed above and perform some sort of reality check overlaying market awareness on the model results. Through the remaining of the year we would update the results on a quarterly basis based on revised CSFB forecasts for the current year and the actual rating actions that had taken place till that point. Let us use the results we presented in Figure 43 and Table 43 above as examples of this process presenting the arguments that we made at the time of publication and avoiding the benefit of

hindsight that one would have if looking at the results at a later time. Figure 43 above indicated that at the beginning of 2003 Ukraine, Bulgaria and Ecuador were particularly underrated and that Hungary, Turkey and Poland were particularly overrated. However, it is important to treat the model results with care as the model forms a judgment purely on the basis of a small sample of macro-variables. For Poland and Hungary, the model pointed to “overrating”, because it failed to capture the fact that these two countries had been offered membership of the EU with effect in 2004. However, this does not mean that the model result for these countries should simply be discarded. The model result does show that if Poland and Hungary had not been shielded by this “EU safeguard”, they would, in the absence of a change in their macro-performance, be treated substantially less generously by the ratings agencies than they currently are. For example if Hungary were located in Latin America, its rating would be much lower than it was at the time.

Figure 43 also suggests that Turkey was substantially “overrated” in January 2003. This reflected to some extent the role that the rate of inflation plays in the model. Our estimations suggest that inflation has tended historically to significantly influence the rating action of the agencies, although some economists would question whether this is rational. At the time of publication of the January 2003 results, Turkey’s inflation was low by Turkish historical standards (and still falling), but it remained high in comparison to the inflation-rates that were recorded in other countries. Another important consideration is the fact that the model failed to capture Turkey’s strategic importance to the US, which created financial benefits for the country (such as large-scale IMF support) that helped boost the country’s ratings. Taking these

factors into consideration, we were more optimistic than the model regarding Turkey's rating level. Again according to the results in Figure 43 above Ukraine and Bulgaria were the most underrated countries. Ukraine's political uncertainty (which our model failed to capture) was expected to block the way for further upgrades in the near future although the country macro-data suggested that upgrades would be warranted. Bulgaria was, however, a strong candidate for upgrades, not just because of the macro-performance that was captured by our model, but also, and arguably more importantly, because of the recent at the time decision by the EU to target Bulgarian membership of the union in 2007. In result we expected that Moody's would proceed with upgrades that would align its rating for Bulgaria with that of S&P and Fitch.

If our macro-forecasts for 2003 turned out to be correct, the strongest candidates for ratings upgrades would have been Ecuador and Romania, both of which were in January 2003 "under-rated", according to Figure 43 and both of which were forecast to see a substantial macro-improvement in 2003 according to Table 43. Amongst the list of countries that appear in Figure 43 as being overrated, Turkey, Hungary, Israel and Colombia were, according to Table 43, the only ones whose macro-fundamentals (as measured by the macro-variables that feed into the model) were expected to improve in 2003. The high rating already assigned by the agencies to these sovereigns seemed to have more than fully discounted such improvement. Therefore should our positive expectations for these counties were to materialize, they would allow for a "catching-up" with the already high ratings rather than justify further upgrades.

Besides the obvious merits of having a model that consistently and successfully captures sovereign credit dynamics on the basis of sound macro-considerations there are also other ways that our model could be utilized. One is to apply the estimated specification on unrated sovereigns and gain a sense of how that sovereign should be rated. This is something we actually explored with very interesting findings but given the sensitivities involved in such results especially without the overlay of the effects from factors not captured by the model we feel that there is little point in presenting these findings here . The reason why such analysis may be useful is that, albeit theoretical, it provides a basis on which one can compare this sovereign to others in a more systematic manner. It also provides a metric that can be applied to the corporate universe of that country given that the sovereign hard currency rating reflects a ceiling applicable to all entities rated in that country. Another way one could utilize the model we constructed would be to attempt to link it to some version of actionable trade recommendations like we did in the case of our currency model. This is however less obvious in the case of the ratings model. The first reason is that in this case we would be indirectly modelling a marketable security and the second is the time frame which does not lend itself for such an exercise. For example the first step would be to link ratings or rating actions to some market price. Candidates could be the price, yield or spread of debt securities issued by the rated entity. Each entity issues a number of debt instruments with different characteristics in terms of maturity, liquidity, coupon, currency, even applicable law. It is far from clear which one would be the most relevant instrument to model and it would be even less clear how exactly one should apply the results to other related

instruments. The second limitation is the fact that we modelled ratings using low frequency annual macro data. In any case all these ideas lend themselves as interesting topics for further research.

5.6 Conclusion

The fifth and final Chapter of the thesis describes our work in building an Emerging Markets Ratings Model. We used rating agency data as input in our Emerging Markets Currency Model, presented in great detail in the first four Chapters of the thesis, and we felt that these input variables are both relevant to markets but also connected to fundamentals. In this chapter we thoroughly investigate these assumptions. Our work on building an Emerging Markets Ratings Model was also guided, much like in the case of our Currency Model, by the mandate to create a tool that would generate results that are theoretically sound but also practically applicable. We aim to model and forecast ratings and rating actions by the two leading ratings agencies, Moody's and S&P, that apply to the long term hard currency debt of 30 emerging market sovereigns globally. We tapped on the relevant literature and explore different alternatives for our dependent and explanatory variables. We test out models and base our selection on annual data from 1998 to 2001 as we share the view that post 1998 rating agencies significantly changed the way they operate. This was done on the back of criticism that followed the delayed agencies' reaction to the major financial crises that hit the emerging markets world in the mid 1990's.

We opt to select specifications that are estimated and applied on a single year basis. The dependent variable we model involves an index that

captures the spectrum of ratings and rating outlooks assigned by the agencies. This index is further transformed in a logarithmic fashion in order to be included in the model in a manner that renders it unbounded and allows a better link to macro fundamentals. The results are again transformed to index format and mapped to actual rating and outlook levels. We tap on the relevant literature and the analysis of the agencies themselves to decide on a group of relevant explanatory variables to consider. The variables we finally select are the real GDP per capita on a PPP basis, the CPI inflation rate and the country's foreign currency debt adjusted for FX reserves and expressed as a ratio to GDP and exports. The importance of these variables is consistent with intuition and economic theory but we remain aware of the limitation of our model that only captures a small selection of hard macroeconomic data and omits the very important element of qualitative factors that clearly matter to rating agencies.

Our models introduce a number of new elements that we feel boost their explanatory power despite the limitations we just mentioned. We make a point of including rating outlooks as well. Outlooks are tools that agencies have opted to use in recent years and have increasingly gained attention in terms of their information content. Our findings support the notion that outlooks help convey information that is very relevant to markets and at a higher frequency than ratings alone. We also opted to use macro data as estimated by Moody's themselves. This allows us to model the way agencies link macroeconomic data to their decisions more directly. We also availed ourselves of estimates from market economists to gauge the forecasting ability of the models and its relevance to market expectations. We use annual data in our estimations and

forecasts, though the latter are updated and reviewed on a quarterly basis.

Our models demonstrate consistently high fitting power, and R-squared measures that range from 70% to 85% in the four years of testing from 1998 to 2001. Again in this period all selected variables carry the signs expected by intuition and economic theory. The higher the GDP per capita, the lower the inflation and the lower the debt ratios, the higher the sovereign ratings assigned. Almost all estimated coefficients are found to be statistically significant in the testing period. Our models forecast around 60% of actual ratings assigned within one rating notch. The results are not biased towards a single year or one of the two agencies. The models demonstrate significant power in predicting rating actions. In the four years of our testing period the models correctly forecast about 60% of the S&P actions and about 85% of the Moody's action in terms of direction. We proceed to apply the models in forecasting 2003 and 2004. This is a real life exercise similar to the one we carried out for our EM Currency Model. Again we find that the model results are equivalent to the ones from our testing period and even improve the forecasting ability of both specifications. In summary we find that the parsimonious, quantitative tool we created bodes well in capturing the dynamics of emerging market sovereign ratings which we have found to be of great importance to market participants.

We acknowledge the limitations of a model that purely reflects quantifiable data and proceed to explore the ways in which this would be understood and managed by real life investors. We present a host of examples that overlay reality checks on the model results and suggest ways in which one would best use such a product. The Ratings Model we produce

stops short of producing actionable trade recommendations. We find that this tool is best used as a lower frequency, theoretically sound product that allows for comparison amongst a large sample of emerging markets globally and directly quantifies their macro-economic fundamentals and prospects.

CONCLUSION

With the research presented in this thesis, we opted to produce two theoretically sound, statistically robust quantitative products that aim to model and forecast emerging market currency and sovereign rating dynamics and provide important additions to the toolbox of a wide spectrum of end users. Critically we find that our models can add value to emerging market investors and their market assessment process. Both models are parsimonious specifications that apply to global emerging markets, rely solely on quantifiable explanatory variables, build on the long literature of currency and debt crises and expand previous work in a number of important ways. They differ with each other in terms of time frame and applicability. We are aware of the limitations that any quantitative tool faces. Limitations that are further magnified when the aim is to create a one-size-fits-all model to describe a part of the unquantifiable Emerging Markets Universe. We succeed however in producing two models that objectively capture two very important aspects of Emerging Markets in a way that can be defended by both economic theory and market awareness.

Our Emerging Markets Currency Models comprise of two separate specifications, called PROBAPP and PROBDEP, which model and forecast the probability of each one of 20 different emerging currencies out or underperforming the USD on a one month forward exchange rate basis. With the use of clearly defined trading rules, the model results are transformed into recommendations to buy or sell the corresponding forward exchange rate on a one month horizon. The dependent variables are dummy variables that

capture the binary event of having or not more than 5% returns on either direction in any given calendar month. The explanatory variables are high frequency, leading indicators that are available on a timely fashion, are not revised following initial release and do not require any significant modification. Their effect is not biased towards a country or time sub sample and this allows us to apply a panel specification and estimate common coefficients for all countries. This in turn ensures that results are comparable across countries and time. In effect we select a small set of common denominators that we include in our final specifications. The Real Effective Exchange Rates (REERs), expressed as deviations from a medium term HP trend are the one purely macroeconomic variable that drives the model results. This is also the one variable that merits near consensus approval from all previous research in areas similar to ours. REERs capture exchange rate valuations, trade links and inflation dynamics and provide some sort of fair value measure that one may reasonably expect currencies to revert to. All other macro economic data were excluded on the back of data availability, intuition or statistical findings which suggested they are more coincident rather than leading indicators. The one factor we included as a global risk appetite indicator is Moody's speculative grade default rate. No other tested variable ticked the boxes of consistency and symmetric performance we would expect a global variable to tick. The last variable we only included in our PROBDEP model and acted as an extra trigger for downside currency pressure. This was the S&P sovereign downgrades. Our findings supported the notion that our selected specifications were statistically solid and practically applicable. We tested the models fitting and forecasting ability on a large in-sample period, a shorter

out-of-sample period and in real life data that spanned one whole calendar year. We assessed the profit making performance of the model based on the trading signals that were generated when applying the models separately, when combining the two models in order to provide signals on each direction and on a portfolio basis where we merge both models and both directions to produce one final outcome. Results amply confirmed that the models could be blindly followed and trusted to produce profit making trade recommendations. The overlay of market awareness and intuition further enhanced the results but in no way cancelled the model power.

The first four Chapters of the thesis outline in great detail the considerations behind building the EM Currency Model. The last Chapter presents our work in creating our EM Ratings Model. Both models are related as two out of the three variables that we include in the currency model are from the rating agencies universe. We model long term hard currency sovereign ratings and outlooks and we do so solely with the use of macroeconomic explanatory variables. In doing so we provide support for our notion that ratings act as a proxy for the macro balance prevailing in any given EM sovereign, which we believe explains why rating agency data performed well when included in the currency model. Indeed we found that a small selection of economic data explain the majority of rating actions. We selected a measure of GDP per capita in PPP terms, a measure of consumer inflation and two measures of a country's FX debt burden adjusted for FX reserves and expressed as a ratio to exports or GDP. We applied both single and multi year analysis on data post 1998 which we find to be a turning point for the way agencies rated sovereigns. We made a strong case of including outlooks

as equivalent to actual ratings and found that this significantly improved our results. We also used input data from the agencies themselves and hence modeled their decisions based on their own assessments. The data used were annual and the results were reviewed quarterly. We finally opted to use a single year specification which performs very well in fitting and predicting both levels and direction of ratings for a universe of 30 emerging markets globally.

It is important to stress that almost all the variables selected on the left and right hand side of our specifications, provide a wide spectrum of information in a compact manner. Some achieve this by expressing more than one series as a ratio of one to the other. The ratios of Debt to GDP or Debt to FX Reserves are such examples. In other cases the macro variables we utilize, are calculated based on a number of other macroeconomic data. For example the REERs incorporate information on terms of trade, inflation differentials and nominal cross currency exchange rates between a country and its major trading partners. The GDP per Capita expressed on a PPP basis incorporates GDP, population dynamics and a measure of cross-country competitiveness. Other variables, like the sovereign ratings assigned by major rating agencies, are by construction intended to provide a proxy for a host of quantitative and qualitative factors. Derivatives of such proxies, like sovereign rating actions and evolution of corporate default rates convey equally diversified information. Finally, in our Currency Model we opt to explain market determined forward exchange rates, a variable that itself merges market intelligence and economic theory. The intention to create valid links between compact dependent and explanatory variables is one of the key

contributions of our work that differentiates ours from similar research.

Emerging Markets as an asset class have been continuously evolving in recent decades. Countries have learned from past crises and have applied a host of reforms on fronts like fiscal dynamics, credit and private sector debt controls, currency regime management, policy intervention, institutional structure, corruption and other social indices, reduction of poverty and illiteracy, entrepreneurship and business leadership, economic data consistency and transparency, clarity of policy and market openness. These improvements have brought emerging economies in the forefront of investable markets and have attracted a rising stream of capital inflows. More importantly these inflows have been changing in nature reflecting more permanent and structural funds as opposed to the trigger happy hot flows witnessed in the past. The crisis of late 2000's that started from the US subprime loans expanded with a lasting effect on all Developed Markets (DM). In late 2011 DM were still trying to recover the lost ground and find ways to support the faltering growth that could trigger a double dip recession while addressing deep problematic fiscal imbalances which called for austerity measures. The inflation – growth debate is still ongoing though at the moment the focus has again clearly shifted towards growth, while inflation has most probably peaked in most ways that burden the consumers and producers of the world. Amidst these diverging and powerful effects Emerging Markets have shown tremendous resilience and have minimized the contagion effect from DM to EM. Policy has remained accommodative in EM for the longest of periods, without triggering destructive inflation spirals. The crisis has brought about a new trend in policy setting in both DM and EM. Faced with the limitations of

traditional monetary policy easing via lowering rates, major DMs have embarked in Quantitative Easing (QE) which involves amongst other measures the enlargement of the CBs balance sheet in order to provide further liquidity to the markets while keeping policy rates low for a long period of time. Emerging Markets, faced with the liquidity waves from the DM QE policies reacted with renewed intervention in FX markets and embarked themselves in Quantitative Tightening (QT). Amongst other measures, QT involves a number of macro-prudential policies that allow policy makers to target specific aspects of the economy and avoid traditional economy wide monetary tightening measures that would risk hurting economic growth. The jury is still out on the full assessment of the success of such policies. And we are in uncharted territory in terms of global dynamics.

Times like this offer themselves for a host of research projects many of which could further expand our work here. We have found that all the explanatory variables included in both models remained very relevant throughout the crisis and this suggests that the models still apply in many ways that are useful. It would however be very interesting to apply both modeling exercises to more recent data and further test our understanding. A very interesting idea in light of recent developments would be to apply the models created and presented in this thesis to developed markets. We believe that the recent crisis has triggered a very interesting change of rules whereby DM face risks and adopt policies that have been traditionally linked to EM and EM have developed to act and be treated more like the DMs of the world. And of course one can always try and expand the usability of the models we have created and attempt to link the results to new markets. In

summary we find that we have created two quantitative products that serve well their purpose of assisting the understanding of complicated financial markets, allow the overlay of objective statistical findings and subjective end users' perceptions and in essence provide useful tools to investors, academics and policy makers alike. This was the purpose of our research to begin with. Future research will hopefully build on these findings and expand on our work in ways that will further assist the understanding of markets. In the words of George E.P.Box, whose name is associated with significant statistical breakthroughs like the Box-Jenkins model and the Box-Cox transformations: "Essentially, all models are wrong, but some are useful." What we set out to do in the research presented in this thesis is to create models that are indeed useful and are also found to be right in a number of important aspects.

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