Currency Crisis Early Warning Systems:

Robust Adjustments to the Signal-Based Approach

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Abstract:

This research proposes and tests several novel strategies for enhancing the strength of conventional, signal-based currency crisis Early Warning Systems (EWS). Using country-level, monthly macroeconomic time-series data, it develops an algorithmic process for identifying periods of elevated currency crisis risk and achieves robust results. The proposed changes to current EWS include: 1) an adjustment to the process by which crises are identified empirically, 2) the addition of control panels to dampen the prevalence of false positives, 3) the addition of inter-temporal interaction terms that strive to bring the forecasting model in line with contemporary theoretical models of currency crisis, and 4) the addition of an algorithm for controlling post-crisis bias in macroeconomic trends. In out-of-sample, post-estimation analysis, the system is able to identify 75% of crisis incidents while generating false positives at a rate of less than 20%. Currency crisis EWS have challenged economists for some time, and though these results are not directly comparable to current EWS based on differences in reporting strategies, they are strong enough to warrant further investigation, particularly for applicability as policy instruments.

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Table of Contents

I. Introduction

In recent years, the tumultuousness of international capital and financial markets has led many researchers in the economics community to begin serious investigations of the determinants of market instability. While market fluctuation is as old as markets themselves, the years since the early 1970s have seen the introduction of a dramatic new volatility to international financial system, resulting in a rapid succession of economic crisis events of a magnitude and frequency that is unprecedented in a historical context (Kindleberger and Aliber 2005). Due to their severity, recent episodes of currency crisis and panic, particularly in the 1980s and 1990s, sparked a renewed interest in this field of study. New metrics, methodologies, and frameworks have been developed and revised over the course of the past several decades in the hopes of gaining a more thorough understanding of the sources of market volatility and, in extreme cases, crisis.

This research focuses on one particular aspect of economic volatility: the currency crisis. A currency crisis, a sudden loss of investor confidence leading to speculative attacks, reversal of capital flows, and in many cases, recession, can have a devastating long-term impact on economic performance (Kindleberger and Aliber 2005). Moreover, the uncertainty regarding risk of currency crisis can be detrimental to financial markets even in times of relative stability (Flood and Marion 1999). After all, investor confidence and day-to-day capital market efficiency depend to a degree on markets behaving according to expectations.

To this end, a more thorough understanding of the determinants and conditions of currency crisis is absolutely critical. Understanding the origin of crisis can allow countries to avoid falling into traps, prevent investors from sparking panics, increase the

efficiency of day-to-day financial market operations, and allow economies of all sizes to achieve growth at their full potential. Even though a rigorous understanding of crisis cannot prevent crisis entirely, it can at least allow countries and investors to adjust their expectations efficiently so as to minimize the damage caused by these events Summers 2000, Krugman 1999a).

The major avenue by which economists have attempted to understand currency crisis is in the development of Early Warning Systems (hereafter EWS). EWS incorporate competing theoretical explanations of currency crisis and, through empirical analysis and post-estimation strategies, strive to develop models capable of forecasting periods of heightened currency-crisis vulnerability. To date, economists have been able to generate some very useful observations regarding empirical regularities in currency crisis origin. Though EWS models have not generated highly robust results, the literature is constantly evolving and improving, laying the groundwork for further developments.

This research introduces and tests several new proposals for currency crisis EWS estimation with the goal of improving the robustness of the results. This research poses a series of questions:

1) Does the addition of inter-temporal interaction terms, generated with the intention of bringing the empirical model in-line with the theoretical model, improve the predictive capacity of the results?

2) Will adding a set of countries which have never experienced crisis to the data help to dampen the prevalence of false-positives, improving the robustness of the results?

3) Can omitting the six months of observations following each crisis incident (on the country level) help control for a post-crisis bias in the behavior of economic indicators, making the systems more robust?

The question of whether or not it is even possible to predict currency crises is seriously debated in the literature. Some have argued that the currency crisis phenomenon is strictly a self-fulfilling prophesy – a vicious cycle sparked by factors which are, by their very nature, unobservable and unpredictable (Obstfeld 1986). More contemporary crisis models suggest otherwise, however. The very pursuit of an EWS assumes *a priori* the possibility that there may exist certain empirical regularities among crisis events which might make them, at least in theory, partially predictable (Berg, Borensztein et al. 2005). The goal of this paper is to build upon modern currency crisis EWS by referring to contemporary theoretical crisis models in an attempt to make the systems more robust and predictive.

II. Literature Review

The following literature review will address several important theoretical and empirical topics. It will first review contemporary theories of currency crises. It will then discuss methods of identifying crises empirically within the data. This is followed by a review of several of the most influential EWS strategies, and the section concludes with a discussion of this research's contribution to the literature.

A. Currency Crisis Theory

The discussion of currency crisis EWS must necessarily begin with a definition of the concept of "currency crisis." The following section reviews contemporary, competing

theoretical models of crises, their origins and processes. Theoretical models of currency crises have evolved greatly over time. The major early contributions in this field have come from Salant and Henderson (Salant and Henderson 1978), Krugman (1979) and Flood and Garber (1984). From this foundation springs forth the intuition behind the early warning systems, the subject of this research. The results of these models will be used to inform the intuition and specifications of the EWS proposed by this paper.

With each passing crisis, economists propose new generations of more complex models. The first generation model operates under the premise that a vicious cycle is created whereby dwindling foreign-exchange reserves can no longer finance a rising debt burden. Countries begin to finance deficit spending through endogenously created credit, which is in turn paid off by deficit spending until the cycle can no longer sustain itself (Krugman 1979).

The second generation model is a more sophisticated rendition of this endogenous credit process (Flood and Marion 1999). It differs from the first generation most significantly in that it recognizes and accounts for the effects of speculative attacks from international investors. Noting that a currency is more expensive to defend when it is under speculative pressure and that speculative pressure is not always based on sound information or rational concerns (other than the fear of collective action failure), in second generation models a crisis may be the result of either deteriorating fundamentals, or of a self-fulfilling prophesy (Obstfeld 1996).

For example, Thailand demonstrated poor fundamentals in the prelude to its 1997 financial crisis. Malaysia, on the other hand, maintained a strong, if highly-leveraged economy. Both countries were vulnerable to crisis due to the conditions of certain

indicators that, to borrow Obstfeld's interpretation and phrase, define "the range of possible equilibria." However, Thailand's dive to crisis equilibrium was driven by its own poor economic management which sparked speculative attack. The speculative attack against Malaysia, and subsequent crisis, was the result of investor concerns regarding regional turmoil, not strictly domestic factors. Thailand and Malaysia came to their crises differently, but he second generation model of currency crisis accommodates both of these narratives (Krugman 1999b).

Corrsetti, Pesenti and Roubini (1999) make several logical amendments to this discussion following the East Asian Crisis. They posit that foreign investors believe there to be an implicit public guarantee of their investments, what Krugman later called "moral hazard lending." Investors maintain this delusion until some sudden loss of confidence leads them to believe otherwise, that the government may default or monetize its debt. This belief compels investors in a race to jettison domestic holdings and currency while they retain value, causing a collective action failure and a crisis.

The most complete and contemporary theoretical model, outlined by Paul Krugman in 1999, focuses on the classic Keynesian idea of a "transfer problem." This model, a synthesis of many of the conclusions drawn by the first and second generation models, is the model upon which the specifications of the EWS proposed by this research are most closely based. Krugman hypothesizes the existence of three separate equilibria: a growth equilibrium, a crisis equilibrium, and a transitional equilibrium. The crisis and the growth equilibrium are stable, while the transitional one is not. The fall from growth to crisis through transition is a three-step process, according to Krugman's stylized facts, which underpin the theoretical strategy employed by research.

The process begins with a loss of confidence, either due to exogenous factors such as contagion, or endogenous factors such as liquidity concerns. This loss of confidence manifests in a sudden stop of foreign investment which can turn a current account deficit into a current account surplus. This potentially leads to a transfer problem, the second step in the model. Governments must then find a way to finance a diminishing current-account deficit. This creates a balance sheet problem, which is the third step in the crisis model. This is the stage which may define the difference between a panic and leading to a recession. Weak currency and shock to demand can create disastrous conditions for domestic business causing widespread default, the impact of which may diffuse through the economy causing long-term damage (Krugman 1999a). This research will use the narrative of the Krugman model in an attempt to develop an early warning system which identifies nations at elevated risk of crisis.

Important to note at this point is that traditional currency crisis models have been established in theoretical frameworks assuming hard fixed exchange rates, in which the devaluation decision is made entirely by a monetary policy institution. The language of the preceding paragraphs, however, is left intentionally ambiguous, because extensions of the model to less rigid exchange rate regimes, such as bands or crawling pegs seems to make little difference empirically (Obstfeld and Rogoff 1995). Even floating exchange rates are not entirely defined by market forces. Target and key interest rates and fiscal intervention can distort purchasing power and other factors that the market incorporates into its valuation of currency with a floating exchange rate (Tirelli 1993). Even floating exchange rates may be in some sense defended, if by different mechanisms. This is an important point to be aware of in understanding currency crises, and a potential extension

of the research might attempt to expand the scope of the project to incorporate a more rigorous treatment of different exchange rate regime classifications.

As theoretical models have evolved, the conceptual understanding of the currency crisis phenomenon has been dramatically altered. Once believed to be caused by irrational and unpredictable collective action failure, economists have come to believe that currency crises may actually be based in part on logical economic processes, and therefore may be partially predictable (Berg, Borensztein et al. 2005). This theoretical conclusion motivates the study and development of currency crisis EWS.

B. Empirical Definitions of Crisis

Understanding the theory underpinning a currency crisis is helpful for the intuition of this research's model, but for the empirical goals of this paper, a precise measure of crisis is also important. There is no clear natural empirical cleavage distinguishing a crisis from a panic, or even a contraction. However, the theoretical concept of multiple distinct equilibriums implies that there *is* some regularity between crisis events that makes them distinct from stable periods. Therefore, an empirical treatment of currency crisis almost certainly requires that a threshold for "crisis" be established (Krugman 2000). Certainly in order to estimate a probability model in the tradition of EWS, the research must first identify the occurrence of a crisis. To this end, there are three major competing indices that exist to identify currency crises – Frankel-Rose (1996), Exchange Market Pressure (EMP), and the Kaminsky-Reinhart (1999) index.

This research tests a variant of the Kaminsky-Reinhart for several reasons. It is more precise than Frankel-Rose and more exclusive in its identification of crisis. It is, however,

more inclusive than the EMP index, which fails to identify a number of very important crisis incidents.

The Frankel-Rose Index is very simple. A crisis is defined at any point at which a country experiences a 25% nominal depreciation in currency that is also a 10% increase in the rate of depreciation (Frankel and Rose 1996). Berg and Pattillo note that this definition is too inclusive and may lead to false positives, particularly as it does not account for the fact that some countries regularly undergo large fluctuations in exchange rate and may therefore take 25% depreciation in stride. The number of countries in which the Frankel-Rose index identifies at least one crisis is greater than the number identified by the Kaminsky-Reinhart index by nearly 60 countries when tested side-by-side using the same data (Kaminskey Reinhart 1999).

The Exchange Market Pressure (EMP) index is used by Bussiere and Fratzscher (2006). While the Kaminsky-Reinhart index is a weighted average of nominal exchange rate and currency reserve fluctuation, the EMP index is a weighted average of real effective exchange rate, currency reserve, and interest rate fluctuation. It is immediately evident, however, that this process for identifying crises is vastly more exclusive than the KR index, the implications of this issue being addressed in the full review of Bussiere-Fratzcher later in the paper. In light of these issues, this research will perform its tests using an adjusted Kaminsky-Reinhart index. Appendix A presents a list of currency crises identified using the Kaminsky-Reinhart Index.

Kaminsky and Reinhart employ a weighted average of change in exchange rate and change in international reserves. The index takes the value ***I***, which is calculated:

$$I = \frac{\Delta e}{e} - \frac{\sigma_e}{\sigma_R}\frac{\Delta R}{R}$$

where e is nominal exchange rate in units of foreign currency per $US, R is reserves, and the standard deviations σ refer to the standard deviation of the percent change in each variable. A crisis is defined when I is three standard deviations above its mean.

Though this index initially seemed to be well calibrated, preliminary testing of the data shows that it may need some adjustment. The problem, as is verified visually by the Kaminsk-Reinhart Index graphs in Appendix B, is that relatively stable countries still fluctuate on a day-to-day basis. A positive shock of three-standard deviations in a stable country is hardly noticeable next to a three-standard deviation shock in a volatile country, giving international investors little reason for concern.

This problem is highlighted by the fact that each of the non-crisis countries added to the sample registers multiple instances of phantom crisis on the Kaminsky-Reinhart index, with the exception of Japan.

One key contribution of this literature is the augmentation of the Kaminksy-Reinhart Index, a process described in the Methods section. This augmentation makes the crisis identification process more responsive to the base-line volatility of countries, and therefore makes the index more widely applicable across countries at different stages of development.

C. Current Early Warning Systems

Now that the method for establishing the start-date of a crisis has been formalized, this research will review several previously established forecasting mechanisms. Five of the most prominent EWS are those by Kaminski, Lizondo and

Reinhart (1998), Berg and Pattillo (1999), Edison (2003), Bussiere and Fratzcher (206), and Kumar, Moory and Perraudin (2006). This research will focus a critical lens on the methods and results of these tests. It builds upon their strategies and proposes several additions to the methodology in the hopes of yielding more robust results and reliable predictions.

1. Kaminsky, Lizondo and Reinhart (1998)

The Kaminski-Lizondo-Reinhart forecasting method was published as the international financial community was still reeling from the East Asian financial crisis. The authors were among the first of many to attempt the project. Though their method was quickly supplanted, many of their ideas can still be found in modern forecasting systems. The authors (hereafter KLR) identify the most commonly cited variables associated with currency crisis[1] and arrange them as time-series for each country. They then normalize the percent change of each indicator to a percentile. The rationale behind normalizing each variable is that investors build expectations based on past performance, and while a 10% fluctuation in money supply may be enough to cause panic among investors in one country, it may be routine for investors in another. It therefore makes results more easily comparable across countries.

Through trial and adjustment, KLR pick a percentile threshold for each variable. If the country-level indicator crosses this threshold, they believe, a currency crisis is likely within the next 24 months. The authors then find noise-to-signal ratios for the correlation between a threshold-crossing and the occurrence of crisis in the subsequent 24 months.

[1] Real exchange rate, terms of trade, M2/reserves, lending rate/deposit rate, exports, bank deposits, international reserves, stock price index, excess M1 balances, real interest differential, domestic credit/GDP, current account/GDP, M2 multiplier, imports, and industrial production.

They then create a composite indicator that is the weighted average of all of the indicators, with weights assigned by the inverse of their noise-to-signal ratio, alongside a composite indicator, similarly weighted. The KLR method is fairly complex, and though it is insightfully crafted, it does not produce robust results. KLR report that the method fails to predict 91% of crises, and 44% of the alarms it produces are false positives.

2. Berg, Pattillo (1999)

Berg and Pattillo (1999), hereafter BP, follow up with a critical evaluation of KLR, citing weak results as the impetus for updating the framework. BP apply the indicators and thresholds identified by KLR to a probit model using a series of regressions in an attempt to uncover a more robust EWS. They first estimate a piece-wise probit regression for each individual indicator using the KLR threshold as the spline point, estimating the likelihood of a currency crisis in the subsequent 24 months. The next regression that they perform is of a set of variables, one dummy for each indicator equal to 1 if it is below the threshold and 0 otherwise. A third regression uses a linear continuous variable for the percent change in each indicator (normalized to a percentile). The final regression places splines at each indicator at the KLR threshold and regresses all of the piecewise functions at once, as a large set of independent variables against the dependent variable of "likelihood of crisis in the subsequent 24 months." While these models edge progressively closer to robust results, they are ultimately not very explanatory, the strongest of the models (the latter) having an adjusted-R^2 of 0.145.

Edison (2003)

Edison (2003) utilizes the existing BP and KLR framework, and expands it to address certain very important issues. He uses KLR's signal extraction technique and BP's

probit-based approach, makes several additions to their strategies. Edison expands the sample by adding five new countries. He also, critically, adds a set of global indicators such as G-7 output and oil price so as to account for overall market conditions. These changes produce small yet robust improvements in the model. Ultimately, Edison's research reinforces the importance of real exchange rate fluctuation, short-term-debt, and M2/reserves ratio in forecasting currency crises. Though his model still produces a very large number of false positives and only achieves, as he puts it, "moderately robust" results for the indicators, he is optimistic that further investigation can lead to stronger results.

Another interesting aspect of Edison's work is that he tests the model's strength using a competing definition of crisis, the Frankel-Rose Index in addition to the Kaminksy-Reinhart Index. The Frankel-Rose Index is much more inclusive, giving Edison a broader sample of crises from which to draw data. However, his results are not significantly different. This result helps to dispel a potential criticism that the results of the EWS may highly dependent upon the definition of crisis.

3. Bussiere, Fratzcher (2006)

Bussiere and Fratzcher's (hereafter BF) "Towards a new early warning system of financial crisis" is one of the most modern, advanced EWS. The BF paper differs from the others discussed in two primary ways. As mentioned previously, it utilizes an EMP index, setting the threshold for currency crisis indication at two standard deviations above the mean. This is a drastically more exclusive index than either the KR or the FR, to the point that BF identify only 24 crisis incidents. What's more, they use only monthly data

from 1990 to 2001. This is attributed to a belief that the characteristics of the international monetary system were fundamentally different in the 1970s and 1980s.

The second major deviation of the BF methodology is that instead of using a binomial probit model, it attempts a multinomial logit model. It assigns outcomes to be $Y_{i,t}=0$ in the case of a tranquil regime, $Y_{i,t}=1$ in the case of a crisis, and $Y_{i,t}=2$ in the case of a regime that is in the process of recovery from a crisis (based on a methodological definition of recovery involving a stabilized EMP). This strives to remove what the authors call a "post-crisis bias" in the results of other models, a term which is grounded in the reasonable assumption that economies behave differently during recovery periods.

The BF multinomial logit model reports significantly stronger results than any of the previous models. The model predicts very strongly in-sample, failing to forecast only one of the 24 crises identified. It is far weaker out of sample, however, a shortcoming which speaks to methodological concerns regarding sample selection. Nevertheless, its results are very promising, and this research's methodology will certainly be informed by the multinomial logit approach identified here. The primary benefit to the multinomial logit approach is that it effectively drops post-crisis periods from the sample based on the assumption that activity in these periods is abnormal.

4. Kumar, Moorthy, Perraudin (2003)

The Kumar-Moorthy-Perraudin model is the closest methodological counterpart to this research design. It follows Berg-Pattillo in the basic structure of a probability model, but diverges in three key aspects.

First, it chooses logit over probit (laying the groundwork for BF). The rationale behind this choice is based upon the skewed distribution of the dependent variable, there being many more non-crisis observations than crisis observations. The logit strategy, the authors propose, is better equipped to process these characteristics.

Second, the authors provide a sound intuition for the use of lagged variables. Previous research has sought to describe crises as the confluence of simultaneous motion across several different metrics. Kumar, Moorthy and Perraudin, on the other hand, add lags to the variables in the hopes of strengthening their results. The lags are not, however, designed in a targeted manner, but rather placed on all variables as a forecasting catch-all.

Finally, the authors select a definition of crisis closely related to Frankel-Rose index, citing the idea that this definition is targeted towards investors whereas the EMP index is more useful for policy. This choice, however, changes the nature of their sample.

Kumar, Moorthy and Perraudin achieve relatively strong results with their model. While it uses a rather short time series (12 years) and a divergent definition of crisis, at its most robust it correctly predicts 34% of crises and 69% of calm periods. However, these results are based on a very particular method of interpretation. The authors divide the 1990s into three time periods – early, mid and late. Their conditional probability reports are referenced to these three time periods. For example, if countries that did experience crisis in the early 1990s register a crisis based on the system, this is recorded as a true positive. If they do not, this is a false negative, and so on. This is a valuable approach in some ways, but is not sufficiently useful to describe the system's efficacy in a policy context.

D. Contributions

Each of these models represents an important contribution to the early-warning system literature, and informs this research. Thanks to this prior literature, the field possible macroeconomic indicators has been narrowed to a select set of key variables. Additionally, the precedent of using monthly observations for forecasting is very important, particularly since the early 1990s as the velocity of money continues to increase. The use of a likelihood function, as well as the identification of piece-wise thresholds, two common features of the literature presented here, represent important intuitive advances of the field as research seeks to adapt the second and third generation model of crises.

The literature lays a solid foundation for further investigation. The research presented here seeks to make several adjustments to the models, building on that foundation. First of all, it includes methodologically selected control observations. Second, it applies the intuition of theoretical currency crisis models to the specification of inter-temporal interaction terms. Third, it reevaluates the crisis identification process to make it more widely applicable, a process described in the Methods section. Finally, it executes an exhaustive, easily replicable series of post-estimation conditional probability tests that will allow more meaningful comparisons of results across the literature.

1. Non-Crisis Control Countries

The first proposed change to the methodology of currency crisis warning system modeling is to add a set of non-crisis countries. This is not a possibility discussed in the any of the papers reviewed by this research, but it could be an important addition. After all, assuming an accurate definition of crisis, the addition of further data has the potential

to make the model more robust. Particularly, the addition of countries in which no crisis has ever occurred should reduce the number of false positives reported by the model by including a larger number of moderate signals with negative outcomes. Even in countries which experience crisis, an observation which does not precede a crisis is a valuable observation as a control point. Full time series from countries without crises should effectively add a large number of observations to the control group.

However, it may also be possible that the addition of these controls will weaken the results. Given the intuition of the second generation crisis model, which allows for the possibility that currency crises are not based entirely on endogenous factors, countries which have never experienced a crisis may be in some way predisposed (whether by governance or some other factor) to avoid crisis. This would cause omitted variable bias and would diminish the results. For this reason, the model is tested both including the non-crisis countries and excluding them.

The non-crisis countries were surprisingly difficult to select. The first attempt involved randomly selecting countries from a list of those that had been volatile enough to experience crises by the hyper-inclusive Frankel-Rose index, but not volatile enough to register a crisis by the Kaminsky-Reinhart index. The problem with this, however, is that the list is mostly composed of countries that are either so torn by war and conflict as to be ineffective in demonstrating the natural processes of a financial system, or so small and closed that speculative pressures which are integral to the crisis model could not possibly be involved. Eventually, this research settled on a working methodology.

The list of non-crisis countries will be the G-20, minus those which are on the Kaminsky-Reinhart list and the United States, which operates with different processes

based on the dollar's status as a reserve currency, and Russia, which underwent a paradigm shift with the fall of the Soviet Union. The list of non-crisis countries is identified in the list of crisis incidence in Appendix A.

2. Inter-Temporal Interaction Terms

The second proposed changed to the methodology of currency crisis warning systems is to add several time-lags to the independent variables and to interact these variables across time periods. The impetus behind this proposal is based on the intuitive considerations of the theoretical models.

The third generation crisis model tells the story of an intricate process by which a specific *sequence* of events triggers a precipitous and abrupt disruption in the exchange market status quo. Most current early warning systems, however, operate under the assumption that by analyzing spot-levels of all relevant indicators in a single time *t*, that sufficient information can be gathered regarding the direction of an economy.[2] This research posits that in order to identify an event that takes place in sequential stages, a regression analysis must mimic the theoretical process and apply time-lags such that the independent variables are treated as sequential stages of a process. This is accomplished by creating inter-temporal interaction terms, a process that is discussed in the Methods section.

The potential benefits from assigning time-lags and creating interaction terms among independent variables are great. The process may enhance the robustness of results while simultaneously offering empirically support for the theoretical crisis model. There are, of

[2] Granted, many of these indicators are measured in first-differences, and therefore technically incorporate two time periods. Nevertheless, these systems measure first-differences for all indicators in the same period.

course, drawbacks to using the lags as well. If the wrong lags were assigned, or lags had turned out to be an inappropriate change to the framework, the results may be weakened. There are also methodological concerns. For example, one of the assumptions of time-lag regressions is that of stationarity – that is, each sample is pulled from an identical normal distribution of possible outcomes. This is almost certainly untrue given the nature auto-correlated time-series indicators, particularly in crisis settings. However, the exact impact of this issue on the results of the regression is difficult to determine.

The two major changes that this research proposes to the regression framework established by priors are the addition of non-crisis countries to the sample, and the addition of theoretically specific time-lags and interaction terms on the independent variables. Both of these changes have the potential to improve the strength of the early warning system, but neither is without potential drawbacks. The third change dealing with an adjustment to the crisis identification index is motivated in the literature review and described in the Methods section.

E. Data

Dr. Andrew Berg of the International Monetary Fund was extremely generous in sharing his data for the following countries: Argentina, Bolivia, Brazil, Chile, Colombia, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Pakistan, Peru, the Philippines, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Urugay, Venezuela and Zimbabwe. For the available countries, this research used Dr. Berg's data on CPI, nominal exchange rate, and international reserves. The original source for this data is the International Monetary Fund's International Financial Statistics database.

Data availability proved to be a tremendous constraint on the execution of this research. Many time series, particularly those associated with developing countries and those involving interest rates, are not available even for the 1990s, much less for series dating back to 1970s.

Gathering a wide breadth of data was an anticipated challenge, but even gathering data which would allow the research to calibrate its methods against the models presented in the literature proved to be impossible. This setback may have been caused by updating of the online databases. Nevertheless, while the data cannot be said to be identical to that used in the literature, it is the most recently available data, and it is, most importantly, internally consistent.

III.Methods

The methods section of this paper is divided into three major segments. It first discusses changes to the crisis identification index. It then engage in an overview of modeling techniques and methods, and follows this with an explanation of the independent variables utilized. Finally, it discusses strategies for post-estimation, analysis, and test of robustness.

A. Adjustment to the crisis identification index

Using the standard Kaminsky-Reinhart process for crisis identification, reasonably stable countries may empirically register crisis based on a very low gross fluctuation; levels which have not, historically, caused investors to panic. A more dynamic crisis identification system, such as the one proposed by this research, would require relatively

stable countries such as Norway to register an *I* value further from the mean than countries which are historically less stable. For this reason, the research presented here will employ the concept of the kurtosis – a measure of "peakness." Instead of simply identifying crisis using the standard deviation of *I*, the research adjusts the standard deviation by a term that incorporates the kurtosis such that more stable countries must experience a greater relative shock to *I* in order to register crisis.

After calculating the index *I*, this research calculated the kurtosis of *I* by country. Kurtoses ranged from 4.2 to 304, a high kurtosis indicating that much of the variance in *I* comes from quick and violent fluctuations (unstable countries), a low kurtosis indicating that the variance is due mostly to lots of moderate fluctuations (stable countries). Observation of the Kaminsky-Reinhart Index indicates that crises are well-identified in the most unstable countries, thus indicating that the adjustment term for the most unstable countries should be equal to about one.

Further observation of the Kaminksy-Reinhart Index indicates that control countries must have a threshold set at about four to five standard deviations above the mean so as not to falsely register crisis. Thus, the research strove to develop an adjustment term that would ordinally re-index the kurtosis measures of *I* to values between 1 and 3 from their original values between 4.2 and 304. The following term was developed to meet these specifications:

$$\sqrt[4]{\frac{350}{Kurt(I)}}$$

Dividing 350 by the kurtosis ensures that the more unstable countries have an adjustment term closer to one, while the more stable countries have higher adjustment terms. The fourth-root compresses the range to approximately 1 to 3, as desired.

Adding two to the adjustment term brings the term back into line with the original index such that unstable countries (with a kurtosis-adjustment term of 1) must register an *I* value 3 standard deviations above their means. Under this new system of crisis identification, a country will register crisis if:

$$I_t > \sigma_I * \left[\sqrt[4]{\frac{350}{Kurt(I)}} + 2 \right]$$

A side-by-side comparison of the crisis lists generated, found in Appendix A, demonstrates the value of this approach.[3] Its ability to pare "junk results" is particularly evident for the "control countries."

B. Independent Variables

Though the breadth of independent variables was significantly constrained by data availability, most of the important concepts discussed in the Krugman 3rd Generation crisis model can be, in some respects, examined.

1. Broad Money

The change in broad money is monitored in an attempt to identify an expanding gap between growth equilibrium and shadow crisis equilibrium. The Krugman model notes

[3] The data has been cleaned such that crises which occur within 18 months of a previous crisis are not considered distinct crises. If there is one observation which registers on both indices, it is preserved. Otherwise, the first crisis chronologically is preserved.

that crisis situations are most likely to occur after periods during which growth in investment exceeds growth in financeable investment. The literature, for the most part, utilizes an M2 money supply indicator to capture this concept. However, for the time period and country sample, the broad money indicator is the closest available substitute. The anticipated sign of this variable is positive.

2. Balance of trade

A positive change in the current account may be the result of a sudden stop in investment from abroad. A country that experiences growth in broad money followed by a reversal in current account may very well be on the verge of experiencing a currency crisis. However, because overall current account data is mostly unavailable, this research utilizes balance of trade, a major component of the current account, as a proxy. This is calculated by subtracting imports from exports (the only data available at the monthly level). The hypothesized sign is positive.

In addition to the change in balance of trade, the research also tests balance of trade directly. This variable may operate as a valuable control, helping to methodologically distinguish developing countries from developed countries in the data. Developed countries will tend to have a positive balance of trade while developing countries will tend to have a negative balance of trade. The hypothesized sign is negative, as developing countries are more prone to currency crisis.

3. Domestic credit

Domestic credit measures the amount of credit extended by domestic institutions to domestic agents. The model anticipates an expansion of domestic credit as a means of maintaining balance of payments in the midst of a current-account reversal. Thus, an

expected positive sign on this variable may be indicative of a government that is in the process of compensating for the withdrawal of foreign capital. The hypothesized sign is positive.

4. International reserves (minus gold)

The sharply negative change in international reserves minus gold in may also be indicative of a government that is attempting to finance a current-account reversal, much like the change in domestic credit. The hypothesized sign is negative.

5. Nominal Exchange Rate

A control for the nominal exchange rate seeks to monitor pressure on the currency. In fixed exchange-rate regimes, a devaluation of the nominal exchange rate might have been forced by speculative pressure, and in regimes which incorporate bands and crawling pegs, quickly dropping nominal exchange rate may indicate a loss of confidence in the currency. The hypothesized sign is negative.

6. Change in GDP for an Aggregate of Advanced Economies

This indicator, following the literature, aims to control for the affect of global demand. The currency crisis model predicts a contraction in global output being a possible explanation for the sudden lethargy of foreign investment. The hypothesized sign is negative.

7. Number of previous crises

Based on the intuition that investors may be more likely to initiate a self-fulfilling prophesy of crisis in countries which they know to be prone to crisis, this variable tallies the number of crises experienced by a country since the beginning of the sample (Pesenti

and Tille 2000). This variable is not accounted for in the literature, though this research believes it may have an important impact with a significant, positive sign.

C. Modeling Strategies

The data limitations faced by this research were the among the primary motivations for the particular modeling strategy it pursues. Since it would be impossible to replicate the results of models reviewed by the literature, it was particularly important to devise a strategy for modeling which would allow for meaningful internal comparisons of the different *conditions* represented by previously published models. This research strives to test the value of adding inter-temporal interaction terms and control countries and the importance of controlling for post-crisis bias. Therefore, it tests models with the interaction terms and without them, and then repeats these tests under three conditions. The first includes control countries and post-crisis periods, the second omits control countries, and the third controls for post-crisis bias by omitting 6 observation-months after each crisis from the time-series (an ersatz analog to BF's multinomial logit approach, but one that facilitates meaningful comparison of results). By using this strategy of comparing different models under multiple conditions, it is possible to make internally consistent comparisons regarding the effect of the concepts that this research strives to test, even if external comparisons are impossible.

Creating the specifications for each specific model was a multi-step process. The dependent variable is standard across much of the literature: a dummy equal to one in the twelve months preceding crisis, the "target zone" for an alarm system, and equal to zero

otherwise. Settling upon the specific independent variables as well as their temporal ordering was more complex.

Across countries and time, macroeconomic indicator data was mostly complete for international reserves minus gold, domestic credit, nominal exchange rate, balance of trade, and broad money, but little else. The literature establishes the fact that gross levels of these indicators should be less important than their percent changes, so this research transformed the data accordingly.

Next, in order to determine the proper order of the time lag, this research calculated Bayes Information Criteria (BIC) scores for regressions of each indicator against the crisis dummy for time-lags *t* through *t-15*. Though there were no definitively significant differences in the BIC scores,[4] there were small, observable minimums for each indicator. The relative position of these minimums initially informed the order of the time-lags in the model specifications.

Once the relative lags had been established, the next step was determining the precise definition of each indicator to be tested. As discussed in the literature review, there is a variety of different possibilities. Some research uses the percent change of each indicator, other research uses a signal-based approach which simply identifies a relevant threshold for each indicator, while still other research uses a spline technique, creating a piece-wise function with a breaking point at the aforementioned threshold. In a series of preliminary tests, this research attempted each of these three processes and found by far the most significant to be the signal-based dummy variable approach. This is unsurprising given the general understanding of the currency crisis phenomenon to be, at least in some sense,

[4] This is particularly true given that there are small holes in the data at various points meaning the sample size for each regression was not identical, making comparisons of BIC scores less meaningful.

self-fulfilling. The most important predictor of impending crisis should be an uncharacteristically violent shock to an indicator, not necessarily how much *more* violent that particular shock is than others. Because of these preliminary findings, this research adopted a signal-based approach to the model. It should also be noted here that the indicator broad money was not found to be significant under any of the tested circumstances.

This research follows KLR in identifying the relevant thresholds for each signal as being the top or bottom 10th percentile of percent change observations for each indicator (Top or bottom determined by hypothesized sign as stated in the section above. For a table of country-specific indicator signal thresholds, see Appendix C). It then created a dummy variable equal to one if the indicator is past the threshold in a given observation, and equal to zero otherwise. After these dummies were established, the model specification process began.

D. Specifications

After determining the order in which the indicators should be placed, the next task of the research was to determine the proper way for the specifications of the model to mimic the process described by the theoretical currency crisis model. Each of the four outlined below are estimated using time-series, panel logit regressions with a Δt of one month and panels defined by countries.

Model 1 simply allowed two time-periods of each macroeconomic threshold indicator to be tested side-by-side. This reflects the concept that each signal should be relevant in

more than one time period, but not necessarily that they are relevant as they interact across time periods. Specifications of this model are as follows[5]:

$$logit(target = 1) = ytCredit_t + ytCredit_{t-1} + ytReserves_{t-1} + ytReserves_{t-2} + ytEXR_t + ytEXR_{t-1} + BOT_t + Crises + AEdGDP + \varepsilon \quad (1)$$

Model 1 serves, in a sense, as a control against which to measure the value of the inter-temporal interaction framework proposed by this research. To that end, the next model tested is a more direct attempt to describe what the theoretical model acknowledges is a sequence of relevant events. Thus, at this stage, it was important that the indicators somehow interact across time periods. Here, the research creates a set of inter-temporal dummy variables, equal to one if an indicator is past its key threshold for *two sequential observations*, and equal to zero otherwise. Using this method to capture the inter-temporal nature of the currency crisis phenomenon, and again using BIC score minimization to determine the relative time lag placement of each interaction term, the research estimated the following model:

$$logit(target = 1) = ytCredit_t * ytCredit_{t-1} + ytReserves_{t-1} * ytReserves_{t-2} + ytEXR_t * ytEXR_{t-1} + BOT_t + Crises + AEdGDP + \varepsilon \quad (2)$$

It was surprising that the only way to achieve significance with the balance of trade indicator was in the form of its gross value. The theoretical model predicts that a current

[5] The prefix *yt* indicates that the variable is a dummy equal to 1 if the indicator is across its threshold. *Credit* refers to domestic credit, *Reserves* refers to international reserves minus gold, *EXR* refers to nominal exchange rate, *BOT* refers to balance of trade, *Crisis* refers to the number of crises experience, and *AEdGDP* refers to the change in GDP for an aggregate of advanced economies.

account reversal is a critical component of the currency crisis process. However, the fact that the gross value is significant offers support for the possibility that it can help distinuish between developed and developing countries.[6] Thus, the subsequent model adds an interaction term with a dummy variable for Organization for Economic Development and Cooperation (OECD) membership, to try to control for this characteristic. The specifications are as follows:

$$logit(target = 1) = ytCredit_t * ytCredit_{t-1} + ytReserves_{t-1} * ytReserves_{t-2} + ytEXR_t * ytEXR_{t-1} + BOT_t + BOT * OECD + Crises + AEdGDP + \varepsilon \quad (3)$$

Finding the interaction term *BOT*OECD* to be insignificant, this research removes it for the next regression. Model 4 is much like model 2, except that it removes the advanced-economy aggregate in an attempt to understand the relevance of this control.

$$logit(target = 1) = ytCredit_t * ytCredit_{t-1} + ytReserves_{t-1} * ytReserves_{t-2} + ytEXR_t * ytEXR_{t-1} + BOT_t + Crises + \varepsilon \quad (4)$$

Each of the models listed above was estimated under each of the three testing conditions. Full results of the estimations are available in Appendix D. The first modeling strategy involves testing both logit and probit models because Kumar, Moorthy and Perraudin use logit while Berg and Pattillo favor probit. KMP's choice of logit is corroborated theoretically (van den Berg, Candelon et al. 2008), based on the fact there are many more observations which *do not* contain a crisis than which do contain a crisis, implying that the error term is likely to be strongly one-sided. Nevertheless, this research found no difference between the two results, and thus presents results only from the logit regressions, being ostensibly theoretically sounder.

[6] The data confirms this: the mean balance of trade is US$584 billion in control countries and - US$115 billion in non-control countries. The difference in means is significant at <1%.

E. Post-Estimation and Tests of Robustness

The significance of the coefficients for an EWS is an important indicator of strength, but it is not a sufficient measure of the robustness of the model, nor of its value as a forecasting system. As the priors indicate, there are many metrics upon which models may be judged as EWS, beyond simply adjusted R^2 values and tests of significance. The most intuitive, and ultimately the most useful metric if the EWS is to be understood as a policy tool, may be one of the simplest: a set of conditional probabilities that can be compared across models, techniques and conditions. This research reports the following statistics for each of the four models under each of the three conditions[7]:

Pr(alarm issued | on target) = Probability that an alarm will sound at some point during the twelve months preceding crisis (true positives)

Pr(not on target | alarm issued) = Probability that a crisis will not occur in the subsequent 12 months given the fact that an alarm has sounded (false positives, type II error)

In order to test these models and conditions, this research used *STATA* to generate a predicted value of the dependent variable for each observation and then normalized this output from a z-score to a probability score. This research then used Excel's "Goal Seek" function to identify an "alarm" threshold for the probability score such that alarm would catch 75% (or as nearly as could be estimated) of all crises. The research then recorded the identified threshold and all of the relevant conditional probabilities (including type I

[7] In these conditions "on target" refers to the fact that the observation is in the twelve month "target zone" that precedes each crisis. An ideally functioning EWS would produce Pr(alarm issued | on target) = 1 and a Pr(not on target | alarm issued) = 0, indicating that every crisis is preceded by an alarm while there are no alarms in any observation other than those which precede crises by twelve months or less.

and type II error). These results are referred to as the in-sample conditional probabilities, as opposed to the out-of-sample conditional probabilities which were tested next.

The rationale behind testing out-of-sample probabilities is well-established in the literature: to simulate the true functioning of an EWS, one should estimate the value of the dependent variable using only the information that would have been available at the time. This research accomplishes the out-of-sample prediction for observation in month t by estimating the model using the data from all countries, but only from time periods before t. It then uses these model specifications to predict the value of dependent variables in all countries for time *t*. This is repeated for each month between January 1970 and December 1997. However, since this means that estimations of earlier observations are based on fewer available observations, this research assumes the predicted values of observations before January 1980 to be based on insignificant models. Therefore the out-of-sample conditional probability tests are based only on predicted values from January 1980 through December 1997.

Though the model estimations yielded highly significant coefficients, initial attempts at performing conditional probability tests yielded type II errors which were convergent to 100%, rendering the EWS nearly useless. Upon this discovery, however, this research began an investigation into the phenomenon and identified one crucial, overlooked characteristic of the data.

F. Adjustment based on Characteristics of the Signal-Based Approach

Upon discovering that its initial EWS tests had failed, this research focused an investigation on the distribution of the predicted values of the outcomes.[8] Mean comparison t-tests revealed that the mean predicted value of the EWS was significantly higher (at <1%) for observations in target zones than for observations outside of target zones. This is a desirable, anticipated outcome. However, a t-test performed comparing the means of the predicted values for control countries versus non-control countries yields surprising results.

Countries which have never experienced crisis, for which there are no observed target zones, have a significantly higher (at <1%) mean predicted value of the EWS than do the countries which *have* experienced crisis. This is an unexpected result, and one that may have gone unnoticed if not for the inclusion of the control countries. However, upon further investigation, this result beings to make sense. The standard deviation of predicted values for the EWS in the control-country group is also significantly higher than that of the non-control countries, and ultimately, this research believes that this is attributable to the signal-based testing approach.

By definition of the signal-based approach, an indicator passes its country-specific threshold if its observed percent-change is in the top or bottom tenth percentile (depending on the indicator) based on a normal distribution. Since the standard deviation of indicators in more stable countries is smaller, the percent change in each indicator needed to register a signal is also smaller.

[8] All investigations discussed here took place using the outcomes of model 3 under condition 1, but can be replicated to analogous results using the other models and conditions.

The signal-based approach seems most useful in modeling phenomenon which depend on a "tipping point." Moreover, it is important to create country-specific signal thresholds for indicators, because investors adjust expectations by country. However, because the signals are defined based on the assumed normal distribution of *single* indicators, the joint distribution of all of the indicators is not controlled. The signal thresholds for indicators in the control countries are so low in gross terms that two signals being issued simultaneously in a control country may go entirely unnoticed by investors, while two simultaneous signals in a non-control country may be catastrophic. In fact, across all observations, the probability that two or more signals are being issued by a control country is almost 1/3 higher than the probability that two or more signals are being issued by a non-control country.

The EWS proposed by this model, as well as many of its priors, sums signals as independent variables. Even though the signals are often benign among more stable countries, the probability of multiple signals being issued simultaneously is greater due to the fact that a far lesser shock is necessary to issue each signal. While this may not affect the outcome of the regressions because, as discussed, control countries are effectively identified in the regression by their Balances of Trade, it is reflected in the predicted values of the EWS, and is largely responsible for the extremely poor performance of the first EWS attempt.

Once the issue was identified, the solution became simple and logical. More stable countries have higher joint probabilities of issuing multiple signals. Therefore, the standard of their EWS predicted values is also much higher. Dividing the normalized EWS predicted values by the country-specific standard deviation of normalized EWS

predicted values yields an adjusted EWS series which is re-indexed to be more sensitive to the nature of joint-probabilities given the signal-based approach. Each EWS (all models under each condition) were adjusted using this process, and the resulting adjusted EWS series was used to perform the final conditional probability tests. [9]

IV. Results

The results section is divided into three major segments. First, this research will present the estimates of final model specifications under the three testing conditions described in the Methods section. It will then present a set of comparisons based on the out-of-sample, post-estimation tests. Finally, it will draw several general conclusions based on these findings.

A. Model Specifications

The full results of the four models specified in the Methods section are presented in three tables in Appendix D, one table for each of the three testing conditions. A preliminary review of the results reveals several important similarities. Most importantly, across models and conditions, no variable changes sign, even with the addition of the controls for advanced economies and balance of trade in OECD countries, all signs remain the same. Moreover, across all iterations of model 1, the temporally distinct signal variables have the same sign as their respective interaction terms in models 2 through 4. This is encouraging because it suggests that the addition of the inter-temporal interaction

[9] Though the standard deviation is not an out-of-sample measure, another indicator could surely capture the concept that it describes. One possible extension of this research would be to identify this indicator.

terms does not change the nature of the model's estimation of the indicators, only the strength.

In addition to experiencing no sign changes across models and conditions, there is remarkably little change in the magnitude of the coefficients. Indeed, the only coefficient which is markedly varied when estimated under different specifications and conditions is the constant term. Across all models, it is about 1/3 less negative under condition two, without control countries, than it is under either of the other two conditions. Interpreted appropriately as the output of a logit model, this indicates that the predicted EWS value is, greater under conditions that include the control panels. This is an expected result.

Interpreting the coefficients of the estimated model specifications also yields few surprises. Both when tested distinctly in two time periods and when conjoined as an interaction term (though some of the signals lose significance when separated) all of the signal-based indicators, domestic credit, international reserves, and exchange rate have positive signs. This indicates that, as desired, when a signal is issued the predicted EWS value rises and the probability of impending crisis increases.

The sign on balance of trade is, predictably, negative. As discussed, this likely has much to do with the fact that the most crisis prone countries are the less developed countries, which historically maintain current account deficits. While the magnitude of this term is extremely low, it is important to remember that balance of trade is measure as a continuous variable from, in this research's sample, about -5,000 to 14,000 units,[10] while most other variables are defined as either zero or one. Moreover, under each of the three conditions, this coefficient becomes slightly less negative with the addition of the (insignificant) balance of trade and OECD interaction term. Even if this variable is

[10] Here units are billions of US$.

ultimately insignificant, it is logical that controlling for the effect of balance of trade in more developed countries would diminish the magnitude of the overall balance of trade coefficient.

When employed, the control variable for growth in GDP of an aggregate of advanced economies is always significant with the expected sign. In years of lower growth among advanced economies, there may be less consumption of imports from developing countries, and a diminished flow of capital to developing markets. This negative shock to a developing economy may be instrumental in pushing the market in the direction of currency crisis.

The one very surprising result is the coefficient for the number of previous crises, which is consistently estimated to be significantly negative. The hypothesis suggests that investors should be wary of countries that are historically prone to crisis, and that a panic would occur more readily than it may in a historically stable country. The model estimations, however suggest otherwise. Interpreting the significantly negative coefficient, the more crises a country has experience, the *less* likely it is to experience another. This might make sense if one were to understand investors as adjusting expectations of stability such that they come to be more comfortable with the volatility of historically volatile markets. However, it is not possible to say whether this is a realistic portrait of investors, as the decision to withdraw capital is certainly based upon a wide variety of unobserved factors.

With the exception of the variable controlling for the number of crises, all of the signs in each of the models and under each of the testing conditions are as hypothesized. What's more, the strong levels of significance for the coefficients in most of the

estimations bodes well for the strength of the model. Though *STATA* does not report R^2 values or mean-squared errors for panel, time-series logit regressions, the truest test of strength for the EWS estimated here is the set of conditional probability tests outlined in the Methods section.

B. Post-Estimation and Conditional Probability Results

The post-estimation and adjustment technique outlined in the Methods section generates 24 different EWS series: four models, tested under three conditions each, predicted using in-sample estimation and then using out-of-sample estimation. By using "Goal Seek" to identify a threshold bringing each alarm system to a level at which it forecasts 75% of crises, comparing the strength of the different models is a trivial matter of examining the type II error. Type I error (false negatives) will be equal to 25% across the board, as it is simply the opposite of the Goal Seek parameter. This research can easily decide which model is most useful for forecasting by identifying the model that produces the fewest false positives given a consistent number of true positives. The complete results, including the identified threshold and a set of conditional probabilities for each of the 24 EWS is available in Appendix E.

Overall, the EWS algorithm performs extremely well. Setting the thresholds of the different series such that an alarm sounded on exactly 75% of crises, the out-of-sample tests yield a false positive rate of only 21.7% averaged across all series. Though, as discussed, because of reporting technique, it is impossible to make an exact comparison of these results against the results of the literature, among currency crisis Early Warning Systems, these results are very strong. Moreover, the choice to test multiple models under

multiple conditions allows this research to make internally consistent comparisons between its results, allowing it to test the value of its proposed additions to the modeling process. Several graphical examples of the functional currency crisis EWS are available in Appendix F.

Both for in-sample and out-of-sample testing, condition 2, the estimations that omitted the control countries, does not perform as well on average as either of the two conditions which do include control countries. This supports the hypothesis that the addition of control panels to the model estimation may help to dampen the prevalence of false positives.

The value of the inter-temporal interaction terms is less clear. Though it seems apparent from the initial estimation that model 1, that which does not include the interaction terms, is far less significant than any of the others, it performs inexplicably well in post-estimation testing. Though out-of-sample, model 4 performs best on average, model 1 is a very close second. Moreover, and somewhat shockingly, in-sample testing reveals model 1 to be the best by several percentage points. Based on these outcomes, the value of the inter-temporal interaction terms for improving the accuracy of EWS is inconclusive.

Controlling for "post-crisis bias" in the tradition of Bussiere and Fratzcher proves to be a valuable addition to the framework. In both in-sample and out-of-sample testing, condition three, the condition which omits six country-months following each crisis incident, outperforms either of the other two conditions. What's more, in both in-sample and out-of-sample testing, the model averaging the lowest type II error achieves its best results under condition 3. These results support the hypothesis that controlling for post-

crisis bias in the model estimation phase can improve the accuracy of currency crisis early warning systems.

C. Discussion

The study of currency crisis forecasting is complex and dynamic. Beyond difficulties emerging from data constraints and inevitably unobserved factors, there lurks possibility that perhaps crises are not predictable after all; perhaps they truly are the result of random, sporadic collective action failures, and the best that economics can do is to identify over-exposed economies. Currency crisis forecasting literature all begins by asking the question "Are crises predictable?" Optimistically it assumes that, given the correct tools and accurate data, the answer is yes. This research follows in that tradition.

This research derives much of its motivation from the existing literature on currency crisis forecasting systems. From the basic framework of the probability model to the very indicators that this research estimates, each portion of the design has a theoretical or literary prior. The proposals that this research has tested, the inclusion of control countries, the testing of inter-temporal interaction terms, and the control of post-crisis bias, were simple but effective. As a policy tool, an Early Warning System which can predict 75% of incoming crises while only sending up only one false signal in five is a valuable result, and one that merits further investigation.

Of most pressing interest for further research is the previously discussed joint-probability issue associated with the signal-based approach. Understanding the true impact of this joint-probability phenomenon, and perhaps developing a more efficient

way to incorporate into the testing methodology, could be very valuable towards the goal of improving the results.

For example, the Peruvian case (for graphical reference, see Appendix F) is problematic algorithmically, even if it is simply interpreted by observation. It exhibits peaks around the appropriate target zones as well a handful of small false-positive peaks. However, the baseline value of the Peruvian EWS in economic stasis is above the alarm threshold. Clearly this is problematic, and by addressing the issue of joint probabilities, it seems as if it would be possible to overcome challenges such as these.

In a similar vein, this research's adjustment to the Kaminksy-Reinhart crisis identification methodology is sufficient for its purposes, but far from ideal. There is much room for improvement in simplifying the empirical definition of these devastating economic events.

A final suggestion for extensions of this research is the development of regional signals. Creating a number of weighted aggregates for each region and including them in the regression with a dummy interaction term such that they are only specified for countries within the given region, may help to control some of the less observable affects of contagion. Though the third generation model indicates that a country must somehow be at-risk for contagion to precipitate a currency crisis, a control for regional turmoil may help to control for this currently unobserved element.

The importance of understanding the origin of currency crisis, both theoretically and empirically, cannot be overstated. The results achieved by this research are strong, but there is still much room for improvement. Steady, incremental progress in the study of currency crisis Early Warning Systems offers much hope for the future of economic

development. It is my hope that subsequent investigations into the field of currency Early Warning Systems will critique and incorporate the contributions and conclusions presented herein.

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VI. Appendices

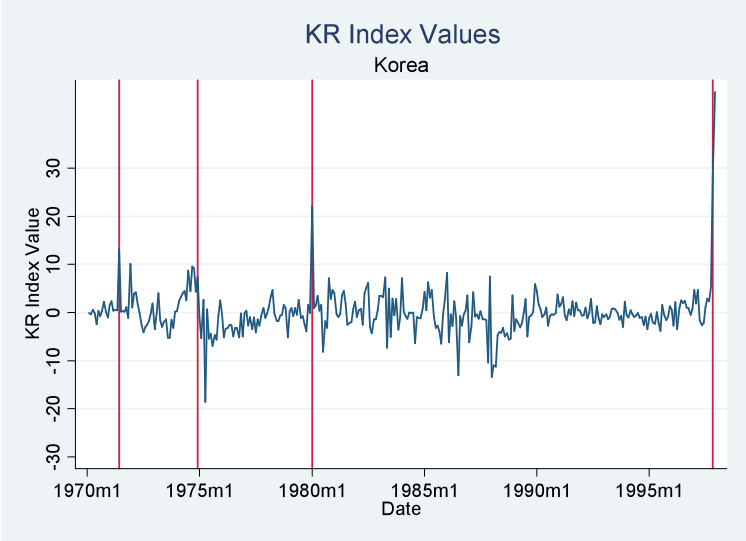
Appendix A

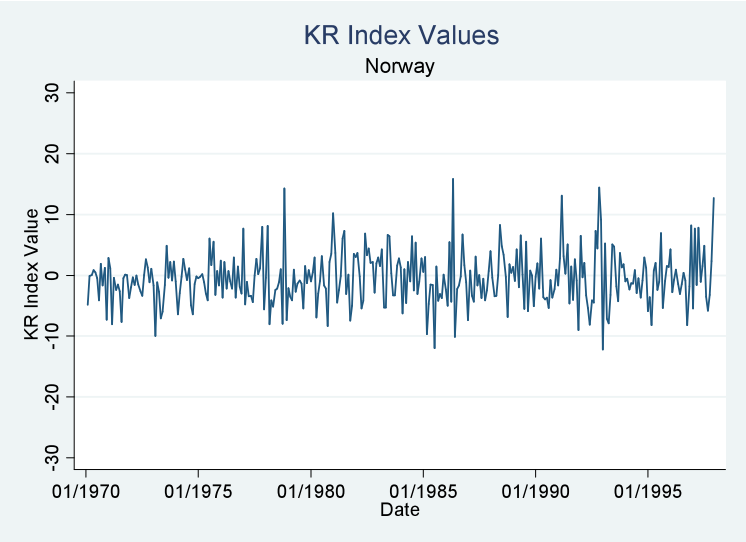
List of Crisis Incidents by Original KR Measurement and Adjusted KR Measurement

Country	date	KR Index	Adjusted KR
Argentina	1975m6	*	*
	1982m7	*	*
	1989m4	*	*
Bolivia	1982m11	*	*
	1985m2	*	*
Brazil	1990m2	*	*
	1994m6	*	
Chile	1972m9	*	*
*Columbia**	1985m4	*	
	1997m1	*	
India	1991m7	*	*
	1993m3	*	*
Indonesia	1977m11	*	*
	1982m4	*	*
	1985m9	*	*
	1996m12	*	*
Israel	1974m11	*	*
	1977m11	*	*
	1983m10	*	*
Jordan	1988m10	*	*
Korea	1971m6	*	*
	1974m12	*	*
	1980m1	*	*
	1997m11	*	*
Malaysia	1975m7	*	*
	1993m12	*	
	1997m8	*	*
Mexico	1976m9	*	*
	1982m2	*	*
	1994m12	*	*
Pakistan	1972m5	*	*
Peru	1974m2	*	*
	1988m9	*	*
	1990m8	*	*
Philippines	1970m2	*	*
	1983m10	*	*
	1986m2	*	*
S.Africa	1975m9	*	*
	1984m7	*	*
	1986m5	*	
Sri Lanka	1977m9	*	*
Taiwan	1987m9	*	*
	1997m10	*	*
Thailand	1981m7	*	*
	1984m11	*	*
	1997m7	*	*
Uruguay	1971m12	*	*
	1982m11	*	*
Venezuela	1984m2	*	*
	1986m12	*	*
	1989m3	*	*
	1994m5	*	
	1995m12	*	*
Zimbabwe	1982m12	*	*
	1991m9	*	*
	1994m1	*	*
	1997m11	*	*
Greece	1983m1	*	*
	1985m10	*	*
	1991m3	*	
Egypt	1979m1	*	*
	1989m8	*	*
	1991m3	*	*
Spain	1976m2	*	
	1991m3	*	
	1992m10	*	
Finland	1982m10	*	
	1991m3	*	
	1992m9	*	*
Sweden	1975m7	*	
	1977m8	*	
	1982m10	*	*
	1992m11	*	*
Norway	1975m7	*	
	1978m11	*	
	1986m5	*	
	1991m3	*	
	1992m10	*	
Denmark	1978m11	*	
	1991m3	*	
China	1986m7	*	*
	1989m12	*	*
	1994m1	*	*
S.Arabia	1978m11	*	*
	1986m6	*	*
Australia	1974m9	*	*
	1976m11	*	*
	1983m3	*	
	1985m2	*	*
	1989m2	*	
Japan	1978m11	*	
	1995m8	*	
Germany	1978m11	*	
	1991m3	*	
Canada	1976m11	*	
	1980m3	*	
	1982m6	*	
	1985m2	*	
Italy	1976m1	*	
	1980m3	*	
	1991m3	*	
France	1978m11	*	
	1982m6	*	
	1991m3	*	
UK	1991m3	*	
	1992m9	*	

[* denotes crisis incident by given definition] [Shading denotes control country]

Appendix B





Crisis Event

Appendix C

Thresholds for Piecewise Functions of Percent Change in each variable, by country*

Country *Upper/Lower threshold*	Domestic Credit *upper*	Broad Money *upper*	Balance of Trade *upper*	Reserves *lower*	Exchange Rate *lower*	Lending Rate *lower*
Argentina	0.1558	0.1587	1.2908	-0.1558	0.0000	-0.1192
Australia	0.0251	0.1292	1.8843	-0.0765	-0.0240	-0.0370
Bolivia	0.2500	0.2221	2.0811	-0.1677	0.0000	-0.1250
Brazil	0.3972	0.1737	1.0633	-0.0690	0.0000	-0.0513
Chile	0.1239	0.1609	2.7481	-0.0994	-0.0059	-0.2226
Canada	0.0211	0.1453	1.9505	-0.1003	-0.0117	-0.0526
Colombia	0.0595	0.1369	1.5417	-0.0667	0.0028	-0.0223
Denmark	0.0498	0.3461	1.1118	-0.1022	-0.0366	-0.0157
Egypt	0.0324	0.1308	1.3109	-0.1493	0.0000	-0.0049
Spain	0.0268	0.0976	0.5902	-0.0381	-0.0293	*N/A*
Finland	0.0250	0.2217	2.2251	-0.1293	-0.0323	*N/A*
France	0.6181	*N/A*	1.6298	-0.0517	-0.0378	*N/A*
Greece	0.0534	0.1129	0.6021	-0.0916	-0.0204	*N/A*
Germany	0.0141	0.1155	0.7335	-0.0349	-0.0413	*N/A*
India	0.0309	0.1290	1.3725	-0.0737	-0.0145	0.0000
Indonesia	0.0846	0.1609	1.2436	-0.0875	0.0000	-0.0148
Israel	0.1131	0.1250	0.5492	-0.0541	-0.0073	-0.0729
Italy	0.0280	0.1239	1.4633	-0.0862	-0.0317	*N/A*
Jordan	0.0587	0.2031	0.6915	-0.1089	-0.0124	-0.0106
Japan	0.0191	0.0972	1.1868	-0.0261	-0.0447	-0.0161
Korea	0.0375	0.1382	1.0864	-0.0793	-0.0046	0.0000
Malaysia	0.0405	0.1334	1.1798	-0.0475	-0.0160	-0.0151
Mexico	0.0683	0.1186	0.6844	-0.1213	-0.0014	-0.1301
Norway	0.0467	0.2755	1.3260	-0.0547	-0.0308	*N/A*
Pakistan	0.0349	0.1780	0.8102	-0.1933	0.0000	*N/A*
Peru	0.1610	0.1677	1.0958	-0.1046	0.0000	-0.1981
Philippines	0.0508	0.1899	0.9778	-0.1259	-0.0037	-0.0720
Saudi Arabia	0.1857	0.4959	*N/A*	-0.0811	0.0000	*N/A*
South Africa	0.0276	0.2517	1.7829	-0.2474	-0.0199	-0.0476
Sri Lanka	0.0378	0.2578	1.7395	-0.0877	-0.0034	-0.0170
Sweden	0.0340	0.3154	2.0917	-0.0750	-0.0309	-0.0109
Taiwan	0.0402	*N/A*	1.1322	-0.0254	-0.0096	*N/A*
Thailand	0.0330	0.0786	0.8516	-0.0387	-0.0060	-0.0333
Turkey	0.0929	0.1113	0.8210	-0.1165	0.0000	*N/A*
United Kingdom	0.0219	0.1489	0.9948	-0.0469	-0.0371	-0.0624
Uruguay	0.0791	0.1075	2.2807	-0.1956	0.0000	-0.0485
Venezuela	0.0744	0.2381	0.7630	-0.0768	0.0000	-0.0959
Zimbabwe	0.0813	*N/A*	2.9227	-0.2398	-0.0137	-0.0109

*Thresholds measure either the 10th percentile or the 90th percentile of the %change in each variable

Appendix D

EWS Specification Estimations
Using Panel, Time-Series Logit
Condition 1

	Model Specifications			
	(1)	(2)	(3)	(4)
$ytCredit_t$	0.208*			
	(0.115)			
$ytCred_{t-1}$	0.103			
	(0.117)			
$ytReserves_{t-1}$	0.509***			
	(0.110)			
$ytReserves_{t-2}$	0.466***			
	(0.111)			
$ytEXR_t$	0.205			
	(0.131)			
$ytEXR_{t-1}$	0.180			
	(0.132)			
$ytCredit_t$*$ytCredit_{t-1}$		0.279*	0.279*	0.281*
		(0.163)	*(0.163)*	*(0.163)*
$ytRes_t$-1*$ytRes_{t-2}$		0.957***	0.955***	0.978***
		(0.191)	*(0.191)*	*(0.190)*
$ytEXR_t$*$ytEXR_{t-1}$		0.560***	0.558***	0.563***
		(0.203)	*(0.203)*	*(0.203)*
BOT_t*OECD			-4.53e-05	
			(0.000130)	
BOT_t	-0.000416***	-0.000411***	-0.000394***	-0.000419***
	(7.09e-05)	*(7.04e-05)*	*(8.57e-05)*	*(7.03e-05)*
$Crises_t$	-0.516***	-0.521***	-0.522***	-0.515***
	(0.0489)	*(0.0483)*	*(0.0484)*	*(0.0481)*
$AEdGDP_t$	-0.0315	-0.0454*	-0.0452*	
	(0.0250)	*(0.0250)*	*(0.0250)*	
Constant	-3.250***	-3.052***	-3.056***	-3.200***
	(0.376)	*(0.372)*	*(0.373)*	*(0.363)*
Observations	11866	11866	11866	11866
Number of panel	37	37	37	37

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Prefix **yt** denotes dummy variable equal to 1 if variable is past signal threshold, Credit denotes Domestic Credit, Reserves and Res denote International Reserves (minus gold), EXR denotes nominal exchange rate, BOT denotes Balance of Trade, Crisis denotes number of previous crises experienced, and AEdGDP denotes change in GDP for an aggregate of advanced economics.*

Appendix D continued

EWS Specification Estimations
Using Panel, Time-Series Logit
Condition 2

	Model Specifications			
	(1)	(2)	(3)	(4)
$ytCredit_t$	0.214*			
	(0.115)			
$ytCred_{t-1}$	0.112			
	(0.116)			
$ytReserves_{t-1}$	0.509***			
	(0.109)			
$ytReserves_{t-2}$	0.467***			
	(0.111)			
$ytEXR_t$	0.200			
	(0.131)			
$ytEXR_{t-1}$	0.173			
	(0.132)			
$ytCredit_t$*$ytCredit_{t-1}$		0.301*	0.301*	0.303*
		(0.161)	*(0.161)*	*(0.160)*
$ytRes_{t-}$1*$ytRes_{t-2}$		0.957***	0.956***	0.978***
		(0.190)	*(0.190)*	*(0.190)*
$ytEXR_t$*$ytEXR_{t-1}$		0.550***	0.549***	0.553***
		(0.203)	*(0.203)*	*(0.203)*
BOT_t*OECD			-2.72e-05	
			(0.000132)	
BOT_t	-0.000402***	-0.000395***	-0.000385***	-0.000404***
	(7.14e-05)	*(7.08e-05)*	*(8.51e-05)*	*(7.07e-05)*
$Crises_t$	-0.507***	-0.513***	-0.513***	-0.506***
	(0.0487)	*(0.0482)*	*(0.0483)*	*(0.0479)*
$AEdGDP_t$	-0.0313	-0.0455*	-0.0453*	
	(0.0250)	*(0.0250)*	*(0.0250)*	
Constant	-2.259***	-2.065***	-2.066***	-2.213***
	(0.190)	*(0.186)*	*(0.186)*	*(0.167)*
Observations	9213	9213	9213	9213
Number of panel	29	29	29	29

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Prefix **yt** denotes dummy variable equal to 1 if variable is past signal threshold, Credit denotes Domestic Credit, Reserves and Res denote International Reserves (minus gold), EXR denotes nominal exchange rate, BOT denotes Balance of Trade, Crisis denotes number of previous crises experienced, and AEdGDP denotes change in GDP for an aggregate of advanced economics.*

Appendix D continued

EWS Specification Estimations
Using Panel, Time-Series Logit
Condition 3

	Model Specifications			
	(1)	(2)	(3)	(4)
ytCredit$_t$	0.218*			
	(0.116)			
ytCred$_{t-1}$	0.132			
	(0.118)			
ytReserves$_{t-1}$	0.504***			
	(0.110)			
ytReserves$_{t-2}$	0.489***			
	(0.112)			
ytEXR$_t$	0.203			
	(0.133)			
ytEXR$_{t-1}$	0.323**			
	(0.134)			
ytCredit$_t$*ytCredit$_{t-1}$		0.304*	0.304*	0.307*
		(0.165)	*(0.165)*	*(0.165)*
ytRes$_t$-1*ytRes$_{t-2}$		0.991***	0.989***	1.016***
		(0.193)	*(0.193)*	*(0.192)*
ytEXR$_t$*ytEXR$_{t-1}$		0.660***	0.659***	0.663***
		(0.205)	*(0.205)*	*(0.205)*
BOT$_t$*OECD			-5.93e-05	
			(0.000130)	
BOT$_t$	(7.07e-05)	(7.01e-05)	(8.50e-05)	(7.00e-05)
	*-0.500****	*-0.503****	*-0.504****	*-0.495****
Crises$_t$	(0.0486)	(0.0481)	(0.0481)	(0.0478)
	-0.0384	*-0.0526***	*-0.0523***	
AEdGDP$_t$	(0.0252)	(0.0252)	(0.0253)	
Constant	-3.240***	-3.025***	-3.030***	-3.196***
	(0.381)	*(0.376)*	*(0.377)*	*(0.367)*
Observations	11562	11562	11562	11562
Number of panel	37	37	37	37

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Prefix **yt** denotes dummy variable equal to 1 if variable is past signal threshold, Credit denotes Domestic Credit, Reserves and Res denote International Reserves (minus gold), EXR denotes nominal exchange rate, BOT denotes Balance of Trade, Crisis denotes number of previous crises experienced, and AEdGDP denotes change in GDP for an aggregate of advanced economics.*

Appendix E

In-Sample Conditional Probability Tests

Regression Condition 1

Model	(1)	(2)	(3)	(4)
Threshold	2.05	1.84	1.84	1.83
Pr(Alarm|Crisis)	0.75	0.75	0.75	0.75
Pr(No Crisis| Alarm)	0.17	0.23	0.23	0.23

Regression Condition 2

Model	(1)	(2)	(3)	(4)
Threshold	2.21	2.07	2.07	1.99
Pr(Alarm|Crisis)	0.75	0.75	0.75	0.75
Pr(No Crisis| Alarm)	0.19	0.25	0.24	0.26

Regression Condition 3

Model	(1)	(2)	(3)	(4)
Threshold	2.19	1.87	1.85	1.83
Pr(Alarm|Crisis)	0.75	0.75	0.75	0.75
Pr(No Crisis| Alarm)	0.13	0.21	0.21	0.22

Out-Of-Sample Conditional Probability Tests

Regression Condition 1

Model	(1)	(2)	(3)	(4)
Threshold	0.11	0.11	0.12	1.18
Pr(Alarm|Crisis)	0.75	0.75	0.75	0.75
Pr(No Crisis| Alarm)	0.19	0.24	0.24	0.21

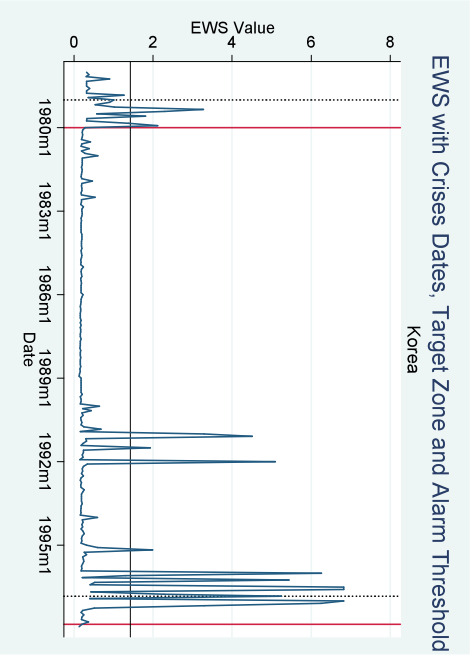
Regression Condition 2

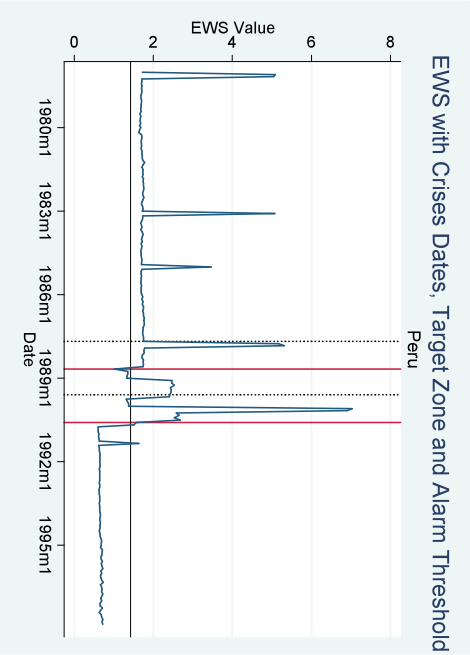
Model	(1)	(2)	(3)	(4)
Threshold	0.28	.32	.34	1.75
Pr(Alarm|Crisis)	0.75	0.73	0.75	0.75
Pr(No Crisis| Alarm)	0.21	0.25	0.25	0.19

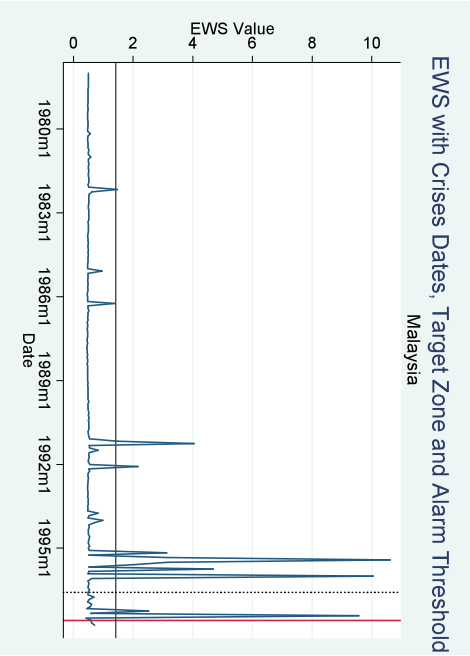
Regression Condition 3

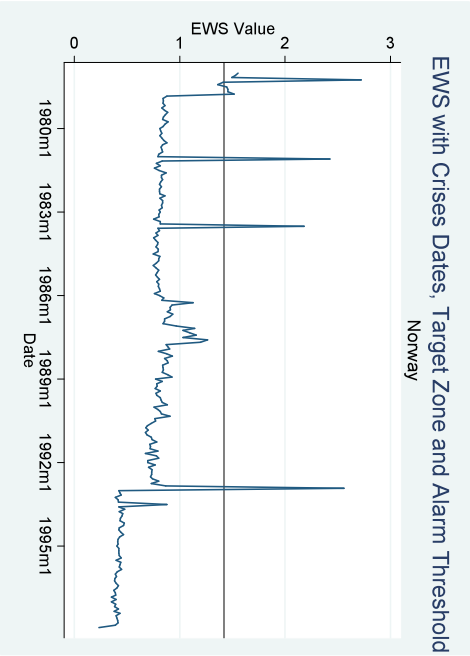
Model	(1)	(2)	(3)	(4)
Threshold	0.12	0.12	0.13	1.42
Pr(Alarm|Crisis)	0.75	0.75	0.75	0.75
Pr(No Crisis| Alarm)	0.19	0.22	0.24	0.17

Appendix F









Crisis Event

Begining of Target Zone

Alarm Threshold