Essays on Currency Crises

A thesis presented

by

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Abstract

Chapter 1: Identifying Extreme Values of Exchange Market Pressure

This chapter contributes to the existing literature on dating currency crisis in three ways. First, we combine the Monte Carlo simulation with a modified Hill's estimator method to obtain more robust results that efficiently deal with bias variance tradeoff in identifying extreme values. Second, we propose a systematic way to choose the reference country in building the Exchange Market Pressure index rather than arbitrary or descriptive reasoning. Third, different data frequencies are applied and the results are evaluated. Our finding suggests that higher frequency data are more appropriate while applying Extreme Value Theory (EVT). It urges researchers to be more cautious in applying EVT and interpreting tail incidences that are obtained from lower frequency data.

Chapter 2: Empirics of Currency Crises: A Duration Analysis Approach

This chapter analyzes the origins of currency crises for 20 OECD countries and South Africa from 1970 through 1998. The main contributions are in three areas. First, it tests for contagious crises and attempts to recognize contagion channels by employing a duration analysis. Second, to minimize the concerns regarding the accuracy of identified crisis episodes, this chapter uses the crisis episodes that are obtained by a relatively more objective method – EVT – in the first chapter. Third, we make use of several robustness checks, including running our models on two different crisis episodes sets that are identified based on monthly and quarterly type spells. Our findings show that high values of volatility of unemployment rates, inflation rates, contagion factors (which mostly work through trade channels), unemployment rates, real effective exchange rate, trade openness, size of economy, increases the hazard of a crisis.

Chapter 3: Currency Crises, Exchange Rate Regimes, and Capital Account Liberalization: A Duration Analysis Approach

This chapter empirically analyzes the effects of exchange rate regimes and capital account liberalization policies on the occurrence of currency crises for 21 countries over the period of 1970-1998. We examine changes of the likelihood of currency crises under *de jure,* and *de facto* exchange rate regimes. We also test whether the impact of the exchange rate regimes on currency stability would be different under free and restricted capital flows. Our findings show that the likelihood of currency crises changes significantly under *de facto* regimes. However, the results are sensitive to the choice of *de facto* exchange rate arrangements. Furthermore, in our sample, capital control policies appear to be helpful in preventing low duration currency crises. The results are robust to a wide variety of sample and models checks.

To my dear mother and the memory of my father

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Contents

General Introduction

The topic of this thesis is currency crises. Currency crises have been a recurrent feature of the international economy from the invention of paper money. They are not confined to particular economies or specific regions. They take place in developed, emerging, and developing countries and are spread all over the globe. Some are scattered over time and some are clustered in points of time. They play an important role in the world economy's turmoil. Countries that experience currency crises face economic losses that can be huge and disruptive. However, the exacted toll is not only financial and economic, but also human, social, and political.

In the recent decades, while the frequency of currency crises has increased, the globalization process and the emergence of integrated international financial markets have propagated domestic crises beyond the borders of individual countries. Now, it is clear that a currency crisis is a real threat to financial stability and economic prosperity. As a result, studying currency crises to find out what drives them and through which channels they spread is of great interest to policy makers, academics, and market participants. Such studies should illustrate the mechanism of the crisis and forecast whether or not, and when, an individual country might experience a currency crisis. Credible studies would help policy makers to come up with solutions for crisis prevention, crisis management, and crisis resolution.

The main objective of this thesis is to analyze the determinants of currency crises for twenty OECD countries and South Africa from 1970 through 1998. It systematically examines the role of economic fundamentals and contagion in the origins of currency crises and empirically attempts to identify the channels through which the crises are being transmitted. It also examines the links between the incidence of currency crises and the choice of exchange rate regimes as well as the impact of capital market liberalization policies on the occurrence of currency crises.

The first chapter of this dissertation identifies the episodes of currency crises in our data set. Determining true crisis periods is a vital step in the empirical studies and has direct impact on the reliability of their estimations and the relevant policy implications. Following Eichengreen, Rose, and Wyplosz (1995 and 1996), we define a period as a crisis episode when the Exchange Market Pressure (EMP) index, which consists of changes in exchange rates, reserves, and interest rates, exceeds a threshold. In order to circumvent the main concerns of this methodology – the priori assumption regarding the distribution of the currency pressure index and arbitrary selection of the thresholds – we apply a more objective approach: Extreme Value Theory (EVT), which was first introduced to the literature by Pozo and Amuedo-Dorantes (2003).

The advantage of EVT over the traditional methods is that EVT does not require knowing the exact distributional form of the index of currency pressure. Instead, it determines crisis episodes by exploiting information at the tails of the distribution. A shape parameter – called the tail index – characterizes the appropriate type of EVT to be applied. In finance and economics, the benchmark estimator for the tail index is Hill's estimator. While it is a consistent estimator, in small samples Hill's estimator is biased and has to deal with the classical bias-variance tradeoff. In the literature there are a number of methods to treat the bias-variance tradeoff concern, such as: Monte Carlo simulation (Koedijk *et al.*, 1990), Hill's plot (Embrechts *et al.*, 1997), recursive least squares (Diebold *et al.*, 1999), and a modified Hill's estimator (Huisman *et al.*, 2001). Among these solutions, the Monte Carlo method appears to be more rigorous and has received more attention. Nevertheless, there are two concerns associated with this method: one is conceptual and the other is computational. These concerns and our solutions to remove them, which use a modified Hill's estimator as a benchmark, are discussed in details in the first chapter.

The first chapter contributes to the dating of currency crises in three areas. First, we combine Monte Carlo simulation with a modified Hill's estimator method to minimize the bias-variance tradeoff and estimate more robust results and precise dating. Second, we select the reference country, which a country's currency pressure index should be built around, in a more systematic way rather than by arbitrary choice or descriptive reasoning. Third, we find that higher frequency data are more appropriate for applying EVT in comparison with lower frequency data. Thus researchers should be cautious in interpreting time aggregation of the tail indices and applying EVT to quarterly and lower frequency data. Furthermore, this chapter attempts to improve the existing literature by: dating crisis episodes with both monthly and quarterly data, covering a wider sample of countries, and applying more sophisticated statistical tests and methods. Comparing our results with other methods shows substantial differences for a number of countries.

The second chapter employs duration models to study the probability of a currency exiting a tranquil state into a crisis state. There is an extensive literature on currency crises that empirically evaluate the roots and causes of the crises. Despite the interesting results of these studies, only very few of them account for the influence of time on the probability of crises. Duration models rigorously incorporate the time factor into the likelihood functions and allow us to investigate how the amount of time that a currency has already spent in the tranquil state affects the stability of a currency. This feature helps us to capture the unobservable determinants of currency stability that are embodied in the baseline hazard functions. We apply semi-parametric duration models to estimate the unrestricted baseline hazard of a currency exiting a tranquil state into a turbulent state. These models do not require any distribution assumptions about the timing of failures and can capably deal with both monotonic and non-monotonic duration dependence.

Furthermore, these models allow us to check whether there is a common pattern for the duration of non-crisis periods among countries, and whether the timing of crises significantly differs across countries. Compared to other duration models, they are more realistic and can produce estimations that are more efficient.

The second chapter contributes to the literature in three areas. First, following Eichengreen, Rose, and Wyplosz (1996), it tests for contagious currency crises and attempts to recognize empirically potential contagion channels while controlling for a set of macroeconomic fundamentals. We apply duration analysis, with focus on semi-parametric models, to estimate a model with unrestricted baseline hazard. These models enjoy the important advantage of not requiring any assumptions on the distribution of the time of failures. This advantage, on one hand, allows us both to capture the monotonic and the non-monotonic nature of duration dependence and to improve the efficiency of our model. On the other hand, they let us to remove the risk of a biased coefficient and provide estimations that are more precise. Second, to minimize the concerns regarding the accuracy of identified crisis episodes that directly affect the final results of the model, this chapter uses crisis episodes that are identified by a relatively more objective method – EVT – in the first chapter. Third, we make use of several robustness checks, including running our models on two different crisis episodes sets that are identified based on monthly and quarterly type spells.

In recent years, the links between the incidence of currency crises and the choice of exchange rate regimes as well as the impact of capital market liberalization policies on the occurrence of currency crises have been subjects of considerable debates. It is of great interest to assess how exchange rate arrangements and financial liberalization will affect episodes of crisis. Policy makers also seek to know what type of exchange rate regime is more sustainable and whether controlling capital flows in fact contributes to the stability of currencies. Yet, the literature is not clear on these issues and presents mixed views. Many economists argue that fixed exchange rates are a cause of currency crises while others find that the intermediate and/or flexible exchange regimes are more crises prone. The role of capital market liberalization is even more controversial. The common view in the literature blames high capital mobility as an underlying cause of currency crises, especially when combined with fixed exchange rates. However, several studies hold that capital mobility restrictions are responsible for crises – as a contributing factor behind the crises – and advocate financial liberalization. It is evident that, for the time being, there is no consensus on these topics and more research is required before the controversies can be settled.

The third chapter examines what types of exchange rate regimes are more susceptible to currency crises in our data set. We adapt the empirical models of the determinants of currency crises, which were presented in the second chapter, as the benchmark models and examine how the likelihood of currency crises is influenced by *de jure* and *de facto* exchange rate regimes. We also study the role of capital mobility and test for currency stability under free and restricted capital flows. We examine whether the hazard of speculative attack changes under the different combinations of exchange rate regimes and the presence or absence of capital controls. This chapter employs two prominent *de facto* exchange rate regime classifications in the literature, those of Reinhart and Rogoff (2004), and Levy-Yeyati and Sturzenegger (2005), to identify the actual exchange rate arrangements. Our index for *de jure* exchange rate regimes is the IMF exchange rate classification. We also categorize capital mobility policies into restricted and open policies with the help of Chinn and Ito's (2005) index of financial openness.

As in our second chapter, duration analysis is our methodology to study the probability of a currency crisis occurrence under different exchange rate regimes and capital mobility policies. The nonlinear nature of duration specification lets us investigate how the different exchange rate regimes or the presence and absence of capital controls can change the sensitivity of currency crises with respect to changes in a set of macroeconomic fundamentals and contagion channels. Furthermore, we use crisis episodes that are identified by extreme value theory to minimize the concerns regarding the accuracy of crisis episodes dating. We apply several robustness checks, including running our models on two different crisis episodes sets that are based on monthly and quarterly-type spells, to verify the reliability of our estimation results.

The third chapter finds that there is a significant link between the choice of exchange rate regime and the incidence of currency crises in our sample. Nevertheless, the results are sensitive to the choice of the *de facto* exchange rate system. When we use Reinhart and Rogoff's (2004) *de facto* classification to categorize the exchange rate regimes, fixed exchange rate arrangements are least susceptible to speculative attacks. However, when we rely on Levy-Yeyati and Sturzenegger's (2005) *de facto* classification, intermediate exchange rate regimes will experience the smallest number of currency crisis incidences. On the other hand, we find that the impact of capital account policies on the occurrence of currency crises, in our sample, demonstrates different results. While the baseline hazard of open-type capital accounts is lower than the baseline hazard of restricted-type capital accounts, when we enter our set of control variables to the models, the hazard of open-type capital accounts appears to be higher than the hazard of restricted-type capital accounts. This relation is more significant at the low duration crisis episodes.

Chapter 1

Identifying Extreme Values of Exchange Market Pressure

1.1 Introduction

Currency crisis is one of major types of financial crises and has caused devastating impacts on the affected economies. In response, numerous empirical and theoretical studies have developed to investigate currency crises, factors that induce them, and their consequences. A large number of these studies investigate timing of crises and attempt to devise an *early warning system* that signals precisely the likelihood of an upcoming crisis, mostly, by relying on macroeconomic fundamentals. Identification of true crisis periods is a vital step in these studies and reliability of their estimations and the relevant policy implications depend on accuracy of the detected crisis episodes.

The origins of current empirical studies on dating currency crisis episodes stem from Eichengreen *et al.* (1995 and 1996). They introduced an index for currency pressure that consists of changes in exchange rates, reserves, and interest rates. They define a crisis period when this index exceeds a threshold in that period of time. Eichengreen *et al.* and many researchers who followed them (*e.g.*, see Kaminsky *et al.*,1998), date crisis periods by putting priori assumptions and by using arbitrary thresholds. However, there are several concerns regarding the validity of the priori assumptions and arbitrary thresholds (see Abiad, 2003). Alternatively, Pozo and Amuedo-Dorantes (2003) suggest a more objective statistical method to identify crises: Extreme Value Theory (EVT).

The advantage of EVT over the traditional methods is that EVT does not require knowing the exact distributional form of the index of currency pressure. Instead, it determines crisis episodes by exploiting information at the tails of the distribution. A shape parameter – called the "tail index" – characterizes the appropriate type of EVT to be applied. In finance and economics, the benchmark estimator for the tail index is Hill's estimator. While it is a consistent estimator, in small samples Hill's estimator is biased and has to deal with the classical bias-variance tradeoff. In the literature there are number of methods to treat the bias-variance tradeoff concern, such as: Monte Carlo simulation (Koedijk *et al.*, 1990), Hill's plot (Embrechts *et al.*, 1997), recursive least squares (Diebold *et al.*, 1999), and a modified Hill's estimator (Huisman *et al.*, 2001). Among these solutions, the Monte Carlo method appears to be more rigorous and has received more attention. Nevertheless, there are two concerns associated with this method: one is conceptual and the other is computational. These concerns will be discussed in detail in the following pages and we will present our solutions, using the modified Hill's estimator as a benchmark.

This paper contributes to the dating of currency crises in three areas. First, we combine Monte Carlo simulation with a modified Hill's estimator method to minimize the bias-variance tradeoff and estimate more robust results and precise dating. Second, we select the reference country, which a country's currency pressure index should be built around, in a more systematic way rather than by arbitrary choice or descriptive reasoning. Third, we find that higher frequency data are more appropriate for applying EVT compare to lower frequency data. Thus researchers should be cautious in interpreting time aggregation of the tail indices and applying EVT to quarterly and lower frequency data. Furthermore, this paper attempts to improve the existing literature by: dating crisis episodes with both monthly and quarterly data, covering a wider sample of countries, and applying more sophisticated statistical tests and methods. Comparing our results with other methods shows substantial differences for a number of countries.

The main objective of this paper is to date currency crises as accurately as possible for 20 OECD members and South Africa during 1970-1998. The identified crisis episodes are to be used in a following paper that studies the empirics of currency crises with the help of duration models.

We proceed as follows. Section 2 presents the currency crisis definition, reviews different methods in dating currency crises, and points to the main concerns regarding the dominant method. Section 3 briefly introduces extreme value theory. Section 4 discusses different methods for the estimation of the tail index. Section 5 describes the data, reports some of their empirical time series properties, and estimates the Hill's index by combining Monte Carlo and the modified Hill's estimator. Section 6 compares our results with some other methods on both monthly and quarterly basis. Section 7 concludes. Some detailed technical results are presented in the appendices.

1.2 Crisis definition

The first step in the analysis of currency crisis is to identify periods of speculative attacks. Currency crises are not restricted to the *events* of realignments of fixed exchange rates or floating a currency that used to be pegged.[1] Although there are overlapping parts between the *events* and crises, currency crisis is a broader concept.

In the simplest approach, a crisis can be defined as a large movement in nominal exchange rates. Frankel and Rose (1996), define an exchange rate depreciation of 25 percent or more over the last year as a currency crash episode.[2] This approach identifies currency crashes but currency crises are not confined only to the crash periods. Massive sell off of a local currency for foreign exchange is called speculative

1. Interestingly, governments deliberately do the realignments in tranquil periods to avoid future crises.
2. To adjust for instances where countries have high inflation, they also require that the depreciation be at least 10 percent higher than the previous year.

attack, which could lead to a crisis. If the attack is successful it can result in a large depreciation of the exchange rate. But not all attacks are successful. Authorities can alternatively repel attacks by using foreign reserves, hiking interest rates, imposing capital controls, or the combination of all of these methods. Thus, devising a broader definition that includes both successful and unsuccessful attacks would be more useful and will help to better understand and identify the origins of currency crises.

Eichengreen, Rose, and Wyplosz (1995 and 1996) introduce an index to capture both successful and unsuccessful speculative attacks. As Eichengreen *et al.* point out, an ideal index of speculative pressure would be obtained by employing a structural model of exchange rate determination, from which one would derive the excess demand for foreign exchange rate. However, most of empirical studies show little success for structural models to forecast foreign exchange in short and intermediate horizons. Consequently, Eichengreen *et al.* choose an *ad hoc* approach on the basis of Girton and Ropper (1977) to build their index of currency pressure. Girton and Ropper, in an exchange rate determination model, define excess demand for foreign exchange to construct an index – called the Exchange Market Pressure (EMP) – for measuring the volume of intervention that is necessary to achieve any desired exchange rate target. The idea is that an excess demand in foreign exchange can be met through several channels that are not necessarily mutually exclusive. Eichengreen *et al.* exploit Girton and Ropper's index and modify it by adding interest rates. Their speculative pressure measure is a weighted average of exchange rate changes, international reserves changes, and interest rate changes.[3] The weights are set in such a manner to equalize the volatility of all three components. All of these variables are measured relative to a reference foreign currency. A logical choice for the reference country would be a country with a fairly strong and stable currency.

Eichengreen *et al.* index of exchange market pressure is defined as:

$$\mathrm{EMP}_{j,t} \equiv [(\omega\ \%\Delta e_{j,t}) + (\lambda\Delta(i_{j,t} - i^{*}_{t})) - (\theta\ (\%\Delta r_{j,t} - \%\Delta r^{*}_{t}))], \tag{1}$$

where $\mathrm{EMP}_{j,t}$ stands for exchange market pressure for country j at time t, $e_{j,t}$ denotes the price of one unit of the reference foreign exchange rate in j's currency, $i_{j,t}$ is the money market interest or similar rates for country j during period t, $r_{j,t}$ indicates the ratio of international reserves of country j in domestic currency to its narrow money (M1) at time t; and ω, λ, and θ are the weights. All factors with an asterisk represent similar variables of the reference country.

3. Interest rates can affect capital flows and speculative attacks.

Eichengreen *et al.* choose large positive values of the EMP index and define crises as periods when the index reaches extreme values.[4] Formally:

$$\text{Crisis}_{j,t} = 1 \text{ if } \text{EMP}_{j,t} > \mu_{EMP} + \delta\sigma_{EMP},$$
$$= 0 \text{ otherwise.} \tag{2}$$

where μ_{EMP} and σ_{EMP} represent the mean and standard deviation of the entire sample of the $\text{EMP}_{j,t}$ and δ is a threshold to be chosen. The result is a binary crisis variable that can be analyzed using limited dependent variable models.[5] In reality, extreme values of EMP date periods of macroeconomic instability that could represent periods of currency crises. Therefore, it seems more appropriate to call the identified periods as currency crisis episodes rather than currency crisis events. We use both terms interchangeably.

This methodology has received extensive attention from other researchers and on its basis a variety of different versions of EMP has been devised to identify currency crisis episodes. For instance, Kaminsky, Lizondo, and Reinhart (1998), and Sachs, Tornell, and Velasco (1996) modify the EMP index by dropping the interest rate component, arguing lack of availability or reliability of data for countries and time periods used in their sample research. They design their own *early warning system* that is called *signaling approach.* A comprehensive literature review on the empirical studies in the field can be found in Kaminsky *et al.* (1998) and Abiad (2003).[6]

Yet, there are a few concerns regarding the identification of crises with this methodology. First, as Eichengreen *et al.* point out, the data are not pure and are subject to some issues and limitations. Available data for international reserves are imperfect. For instance, some technicalities – balance sheet transactions, third-party intervention, stand-by credits and foreign liabilities that are relevant for exchange market intervention – are usually omitted or incompletely reported. Furthermore, not all changes in international reserves are due to intervention in exchange markets. On the other hand, the availability of market-determined data of interest rates for developing countries is rare. Hence, for this group of countries, EMP is built with the first two components.

4. Negative values show large appreciations or large increases in reserves that are considered fundamentally different from depreciation pressure crises.
5. Some researchers argue that transforming continuous variables into binary variables may result in loss of information. Thus, they treat EMP as a continuous dependent variable (see *e.g.* Eliasson and Kreuter, 2001).
6. In the literature, there also exists another systematic methodology that identifies currency crises with help of Markov switching models (see *e.g.*, Martinez-Peria, 2002; and Abiad, 2003). In this methodology, states of crises are determined endogenously.

Second, weighting the three components of the index is critical.[7] A simple and easy option for weighting the components can be an un-weighted scheme. However, the volatilities of exchange rates, international reserves, and interest rates are very different and in case of un-weighted components the index will be heavily dominated by the international reserves that have higher volatility compared to exchanges rate and interest rates, respectively. Consequently, it seems more plausible to weigh the components in a manner that their volatilities are equalized and EMP index is not dominated by only one of the components. One common approach is to weigh each component by the inverse of its own standard deviation. Although this approach adjusts each component's weight with its own volatility, it does not exactly equalize the share of the components. Nevertheless, the weights can be normalized to sum up to unity if each weight is divided by the sum of the inverse of standard deviations of all variables. In this case, for instance ω will be:[8]

$$\omega = \frac{1/\sigma_e}{1/\sigma_e + 1/\sigma_i + 1/\sigma_r} \tag{3}$$

This weighting technique is called "precision weight". However, this technique may not be successful in dating periods of crisis, if the volatilities of the components are mostly driven by the policy reaction function of the central banks rather than being market determined. In "precision weighting", higher volatility will result in lower weight, which can potentially lead to biased identifications of the crisis episodes. If the volatility of a component is pretty low, the weights of the other components will be close to zero and the EMP index would be dominated by the stable component. Willett *et al.* (2004) present two instances, Argentina in1995 and Hong Kong in 1998, that the EMP index failed to identify the attacks. In these two cases, the monetary authorities could manage to keep the exchange rates fixed by spending large amount of their international reserves and increasing the interest rates.[9]

In order to avoid averaging and weighting issues, Zhang (2001) breaks down the EMP index into its components and treats each component separately. He identifies crisis episodes when one of the

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7. As Eichengreen *et al.* mention the ideal weights should be the slope coefficients that reflect how much official intervention (change in international reserves and/or interest rate) would be required to avoid one percent change in the exchange rate. However, there is no reliable theoretical model for the foreign exchange that the profession agrees upon and the reduced form models provide a good fit.
8. Angkinand, Li, Willett (2006).
9. The weights can be driven from either each country-specific sample [own country precision weights; see *e.g.* Eichengreen *et al.* (1995) and Aziz *et al.* (2000)], or entire sample of countries [pooled precision weights; see *e.g.* Kaminskyand Reinhart (1998) and Glick and Hutchison (2001)]. Some researchers believe pooled weights may lessen this problem but at the cost of probable heterogeneity.

components crosses a sample-dependent threshold.[10] He uses a three-year moving window to compute the standard deviations of the thresholds.

Third, the arbitrary choice of crisis-identification thresholds and their underlying priori assumptions are problematic. While large deviations of the EMP index from its mean is defined as extreme values, the selection of the threshold is fairly arbitrary. Obviously, different choices result in different crisis episodes. In the literature, range of the threshold varies from 1.5 to 3 standard deviations. More surprisingly, as Abiad (2003) notes, some researchers, Kamin *et al.* (2001) and Caramazza *et al.* (2000), treat the threshold as a free parameter to fulfill their research objectives. Furthermore, use of the mean and standard deviation approach to pick up extreme observations is based on that the underlying assumption series of EMPs are well behaved and normally distributed. However, it is well known that speculative price series turn out to be more compatible with fat-tailed distributions than normal ones (Jansen and de Vries, 1991). Therefore, the arbitrary choice of thresholds in picking up extremely large values of EMPs becomes even more inappropriate. Accordingly, we apply an alternative methodology to capture the dispersion of the series and label their extreme values in a rigorous manner.

1.3 Extreme value theory

The dispersion of the EMP index determines periods of successful and unsuccessful speculative attacks. As stated above, well behaved normality does not necessarily hold due to fat tails and skewness in the series. Alternatively, Pozo and Amuedo-Dorantes (2003), following Koedijk *et al.* (1990), suggest applying extreme value theory (EVT) to exploit information in the tails of the series. EVT identifies crisis dates with the help of more rigorous statistical methods and there is no need to set arbitrary assumptions and/or thresholds.

In this section we briefly introduce EVT, its different types, fat-tailed distributions, and tail indices. A comprehensive, detailed and technical introduction can be found in de Haan and Ferreira (2006) and Embrechts, Kluppelberg and Mikosch (1997).

EVT provides a framework to study the behavior of the tails of a distribution. It enables us to apply extreme observations to measure the density in tails and build statistical models for rare phenomena like

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10. He also claims his method can overcome Flood and Marion's (1999) argument. Following Krugman (1979), Flood and Marion argue since the interest rate falls back and reserves flow back right after the devaluation, these two effects may cancel out some part of changes in exchange rates and dampen the EMP index. So, in the case of predictable devaluations, the EMP index may fail to identify a crisis.

stock-market crashes or speculative attacks. EVT is quite similar to the *central limit theorem* and both have common mathematical backgrounds. As the limiting distribution of sample averages is a normal distribution, the limit laws of order statistics are characterized by a class of EVT. This theory deals with asymptotic distribution of maxima without generalizing about the distribution of the whole series. It only studies the tails' distribution. Fortunately, analogous to the *central limit theorem* the limit laws provided by EVT do not require a detailed knowledge of the original distribution that extreme observations belong to. There are two approaches to study the extreme events by EVT. One is direct modeling of either maximum or minimum realizations. The other one is modeling of the exceedances of a certain threshold.

Consider $X_1, X_2, \ldots, X_n$ to be a sequence of stationary random variables that may be either *i.i.d.* or dependent with a distribution function $F(x)$.[11] We are interested in the probability that the maximum[12]

$$M_n = \max \{X_1, X_2, \ldots, X_n\}, \tag{4}$$

of the first n random variables be less than a certain level x. This probability is given by:

$$\Pr\{ M_n \le x\} = \Pr\{ X_1 \le x, X_2 \le x, \ldots, X_n \le x\} = [F(x)]^n. \tag{5}$$

Unfortunately, in most cases $F(x)$ is not known and for most cases that it is known, it is not practical to calculate $[F(x)]^n$ even for moderate values of n. However, EVT is able to appropriately provide the limiting distribution of the order statistic M_n. One can normalize M_n by a location parameter (b_n) and a scale parameter ($a_n > 0$) as:

$$\Pr \{a_n (M_n - b_n) \le x\} \xrightarrow{w} G(x); \tag{6}$$

and in the case that the X_i are *i.i.d.*

$$[F((x/ a_n) + b_n]^n \xrightarrow{w} G(x), \tag{7}$$

where $G(x)$ is the limit law of M_n and is a *max-stable* distribution and w stands for weak convergence. If equation (5) holds, F will belong to the domain of attraction of G. *Max-stable* distributions are the possible class of limit laws for equation (5). A non-degenerate density function $G(x)$ is called *max-stable*, if there exist real constants $A_n > 0$ and B_n such that for all real x and positive integer n:

11. This part is heavily drawn from Hols and de Vries (1991).
12. Since by changing the sign of the Xs one can switch from the study of maxima to minima, we just concentrate on positive random variables.

$$[G(A_n\, x + B_n)]^n = G(x). \tag{8}$$

Based on the *Fisher-Tippet theorem*, every *max-stable* distribution is one of the following types:

$$
\begin{array}{lll}
\text{Type I (Gumbel):} & \Lambda(x) = \exp(-\, e^{-x}) & x \in R; \\
\text{Type II (Frechet):} & \Phi_\alpha(x) = 0 & x \le 0, \\
 & \quad = \exp(-x^{-\alpha}) & x > 0, \\
 & & \alpha > 0; \\
\text{Type III (Weibull):} & \Psi_\alpha(x) = \exp(-(-x)^\alpha) & x < 0, \\
 & & \alpha > 0; \\
 & \quad = 1 & x \ge 0.
\end{array} \tag{9}
$$

The theorem suggests that the asymptotic distribution of the maxima belongs to one of the three distributions above, regardless of the original distribution of the observed data. While α goes toward ∞ or $-\infty$, Frechet and Weibull distributions attain the shape of a Gumbel distribution, respectively. Weibull family tails decline with a finite tail index. They are thin-tailed distributions with a finite upper endpoint.

The possible limit laws for $G(x)$ can also be represented in a unified model with a single parameter. This presentation is known as the Generalized Extreme Value distribution (GVE):

$$
\begin{aligned}
H_\gamma(x) &= \exp\{-(1+\gamma x)^{-1/\gamma}\} \quad \text{if } \gamma \neq 0 \text{ and } 1+\gamma x > 0, : \\
&= \exp\{-\exp(-x)\} \qquad \text{if } \gamma = 0.
\end{aligned} \tag{10}
$$

where $\gamma = 1/\alpha$ is the shape parameter and α is the tail index.

Intuitively, these functions represent three possibilities for decaying of density functions in the tail. Loosely speaking, the tails of the distribution fall in three different categories:

1) They decline exponentially and all of their finite moments exist. Cases like normal, log-normal, and gamma distributions lie within Gumbel type tails.
2) Tails can also decay by power but not quick enough when weighted by the tail probabilities and consequently cannot be integrated. This type of distributions, like Stable, Paretian, and Student's *t* are said to be fat-tailed and are among Frechet type tails.
3) Weibull family tails fall within a finite tail index. They are thin-tailed distributions with a finite upper endpoint.

Economic theory tends not to be informative about the specific density function that applies. However, the qualitative characteristic of an economic process may point to the relevant limit law. On the basis of the strong fat-tailed and the unbounded nature of exchange rate returns[13], as well as the EMP index, the possibility of type I and III distributions can be ruled out, leaving type II limit laws as the relevant one (if the maxima distribution converges at all). Thus, we will concentrate on the Frechet domain of attraction that includes a range of distributions: Student's *t*, the stable distributions, and ARCH type process.

The tail index (α) is the unifying feature across the limit laws distributions and is used to capture the weights of the tail in the distribution of X_i. In different cases, the scaling parameter (a_n) and the location parameter (b_n) may need to be modified but, since α is the unifying feature, it remains unaffected. The tail index also indicates the number of bounded moments of the distribution that exist; the moments less than α are finite and well defined while those bigger than α are infinite.

For *i.i.d.* stable random variables[14] (not to be confused with *max-stable*) that have an invariant density function under addition, tail index α equals the characteristic exponent (shown by β).[15] The effect of dependency would be larger values that tend to come in clusters. Student's *t* is also in the domain of attraction of type II. Degrees of freedom are equal to the tail index ($\alpha \geq 2$). Student's *t* has well defined mean and variance while stable distributions have a finite mean but no finite variance.

For the ARCH or GARCH processes, though their building blocks can be normal variates, the unconditional distribution of the realizations are fat-tailed. In the case of ARCH (1), the tail index is equal or greater than two. Formal generalizations to higher-order processes are nonexistent, but some generalizations can be easily obtained.

As shown above, having a fat (heavy) tail is the main characteristic of type II limit law. But how to distinguish fat tails? Loosely speaking fat tail or *leptokurtic* distributions exhibit extremely large kurtosis particularly with respect to normal distribution and follow power-law decay.[16]

Formally, one can say there is a heavy upper tail for the positive X_i, if for large *x*:

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13. See, for example, Boothe and Glassman (1987), Jansen and de Vries (1991), and Koedijk and Kool (1994).
14. Normal distribution belongs to the stable class but it has all moments and is not fat tailed.
15. For Cauchy distribution $\alpha=\beta=1$, for normal distribution $\beta=2$, and for chi square distribution $\beta=1/2$.
16. In a few cases this measure might be misleading. For instance, discrete mixtures of the normal, mixed jump processes, and the power exponential all exhibit higher kurtosis but nevertheless possess all moments and are thin tailed. Anyhow, there is no unique definition for fat-tailed distributions in the literature.

$$1\text{-F}(x) = x^{-\alpha}\,\text{L}(x) \;\text{ as }\; x\to\infty,\ \alpha>0, \tag{11}$$

where L(x)is such that for any $x>0$

$$\lim_{t\to\infty} \frac{L(tx)}{L(t)} = 1. \tag{12}$$

As shown in equation (11), the tail of a distribution can be divided into two parts: the L(x) function and the power part. The L(x) function is asymptotically unimportant since L(tx)$\approx L(x)$ for large t. The sufficient and necessary condition for a distribution to be fat-tailed is the property of regular variation that means L(·) varies regularly at infinity. Therefore, the tail of the distribution is dominated by the power part $x^{-\alpha}$. Due to the power part, the tail of F(x) always falls more slowly than the tails of distributions that decline exponentially, like normal distribution. From (10) it is obvious that there is an inverse relation between α and the size of a fat tail; larger α results in a lower fat tail. When L(x) is constant then F(x) is the Pareto distribution.

From the above discussion, it is obvious that competing fat-tailed density functions are nested within their limit law G(x), and are distinguished by different values for the tail index (α). In fact, the tail index characterizes the limit law. Now we examine how to estimate tail indices.

1.4 Tail index estimation methods

In this section we review some parametric and nonparametric estimators of the tail index with more stress on the type II limit law. We introduce Hill's estimator as the benchmark estimator of the tail index and consider its bias-variance tradeoff in small samples. As a solution for bias problem the modified Hill's estimator is introduced.

In general, there are two different procedures for estimating the tail index (α). The first class of estimators follows parametric approach and directly estimates α with maximum likelihood or regression techniques. Jansen and de Vries (1991) show that under the type II limit law, direct estimation of α by maximum likelihood is consistent but not the most efficient. This approach assumes each period's maximum follows exactly one of the three limit laws. Obviously, this assumption is too strong and can cause misspecification bias. Furthermore, parametric approach requires estimation of an extra scale parameter, which can be interpreted as another drawback of this approach.

An efficient approach for estimation of the tail parameter is to use all realizations from a single sub-sample that are above a certain high threshold (*exeedance*). Some efficient semi-parametric estimators have been proposed on this basis. These estimators use the largest order statistics and all they require is the original distributions that generate the observations be well behaved. It implies that the remaining estimation errors can be attributed to the use of finite samples.

Suppose $X_1, X_2, \ldots, X_n$ is a stationary sequence such that M_n has a type II distribution. By arranging the observations in an ascending order $X_n \geq X_{n-1} \geq \ldots \geq X_m \geq X_{m-1} \geq \ldots \geq X_1$, two alternative estimators for γ – based on the largest order statistics X_i – are introduced as follows:

Pickands' estimator:

$$1/\hat{\alpha} = \hat{\gamma}_{\mathrm{P}} = (\ln \frac{X_{(m)} - X_{(2m)}}{X_{(2m)} - X_{(4m)}}) / \ln 2. \tag{13}$$

This estimator has been shown to be weakly consistent. Its strong consistency and asymptotic normality has also been obtained when the maximum order value *m* rises rapidly enough relative to the sample size *n.* Pickands' estimator is a general estimator and can provide estimations for all three types of limit laws.

Hill's estimator:

$$1/\hat{\alpha} = \hat{\gamma}_H = \frac{1}{m} \sum_{j=1}^{m} \ln X_{n-j+1} - \ln X_{n-m}. \tag{14}$$

First presented by Hill (1975), has been proven to be a consistent estimator of γ with $(\hat{\gamma}_H - \gamma) m^{1/2}$ being asymptotically normal with mean zero and variance γ^2. Hill's index is more efficient than the maximum likelihood estimator since it has smaller variance and beats the Pickands' estimator on the consistency basis. It is the bench-mark estimator for the tail index of type II limit law.

In both nonparametric estimators, the final tail index estimate relies heavily on the choice of cut-off point *m*. While all estimation procedures require that *m* goes to infinity at a lower rate than the sample size *n*, there is little instruction on how to choose *m* optimally. Like other upper-order observations that deviate from an exact Pareto-tail, the choice of *m* ultimately involves the classic tradeoff. This problem would even be more severe in small samples. If *m* is chosen conservatively with few observations from the tail, then the tail index estimate will be sensitive to outliers in the distribution and will have larger variance. On the other hand too many observations from the tail and too few from the central part of the distribution can result in a more stable index, but of course, with a higher degree of bias.

There are a number of solutions to deal with the sensitive tradeoff issue. Danielsson *et al.* (2001) use a two-step subsample bootstrap method to estimate the number of order statistics (*m*). Their approach does not require prior knowledge of second-order parameters and is a statistically optimal solution. Unfortunately, it is only appropriate for large enough samples. Another possibility is what Embrechts *et al.* (1997) call Hill's plot. In this method α is estimated for different values of *m* and then an optimal value of *m* will be chosen from the region where the estimated tail parameter (α) is stable. Even if such a region exists, however, selecting the specific *m* within this region may not be precise. Koedijk *et al.* (1992), Longin and Solnick (2001), Haile and Pozo (2006 and 2008), among others, use the asymptotic properties of Hill's estimator to choose *m*. By exploiting asymptotic normality property of Hill's estimator they apply Monte Carlo simulation method to find the optimum level of *m*. They minimize the mean square error (MSE) of the estimated γ, conditional upon a sample size *n* and degrees of freedom of F(*x*). The Monte Carlo simulation appears to be rigorous and helpful in optimizing the tradeoff between bias and inefficiency.

Huisman *et al.* (2001) apply the weighted least square (WLS) method to solve the problem. While the Hill's index is asymptotically unbiased, it is shown to suffer from bias in small sample estimates. They exploit information obtained from a set of Hill's estimates, each conditioned on a different number of tail observations. They calculate a weighted average over a range of estimated Hill indices where weights are measured by simple least square techniques. A brief review of this approach comes as follows.

It is shown that for a general class of distribution represented by:

$$F(x) = 1- ax^{-\alpha}(1+bx^{-\beta}). \tag{15}$$

depending on the parameters values, $F(\cdot)$ can represent some specific distributions, e.g. $F(x)= 1-x^{-\alpha}$ for $a=1$ and $b=0$. Hall (1990) show that in most cases the expected value of the Hill index for given *m* is:

$$E(\gamma(m)) \approx \frac{1}{\alpha} - \frac{b\beta}{\alpha(\alpha+\beta)} \alpha^{-\frac{\beta}{\alpha}} (\frac{m}{n})^{\frac{\beta}{\alpha}}. \tag{16}$$

It is clear that bias is increasing in *m* and Hill's index would be a biased estimator for any *m* greater than zero in small samples. To approximate bias and make it linear in *m*, Hall imposes an $\alpha = \beta$ condition that is warranted not to be harmful.

Hall also derives the asymptotic variance of Hill's estimator for the above class of distribution as:

$$\mathrm{var}(\gamma(m)) \approx \frac{1}{k\alpha^2}. \tag{17}$$

As it is clear from (15) and (16), a small *m* is desirable from the perspective of unbiasedness, while a large *m* is preferred for the sake of efficiency.

Huisman *et al.* (2001) claim that for values of *m*, which are smaller than a threshold value *M*, the γ estimates are seen to increase almost linearly in *m* and for larger values of *m*, the pattern of γ depends on values of β/α exponents. Therefore, they suggest approximating the bias term for small enough values of *m* by:

$$\gamma(m) = \beta_0 + \beta_1 m + \varepsilon(m), \qquad m=1,2,3,\ldots, M. \tag{18}$$

They propose to estimate the tail index of the distribution by computing Hill's index for *m* from 1 to *M*. The intercept value or β_0 in equation (17) should be an unbiased estimator of γ while *m* approaches zero. This approach may solve bias-variance tradeoff by exploiting information from the certain range of conventional Hill's estimators based on values of *m*, where γ varies linearly. They show that estimates of tail index are quite robust with respect to the choice of *M*, as long as $M \leq n/2$.

Huisman *et al.* choose to apply WLS instead of OLS to estimate (17) to overcome two problems. First, from equation (16) it is clear that the variance of Hill's estimator is not constant and varies based on values of *m*, consequently, $\varepsilon(m)$ in equation (17) is heteroscedastic. Second, different estimates of γ are correlated through different values of *m*. $\gamma_{(m)}$ and $\gamma_{(k)}$, where $m \neq k$, are based on $1+min\,(m,k)$ common observations. In a matrix notation, equation (17) can be shown as:

$$a\gamma^* = Z\beta + \varepsilon. \tag{19}$$

where γ^* is a vector of γ for different values of *m* from 1 to *M*, *Z* is a $(M \times 2)$ matrix with ones in the first column and a vector of $\{1,2, \ldots, M\}$ in the second. To apply WLS they propose a $(M \times M)$ weighting matrix W that has { $\sqrt{1}, \sqrt{2}, \ldots, \sqrt{M}$ } as the main diagonal elements and zeros elsewhere. WLS estimates of β are:

$$b_{wls}=(Z'W'WZ)^{-1}Z'W'W\gamma^{*}, \tag{20}$$

The estimated tail index γ would be equal to the first element of the vector b_{wls}. Consequently, their modified Hill estimator is a weighted average of the traditional Hill's estimators:

$$\gamma(M) = \sum_{m=1}^{M} w(m)\gamma(m). \tag{21}$$

In order to minimize the bias-variance tradeoff and obtain an unbiased and robust estimation of Hill's estimator, we combine Monte Carlo methods suggested by Longin and Solnik (2001) and the modified Hill's estimator by Huisman, Koedijk, Kool, and Palm (2001) approach to estimate Hill's index.

1.5 Empirical estimation

1.5.1 Data. The source of all data is the International Financial (IFS) of the IMF. Available monthly and quarterly data from January 1967 to the end of 1998 (when 10 countries in our sample left their own national currencies and joined the Euro currency system) are collected for the period average of the exchange rate (IFS, line rf.), total reserves minus gold (IFS, line 1l.d), M2 or money plus quasi money (IFS, line 34 plus IFS, line 35), and short term interest rates given by a money market or a similar rate (IFS, line 60b and if not available IFS, line 60). It should be mentioned that short duration attacks may not be evident (especially unsuccessful ones) even for monthly data, which is the highest available frequency. If an attack takes place and be fended off within a few days the average interest rate and international reserves data may not be able to show the intensity of speculative pressure.

Our sample includes 21 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, and the UK. Availability of higher frequency data (monthly) and greater chance of reliability are the determining factors for selecting these countries.

In order to compute the EMP index we need to select an appropriate currency of reference for each country. Some studies (for example, Eichengreen *et al.*, 1995) choose one currency while other (for example, Tudela, 2003) chooses two currencies – either the DM or the USD – as the reference. In some cases, for example the US Dollar (USD) for Canada or the Deutsche Mark (DM) for Austria, choice of the reference currency seems straightforward. But in other cases this choice is not clearly exclusive. For example, in case of UK or Greece both of the DM and the USD look equally good candidates. In previous studies, to the best of our knowledge, choice of the reference currency has been an arbitrary selection between the USD and the DM; with or without descriptive reasoning. However, we attempt to select the reference currency in a more systematic approach. The key criterion that we use to fulfill this task is the stability of the exchange rate during the sample period. For each local currency, we select the reference currency based on the lowest volatility of the local currency against potential candidate references. To conserve the degrees of freedom, we confine potential candidates to the USD and the DM, which during our sample period have been consistently strong and very well accepted internationally. [17]

As the first step, we compute variations of the local currency in terms of both candidates to capture the stability of the local currency against the DM and the USD. In this regard, the simplest approach is to compare the unconditional time invariant variances during the whole sample period and choose the currency with the smaller variance as the reference. Nevertheless, the volatility of economic and financial time series are barely independent during the time. To overcome this concern, we employ the Auto Regressive Conditional Heteroscedasticity (ARCH) models, which are the most efficient method in the literature to capture the time-dependent volatility.

There are several different types of ARCH models that estimate time-dependent volatility as a function of prior volatilities. Specifically, two versions of ARCH models – General ARCH (GARCH) and Exponential GARCH (EGARH) models – are widely applied in financial time series. While GARCH models assume symmetric impacts for the innovations (the good and bad news have the same impacts) and can only account for bounded parameters, EGARCH models relax the symmetric assumption and consider asymmetric impacts of innovations and can also handle unbounded parameters.[18] Hence, we use EGARCH models to capture time-dependent volatilities. Our index in capturing volatility of the exchange rate series is unconditional standard deviation. However, in several cases EGARCH models do not converge. As an alternative method, we also calculate a three-year rolling standard deviation of the exchange rate series to deal with the time-varying volatility. The average of the three-year moving window standard deviations is used as an alternative for the unconditional standard deviation of each country. Results are reported in Table 1.

17. During our sample period, the USD has experienced weak periods in the 1970's (1971-1973) and mid 1990's.
18. For a comprehensive introduction and comparison of ARCH family models, see Enders (2004).

Table 1. Volatility of exchange rates in terms of the DM and the USD

	monthly				quarterly			
	EGARCH unconditional std. dev.		three-year window standard deviation		EGARCH unconditional std. dev.		three-year window standard deviation	
Country	*DM*	*USD*	*DM*	*USD*	*DM*	*USD*	*DM*	*USD*
Australia	3.81	…	3.13	1.96	…	…	5.48	3.39
Austria	…	3.29	0.42	2.44	…	…	0.49	4.35
Belgium	…	4.09	0.71	2.43	2.73	5.25	1.12	4.34
Canada	3.49	1.34	2.72	0.93	6.83	…	4.79	1.42
Denmark	…	2.71	0.87	2.35	…	…	1.34	4.24
Finland	…	…	1.76	2.2	…	…	3.01	4.13
France	…	…	1.18	2.5	3.17	…	2.02	4.37
Greece	2.94	…	1.86	1.94	…	…	3.32	3.57
Iceland	…	…	3.36	3.31	…	13.13	5.43	5.46
Ireland	…	…	1.53	2.29	…	…	2.45	4.24
Italy	2.77	…	1.7	2.18	…	…	2.88	4.14
Japan	2.63	5.24	2.37	2.5	5.7	6.99	4.38	4.44
Netherlands	…	4.35	0.52	2.43	…	…	0.8	4.3
New Zealand	…	…	2.89	2.19	…	…	4.74	3.77
Norway	…	…	1.27	2.05	2.75	7.42	2.19	3.73
Portugal	…	…	1.57	2.34	4.14	…	2.53	4.15
South Africa	…	4.99	2.98	2.39	7.13	3.41	5.06	4.63
Spain	…	…	1.98	2.25	…	…	3.4	4.16
Sweden	2.06	6.84	1.74	2.15	…	13.01	3.19	4.15
Switzerland	1.31	3.67	1.38	2.78	…	…	2.3	4.94
UK	…	1.37	2.23	2.34	…	…	4.08	4.49

… implies that either there exists no ARCH effect in the series or EGARCH model does not converge.

Based on presented results in Table 1, the USD is chosen as the reference currency for Australia, Canada, New Zealand, and South Africa while the DM is selected as the reference for all other countries in our sample.[19] The results are in line with previous studies with more than one reference country (for example, Tudela, 2003; or Haile & Pozo, 2006), except for Japan. In these studies, the USD is the reference currency for Japan but our results indicate that the DM is a more appropriate reference currency for Japan. As mentioned earlier, the selected reference currencies are based on the stability of exchange rate relation during our sample period, therefore, the reference currency will be different if the period horizon changes.

19. Case of Iceland can be a little confusing. While monthly data show Krona is marginally more stable in term of the USD, quarterly data indicate different direction and show that Krona is more stable in term of the DM. Considering its major economic partners, our final selection is made based on quarterly data.

1.5.2 Empirical EMP series. EMP indices are built following Eichengreen *et al.* (1995) as a weighted average of three components: exchange rate changes, variations of the ratio of international reserves in local currency to M2 (money plus quasi money), and money market or similar interest rate changes. All components are measured with respect to the related reference country. The weights are calculated from each country's specific sample such that to equalize the volatilities of the components. Since the conditional standard deviations of three components of the EMP index are not constant, the weights are chosen to be time-varying. This technique will help to prevent the dominance of high volatility periods over the whole sample (Zhang, 2001). Finally, in order to account for conditional time-varying standard deviations and capturing the potential asymmetries of crises, weights are estimated by applying EGARCH models to the series of each component.[20]

Before starting EVT analysis, it is important to check statistical properties of EMP series and verifying that these series are fat-tailed. Some statistics of the monthly and quarterly EMP indices are reported in Tables 2 and 3, respectively. Although both monthly and quarterly series present similar patterns, there are some differences. For monthly series, Shapiro-Wilk test results suggest that none of monthly EMP indices are normally distributed.[21] All of these series exhibit excess kurtosis and most of them are skewed to the right – all series except for the Netherlands and Switzerland. These features indicate that monthly EMP series are fat-tailed and fall asymptotically within the domain of attraction of the Frechet distribution. For quarterly series, all indices exhibit excess kurtosis too, however, less than the case of monthly series. Also, fewer indices are skewed to the right. The Shapiro-Wilk test results show that five quarterly EMP series – Canada, Finland, Greece, Ireland, and Switzerland – are normally distributed.

Stationarity is a vital condition in EVT analysis. For robustness purposes, we use both parametric and non-parametric tests to verify stationary condition of the series. First, for each series the Dickey-Fuller Generalized Least Square (DFGLS) test is run and the optimum number of lags that minimizes the Modified Akaike Information Criterion (MAIC) is obtained. Then, the Dickey-Fuller (DF) test is run with the optimum number of lags that are attained through DFGLS. Second, as a non-parametric test, the Phillips-Perron test for unit root is run. Results are shown in Tables 2 and 3.

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20. Each conditional variance of the three components are estimated based on the EGARCH(1,1) model: $y_t = x_t\varphi + \varepsilon_t$ where $\ln\sigma_t^2 = \nu_0 + g(z_{t-1}) + \nu_1 \ln\sigma_{t-1}^2$, $\varepsilon_t = z_t\, \sigma_t$, and $g(z_t)$ is a well defined function of z_t. In the mean equation, y_t represents one of the three components and x_t is a lagged values of y_t. The fitted conditional standard deviation ($\sigma^h{}_t$) is used to generate weights in the EMP index. For conditional volatility, there is no concern about non-convergence.
21. In order to make the outcomes visually evident too, histograms of the EMP series are overlaid by the standard normal distribution density and are reported in Appendix B. Generally, centers of histograms are more peaked and there is a greater mass in the tails that confirms they have fat tails.

Table 2. Statistical properties of the monthly EMP series

Country	*N*	*mean*	*sd.*	*skew.*	*kurt.*	*norm.*[1]	*station.*[2]	*staion.*[3]	*indep.*[4]	*ARCH*[5]
Australia	348	0.08	1.08	0.41	5.5	0	0	0	0	0
Austria	346	0.03	0.53	0.83	13.61	0	0	0	0	0
Belgium	345	0.08	0.8	1.12	7.54	0	0	0	0	0.02
Canada	348	0.47	0.71	0.48	4.36	0	0.15	0	0	0.13
Denmark	348	0.11	1.06	0.65	8.48	0	0	0	0	0.05
Finland	348	0.05	0.91	1.24	9.88	0	0	0	0	0.04
France	342	0.05	0.95	0.52	6.56	0	0	0	0	0
Greece	348	0.15	0.63	0.91	7.58	0	0.05	0	0	0.61
Iceland	348	0.36	1.29	0.85	6.95	0	0	0	0.21	0.76
Ireland	348	0.1	0.69	1.78	11.13	0	0	0	0.33	0
Italy	348	0.15	1.32	1.05	9.95	0	0	0	0.03	0
Japan	348	-0.02	0.86	0.5	6.99	0	0	0	0	0
Netherlands	348	0.02	0.68	-0.31	15.88	0	0	0	0	0.19
New Zealand	348	0.06	1.48	3.85	62.25	0	0	0	0.04	0
Norway	348	0.09	0.64	0.93	5.88	0	0	0	0	0
Portugal	348	0.29	1.39	1	14.58	0	0.03	0	0	0
South Africa	348	0.14	1.37	0.25	5.71	0	0	0	0	0
Spain	348	0.17	1.48	0.69	6.73	0	0	0	0.39	0
Sweden	348	0.12	1.53	2.26	24.88	0	0	0	0.25	0
Switzerland	348	-0.06	0.8	-0.31	5.28	0	0	0	0	0.01
UK	348	0.15	1.3	0.75	5.46	0	0	0	0	0.57

1. p-value of Shapiro-Wilk test for normality. (null of normality)
2. Mackinnon approximate p-value of Dickey-Fuller test for stationarity. (null of having uint root test)
3. Mackinnon approximate p-value of Phillip-Perron test for stationarity. (null of having uint root test)
4. p-value of White noise test for autocorrelation. (null of no aurocorrelation)
5. p-value of Lagrange Multiplier (LM) test for ARCH. (null of no ARCH effect)

Based on the Philips-Perron test, all monthly and quarterly series are stationary. However, the DF test shows that Canada in monthly series and six other countries: Belgium, Denmark, Greece, Iceland, Ireland, and Switzerland in quarterly series, have non-stationary EMP series. This unit root problem may stem from structural changes in theses series.

We apply the Lee and Strazicich (2004) Lagrange Multiplier (LM) unit root test to account for structural breaks in the non-stationary diagnosed series. This powerful test is able to allow for one-break in intercept and/or trend without showing size-distortions in the presence of a break under the null. [22] Lee and

21. Having correct size and high power results are two main desired factors in every statistical test. In unit root tests, presence of cross-sectional correlation causes size distortion that leads to over-reject of the unit root null.

Strazicich test accounts for the endogeneity of the time break (TB) by minimizing a LM statistic. The test results show that the null of "non-stationary" can be rejected for all of the series that are diagnosed with unit root. Table 4 reports the results.

Table 3. Statistical properties of the quarterly EMP series

Country	*N*	*mean*	*sd.*	*skew.*	*kurt.*	*norm.*[1]	*station.*[2]	*staion.*[3]	*indep.*[4]	*ARCH*[5]
Australia	116	0.23	1.84	0.37	5.69	0.00	0.00	0.00	0.22	0.00
Austria	115	0.03	0.59	-1.85	14.79	0.00	0.00	0.00	0.00	0.59
Belgium	115	0.14	1.11	0.46	4.84	0.00	0.14	0.00	0.56	0.11
Canada	116	0.13	1.20	-0.08	3.33	0.49	0.01	0.00	0.07	0.44
Denmark	116	0.28	1.65	0.61	3.85	0.00	0.21	0.00	0.93	0.00
Finland	116	0.24	1.49	0.48	3.68	0.13	0.05	0.00	0.24	0.66
France	114	0.12	1.48	0.43	4.45	0.00	0.00	0.00	0.02	0.00
Greece	116	0.56	1.13	0.30	3.04	0.50	0.60	0.00	0.41	0.45
Iceland	116	1.14	2.40	0.58	4.03	0.00	0.40	0.00	0.00	0.65
Ireland	116	0.42	1.63	0.40	3.23	0.12	0.30	0.00	0.29	0.52
Italy	116	0.45	1.82	1.71	10.65	0.00	0.00	0.00	0.32	0.00
Japan	116	-0.05	1.41	0.84	6.00	0.00	0.00	0.00	0.39	0.21
Netherlands	112	0.06	1.11	-0.20	11.57	0.00	0.00	0.00	0.00	0.02
New Zealand	116	0.15	2.64	2.60	19.94	0.00	0.00	0.00	0.59	0.24
Norway	116	0.23	1.09	0.48	3.36	0.05	0.00	0.00	0.29	0.04
Portugal	116	0.72	2.01	0.64	5.74	0.00	0.01	0.00	0.01	0.69
South Africa	116	0.34	2.22	0.34	3.88	0.02	0.00	0.00	0.02	0.92
Spain	116	0.36	2.36	0.28	5.91	0.00	0.00	0.00	0.04	0.18
Sweden	116	0.32	1.90	2.35	14.58	0.00	0.00	0.00	0.39	0.76
Switzerland	116	-0.12	0.95	0.23	3.30	0.51	0.17	0.00	0.00	0.73
UK	116	0.18	7.22	-1.90	14.99	0.00	0.07	0.00	0.01	0.48

1. p-value of Shapiro-Wilk test for normality. (null of normality)
2. Mackinnon approximate p-value of Dickey-Fuller test for stationarity. (null of having uint root test)
3. Mackinnon approximate p-value of Phillip-Perron test for stationarity. (null of having uint root test)
4. p-value of White noise test for autocorrelation. (null of no aurocorrelation)
5. p-value of Lagrange Multiplier (LM) test for ARCH. (null of no ARCH effect)

We also test the series for serial correlation and ARCH effects. The White noise and ARCH LM tests results are shown in Tables 2 and 3. Monthly series contain more cases that are diagnosed with serial correlation than quarterly series. In addition, monthly series are more diagnosed with ARCH-type dependence than quarterly series. Hence, one may expect larger values of EMP indices to come in clusters more often in monthly than in quarterly series. As Wagner and Marsh (2000) point out using higher frequency data to have more observations may come at the cost of greater bias-variance trade-off.

Table 4. Lee and Strazicich LM structural break unit root test

Country	*model*	*min test statistics*	*break point*	*lambda*	*result*
BelgiumQ	A	-9.36	67		*no unit root at 1%*
	C	-9.71	44	0.4	*no unit root at 1%*
CanadaM	A	-17.66	186		*no unit root at 1%*
	C	-17.64	162	0.5	*no unit root at 1%*
DenmarkQ	A	-11.1	49		*no unit root at 1%*
	C	-10.82	73	0.6	*no unit root at 1%*
GreeceQ	A	-4.38	60		*no unit root at 1%*
	C	-5.29	83	0.7	*no unit root at 1%*
IcelandQ	A	-8.29	74		*no unit root at 1%*
	C	-8.42	74	0.6	*no unit root at 1%*
IrelandQ	A	-10.54	67		*no unit root at 1%*
	C	-10.45	73	0.6	*no unit root at 1%*
SwitzerlandQ	A	-3.05	64		*unit root*
	C	-6.54	46	0.4	*no unit root at 1%*

Model A (crash model): break in intercept only (critical value at 1%, 5%, and 10% are: -4.239, -3.566, and -3.211). Model C: break in intercept and time trend. Critical values in model C (intercept and trend break) depend on the location of the break (λ = TB/T) and are symmetric around λ and (1-λ). Model C critical values additional break locations can be interpolated. Critical values at 1%, 5%, and 10% are: (for λ=.3) –5.05, -4.50, and -4.18, (for λ=.4) –5.05, -4.50, and -4.18, (for λ=.5) -5.11, -4.51, and -4.17.

From the presented statistics of EMP series, we can conclude that monthly series are more likely to be non-normally distributed, stationary, and dependent while there are more incidences of normally-distributed and independent indices in quarterly series. Thus, one may conclude that EMP indices that are constructed from lower frequency data are less likely to be fat-tailed and quarterly series compared to monthly series are less appropriate for applying EVT. It suggests that, we should be cautious in interpreting the tail indices that are obtained from time aggregation of quarterly and lower frequency data while relying on EVT.

1.5.3 Hill's index estimation. As mentioned earlier, Hill's estimator is optimal under independent draws from an exact Pareto distribution. Even if EMP indices are exactly from a Pareto distribution, bias-variance tradeoff plays an important role in the estimation of tail thickness for small samples. We combine two methods – Monte Carlo simulation and the Modified Hill's estimator – to deal with the bias-inefficiency tradeoff. These two methods are discussed in the following.

The Monte Carlo method: We design the simulation in a way to minimize mean square error (MSE) of the given sample size *n* with density function F(*x*). MSE combines both bias and inefficiency to capture the tradeoff elements carefully.[23] Monte Carlo method exploits the asymptotic normality of Hill's index to select the optimum cutoff value (*m*). We follow the simulation steps as provided in Longin & Solnik (2001) and Haile & Pozo (2008) to estimate the tail index. A summary of the adopted steps is presented in the Appendix A.

Nevertheless, there are two concerns with the Monte Carlo method: one conceptual and one computational. First, it only considers Student's *t* as the possible class of distributions to simulate the tail index while there are two other possibilities – stable laws and ARCH type distributions. Second, selection of the optimum cutoff value is based on the results of a statistical test, which determines the degrees of freedom of the Student's *t* that the actual data are from. For each $\gamma^h(m^*(\alpha))$ there are several highly significant test results, nevertheless, there is no systematic way to rigorously distinguish the most reliable test result. For instance, in case of the monthly EMP of Austria, the null of "actual data are not from Student's *t* distribution with α degrees of freedom", has several results that are significant at lower than one percent. Its two smallest p-values are: 1.8e-5 and 6.3e-4, which represent α equal to 5.2 and 3.3, respectively. While it is not very clear that how much 1.8e-5 and 6.3e-4 are statistically different, α equals to 5.2 implies that the optimum cutoff value will be 11 and α equals 3.3 implies that the optimum cutoff value will be 19. We apply the Huisman *et al.* (2001) method to circumvent these two concerns.

1.5.4 Modified Hill's estimator: Huisman *et al.* (2001) show that their modified Hill's estimator can equally perform well under the GARCH (1,1) model. It is quite common in financial econometrics to capture second-order (ARCH type) dependence as reflected in clusters of high and low volatility by GARCH models. Thus, the modified Hill's estimator should be capable of replacing the ARCH type distributions.[24] We also attempt to overcome the computational concern by a screening process. The modified Hill's estimator is insensitive with respect to the choice of the maximum number of tail observations to include, as long as it is less than half of the sample size. Therefore, having the idea of Hill's plot in mind, the modified Hill's estimator of each EMP series are computed, to roughly obtain the stable region for the estimated modified Hill's indices. Then, we go back to simulation results and select the most significant optimum cutoff value (m^{**}) within the region of stable modified Hill's estimations.

23. MSE of S simulated observations of the estimator $X_s^{\sim}$ can be decomposed as: $MSE((X_s^{\sim})_{s=1,2,\ldots,S}, X) = (X^{-} - X)^2 + 1/S\ \Sigma_{s=1}^{S}(X_s^{\sim} - X)^2$, where X^{-} represents the mean of S simulated observations. The first part measures the bias and second part the inefficiency.

24. The other class of distributions that can account for fat tails are stable laws. But as Wagner & Marsh (2005) argue, although symmetric stable laws with $\alpha<2$ are theoretically justified for extreme value theory, applications of Hill's estimator do not seem promising for stable laws in small samples.

Table 5. Hill's index and number of tail observations

	Monthly			*quarterly*		
Country	*Hill's index*	*degree of freedom**	*tail observations*	*Hill's index*	*degree of freedom**	*tail observations*
Australia	0.19	5.3	13	0.21	4.8	7
Austria	0.3	3.3	19	0.24	4.2	8
Belgium	0.34	2.9	22	0.22	4.6	7
Canada	0.28	3.6	18	*0.5*	*normal*	9
Denmark	0.26	3.9	17	0.23	4.3	9
Finland	0.3	3.3	19	*0.5*	*normal*	11
France	0.42	2.4	25	0.4	2.5	15
Greece	0.4	2.5	24	*0.5*	*normal*	10
Iceland	0.5	2	32	0.36	2.8	14
Ireland	0.34	2.9	20	*0.5*	*normal*	10
Italy	0.26	3.8	17	0.27	3.7	9
Japan	0.2	5	11	0.23	4.4	7
Netherlands	0.26	3.8	17	0.29	3.5	10
New Zealand	0.33	3	21	0.26	3.8	10
Norway	0.29	3.5	19	0.26	3.9	8
Portugal	0.34	2.9	22	0.27	3.7	9
South Africa	0.25	4	15	0.26	3.9	8
Spain	0.28	3.6	18	0.32	3.1	11
Sweden	0.34	2.9	22	0.38	2.6	10
Switzerland	0.27	3.7	17	*0.5*	*normal*	8
UK	0.32	3.1	21	0.37	2.7	13

* degree of freedom of the Student's *t* that the actual data are from.

Estimated tail indices and number of tail observations for monthly and quarterly series are reported in Table 5. Hill’s index, γ, is the inverse of the tail index, α, or the degrees of the freedom of the closest Student’s *t*. For those quarterly series that are well behaved and normally distributed, the number of observations is estimated from conventional methods. Hence, any observation larger than the mean of the series plus one and half of its standard deviation is counted as a currency crisis episode.

In the literature, some studies put exclusion window to avoid counting the same crisis more than once. In different studies, width of the window varies from one quarter to two years. However, as mentioned earlier, in our research project recognizing the number of crisis periods is a vital step. It is more important to correctly identify the crisis periods than distinguishing whether the period is a new crisis or it is the continuation of the previous one. Furthermore, exclusion windows can cause potential problems. First, it introduces artificial serial correlation (see, *e.g.* Abiad 2003). Second, it equalizes the length of all spells and eliminates any information that the duration of spells may contain. Finally, same as the choice of threshold level, it requires another arbitrary selection. Hence, we choose not to have exclusion window.

It is important to recognize how the crisis episodes are scattered through the time. Figures 1 and 2 show the percentage of the countries that experience a currency crisis (monthly or quarterly) over the period of

Figure 1. Percentage of crisis episodes per month

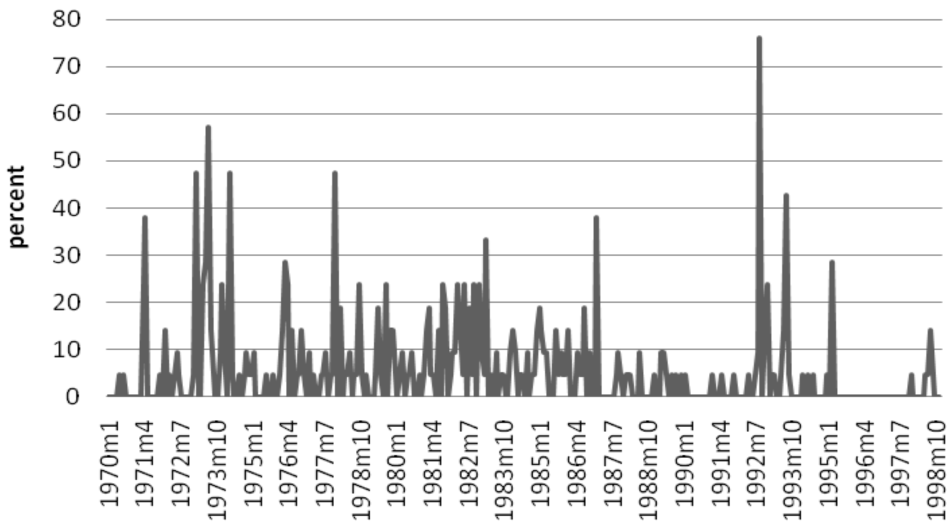
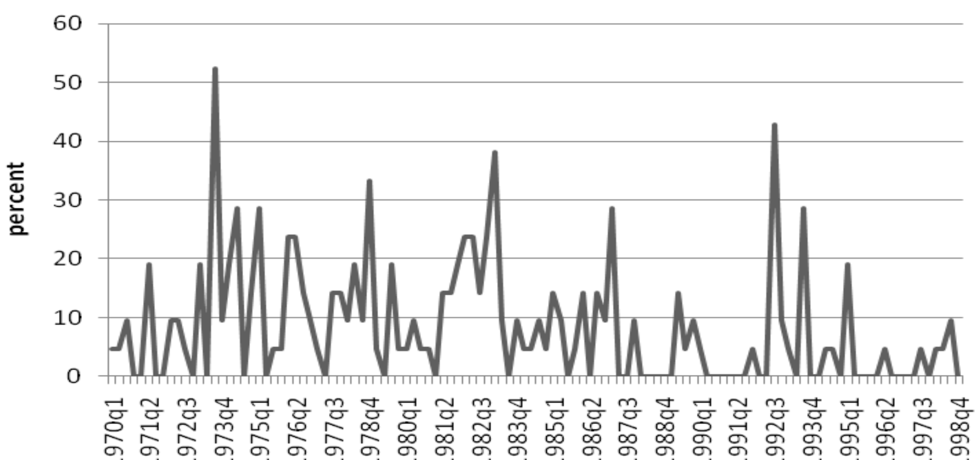


Figure 2. Percentage of crisis episodes per quarter



1970-1998. As it is evident, the number of crisis episodes peaks in some specific periods. Two periods have the largest number of crisis incidences: the third quarter of 1973 (the breakdown of the Bretton Woods system) and September 1992 (the collapse of the British pound and crisis in the EMU). It can potentially be interpreted as a sign of the contagious nature of currency crisis. We will come back to this point and will pay close attention to it in the next chapter.

1.6 Comparison

In this section we compare the results of our approach with four other methods. First, currency crisis episodes are estimated by the time varying conventional Eichengreen *et al.* (1995) method, for a threshold equal to 1.5 and 2 standard deviations (only corresponding results to 1.5 standard deviations that produces more significant results are reported). Next, the crisis periods are recognized with the method that is introduced by Zhang (2001). We also identify the crisis episodes by Haile and Pozo (2006) approach. They apply EVT and select the optimum cutoff values with Monte Carlo simulation method.

Finally, following Pozo and Dorantes (2003), Lestano and Jan (2007), and Pontines and Siregar (2008), we employ the recursive least squares method to estimate the number of tail observations. In the recursive method, first, each series is arranged in descending order and the Hill's estimator are computed for the first thirtieth percentile. In the next step, the computed amounts for Hill's index are regressed on a constant and time trend variable successively. Then, the recursive residuals are derived to find the structural break. The optimum *m* is picked where the value of recursive residuals lies outside of the two-standard errors band. Table 6 reports the results.

Total number of the identified crisis episodes by Eichengreen *et al.* (1995) method is almost close to that of this paper. However, distributions of these two types of crises are substantially different.

Results of the Zhang's method seem inconsistent with our data and are not reported. This method, in one hand, does not identify any crisis episodes for most of the countries. On the other hand, for those crisis periods that it recognizes, crisis periods all occur consecutively.

The recursive method outcomes are different. In general, it identifies much more crisis periods compared to other approaches. Similar to Zhang's method, this method identifies a small number of crisis episodes for some countries while finds a very large amount of crisis periods for the others. In some cases, it cannot recognize any optimum cutoff value (*m*) at all.

Table 6. Number of currency crisis episodes with different methods

	Monthly				Quarterly			
Country	*Mod. EVT*	*Eichen.*[*]	*Rec.*	*Haile.*	*Mod. EVT*	*Eichen.*[*]	*Rec.*	*Haile.*
Australia	13	23	13	6	7	9	…	6
Austria	19	15	…	34	8	7	11	21
Belgium	22	21	12	42	7	9	44	26
Canada	18	23	…	23	9	9	21	17
Denmark	17	24	53	19	9	10	12	14
Finland	19	21	88	18	11	11	18	11
France	25	25	18	39	15	8	24	20
Greece	24	23	12	27	10	10	..	18
Iceland	32	26	50	38	14	10	6	24
Ireland	20	22	98	34	10	10	8	24
Italy	17	20	69	13	9	5	37	8
Japan	11	21	59	9	7	8	35	7
Netherlands	17	16	…	41	10	6	40	24
New Zealand	21	8	…	27	10	1	30	16
Norway	19	21	7	29	8	9	37	18
Portugal	22	14	5	28	9	7	…	11
South Africa	15	22	12	21	8	6	37	12
Spain	18	26	15	24	11	7	42	14
Sweden	22	18	83	36	10	5	27	22
Switzerland	17	16	…	29	8	8	6	14
UK	21	23	60	36	13	8	…	18

** Reported numbers correspond to threshold equals to1.5 of standard deviations.*
… implies that there exists no structural break in the selected range.

Haile and Pozo (2006) method generally identifies more episodes of crisis compared to our approach. It indicates that determining extreme values of the EMP series just by relying on Monte Carlo simulation (not combining with the modified Hill's estimator) can potentially increase number of the crisis episodes by picking the less significant EMP indices. However, recognizing higher number of crisis periods comes at a cost of more wrongly determined episodes of crisis. While our approach mostly identifies severe crisis periods as episodes of currency crisis, the mentioned method besides the severe crisis times determines slight and mild stressed periods of macro economy as crisis.

It is a very difficult task to officially evaluate performance of the different methods and approaches for identification of currency crisis periods since there is no consensus on a formal definition of currency crisis in the profession. Furthermore, no international organization systematically categorizes currency

Table 7. Identified Canadian currency crisis episodes through 1970-1998

year	*crisis episodes* *month*	*crisis episodes* *quarter*	*chronology of economic and political events*[*]
1976	11		Political uncertainties following the Parti Québécois win in Quebec election on November 15 and softening prices for non-energy commodities.
1977	10		Rising cost and wage pressures and substantial current account deficit.
1978	2 and 9		Inflation pressure leads to increase in interest rates and tight monetary policy by the Bank of Canada.
1979	1 and 5	I	The Bank of Canada Rate rises by 375 basis points to 11.25 per cent in the beginning of January 1979.
1980	3 and 11	II and IV	Quebec Referendum and its political concerns, weakening prices for non-energy commodities, and the introduction of the National Energy Program by the federal government in October.
1981	7	III	Sharp rise in short term interest rates through 1980 and into summer 1981. The Bank of Canada Rate touches an all-time high of 21.24 per cent in early August.
1982	2,3, and 6	II	Growing concerns about the commitment of Canadian authorities to an anti-inflationary policy stance and cancellation of a number of large energy projects. Bank of Canada allows the short term interest rates rise to prevent from turning into a speculative rout. Bank of Canada abandons M1 as an anchor against inflation.
1984	3 and 6	II	The high interest rates and favourable investment opportunities in the United States attract funds.
1985	2		Outflow of funds into the US.
1986		I	Weak economic and financial prospects, esp. following the failure of Canadian Commercial Bank and Northland Bank. The CAD depreciates to US$0.6913 on February 4.
1992	9 and 11	IV	The ERM in Europe comes under repeated attack. Defeat of Charlottetown Accord on October 26.
1995		I	Mexican Peso crisis and weakness of Canada's fundamental, esp. large fiscal and current account deficit.
1998	8		Crisis in emerging-markets economies widens and intensified by the debt default in Russia. The CAD falls toUS$0.6311 on August 27.

* Source: Powell, J. (2005). A History of the Canadian Dollar. Bank of Canada, Ottawa.

crisis periods. An alternative solution is to verify the reliability of the identified crisis episodes with chronology of the economic and political events. Unfortunately, a full chronology of the events for countries of our sample is not available. Consequently, as an example, we present the identified crisis episodes for Canada in Table 7 and validate their accuracy with chronology of the economic and political events over the 1970 to 1998 time period. The identified crisis episodes match very well with the chronological events. Although there is a good overlap between the monthly and quarterly crisis periods, there are a few episodes that are only identified by one set of data – either monthly or quarterly. Nevertheless, it can be attributed to the nature of data and severity of the crises.

1.7 Conclusion

Identifying crisis periods is a substantial step in most of empirical studies in the field. This paper analyzes and estimates the dating of currency crises for 21 countries from 1970 to 1998.

In our approach, we constructed EMP series from monthly and quarterly data and defined those large values that lie in tail of the EMP distribution as episodes of currency crisis. In order to identify the tail observations, we applied a more objective statistical method based on extreme value theory rather than conventional methods which is based on arbitrary thresholds and priori assumptions. We showed EMP series – especially for higher frequency data – are fat-tailed and are more appropriate for applying EVT than assuming they are well behaved and normally distributed series. However, the EVT method for low frequency data should be applied cautiously.

We combined Monte Carlo simulations with a modified Hill’s estimator method to carefully minimize the bias-variance tradeoff and overcome the related concerns with Monte Carlo application. This paper also attempted to introduce a systematic way to select the reference country around which a country’s currency pressure index should be built. This approach can help us to identify the currency crisis periods more precisely and in the following chapters it will result in a better understanding of the roots and determinants of the currency crises.

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Appendix A

To determine the optimum cutoff value by Monte Carlo simulations, we adopt the simulation steps from Longin & Solnik (2001) and Haile & Pozo (2008) and run them with R software. These steps are:

1. S time series containing n observations of EMP are simulated. Each S is derived from a known Student's t distribution with α degrees of freedom, where α ranges from 1 to K. The class of the Student's t distribution is chosen to consider different degrees of tail fatness. Since the tail index γ is inverse of α (γ=1/α), the lower the degree of freedom is, the fatter the distribution will be. In our simulation α is allowed to take values from 1 to 10 with increment of 0.1 and number of replications (S) equals 1000.

2. For different numbers of m of the extreme EMPs, a tail index $\gamma_s^h(m,\alpha)$ corresponding to the sth replication from the Student's t with α degrees of freedom is estimated. Values of m can vary from %1 to %30 of n, where n is the sample size of the actual EMP data.

3. For a particular Student's t distribution with α degrees of freedom and for each value of m, MSE of the S tail index estimates, which is denoted by MSE ($\gamma_s^h(m,\alpha)_{s=1,2,\ \ldots,S}$), is computed. This computation repeatedly continues for different values of m and particular Student's t with α degrees of freedom. Then the optimal m, denoted by $m^*(\alpha)$, which minimizes MSE for the particular Student's t distribution with α degrees of freedom is selected.[25] Optimum values of m for different Student's t distributions are repeatedly selected. A total of K optimal values of m^*, $(m^*(\alpha))_{\alpha=\ 1,2,\ \ldots,K}$, are subsequently selected for K possible theoretical distributions.

4. Using each of K optimum values of m that are obtained in last step, the Hill index, $\gamma^h(m^*(\alpha)$, is estimated from actual EMP series. For all α from 1 to 10, the tail indices, γ^h, are estimated from actual EMP series.

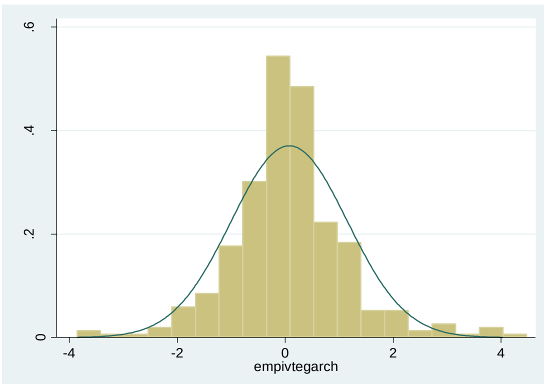
As the final step, we select one single number (say m^{**}) from the K optimum tail indices, m^*, for each EMP series such that the estimated tail index from the actual data (step 4) is statistically the closest to the corresponding tail index of the theoretical distribution. The main objective of the whole exercise is to

25. As explained by Jansen and de Vries (1991), there is a U-shaped relation between MSE($\gamma_s^h(m,\alpha)_{s=1,2,\ldots,\ S}$) and m that expresses the tradeoff between bias and inefficiency. Choosing a few observations from the tail makes the bias part of MSE dominant over the inefficiency part. On the other hand, including too many observations from the tail makes the inefficiency part of the MSE dominant over the bias part.

determine the number of extreme observations for each EMP series. This value, m^{**}, that is corresponding to the optimum tail index, specifies the number of observations as the largest EMPs or episodes of currency crises.

Appendix B

Australia M



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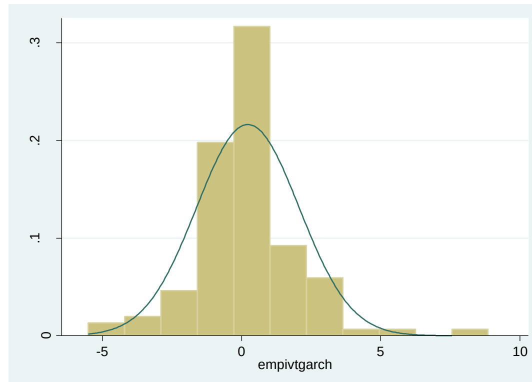

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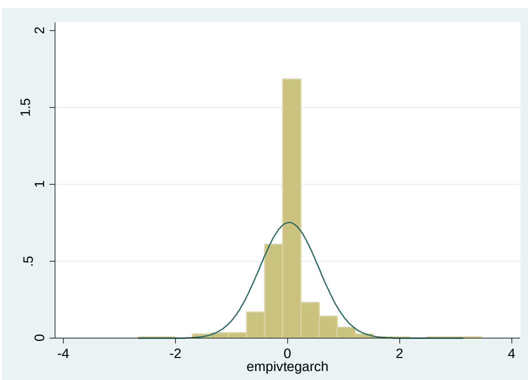

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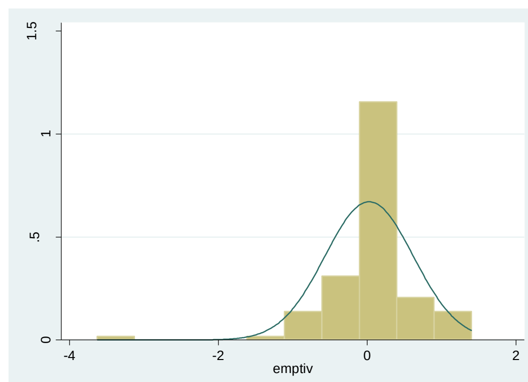

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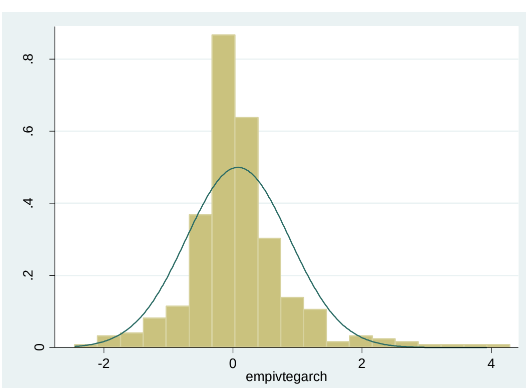

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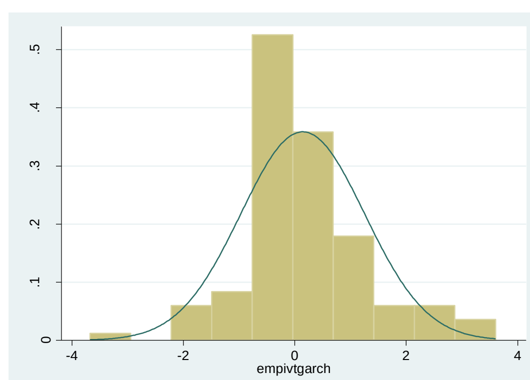

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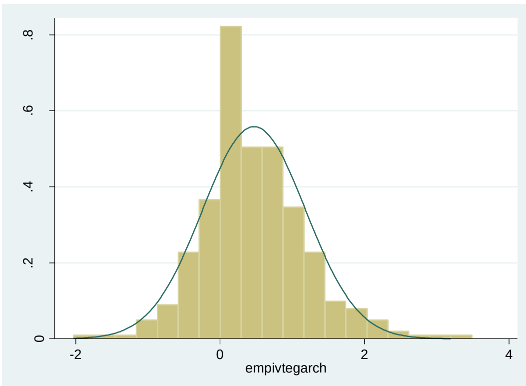

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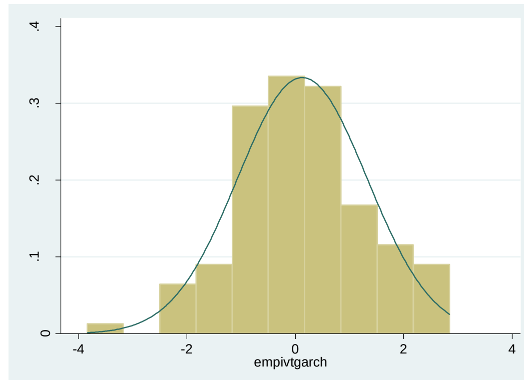

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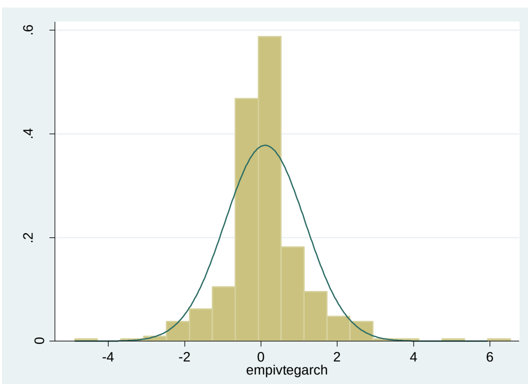

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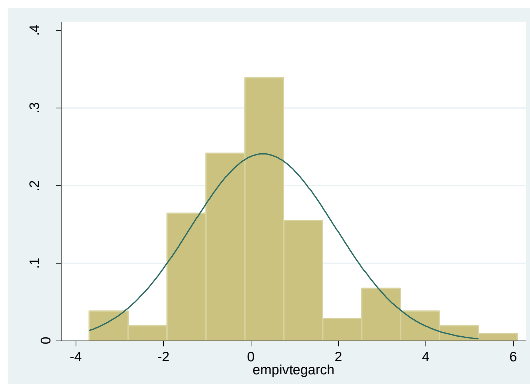

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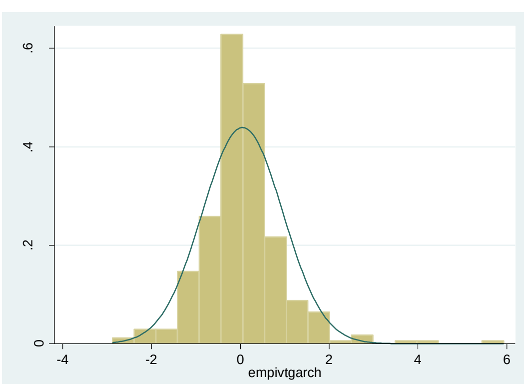

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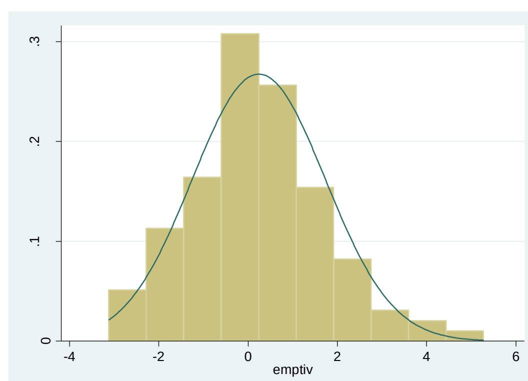

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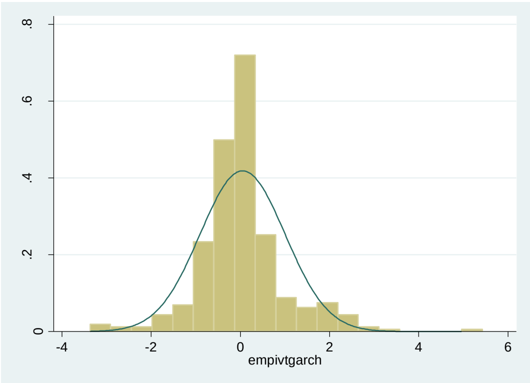

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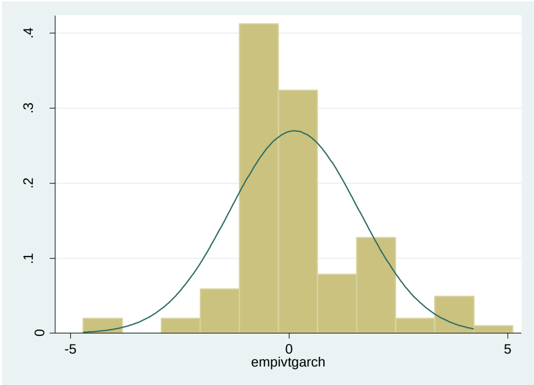

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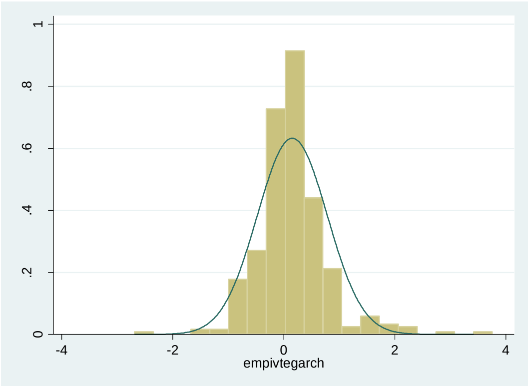

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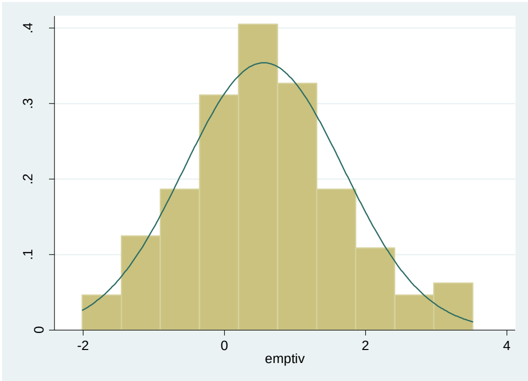

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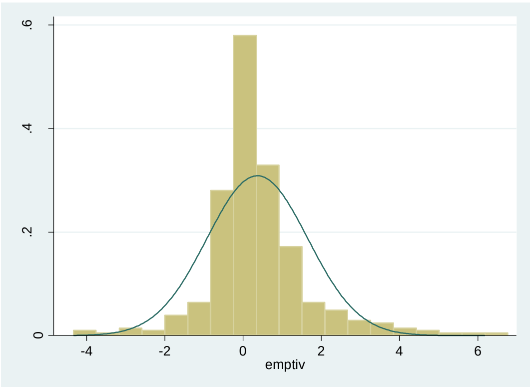

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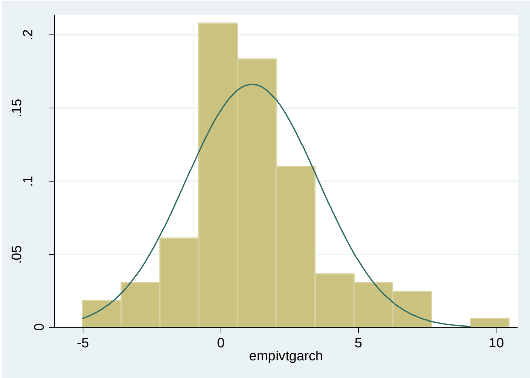

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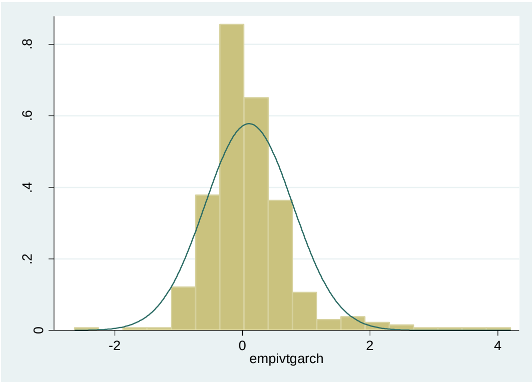

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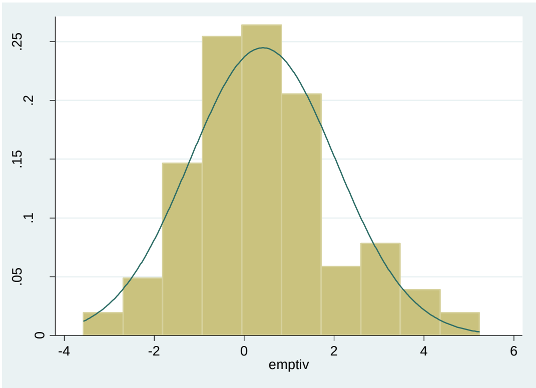

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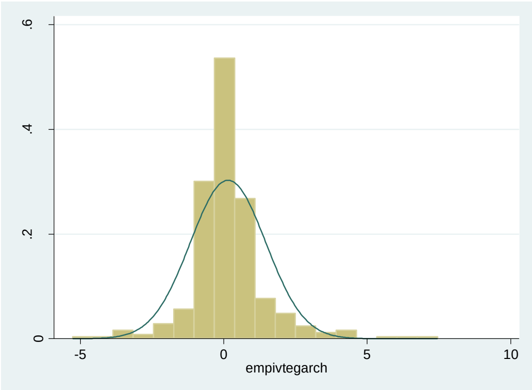

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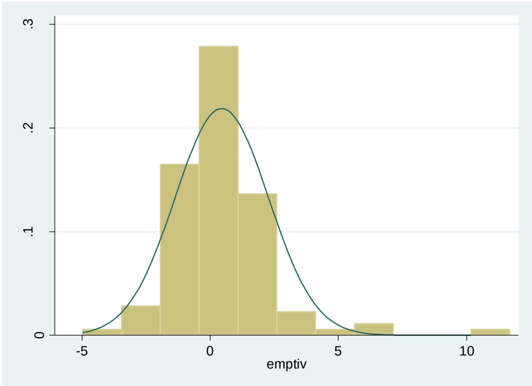

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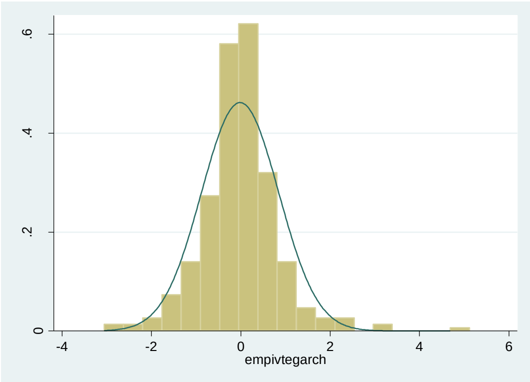

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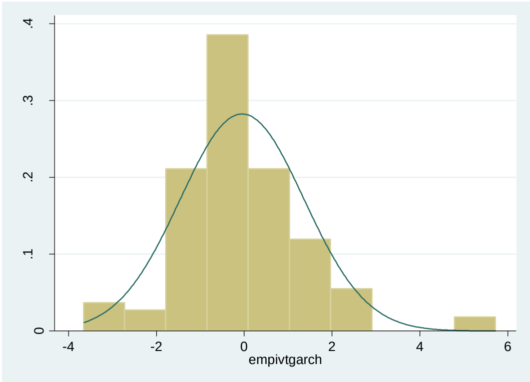

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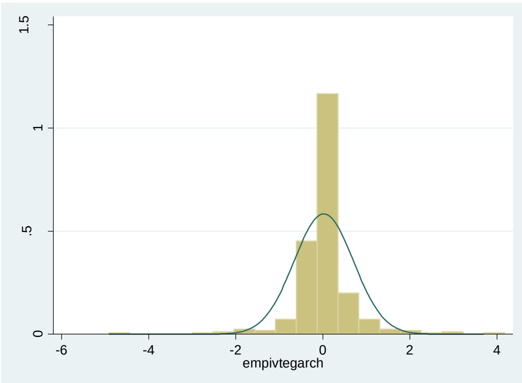

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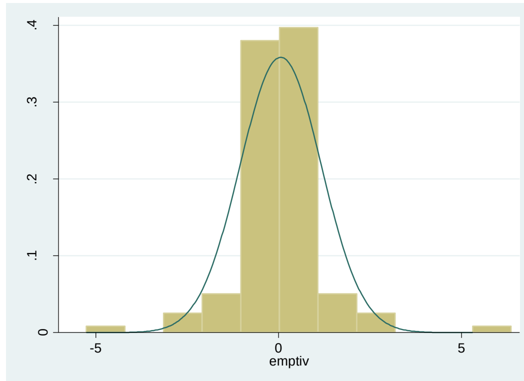

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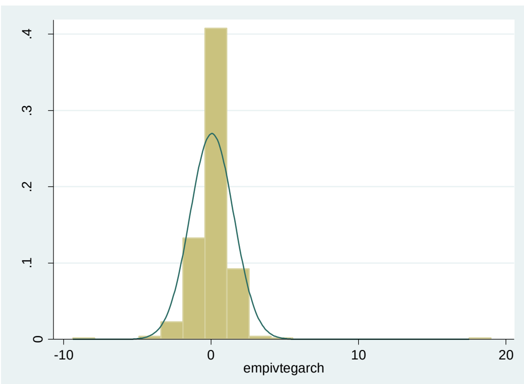

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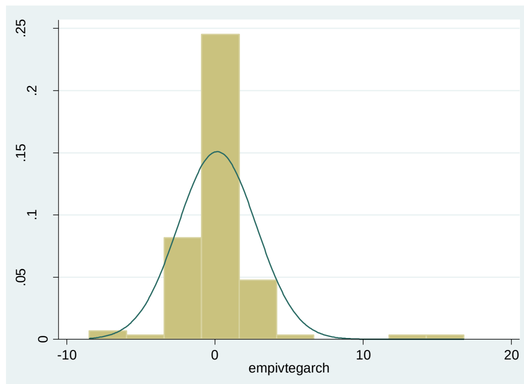

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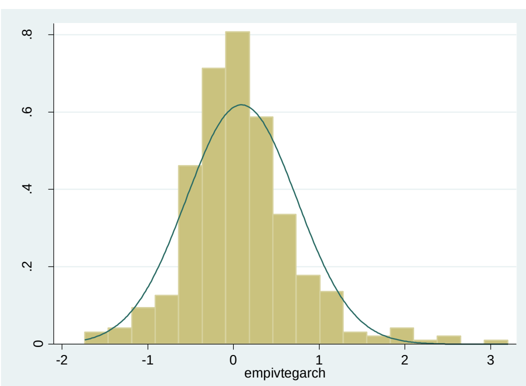

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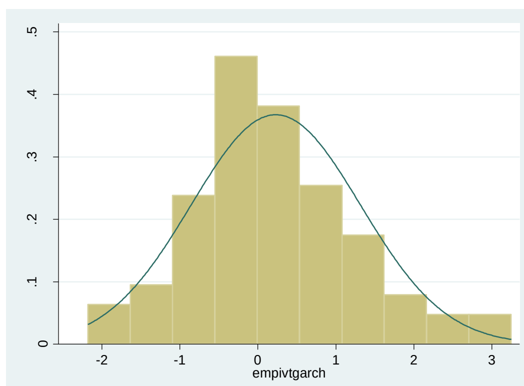

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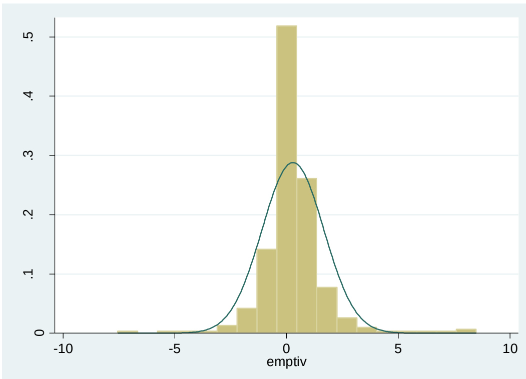

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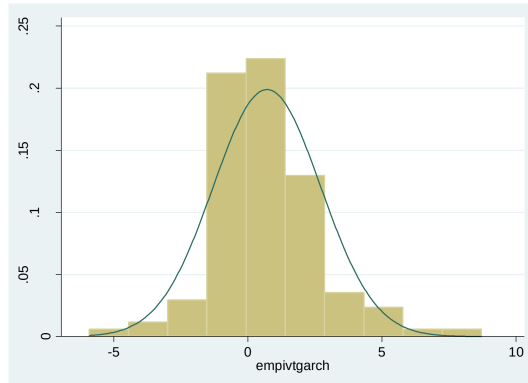

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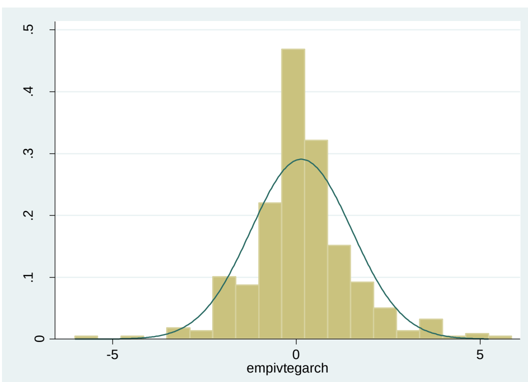

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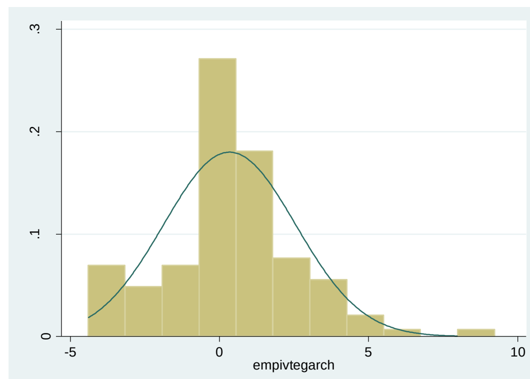

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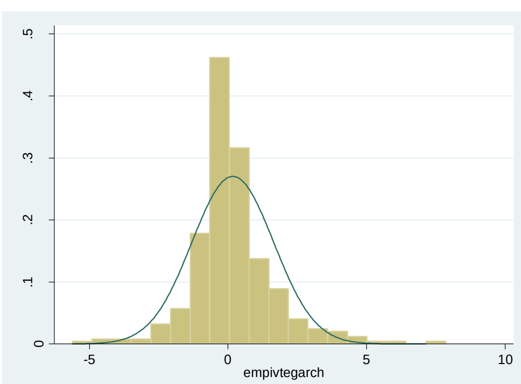

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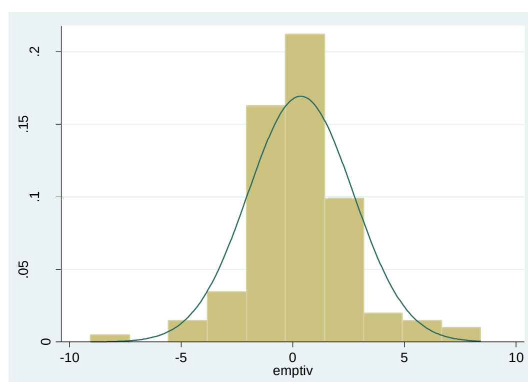

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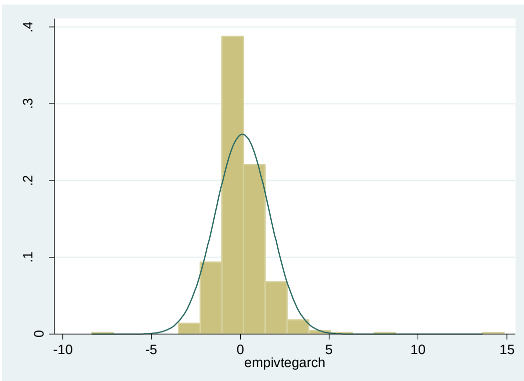

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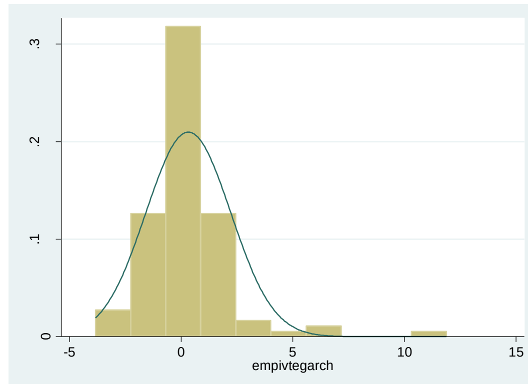

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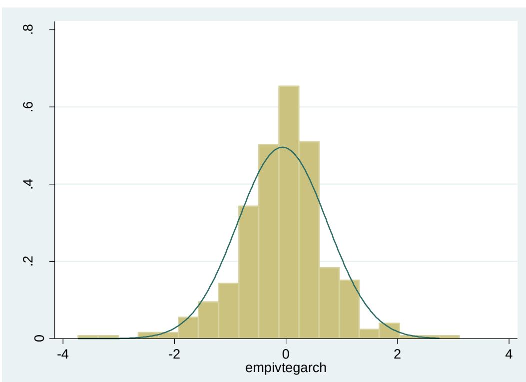

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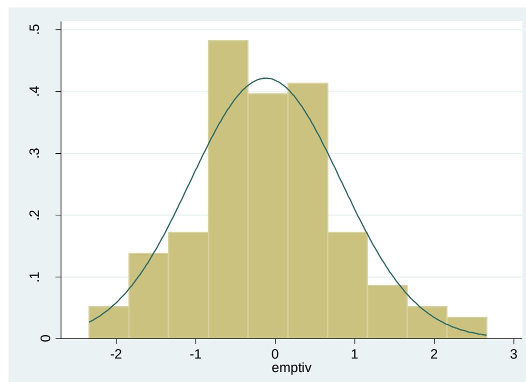

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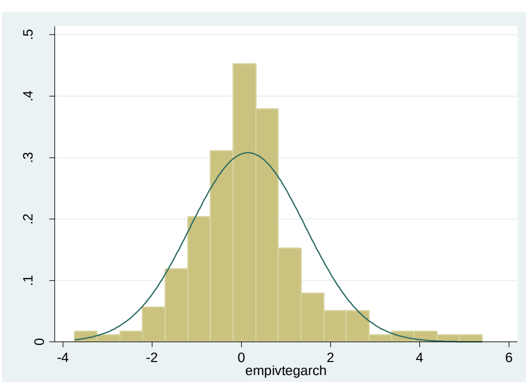

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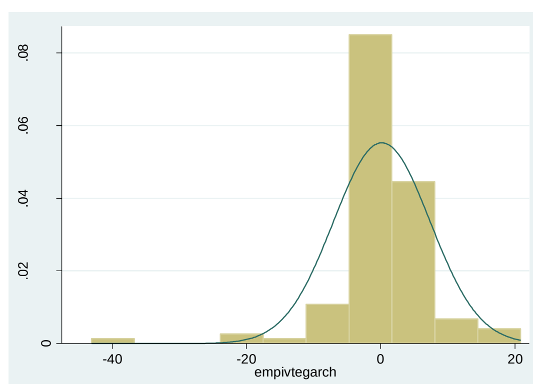

Chapter 2

Empirics of Currency Crises: A Duration Analysis Approach

2.1 Introduction

Currency crises have been a recurrent feature of the international economy from the invention of paper money. They are not confined to particular economies or specific region. They take place in developed, emerging, and developing countries and are spread all over the globe. Some are scattered over time and some are clustered in points of time. They play an important role in the world economy's turmoil. Countries that experience currency crises face economic losses that can be huge and disruptive.[1] However, the exacted toll is not only financial and economic, but also human, social, and political.

In the recent decades, while the frequency of currency crises has increased[2], the globalization process and the emergence of integrated international financial markets have propagated domestic crises beyond the borders of individual countries. Now, it is clear that a currency crisis is a real threat to financial stability and economic prosperity. As a result, studying currency crises to find out what drives them and through which channels they spread is of great interest to policy makers, academics, and market participants. Such studies should illustrate the mechanism of the crisis and forecast whether or not, and when, an individual country might experience a currency crisis. Credible studies would help policy makers to come up with solutions for crisis prevention, crisis management, and crisis resolution.

The main objective of this paper is to analyze the determinants of currency crises for twenty OECD countries and South Africa from 1970 through 1998. It systematically examines the role of economic fundamentals and contagion in the origins of currency crises and empirically attempts to identify the channels through which the crises are being transmitted. Our goal is to shed light on the mechanisms of the crises by studying the realization of time-varying explanatory variables, constructed on quarterly data, as well as the duration pattern of non-crisis periods.

There is an extensive literature on currency crises that empirically evaluates the roots and causes of the crises. Despite the interesting results of these studies, only very few of them account for the influence of time on the probability of crises. In a pioneering work, Klein and Marion (1997) provided a key early contribution on the duration of fixed exchange rates and showed that, time matters as a determinant of the exchange rate survival. They introduced the duration of exchange rates of seventeen emerging and developing countries as an explanatory variable in a logit specification.[3] Tudela (2004) adopted a more sophisticated approach – duration models – to study the determinants of currency crises for twenty OECD countries. With the help of this methodology, she incorporated the length of time that a currency had

1. To observe the output behaviour during currency crisis episodes, see Bordo *et al.* (2001), Bussièr *et al.* (2010), Gupta *et al.* (2007), and Milesi-Ferretti and Razin (1998).
2. See Eichengreen and Bordo (2002).
3. Nevertheless, this approach is not a full duration analysis and implicitly assumes monotonic duration dependence.

already spent in non-crisis periods as a determinant of the likelihood of movement into a crisis state. There are also a few other papers that apply duration analysis to study some related topics such as exchange rate regimes and financial stability.[4]

We employ duration models to study the probability of a currency exiting a tranquil state into a crisis state. It appears that maintaining currency credibility gets harder over time.[5] Duration models can help us to examine how the passing of time can affect the stability of a currency. The starting point is that each crisis episode can be treated as a random process. By incorporating the randomness, we recognize that some important determinants of currency stability remain unobservable at the aggregate time series level. The unobservable factors can be embodied systematically in the baseline hazard of the attacks, which is easily captured by duration models. Furthermore, we check whether there is a common pattern for the duration of non-crisis periods among countries, and whether the timing of crises significantly differs across countries.

This paper contributes to the literature in three areas. First, following Eichengreen, Rose, and Wyplosz (1996), we test for contagious currency crises and attempt to recognize empirically potential contagion channels while controlling for a set of macroeconomic fundamentals. We apply duration analysis, with focus on semi-parametric models, to estimate a model with unrestricted baseline hazard. These models enjoy the important advantage of not requiring any assumptions on the distribution of the time of failures. This advantage, on one hand, allows us to capture both the monotonic and the non-monotonic nature of duration dependence and improve the efficiency of our model. On the other hand, they let us remove the risk of a biased coefficient and provides estimations that are more precise.[6] Second, to minimize the concerns regarding the accuracy of identified crisis episodes that directly affect the final results of the model, our paper uses crisis episodes that are identified by a relatively more objective method based on extreme value theory. Third, we make use of several robustness checks, including running our models on two different crisis episodes sets that are identified based on monthly and quarterly type spells.

The remainder of this paper proceeds as follows. Section 2 concisely reviews the literature on currency crises. Section 3 presents a brief review of theoretical and empirical contagion models. Section 4 concentrates on methodology and related issues. Section 5 introduces the variables and describes the data. Section 6 presents the main empirical findings and robustness tests. Section 7 discusses the results and concludes. Methodology details and some technical results are presented as appendices.

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4. See Setzer (2004), Wälti (2005), Pe´rez-Bermejo *et al.* (2008), and Razo-Garcia (2011) for duration of exchange rate regimes and Aka (2006) for duration of financial stability under liberalization.

5. It may be called *currency stability fatigue*.

6. Pesaran and Pick (2007) claim since panel data models typically assume that equation errors across countries are independently distributed, they could introduce a substantial bias in the estimation of contagion coefficients.

2.2 Literature review

The pervasiveness of currency crises around the world has fueled vast theoretical and empirical studies on the causes and origins of speculative attacks. These studies have evolved over time in relation to changes in the nature of the crises. In what follows, the main branches of these theories and empirical studies are briefly reviewed.

2.2.1 Theory

The literature on currency crises has grown rapidly in the past few decades in order to explain several incidences of crises in the world. The early work on currency crises, now known as *first-generation*, begins with the seminal work of Krugman (1979).[7] It essentially explains the balance of payment crises that occurred during the 1970s and early 1980s. Accordingly, the crisis is generally driven by persistent budget deficits that, monetized by a central bank, would lead to a gradual decrease of foreign reserves. The first-generation models show how inconsistent domestic monetary and fiscal policies as well as international commitments (*e.g.* a fixed exchange rate) *push* the economy into the crisis. Weak economic fundamentals invite speculators to attack the currency. In this type of models, attacks take place when the shadow exchange rate (the rate that would dominate the exchange market at the event of floating) equals the current fixed exchange rate. At the time of the attack the central bank should voluntarily devalue or float the exchange rate, otherwise intervention to support the fixed rate would not be successful and would only result in the instant depletion of foreign reserves.

A number of stylized facts, which are consistent with deteriorating economic fundamentals, have been noted to occur prior to the incidence of currency crises. These include increasing interest rate differentials, declining international reserves, substantial real exchange rate appreciation, and weak banking systems. Flood and Garber (1984) develop a comprehensive analytical framework to examine the speculative attacks by modeling these stylized facts. Flood and Marion (1999) provide a detailed review of first-generation models.

First-generation models are simple and can explain a number of crises. However, they have a linear behavioral function and represent the government policies in a very rigid and mechanical manner. More importantly, they do not fit very well with what actually happened during several currency crises, especially in advanced countries. The *second-generation*[8] models were designed to answer these shortcomings and to capture features of speculative attacks in the European Exchange Rate Mechanism

7. This work is related to the earlier work of Henderson and Salant (1978) on speculative attacks in the gold market.
8. The terminology of *first* and *second-generation* models was first introduced by Eichengreen *et al*. (1995).

and in Mexico in the 1990s. Second-generation models are non-linear such that agents incorporate the response of policies and the related changes in the economy to their expectations. These models show that speculative attacks can occur in the absence of poor macroeconomic fundamentals. Even when policies are consistent with the fixed exchange rate, attack-conditional policy changes can *pull* the economy into an attack. These models allow speculative attacks to be self-fulfilling[9] and set forth possibilities for multiple equilibria.[10] Herding behavior, information cascades, political environments, banking systems, business cycles, and contagion all play a role in second-generation models. Unlike the first generation models, the timing of the attack is indeterminate in these models because it is too dependent on peoples' expectations and the related coordination problem. Obstfeld (1996) offers the most influential modeling strategy among second-generation models. Flood and Marion (2000) and Rangvid (2001) provide reviews and Saxena (2004) and Breuer (2004) offer surveys of these models.

Yet the Asian crisis in 1997-98 showed that the two generations of currency crisis were not sufficient to analyze the crises, and it motivated the development of *third-generation* models. These models emphasize interconnections between foreign exchange markets, financial fragility, and financial institutions. Corsetti, Pesenti, and Roubini (1999) show how speculative attacks burst the bubbles that are financed by foreign capital and cause a severe currency crisis. Krugman (1999) argues that balance sheets of private-sector institutions, which are heavily loaded with foreign currency debt, play a key role in the development of a crisis.[11] He argues that speculative attacks initiate currency depreciation and sharply worsen balance sheets, as the domestic value of foreign debts rises. This discourages capital inflows and triggers capital flight, which puts even more pressure on the local currency and induces the start of a new round of balance sheet deterioration. On the other hand, the poor financial condition of firms will depress the domestic economy and lead to further currency depreciation. This cycle of events results in a vicious currency crisis.

Numerous works contribute to third-generation models. Among many Chang and Velasco (2001), Burnside *et al.* (2001 and 2004), and Braggion *et al.* (2009) can be mentioned. Interestingly, some researchers, *e.g*. Krugman (2010), find similarities between the recent subprime crisis and the Asian crisis and seek third-generation models to help them clarify subprime crisis mechanisms and devise efficient policy implications.

9. It can happen if a sufficient number of agents expect devaluation in the near future and put enormous pressure on the central bank by converting domestic currency to foreign currency and force the central bank to actually devalue.
10. The government whose currency is under attack is able to defend the exchange rate; however, it may find that its commitment to a fixed exchange rate is interfering with the achievement of domestic objectives, especially full employments, and may thus decide not to defend it.
11. He claims that most of these debts are financed through "moral-hazard-driven" loans and are "over-borrowed".

It is clear that each generation of models presents different – though related – explanations for a currency crisis and consequently offers distinct policy recommendations. The first-generation models simply advise policy makers to ensure consistency in their domestic and foreign policies. The second-generation models invite authorities to control their *temptation* for more expansionary domestic policies and continue the policies that are consistent with the fixed exchange rate. The third-generation models recommend policies that bring more *transparency* of risk and reward to investment opportunities in order to reduce the asymmetry of information and to minimize the moral hazard problem.

2.2.2 Empirics

The empirical literature on predicting currency crises has taken several directions.[12] However, Flood *et al.* (2010) categorize them in three main branches: structural models, panel data and discrete-variable techniques, and signaling methods.[13]

Structural models apply the theories of currency crisis to predict the speculative attacks. Some notable examples of structural models include Blanco and Graber (1986), Cumby and van Wijnbergen (1989), Goldberg (1994), and Jeanne and Masson (2000). These studies provide insight about specific currency crisis episodes and the merits of structural models, though they only concentrate on large and infrequent devaluations after an attack. Nevertheless, Eichengreen *et al.*(1995) claim that structural models are "narrowly defined" and adopt a non-structural model (which does not test or estimate any particular speculative attack theories) to systematically examine the crises.

The second branch uses panel data and discrete-variable techniques to predict crisis events in a sample of countries. This branch can be divided into two sub-branches based on how they determine the attack periods. Much of the literature on discrete choice models constructs the Exchange Market Pressure (EMP) index and defines the episodes of attack as occurring when the EMP reaches extreme values.[14] Then the binary crisis variable is treated as endogenous and would be explained by a set of explanatory variables. This approach lets the researchers take into account both successful and unsuccessful attacks and, in a dynamic way, it distinguishes between before and after the attack periods. In their influential study, Eichengreen, Rose, and Wyplosz (1995) first develop this approach and then apply panel logit models to analyze the exchange market crises in twenty OECD countries. Subsequently, different varieties of limited dependent variable models have been used to study the crisis events.

12. Kaminsky, Lizondo, and Reinhart (1998) and Abiad (2003) provide comprehensive surveys on empirical works.
13. Researchers have used several other mathematical and statistical techniques to empirically analyze currency crises. Vector Auto-Regressive (VAR) models have received more attention compare to the others. Martinez-Peria (2002) and Abiad (2003) employ Markov-switching models to study ERM and Asian crises respectively.
14. Our previous paper, "*Identifying Extreme Values of Exchange Market Pressure*", elaborates how to construct EMP and identify its extreme values.

Other discrete choice models do not rely on the EMP and define the crisis periods by their own methods. The following cases provide some instances. Frankel and Rose (1996) define a currency crisis as occurring when a country's currency depreciates at least 25 percent and exceeds any depreciation in the previous year by at least 10 percent. They run a panel probit model on over 100 developing countries to characterize large currency depreciation. Otker and Pazarbasioglu (1997) identify the episodes of speculative attack by estimating the one-step-ahead probability of a regime change. They apply probit analysis to estimate the probability of devaluations for six ERM countries. Kumar *et al.* (2003) define the currency crash by large devaluations, compare them to previous devaluations, and adjust them for interest rate differentials. They use panel logit model to investigate the predictability of currency crashes in 32 emerging countries.

The third branch of empirical literature on currency crisis models relies on the signaling approach. In their pioneering work, Kaminsky, Lizondo, and Reinhart (1998) introduced this method to evaluate the usefulness of potentially informative variables to detect the forthcoming crises. They monitored the evolution of some economic indicators and noticed that when these indicators exceed a certain threshold they can signal the potential risk of an imminent crisis. The threshold values are calculated to adjust the balance between the number of crises that have occurred and the model failed to predict them (similar to the concept of the type I errors in the statistical test), and the number of crises that model has falsely predicted and they never took place (similar to the concept of the type II error).[15] The signaling approach is also a bivariate method and, to date the crisis episodes, they used a modified version of the EMP index. Kaminsky and Reinhart (1999) adopted a signaling approach and examined the behavior of a couple of indicators leading up to the twin crises, currency and banking, in 20 countries. Bussiere and Fratzcher (2006) offer some recent innovations in applying dynamic versions of *early warning system*, and Candelon *et al.* (2010) propose a new statistical framework to assess them.

The last two branches are standard methodologies to study currency crises. They have been implemented extensively in applied studies. Berg and Pattillo (1999) evaluate some models that systematically attempt to predict crises and find that these models perform modestly in predicting crises *ex ante*. They also show that the probit model outperforms the signaling approach. However, Kumar *et al.* (2003) recommend the use of the logit model over the probit model. They argue that crisis events lie in the tail of events' distribution (that is, crises are less frequent than non-crisis events) and therefore the logit models can perform better than the probit ones.[16]

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15. In other words, the thresholds are determined in order to minimize the noise-to-signal ratio of the indicators.
16. Logit models follow logistic distribution that has heavier tails than normal distribution (which probit models follow) and can better accommodate discordant outliers.

There are several studies, including Berg and Pattillo (1999) and Kumar *et al.* (2003), which recommend a panel data approach by pooling the available data from different countries rather than considering individual countries. A panel data approach increases the number of observations and improves the power of estimation. Nevertheless, Berg *et al.* (2008) show pooling all possible countries can cause a heterogeneity problem. Thus, they encourage the researchers to perform a preliminary analysis to select the optimal country cluster before setting the panel logit model.

2.3 Contagion

Financial crises have demonstrated more contagious characteristics in recent years. Crises in one region have been followed by crises in countries that are in other regions, have different economic structures, and share few direct economic links. There are various instances of currency crises that have quickly spread to other countries. In 1992, the ERM crisis spilled over from Finland to other EU members and non-members. The Mexican peso crisis in 1994-95 was transmitted to other countries, even in different continents. The Thai baht crisis in 1997 spread to Malaysia, Indonesia, and the Philippines. It also contaminated Korea, Hong Kong, Singapore, and surprisingly, Brazil and Russia. The most recent case, the subprime crisis, propagated from the U.S. to most of the financial markets around the globe. From those instances one may conclude that in internationally integrated financial markets, shocks do not remain confined to the market where they are generated, and tend to propagate to other markets and cause clusters of crises.

In the following, the theoretical and empirical literature on contagion is reviewed with regards to how economists analyze the spread of currency crises across borders.

2.3.1 Theoretical literature

Despite the extensive use of the term contagion in the literature, little agreement exists on what exactly it entails. In fact, there is a considerable interference between contagion and interdependence.[17] While one group of contagion models emphasizes the role of economic interdependence, the other group of models stresses changes in market sentiment and shifts in the behavior of market participants as the main cause of the propagation of crises.

Masson (1999, 2004) identifies three different types of macroeconomic linkages behind contagion. The first category is *monsoonal effects* that point out that crises are transmitted to other markets because macroeconomic fundamentals depend on a common source. The second type of linkages that spread

17. There are also several studies that give little importance to differentiate between interdependence and contagion and mainly aim to explore the channels through which the negative shocks propagate.

crises is called *spillovers*, which are driven by the correlation between external links such as trade and finance. And finally, *pure contagion* links suggest that crises spread through changes in market sentiment by self-fulfilling expectations while there are no changes in macroeconomic fundamentals, with markets jumping between multiple equilibria. Monsoonal effects and spillovers are examples of the interdependence, while pure contagion refers strictly to the contagion.[18] This classification helps to distinguish between interdependence and contagion. Following Forbes and Rigobon (2001), Pesaran and Pick (2007) define contagion as a significant increase in the likelihood of a crisis in one country due to a crisis arising in another country over and above the level implied by economic fundamentals.[19] Dornbusch *et al.* (2000), Rigobon (2001), and Pericoli and Sbracia (2003) provide surveys on contagion models and Dungey *et al.* (2005*a*), Dungey *et al.* (2005*b*), and Massacci (2007) comprehensively review the methodologies.

Whether there is interdependence or contagion, it is of great importance to recognize the channels through which the crises are being transmitted. Below, we introduce the main channels.

Common shocks can spread a crisis to different countries around the world. An aggregate or global shock (*e.g.* international petroleum prices or interest rates) can simultaneously affect fundamentals of several countries and cause a crisis. For instance, Calvo and Reinhart (1996) claim the sharp increase in the U.S. interest rates in the early 1980s and 1994 was a key reason for both Mexican crises in 1982 and 1994-5.

Trade linkages are another transmission channel. Trade linkages between two countries include both bilateral trade and competition in third markets. Crisis and significant currency depreciation in one country have negative impacts on its trade partners. Currency depreciation temporarily improves the international competitiveness of the country in crisis compared to its trade partners (price effects) and at the same time decreases its demand for imports from them (income effects). It also adversely affects the trade competitors in the third party export markets. Gerlach and Smet (1995) and Glick and Rose (1999) show that a crisis is likely to spread from the county under attack to its major trade partners.

Financial linkages can act as another passage to propagate the crises. In the literature, there are different models that explain how crises spread through financial channels. In some of these models (*e.g*. liquidity and direct financial links), a crisis spreads to other countries by changing their fundamentals while in others (*e.g*. herding behavior) fundamentals remain unchanged.

18. As Pesaran and Pick (2007) argue, in principle, if the interdependence between countries is known, the likelihood of a crisis in one country given that the other country is in crisis can be evaluated.
19. See Pericoli and Sbracia (2003) for a comprehensive review of contagion definitions. Also, for different levels of definition for contagion provided by World Bank, look at:
http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTPROGRAMS/EXTMACROECO/0,,contentMDK:20889756~pagePK:64168182~piPK:64168060~theSitePK:477872,00.html

During crisis time, international financial institutions act more cautiously and enforce tougher requirements when making loans. Therefore, countries in different parts of the world experience financial liquidity problems and may eventually face currency crisis. There are also other ways that international financial institutions can propagate crises. For example, when open-end mutual funds foresee future redemption in the country, which is in crisis, they raise cash by selling assets in other countries. Furthermore, when leveraged institutions (*e.g*. hedge funds) face regulatory requirements, international provisions practices, or margin calls, they rebalance their portfolios by selling their assets in other countries that are still unaffected by the initial shock. These mechanisms spread the crisis across countries. Van Rijckeghem and Weder (2001), Kaminsky and Reinhart (2000), and Caramazza *et al.* (2004) examine the role of *bank lending* in the spreading of crises and show that *common lenders/creditors* are an important transmission channel. Kaminsky *et al.* (2004), and Broner *et al.* (2006) study the trading strategies of mutual funds and their role in the spread of crisis.

Financial linkages can also be attributed to investors' behavior, whether rational or irrational. In an international financial atmosphere in which there is an asymmetry of information, investors might shift their assessments about countries even without any change in fundamentals. In an environment in which information is costly, less informed investors might try to gain information by observing the actions of supposedly informed market participants, although observed actions may be misinterpreted. This could lead to herding behavior and reinforce the propagation of crisis. Calvo and Mendoza (2000) argue that globalization promotes contagion through herding by weakening incentives for gathering costly information and by strengthening incentives for imitating arbitrary market portfolios. Herding may also arise from financial managers' incentives. Rajan (2005) claims that since the funds managers' performance is often assessed compared to their peers rather than on the basis of absolute returns, they have strong incentives to follow the others in the industry and not to endanger their reputation and compensation by deviating from what other managers do.

Political linkages are another way to transmit crises. These links, which are also considered as a regional or neighborhood channel, indicate the probability of devaluation increases, if other countries in the region devalue. Drazen (2000) shows that, in a context of political cost, once a country devalues, policy makers in other countries are more willing to give up exchange rate parity because their reputation loss is lower.

Macroeconomic similarities are the last transmission channel we will review. In an international financial setting with incomplete information, investors tend to treat the countries with similar macroeconomic fundamentals in almost the same way. Therefore, a crisis in one country can serve as a *wake-up call* and induce financial markets to interpret it as the most probable scenario to happen to other countries with similar fundamentals. Ahluwalia (2000) shows a country is vulnerable to shifts in investors' sentiments, if it exhibits macroeconomic fundamentals, which are similar to those of the countries affected by the crisis.

The way contagion is defined and the channels through which it can be transmitted propose different policy implications at national and international levels. If the contagion is identified more as pure contagion and interpreted as jumps between multiple equilibria, an intervention policy might work and may prevent a crisis from spreading. However, if the contagion is classified as interdependent, an intervention policy is less likely to be effective. In this case, especially when the transmission channel is through trade linkages, a coordination policy (*e.g.* bilateral or regional agreement) might be more appropriate to lessen the negative impact of a looming crisis. In both cases, pure contagion and interdependence, access to facilities provided by a lender of last resort is crucial. A supra-national institution, such as the World Bank or the International Monetary Fund, or regional institutions, such as the Chiang Mai Initiative in Asia or the Fondo Latino Americano de Reservas in Latin America can take this role.

2.3.2 Empirical literature

There is a large volume of empirical literature on financial contagion. In particular, two main categories are recognizable. The first category examines contagion by testing for higher correlation across markets during crises times. The second category attempts to capture contagion through changes in fundamentals and seeks to identify the transmission channels.

The most common test for contagion is the cross-market correlation-based approach. This type of empirical test assesses the presence of contagion by testing whether there is a significant increase in the level of correlation between markets in crisis periods compared to tranquil ones. Following King and Wadhwani (1990), Calvo and Reinhart (1996) apply this approach and show some evidence for the increase of co-movements across Latin American markets in the wake of the Mexican crisis. Baig and Goldfajn (1999) also provide support for the significant rise in cross-market correlation during the Asian crisis. Nevertheless, Karolyi (2003) argues that the evidence of a contagion effect is weak and changes in correlation coefficients do not significantly support the existence of contagion. Despite the simplicity, a number of studies have detected limitations with this approach and have attempted to upgrade their contagion test procedure. For example, Forbes and Rigobon (2002) deal with the possibility of biased correlation coefficients in the presence of heteroscedasticity, Rigobon (2003) addresses the chances for heteroscedasticity, endogeneity, and omitted variables biases in the conditional correlation analysis, and Dongey *et al*. (2005*a*) highlight the identification problem in contagion tests. Yet, as Pesaran and

Pick (2007) point out, since the correlation-based approach requires *a priori* specification of crisis periods, all the related contagion tests are subject to the sample selection bias problem.

Another class of empirical studies stresses fundamental changes and chooses a probabilistic approach to test for contagion. Following Eichengreen *et al.*(1996), this approach applies discrete-choice techniques to examine whether the probability of a crisis in one country significantly increases given the occurrence of a crisis in another country. The probabilistic approach is capable of statistically testing the existence of contagion and systematically inspecting the channels through which contagion can propagate. Eichengreen *et al.* (1996) use a panel probit model for 20 OECD countries from 1959 through 1993 and show that the probability of a currency crisis significantly increases if speculative attacks take place in another country. They found that crises are more likely to transmit through trade linkages and macroeconomic similarities channels. Glick and Rose (1999) apply a panel probit for 161 countries from 1970 to 1998 and find evidence that currency crises tend to be regional and propagate through trade links. Van Rijckeghem and Weder (2001) use a panel probit for 118 countries during the Mexican, Asian and Russian currency crises and provide empirical support for the transmission of contagion through financial linkages. Kumar *et al.* (2003) run a panel logit and demonstrate that contagion has an important role in explaining the incidence of crises, and works regionally and through the export channel.

Nevertheless, Pesaran and Pick (2007) suggest that this class of models might be subject to biased estimation. They argue that since these studies, which assume contagion indices, are pre-determined and the equation errors across countries are independently distributed, the use of panel data models can result in biased contagion coefficients. Haile and Pozo (2008) address part of these concerns regarding the unobserved group effect. They apply a random effects panel probit for 37 advanced and emerging countries from 1960 through 1998. Their results verify that contagion is a significant factor that operates regionally and more specifically through trade channel.

2.4 Methodology

This paper applies the panel data and discrete choice models approach to study the currency crisis. We adopt duration models to assess the probability of a currency exiting a non-crisis state and entering into a crisis state. Duration models have some advantages over the logit and probit models that are widely used in the literature. First, these models are dynamic and not only they can assess the impact of time-varying covariates on currency stability, they are also able to evaluate whether the duration of time spent in tranquil periods has any significant influence on the probability of exit into turbulent episodes. Second, these models can accommodate the censored observations. Third, while probit and logit models require strong assumptions about the distribution of the time to failure and implicitly imply the monotonic hazard function, some versions of duration models are able to capture the real relationship between the probability of an exit and the duration of tranquil states.

2.4.1 Duration analysis

In what follows, we briefly introduce the basic setting of duration analysis and present the Cox proportional hazard model. A detailed and comprehensive statistical discussion of duration models can be found in Kalbfleisch and Prentice (2002) and Klein and Moeschberger (2010). Also, Kiefer (1988) and Lancaster (1990) provide econometrics applications and the related technicalities.

Let T be a nonnegative random variable denoting the time to a failure event – *e.g.* a currency exits a tranquil state and entering into a crisis state. The cumulative probability distribution is $F(t) = Pr(T \leq t)$, and the survivor function is given by $S(t) = Pr(T > t) = 1 - F(t)$, where t is time, and $Pr(T > t)$ is the probability that the timing of the failure event, T, is greater than t. The survivor function indicates the probability that a currency still remains in tranquil state beyond time t. One can alternatively describe the time to exit using a hazard function (or the instantaneous probability) of exits. The hazard is a measure of the probability that a currency will exit the tranquil state in time t, given that it has survived up to time t. The hazard function can be defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t+\Delta t > T > T+t | T > t)}{\Delta t} = \frac{f(t)}{S(t)} = \frac{-d\ln S(t)}{dt}, \quad (1)$$

where, $f(t)$ denotes the probability density function associated with $F(t)$.

Equation (1) specifies that there is a one-to-one mapping between the probability density function, the cumulative distribution function, the survivor function, and the hazard function. Given one of these functions that describe the probability distribution of failure times, the others are completely determined. However, in the literature, it is more common to think in terms of the hazard rather than the traditional density and cumulative distribution functions. Hazard function can be specified by parametric, semi-parametric, and nonparametric models. Parametric hazard models assume that the time of failure and covariates follow exact statistical patterns. A semi-parametric hazard approach assumes time's distribution is nonparametric, but the effect of covariates is still parameterized. A nonparametric hazard model entirely puts aside any assumptions and lets the dataset speak for itself.

In a parametric model, time to failure is assumed to follow a specific distribution. A parametric hazard function in continuous time can be specified as:

$$h_j(t) = \phi(x(t), \beta, h_0(t)), \quad (2)$$

where $x(t)$ denote time-varying covariates, β is the vector of unknown coefficients, $h_0(t)$ refers to the baseline hazard that the mean of individuals faces, and $\phi(.)$ represents a specific distribution, *e.g.* Lognormal Weibull, Gompertz, and *etc*.. The $\phi(.)$ describes how the hazard changes between individuals endowed with different *x*'s and given the length of the time spent in the tranquil periods. The estimation of the coefficients in hazard models is carried out by maximum likelihood method. The likelihood function for a sample of size *n* (failure times $t_1, \ldots, t_n$) is:

$$L\{\beta | (t_1, x(t_1)), \ldots, (t_n, x(t_n))\} = \prod_{i=1}^{n} S(t_i | x(t_i), \beta) h(t_i | x(t_i), \beta), \tag{3}$$

since the probability density function of t_i equals $f(t_i) = S(t_i)h(t_i)$.

A very well known way to represent the hazard function is to write it as:

$$h_j(t) = h_0(t)\phi(x_j(t), \beta), \tag{4}$$

This method is called proportional hazards because subject *j* faces the hazard that is multiplicatively proportional to the baseline hazard. The popular Cox (1972) article uses this technique and assumes the covariates multiplicatively shift the baseline hazard function.[20] The Cox model leaves the baseline hazard, $h_0(t)$, unspecified and assumes all subjects at risk face the same baseline hazard, which is a restricted assumption. This innovation lets the Cox models enjoy the important advantage of not requiring any assumptions on the distribution of the time of failures (or the shape of the hazard over time) and helps these semi-parametric models to be robust to misspecification of the baseline hazard. In fact, the baseline hazard, $h_0(t)$, will be canceled out in building the likelihood function. This model presents the ratio of hazard rates for subject *j* to subject *k* as:

$$\frac{h_j(t)}{h_k(t)} = \frac{h_0(t)\phi(x_j(t), \beta)}{h_0(t)\phi(x_k(t), \beta)} = \frac{\phi(x_j(t), \beta)}{\phi(x_k(t), \beta)}, \tag{5}$$

Therefore, one can write the conditional probability of i^{th} observation that fails at time t_i, given all of the *n* observations have exited by time t_n, as:

$$\frac{h_i(t)}{\sum_{i=1}^{n} h_i(t)}, \tag{6}$$

Thus, the likelihood function will be:

20. The most common specification of $\phi(.)$ is in exponential form. Hence, the hazard can be represented as: $h_j(t) = h_0(t)exp(x_j(t), \beta)$, which is convenient to deal with non-negative values of $\phi(.)$ and has computational feasibility.

$$L\{\beta|(t_1, x(t_1)), \dots, (t_n, x(t_n))\} = \prod_{j=1}^{n} \left(\frac{\phi(x_j(t), \beta)}{\sum_{i=j}^{n} \phi(x_i(t), \beta)} \right). \tag{7}$$

and the estimation of coefficients, β_x, can be obtained conditional on the failure times.

2.4.2 Adopted model

In the first step, to grasp a clear idea on what exactly the data offer, we graphically describe the empirical hazard of the spells (the length of tranquil time between two states of crises) in our sample.[21] The graph visualizes the actual pattern of the observed spells and provides justification for the choice of the model to estimate the probability of the crises. Figure 1 shows the measured empirical hazard of the monthly and quarterly type spells over 20 quarters.[22] On that figure the vertical axis represents the hazard (the probability that a currency exiting a tranquil state into the crisis state) and the horizontal axis measures the successive number of quarters in tranquility. As the graph illustrates, the hazards increase sharply over the first three quarters and then, with some fluctuations, decline before abruptly rising again. It can be interpreted that at the beginning of the tranquil period, market participants are not very confident about stability of the currency and there will be plenty of speculative attacks to test the credibility of the new peg. After the first three quarters, if the monetary authorities can successfully repel the attacks, the currency will be stabilized and its hazard declines. Nevertheless, after the 18th quarters, the *currency stability fatigue* will increase hazards and, consequently, maintaining currency credibility will be harder. Furthermore, the graph also presents two stylized facts. First, the hazard of monthly-type spells is generally larger than the hazard of the quarterly-type. Second, and more importantly, the hazard functions of none of the monthly or quarterly type spells behave monotonically.

As discussed earlier, the duration models generally allow for the use of either parametric or semi-parametric estimation techniques. The parametric specifications impose *ex ante* characteristic shapes for the hazard of spells, however, the exhibited shape of the empirical hazard functions in Figure 1 implies that these models are not very proper to capture the relationship and can cause biased coefficients. We present the best fitting parametric models (the Gompertz model), which are obtained after experimenting with the typical parametric functions – the Weibull, the loglogistic, the lognormal, the gamma, the Gompertz and/or discrete hazard model with the parametric baseline – in Figures 2 and 3. These graphs show a great deal of discrepancy between the empirical and the estimated hazard functions. The other option is the semi-parametric models, which require no assumption on their baseline hazards. The

21. The empirical hazard can be measured from the following equation: $EmpHaz. = exit(t + dt]/\{N - exit(0, t]\}$, where $exit(t + dt]$ is the number of the individual spells that end between time t and $t + dt$, N is the total number of spells, and, $exit(0, t]$ is the sum of ended spells by time t.

22. More than 90% of the monthly type spells and almost 85% of the quarterly type spells exit within 20 quarters.

Figure 1. Estimated empirical hazard for monthly and quarterly-type spell

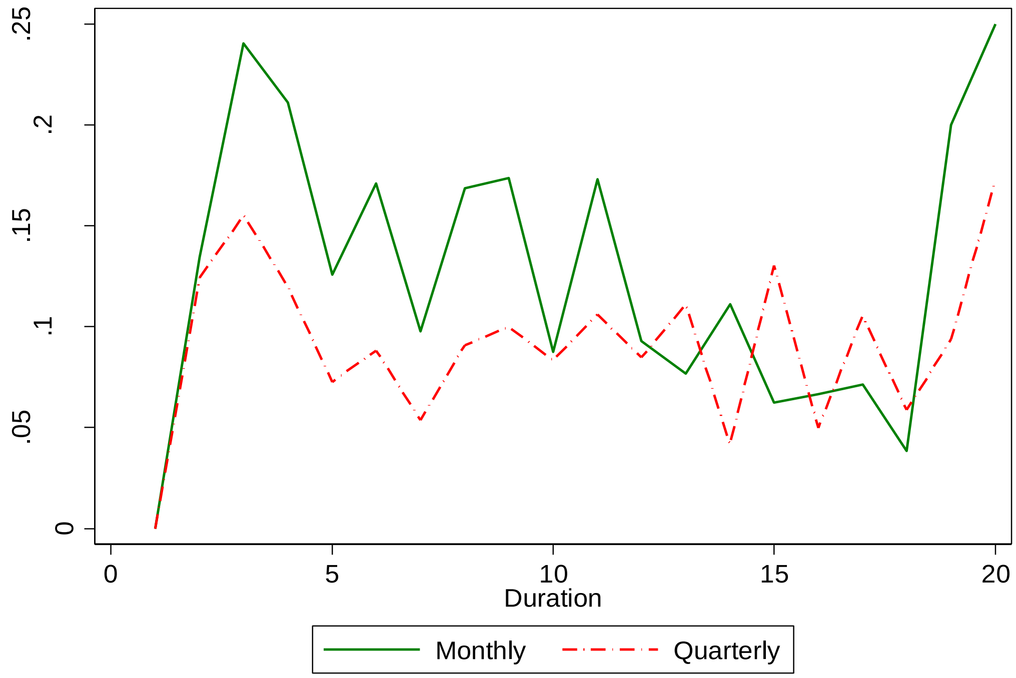


Figure 2. Estimated hazard for monthly-type spells by Gompetrz model

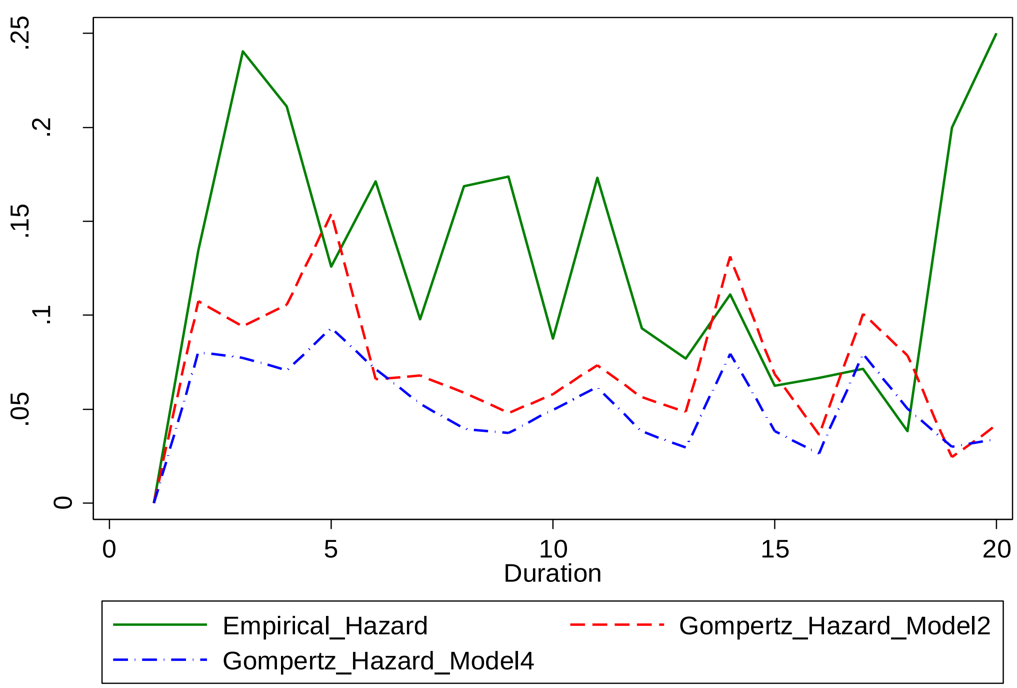
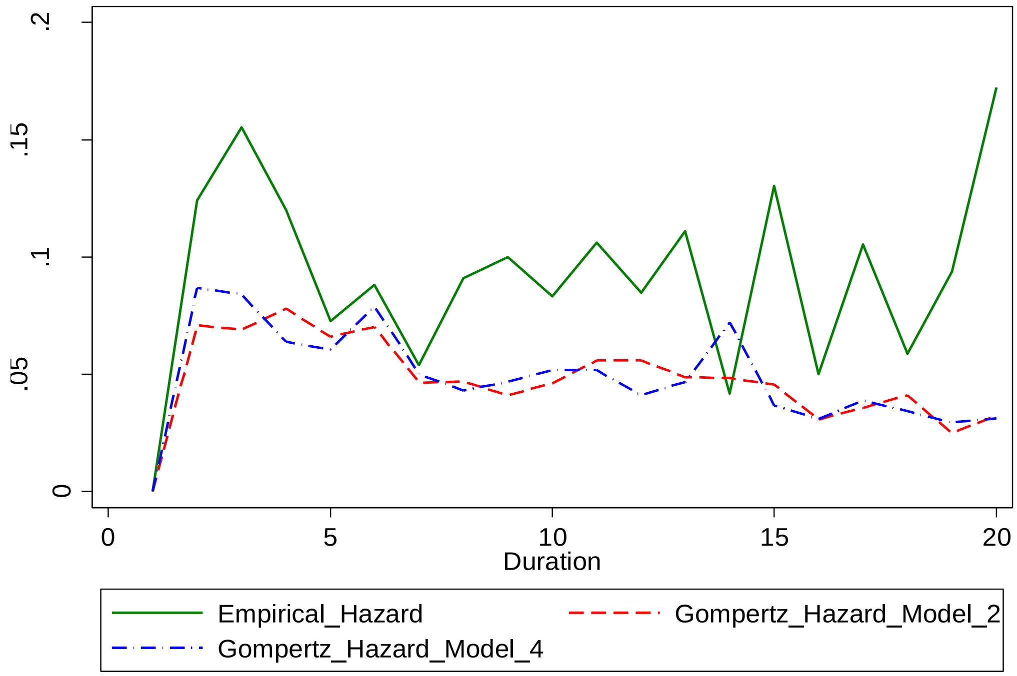


Figure 3. Estimated hazard quarterly-type spells by Gompetrz model



continuous Cox proportional and the discrete hazard models, with their flexible non-parametric baseline, are the suitable candidates to produce estimates that are more robust to the misspecification error.

The continuous Cox semi-parametric models are elegant and illustrative. They give clear insight into the actual risk process (the hazard function) that causes failure and enlighten how the risk changes with the values of covariates. The continuous Cox models have a number of advantages over the discrete models. First, continuous models have developed much more extensive tests for potential model misspecification. Second, calculation of the marginal effects in continuous models is more meaningful and feasible, while the calculation of marginal effects in discrete model becomes problematic (and not reported). Third, in general, censoring is better handled by continuous than discrete hazard models. Continuous hazard models, such as the Cox model, allow information from the censored variables to enter the likelihood function while the discrete hazard models cannot separately write the contribution of the censored observations to the likelihood function. This shortcoming can lead to a selection bias for those estimates at the end of the observation period and most likely affect the time related variables. Considering the mentioned advantages, we employ the continuous Cox models as our basic model and then adopt other alternative models to assess the robustness of our findings.

The main goal of this paper is to examine how the probability of a currency exiting a tranquil state into a crisis state depends on the length of time already spent in a non-crisis spell along with the occurrence of crisis in other countries and a set of macroeconomic fundamentals. In addition, following Haile and Pozo (2008), we attempt to empirically identify the relevant contagion channels through which the crises transmit across borders.

Our basic model is non-structural and estimates the probability of a speculative attack on an individual currency, *j*, at time *t* given the currency has already passed *t* –1 tranquil periods. It can be specified as:

$$h_j(t) = h_0(t)exp(\beta' X_{jt} + \gamma_1 Ttrade_{jt} + \gamma_2 Finance_{jt} + \gamma_3 MacSim_{jt}). \tag{8}$$

where *j*=1, …, *n*, is the number of countries in the sample, and *t*=1, …, *T*, representing the periods of time (in quarters). $h_0(t)$ is the baseline hazard which is the same for all the currencies. X_{jt} is a vector of macroeconomic control variables, to be introduced in the next section, and β is the vector of corresponding coefficients. The other components of equation (8) are to capture the various channels by which contagion may spread through.

$Ttrade_{jt}$ represents the trade contagion channel. It is a weighted average of the crises elsewhere; $\sum_{i=1}^{n-1} k_{ji}^{trade} c_{it}$, *i*≠*j*, where c_{it} stands for crisis in country *i* at time *t*. The weight, k_{ji}^{trade}, is designed to reflect the degree of trade linkages (bilateral trade or competition in the other markets) between country *j* and country *i*. When the crises occur in a number of countries (say *i*+1, *i*+2, and *i*+3) at time *t*, all may not have an equal impact on the probability of a speculative attack on the currency of country *j*. Therefore, different weights should be assigned to the crises in the other countries proportional to the extent of trade linkages between country *i* and each of the other countries. Thus, the coefficient on the trade linkage, γ_1, measures the accumulated trade-weighted effects of crises elsewhere on the probability of the crisis on the currency of the representative sample country. Statistical significance of γ_1 will be taken as evidence for contagion through the trade linkages.

$Finance_{jt}$ represents the financial contagion channel. It weighs the crises elsewhere by financial linkages via: $\sum_{i=1}^{n-1} k_{ji}^{finance} c_{it}$, *i*≠*j*. The financial weights, $k_{ji}^{finance}$, due to lack of available data, concentrate on bank lending as a channel and ignores the other players of financial markets.[23] A γ_2 that is statistically different from zero, can verify the existence of contagion that works via financial linkages.

In the same manner, $MacSim_{jt}$ is an indication of the macroeconomic similarities contagion channel given by $\sum_{i=1}^{n-1} k_{ji}^{MacSim} c_{it}$, *i*≠*j*. The statistical significance of γ_3 evaluates the validity of this channel.

23. As Van Rijckeghem and Weder (2001) claim, the size and the volatility of banks credit in the net capital flows may justify this simplification, especially in the 1970's and 1980's.

We construct the weights in line with the methodologies presented in Glick and Rose (1999) for trade linkages, in Van Rijckeghem and Weder (2001) for financial linkages, and in Eichengreen *et al.* (1996) for macroeconomic similarities. Appendix A illustrates the details.

2.5 Data and variables

This paper analyzes a panel of quarterly data from 1970 through 1998 for 21 countries; a total of 2436 observed quarters.[24] The countries in our sample includes: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, and the UK.

The motivation for choosing this sample of countries is twofold: first, in order to minimize the heterogeneity concerns, put forwarded by Berg *et al.* (2008), we attempt to pool the countries that at least share general similarities, and; second, we have to take the availability of data into account. The sources of our data are International Financial Statistics (IFS), Direction of Trade Statistics (DOTS), Government Finance Statistics (GFS), and Balance of Payment Statistics (BOPS) published by the IMF, Main Economic Indicators (MEI) published by the OECD, and "Consolidated Banking Statistics" published by the Bank for International Settlement.

This paper uses the episodes of currency crises identified in our previous paper, "*Identifying Extreme Values of Exchange Market Pressure*", to distinguish the states of crises from the tranquil states. Here, episodes of crises are identified on the basis of monthly and quarterly data.[25] Accordingly, there are two different types of spells based on the type of identified crisis episodes: monthly-type spells and quarterly-type spells. Since there are more observations for non crisis periods rather than crisis periods, we define a spell as the time (number of quarters) during which a particular currency does not experience speculative attack. A spell ends when the currency leaves the tranquil state and enters the turbulent state; otherwise, the spell is right censored.

Table 1 presents the summary of the descriptive statistics of the spells. The number of identified crisis episodes is greater when based on monthly than when based on quarterly data; therefore, more spells are generated for the monthly-type than the quarterly-type. The average length of monthly-type spells is 10.3 quarters while the average length of quarterly-type spells is 14.8 quarters. In other word, on average, a currency remains in tranquil state for almost 10 quarters, without experiencing even one turbulent month, and/or a currency can maintain its non crisis state for almost 15 quarters without experiencing a quarter

24. Nevertheless, due to missing data, our panel is technically unbalanced.
25. However, even the crisis episodes that are identified based on monthly data, are transformed to the quarterly basis. If at least one month within a quarter is recognized as the incident of crisis the whole quarter is marked as the crisis episode.

Table 1. Descriptive statistics of monthly and quarterly-type spells

	monthly-type	*quarterly-type*
total number of spells	266	190
number of right censored spells	21	21
mean of duration of spells	10.3	14.8
median of duration of spells	5	8
shortest completed spell	2	1
longest completed spell	55	70

which is marked as an episode of speculative attack. However, the medians show that a large number of spells does not live for very long. The median length of monthly-type spells is 5 quarters while the same number for the quarterly-type spells is 8 quarters. It indicates that half of the monthly-type spells exit in less than six and half of the quarterly-type spells end within eight quarters. One may interpret it as follows: with fifty percent probability, a currency will undergo at least one turbulent month within five quarters and/or in the content of quarterly-types, with fifty percent of probability, a currency will suffer at least one quarter of speculative attack within eight quarters. The comparatively small values of the medians indicate that the probability of speculative attack is higher at the early stages of a tranquil state.

In order to model the timing of spells exit, both non-time varying and time varying covariates are used. Non-time varying covariates, which include continuous and categorical variables, are employed to capture possible differences across countries. We construct the related covariates to examine whether the hazard shifts with respect to job market and inflation variability, size of economy, the total real growth of economy over the whole period, and previous crisis episodes.

Most of our time varying covariates are adapted from the existing literature on currency crises. We use GDP growth rates, inflation rates, unemployment rates, and growth of share price index to denote domestic economic conditions. Money and quasi money growth rates are included to consider the monetary situation of the economy. Shares of budget deficit to GDP incorporate the fiscal policy characteristic to our models. The ratios of current account, capital account, and financial account to GDP as well as trade openness quantify the external position of the economy. Moreover, we add the real effective exchange rate as an indicator of competitiveness to measure how terms of trade adjust for the relative movements in cost indicators. Appendix B provides details regarding the construction of covariates and reports limitations of the available data.

2.6 Empirical findings

This section first presents our estimation results of four different models for each monthly and quarterly type spells and then evaluates models and reports the robustness tests.

2.6.1 Estimation results

We estimate equation (8) with four differently specified Cox proportional hazard models. Models 1 and 2 estimate the equation with contemporaneous variables while models 3 and 4 use one quarter lagged data. The lagged data are to mitigate the potential problem of reverse causality (impact of the crises on macroeconomic fundamentals rather than impact of the macroeconomic fundamentals on the occurrence of currency crises). The variables of each country in model 1 and 3 are independently corresponding to that specific country. However, all time varying variables in model 2 and 4 are measured relative to the reference countries; Germany or the U.S.[26] In fact, each time varying variable in model 2 and 4 is the deviation from the corresponding variable of the reference country.

Tables 2 and 3 present the estimation results for monthly and quarterly type spells, respectively.[27] In interpreting these outcomes, it is important to remember that the estimated coefficients measure a proportional changes in the hazard ratio, the ratio of the actual hazard to the baseline hazard. Thus, the key feature for variable significance is whether the coefficient estimate of each covariate is significantly greater or less than unity, which implies an increase or decrease in the hazard ratio. However, for simplicity purposes, the reported results in Table 2 and 3 are transformed such that the positive coefficients indicate an increase and the negative coefficients indicate a decrease in the hazard ratio.

Examination of the presented results in Table 2 reveals that some coefficients are constantly significant. The estimated coefficients for unemployment volatility, inflation, the ratio of financial account to GDP, and trade linkages are persistently significant in all models of monthly-type spells. In addition, the coefficient of size of the economy is significant in three models. We apply Akaike Information Criterion (AIC) approach to determine the model that best fits the data.[28] The results show that model 2 outperforms models 1 and 3 and is slightly more efficient than model 4. Model 2 implies that an increase in values of volatility of unemployment rate, whole period GDP growth, inflation, trade openness, and trade linkages[29] raise the probability of a currency exiting the tranquil state into the turbulent state, while an increase in ratio of financial account to GDP will decline the likelihood of speculative attack. Model 4 produces similar results to those that are built by model 2. However, the estimated coefficients for the

26. The United States is the reference country for Australia, Canada, New Zealand, and South Africa while Germany is the center for all the other countries. Our previous paper proposes a systematic way to choose the reference country.
27. The models are interacted with different linear and non-linear time functions. The presented estimation results are outcome of interaction with logarithm form of time.
28. In general, AIC can be specified as: $AIC = 2(k + c) - 2\ln(L)$, where k is the number of model covariates, c is the number of model-specific distributional parameters (in semi-parametric Cox model equals to zero), and L is the maximized value of the likelihood function. A model with greater AIC value outperforms alternative models.
29. The reported coefficients for trade linkages, which are constructed on basis of competition in the third export market, always surpass the coefficients that are built on basis of bilateral trade (not reported).

Table 2. Cox proportional hazard estimation results (monthly-type spells)

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Unemployment volatility	0.05*	0.05**	0.06**	0.07**
	(1.93)	(2.54)	(2.48)	(2.52)
Inflation volatility			-1.89	-0.85
			(-1.01)	(-0.51)
Size of economy	0.96**		0.83**	0.83*
	(2.40)		(1.97)	(1.85)
Whole period GDP growth		0.02*		0.01
		(1.78)		(0.87)
Previous crises				
GDP growth rate	0.03	0.02	-0.08	-0.05
	(0.35)	(0.30)	(-0.94)	(-0.54)
Inflation rate	0.30***	0.25**	0.26***	0.21*
	(3.38)	(2.21)	(2.82)	(1.87)
Unemployment rate	-0.01	-0.02	0.00	0.00
	(-0.26)	(-0.73)	(0.14)	(0.00)
Share price index growth	-0.03***	0.00	0.00	0.00
	(-3.44)	(-0.46)	(-0.67)	(0.17)
Real effective exchange rate	0.00	0.00	0.00	0.02**
	(-0.34)	(1.21)	(1.21)	(2.36)
Money growth	0.02	-0.02	0.01	0.02
	(1.51)	(-0.91)	(0.42)	(0.53)
Trade openness	-0.12	0.05***	-0.31	0.01
	(-0.24)	(2.80)	(-0.51)	(0.62)
Current account / GDP	0.00	0.00*	-0.05	0.00
	(-0.02)	(-1.88)	(-1.22)	(-0.43)
Capital account / GDP	0.29	0.00	-0.56	0.00
	(0.92)	(-0.09)	(-0.62)	(-0.47)
Financial account / GDP	0.10*	0.00*	-0.12**	0.00*
	(1.77)	(-1.71)	(-2.08)	(-1.67)
Budget deficit / GDP	0.02	0.00	0.01	0.00
	(2.08)	(0.77)	(1.16)	(0.20)
Trade linkages	0.14**	0.12*	0.15**	0.19**
	(2.51)	(1.73)	(2.30)	(2.04)
Financial linkages	-0.03	0.00	-0.01	-0.02
	(-1.08)	(-0.22)	(-0.44)	(0.52)
Macroeconomic similarities	0.03	0.06	-0.02	-0.06
	(0.58)	(0.94)	(-0.29)	(0.49)
Log likelihood	-107.93	-87.45	-106.85	-82.49

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

whole period GDP growth and trade openness lose their significance and, instead, the coefficients of size of economy and real effect exchange rate become statistically significant.

Reviewing the results that are presented in Table 3 demonstrate a similar pattern to those observed in Table 2. The estimated coefficients for inflation and trade linkages are constantly significant in all models of quarterly-type spells while the coefficient of real effective exchange rate is significant in two models. The AIC indicates that model 4 outperforms all other models. This model predicts higher values of inflation, unemployment rate, real effective exchange rate, trade openness, and trade linkages increase the probability of a currency exiting the non-crisis state into the crisis state.

The produced results by our preferred models (model 2 of monthly-type and model 4 of quarterly-type spells) are compatible with the literature on currency crises. Unemployment rate and its volatility put forward the importance of job market's dynamic and the associated political concerns. They advocate the second-generation models with contingent policies that lead to multiple equilibria and self-fulfilling attacks. The whole period GDP growth, inflation, real effective exchange rate, and the ratio of financial account to GDP correspond to the first-generation models. Size of economy and trade openness correspond to the second and/or the third-generation models. Trade linkages document the role of contagion in origins of currency crises and provide support for the third-generation models.

Tables 2 and 3 show that there is stability in the size and sign of those estimated coefficients that are significant (the only exception is the ratio of financial account to GDP). These tables also demonstrate the models that use relative variables (models 2 and 4) always surpass the models that use country specific variables (models 1 and 3). It may be interpreted as a sign for appropriateness of the choice of the reference countries.

Inclusion of non- varying time covariates to our models considerably improves the overall explanatory power of the models. The overall increment in likelihood of the models varies from five to 13 percent (the estimation results from running our models without non-time varying covariates are not reported). We start running our models with all of non-time varying covariates, however, drop out those non-varying time covariates that their estimated coefficients are not statistically significant and their impact on likelihood improvement is nil.

2.6.2 Model evaluation

In this part, we report the test procedures that are used to assess whether the adopted methodology is appropriate to our data and, consequently, whether the estimation results that we presented before are consistent.

Table 3. Cox proportional hazard estimation results (quarterly-type spells)

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Unemployment volatility	0.02	0.03	0.04*	0.02
	(1.00)	(1.02)	(1.67)	(0.75)
Inflation volatility	-0.57	-1.42	-0.32	
	(-0.34)	(-0.86)	(-1.71)	
Size of economy	0.27		0.53	0.38
	(0.74)		(1.30)	(1.06)
Whole period GDP growth	0.01		0.01	
	(0.39)		(0.77)	
Previous crises	-0.41*	-0.38		-0.36
	(-1.82)	(-1.48)		(-1.22)
GDP growth rate	0.02	0.05	0.12	0.08
	(0.23)	(0.66)	(1.39)	(0.91)
Inflation rate	0.22***	0.21**	0.17*	0.20*
	(2.73)	(2.09)	(1.78)	(1.87)
Unemployment rate	0.04**	0.03	0.08**	0.04*
	(2.05)	(1.37)	(2.34)	(1.74)
Share price index growth	-0.02*	0.00	-0.02*	-0.01
	(-1.91)	(-0.66)	(-1.70)	(-0.66)
Real effective exchange rate	0.00	0.00	0.02***	0.02***
	(0.62)	(0.59)	(2.61)	(2.69)
Money growth	-0.03	-0.03**	0.02	0.02
	(-1.91)	(-2.10)	(0.89)	(0.65)
Trade openness	0.18	0.02	0.17	0.04*
	(0.49)	(0.39)	(0.40)	(1.85)
Current account / GDP	0.00	0.00	0.03	0.00
	(1.35)	(0.69)	(0.45)	(-0.05)
Capital account / GDP	0.00	0.00	-0.12**	0.00
	(0.62)	(0.52)	(-2.02)	(1.12)
Financial account / GDP	-0.02	0.00	0.00	-0.02
	(-1.05)	(-0.88)	(-0.05)	(-1.18)
Budget deficit / GDP	0.00	0.00	0.01	0.00
	(1.08)	(0.77)	(0.87)	(0.85)
Trade linkages	0.19*	0.19**	0.18**	0.19*
	(1.75)	(2.22)	(1.88)	(1.80)
Financial linkages	0.00	0.00	0.00	0.00
	(-0.81)	(-0.63)	(-1.56)	(-0.92)
Macroeconomic similarities	0.00	0.00	0.02	-0.07
	(-0.44)	(-0.51)	(0.22)	(-0.60)
Log likelihood	-118.92	-106.24	-115.62	-96.79

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

In the first step, it should be recalled that running our models on two different monthly and quarterly type spells is a significant robustness check. The observed consistency between results of both approaches is a proof for stability of our models.

The use of Cox models is only appropriate, if the hazards are proportional to the values of the covariates. We apply Schoenfeld residual test to examine whether the hazard which are generated by the estimated covariates are truly proportional. The results of this test demonstrate that only in model 1 and model 3 of monthly-type spells, one covariate fail to pass the test. All covariates in other models individually and jointly pass the test for proportionality. The test results for all models are reported in Appendix C.

We also test model specification and overall fit by comparing the estimated hazards with the empirical hazards for monthly and quarterly type spells. Figures 4 and 5 illustrate the results for our model specifications. However, for visual purposes, in each figure, we only present two models that have the best performance based on AIC results; models 2 and 4. By inspection, we can see that both models closely follow the overall pattern and reproduce similar shapes of empirical hazards. Visually, during the first five quarters and from quarter fifteen to quarter twenty, models 2 and 4 produce the best representation of the slopes of the empirical hazard functions but underestimate their absolute size. Furthermore, comparing Figures 4 and 5 with Figures 6 and 7, which are produced by discrete model, and those of parametric specification (Figures 2 and 3) reconfirm the appropriateness of Cox model which compared to the alternative models.

A more formal test of overall fit can be performed with the use of Cox-Snell residuals. Here, a model fits the data perfectly if the plot of the cumulative hazard versus the Cox-Snell residuals lies directly along a 45-degree line. The results of AIC suggest that models 2 and 4 of monthly-type spells and model 4 of quarterly-type spells will perform better than the others. The presented figures in Appendix C confirm that suggestion. In the related figures, the cumulative hazard either lies very close to the 45-degree line or somehow stays parallel to that. In fact, the Cox-Snell results for models 2 and 4 perform almost equally well. Cumulative hazard of other models sharply diverge at some point, which is a visual confirmation of the AIC results.

The other robustness test is how to deal with the ties (the spells with the same length) issues. In the data set, there are incidences of crises that take place in the same quarter and due to lack of higher frequency data than quarterly level, it is impossible to determine the exact order of those failures. Although it is a defect and negatively affects the precision of estimation, the choice of alternative approximation

Figure 4. Estimated hazard by Cox continuous model (monthly-type spells)

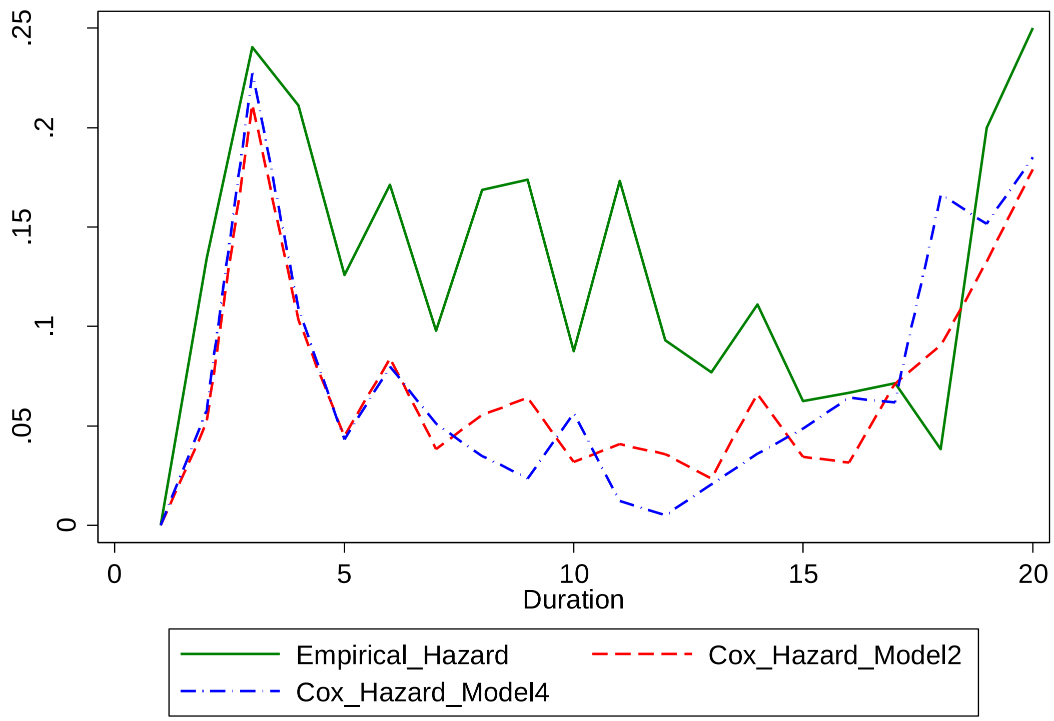


Figure 5. Estimated hazard by Cox continuous model (quarterly-type spells)

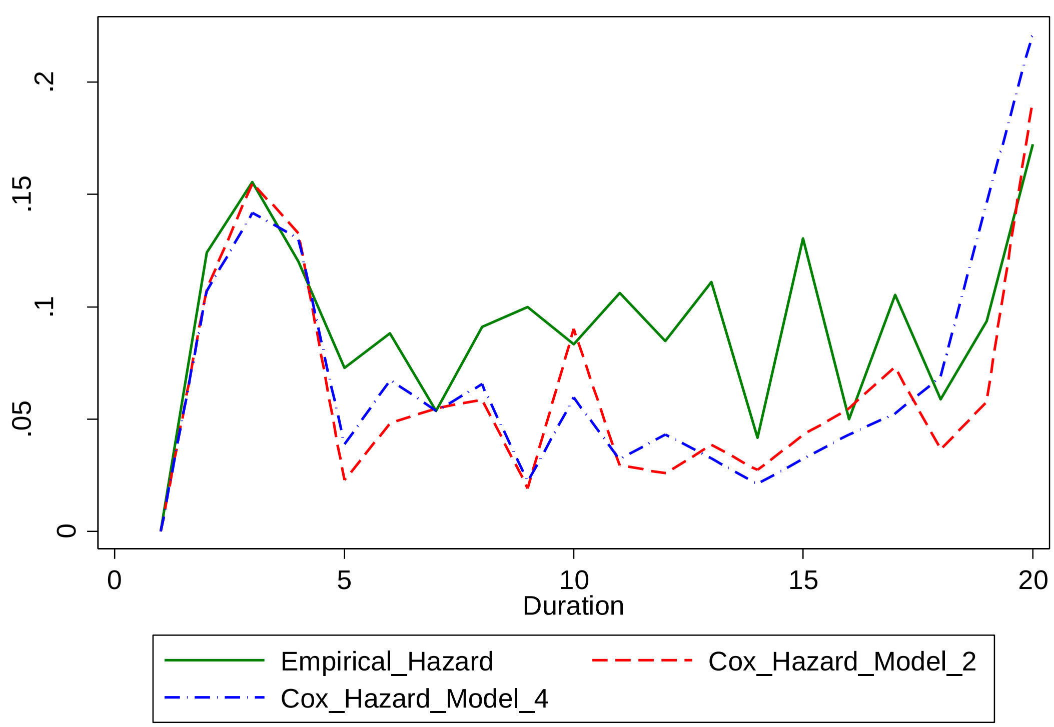


Figure 6. Estimated hazard by discrete semi-parametric model (monthly-type spells)

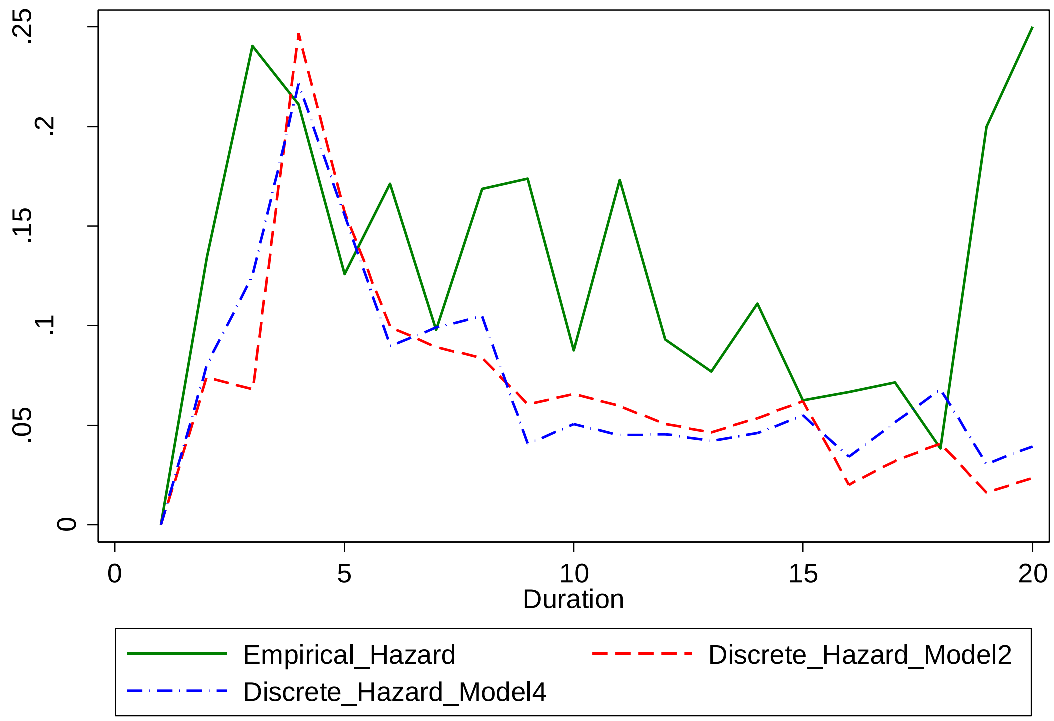
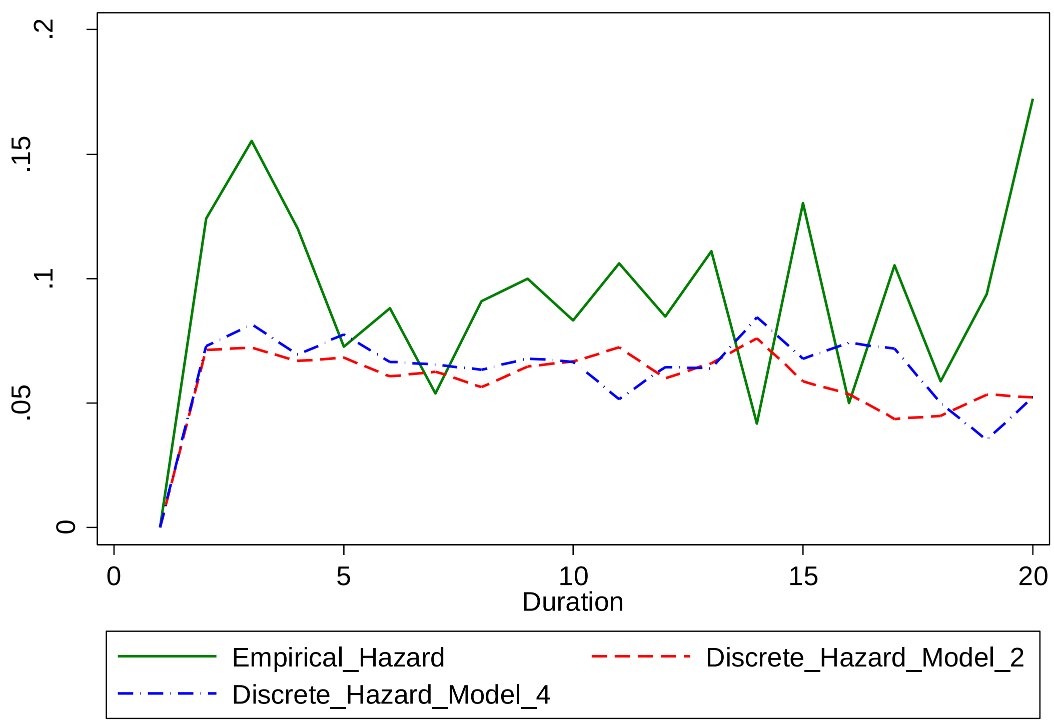


Figure 7. Estimated hazard by discrete semi-parametric model (quarterly-type spells)



techinques can improve the estimation results.[30] In order to deal with the tied spells, we run our models using two alternative methods: the Efron and the partial calculation. Both methods somehow generate similar results. Table 4 presents the estimation results for our preferrd models. The similiraties of the estimated coefficient implies that ties are not a significant issue in our tests.

Another ground for a robustness test is to verify the existence of unobservable heterogeneity in our models. The potential concern is whether the observed differences across duration of spells (the covariates) as well as the unobserved common aspects of the failures (the baseline hazard) account well for the prospect of the currency crises incidents. That is, while the analysis above has focused primarily on the contribution of the covariates, it is the estimated baseline hazard that captures the common elements of duration dependence. However, duration dependence can arise for two very different types of reasons: spurious state dependence (SSD) and true state dependence (TSD). SSD arises when unobserved heterogeneity is present in the model, in which case the baseline hazard does not capture the true cycle dependence on duration.

Models that do not control for SSD assume implicitly that all observations with common values for their covariates are in all other dimensions identical. If this is not the case, the model is mis-specified. Therefore, to account for the possibility that unobserved heterogeneity is present in our preferred models, we explicitly introduce a multiplicative form of unobserved heterogeneity into the model.[31] Here a gamma distribution is used to proxy unobserved heterogeneity. However, after allowing for this form of unobserved heterogeneity, re-estimation found that the assumption of no unobserved heterogeneity – the observation of the identical values for the covariates – did not fail. This allows us to conclude that multiplicative unobserved heterogeneity is not a significant issue in our model and gives us greater assurance that the estimated baseline hazard does capture true duration dependence.

In last robustness test we examine how much different are our results from those delivered by the best of the alternative parametric and semi-prarametric hazard specifications. Table 5 presents the results of our preferred estimating models by using: a) the discrete hazard model with semi-parametric baseline (piece-wise constant model), and; b) the best fitting of the parametric hazarad models – the Gompertz.

Despite the potential differences between the Cox models, the discrete semi-parametric models, and the Gompertz models, the results are broadly consistent with those found in Table 2 and 3. The estimated coefficients all indicate the same directional change with roughly the same degree of significance.

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30. In general, ties issues are handled better by discrete hazard models.
31. The instantaneous hazard rate can now be specified as: $h_j(t) = \vartheta_j h_0(t) exp\left(x_j(t), \beta\right)$.

Table 4. Treatment of ties: Efron[(a)] versus the partial calculation[(b)] estimation results

Variable	*Monthly-type*		*Quarterly-type*	
	Model (II)[(a)]	*Model (II)[(b)]*	*Model (II)[(a)]*	*Model (II)[(b)]*
Unemployment volatility	0.05	0.05	0.02	0.02
	(2.71)	(2.54)	(0.72)	(0.75)
Inflation volatility				
Size of economy			0.39	0.38
			(0.97)	(1.06)
Whole period GDP growth	0.02	0.02		
	(1.80)	(1.78)		
Previous crises			-0.38	-0.36
			(-1.28)	(-1.22)
GDP growth rate	0.02	0.02	0.08	0.08
	(0.24)	(0.30)	(0.91)	(0.85)
Inflation	0.22	0.25	0.20	0.20
	(2.05)	(2.21)	(1.87)	(1.70)
Unemployment rate	-0.02	-0.02	0.04	0.04
	(-0.73)	(-0.73)	(1.74)	(1.63)
Share price index growth	0.00	0.00	-0.01	-0.01
	(-0.28)	(-0.46)	(-0.66)	(-0.62)
Real effective exchange rate	0.01	0.00	0.02	0.02
	(1.09)	(1.21)	(2.69)	(2.26)
Money growth	-0.02	-0.02	0.02	0.02
	(-1.52)	(-0.91)	(0.65)	(0.66)
Openness index	0.04	0.05	0.02	0.04
	(2.82)	(2.80)	(1.85)	(1.99)
Current account / GDP	0.00	0.00	0.00	0.00
	(-1.81)	(-1.88)	(-0.05)	(-0.04)
Capital account / GDP	0.00	0.00	0.00	0.00
	(-0.10)	(-0.09)	(1.12)	(0.89)
Financial account / GDP	0.00	0.00	0.02	-0.02
	(-1.98)	(-1.71)	(-1.18)	(-0.73)
Budget deficit / GDP	0.00	0.00	0.00	0.00
	(0.76)	(0.77)	(0.85)	(0.44)
Trade linkages	0.10	0.12	0.20	0.19
	(1.59)	(1.73)	(1.80)	(1.28)
Financial linkages	-0.01	0.00	0.00	0.00
	(-0.07)	(-0.22)	(-0.92)	(-0.69)
Macroeconomic similarities	0.07	0.06	-0.07	-0.07
	(1.08)	(0.94)	(0.60)	(-0.42)

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 5. Semi-parametric discrete hazard[(a)] and Gompertz parametric hazard[(b)] estimation results

Variable	*Monthly-type*		*Quarterly-type*	
	Model (II)[(a)]	*Model (II)[(b)]*	*Model (II)[(a)]*	*Model (II)[(b)]*
Unemployment volatility	0.01	0.03*	0.02	0.04*
	(0.60)	(1.88)	(0.63)	(1.82)
Inflation volatility				
Size of economy			-0.17	0.38
			(-0.46)	(1.08)
Whole period GDP growth	0.00	0.02*		
	(-0.86)	(1.76)		
Previous crises			-0.07	-0.22
			(-0.30)	(-0.85)
GDP growth rate	-0.16	-0.05	-0.04	0.09
	(-1.33)	(-0.04)	(-0.29)	(0.57)
Inflation rate	0.32**	0.27*	0.25	0.29**
	(2.10)	(1.89)	(1.36)	(1.92)
Unemployment rate	-0.06	-0.00	0.02	0.07
	(-1.26)	(-0.09)	(0.63)	(1.44)
Share price index growth	-0.01	0.00	-0.03	-0.01
	(0.62)	(0.05)	(-1.20)	(-0.65)
Real effective exchange rate	0.00	0.01	0.02*	0.03**
	(-0.81)	(1.40)	(1.79)	(2.21)
Money growth	0.01	0.01	0.01	0.00
	(0.73)	(0.61)	(0.74)	(-0.13)
Trade openness	0.7***	0.06***	0.02	0.05*
	(2.80)	(2.70)	(0.60)	(1.86)
Current account / GDP	0.00	0.00*	0.00	0.00
	(0.14)	(-1.69)	(-0.32)	(-0.52)
Capital account / GDP	0.00	0.00	0.00	0.00
	(0.70)	(0.11)	(0.21)	(0.68)
Financial account / GDP	0.00*	0.00**	0.00	-0.05
	(-1.89)	(-2.45)	(-0.83)	(-1.04)
Budget deficit / GDP	0.00	0.00	0.00	0.00
	(0.80)	(-0.09)	(0.16)	(-0.15)
Trade linkages	0.26***	0.19***	0.21**	0.22
	(3.21)	(3.14)	(2.04)	(1.02)
Financial linkages	-0.01	0.01	0.07*	0.00
	(-12)	(0.25)	(1.69)	(-0.03)
Macroeconomic similarities	0.01	0.07	0.01	0.01
	(0.16)	(0.86)	(0.09)	(0.03)
Log likelihood	-153.80	-57.41	-140.36	-56.06

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Furthermore, since the discrete semi-parametric model is indeed the conditional logit model, we can also compare the results of the Cox model with conditional logit model, which as depicted earlier (in Figures 4 through 7) the Cox model outperforms this type of logit models.

The sets of our robustness tests reassure us that many of the potential problems associated with using the Cox formulation are not present in our models.

2.7 Concluding remarks

In this paper, we adopted duration analysis to study the mechanism of currency crisis incidents in 21 countries from 1970 through 1998. We tested the role of economic fundamentals in the origins of currency crises and empirically identified the channels through which the crises are transmitted. With our preferred Cox semi-parametric model, we estimated unrestricted baseline hazard, which allows us to account for real duration dependence and improve the efficiency of our results. It also helped us to estimate unbiased and robust estimated coefficients.

Our data generate hazard functions that recommend to us the probability of currency crisis rises with undesired changes in job markets as well as increase in values of inflation rates, real effective exchange rate, size of economy, trade openness, and trade linkages. They represent first, second, and third-generation models in our data set. We also found that the duration dependence in our data is non-monotic: the probability of speculative attack sharply increases at the start of the tranquil period for three quarters, then it declines over the time and abruptly rises again after the 20^{th} quarter.

Among the three contagion channels that are considered in this paper, the estimation results for trade linkages were constantly significant in all of our models. However, the results for macroeconomic similarities channel were not significant in any of the estimations. It also appears that financial linkages need to be constructed with more comprehensive data than common bank lenders and requires further empirical tests. The significance of contagion factor indicates that countries cannot only rely on their own policies to prevent currency crises.

Researchers used to recommend to policy makers to fix their exchange rates with their major trade partners and/or even constitute currency union to avoid currency crises. Yet, the current Euro zone crisis showed those recommendations might prevent currency crisis incidents but they can lead to other types of financial crises. In a world of integrated financial markets, coordinating policies with major economic partners is definitely required for any variety of prevention, resolution, and management of crises.

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Appendix A

This appendix heavily relies on Eichengreen *et al.* (1996), Glick and Rose (1999), and Van Rijckeghem and Weder (2001). It illustrates how the weights of different contagion channels are constructed.

Glick and Rose (1999) quantify the importance of international trade links between countries mostly by focusing on competition in foreign export markets. Their measure of trade links is similar to Grubel-Lloyd (1971) measure of cross-country intra-industry trade. They compute how much country *j* competes with country *i* in the third export market, country *k*, as follows:

$$k_{ji}^{trade} = \sum_k \{[(x_{jk} + x_{ik})/(x_{j.} + x_{i.})]\,[1 - |(x_{ik} - x_{jk})|/(x_{jk} + x_{ik})]\} \text{ for } k \neq j \text{ or } i$$

where x_{jk} denotes aggregate bilateral exports from country *j* to country *k* and $x_{j.}$ denotes aggregate bilateral exports from country *j* (*i.e.*, $\sum_k x_{jk}$). This index is a weighted average of the mutual importance of exports from countries *j* and *i* to each country *k*. The mutual importance of exports to country *k* is defined to be greatest when it is an export market of equal importance to both *j* and *i*, as measured by bilateral export levels. The weights are proportional to the importance of bilateral exports of countries *j* and *i* to country *k* relative to their combined aggregate trade. Higher values of k_{ji}^{trade} denote greater trade competition between *k* and *i* in foreign export markets.

Glick and Rose (1999) accept this measure is clearly an imperfect measure of the importance of trade linkages between countries *j* and *i*. This index relies on actual rather than potential trade, and aggregate data. It ignores direct trade between the two countries and disregards cascading effects. Countries of vastly different size are also a potential problem.

We follow Glick and Rose (1999) to construct our weight for international trade. In order to check the sensitivity of our measure, we also computed different weight using bilateral trade shares rather than bilateral exports.

Van Rijckeghem and Weder (2001) compute the financial linkages between the countries from their competition for funds. Analogous to Glick and Rose (1999), they measure how much country *j* compete country *i* for funding from the same lender. Their indicator is constructed as follows:

$$k_{ji}^{finance} = \sum_k \{[(b_{jk} + b_{ik})/(b_{j.} + bx_{i.})]\,[1 - |(b_{ik} - b_{jk})|/(b_{jk} + b_{ik})]\}$$

where b_{jk} represents bank lending from the common lender country k to country j and $b_{j.}$ denotes total bank lending to country j (*i.e.*, $\sum_k b_{jk}$). This index measures the similarities in borrowing patterns of countries j and i. The first component of the equation is a measure of the overall importance of the common lender country for countries j and i. The second component captures the extent to which counties j and i compete for funding from the same creditor country.

We construct our financial linkages weight in line with Van Rijckeghem and Weder (2001) methodology. We also construct a variant of this measure using the share of borrowing from the common lender, rather than the absolute value of credits obtained from the common lender, for sensitivity analysis purpose.

Eichengreen *et al.* (1996) introduce a weighting scheme to capture macroeconomic similarities whose existence is a potential channel for contagion. They argue two countries are "similar" if they display similar macroeconomic conditions – for instance, if they have similar rates of growth of gross domestic product. Then, they test the hypothesis that an attack on the currency of country j affects the probability of an attack on the currency of country i.

To measure the "similarities" between countries, they concentrate on seven "focus variables" that appear to be the subject of considerable attention among participants in foreign exchange markets: 1) output growth; 2) domestic credit growth; 3) money growth; 4) inflation; 5) the unemployment rate; 6) the current account (in nominal GDP percentage points); and 7) the government budget deficit. They multiply the rate of GDP growth, the current account and the government budget by minus one in order to allow for easier comparison with the other four variables; this means that higher values are associated with greater risk. They standardize the variables by subtracting sample means and dividing the result by the sample standard deviation. In practice, they standardized the variables in two ways: 1) "country-specific" approach in which a country is compared only with itself (*e.g.* the average rate of growth of French domestic credit is subtracted from the raw series and then divided by the sample French credit growth standard deviation); and alternatively, 2) "time-specific" approach in which the observations at one point in time are compared with observations for all 21 countries at that same point in time. The first approach is appropriate if currency speculators compare credit growth in a country in a quarter to that country's own past credit growth; the second is relevant if speculators compare the country's credit growth to that typical of other countries in the same quarter.

Having standardized the variables, we compute the macro weights as follows for the "country-specific" and "time-specific" standardizations respectively:

$$k_{ji}^{MacSim} = \sum_j\{1 - (\Phi[(x_{jt} - \mu_i)/\sigma_i] - \Phi[(x_{it} - \mu_i)/\sigma_i])\}$$ for any $i \neq j$, and

$$k_{ji}^{MacSim} = \sum_j \{1 - (\Phi[(x_{jt} - \mu_t)/\sigma_t] - \Phi[(x_{it} - \mu_t)/\sigma_t])\} \text{ for any } i \neq j,$$

where, Φ (.) is the cumulative distribution function of the standardized normal function, μ_i (μ_t) is the "country-specific" ("time-specific") sample average of variable *x*, σ_i (σ_t) is the "country-specific" ("time specific") standard deviation of variable *x*, and the *x*'s are the seven macroeconomic "focus" variables.

This specification implies that if country *j* is attacked at time *t* and it is similar to country *i*, in the sense of having similar standardized growth rates of relevant macroeconomic variables, then it receives a high weight on the contagion variable. If *j* and *i* have identical (standardized) domestic credit growth rates, the weight is unity; the more dissimilar are the growth rates (in the sense of being distant in terms of the cumulative distribution), the lower is the weight. If *i*'s credit growth is at the extreme lower-end of *i*'s cumulative distribution while *j*'s is at its upper end, then the weight is zero.

Following Eichengreen *et al.* (1996) we computed 14 macroeconomic contagion weights; given two standardizing techniques (country- and time-specific) and seven focus variables.

Appendix B

Our panel of data is unbalanced. There are several cases in which quarterly data in certain periods is either not available or missing for some or all countries. However, whenever annual data is available, the missing quarterly series are interpolated by using the MATLAB cubic spline procedure.

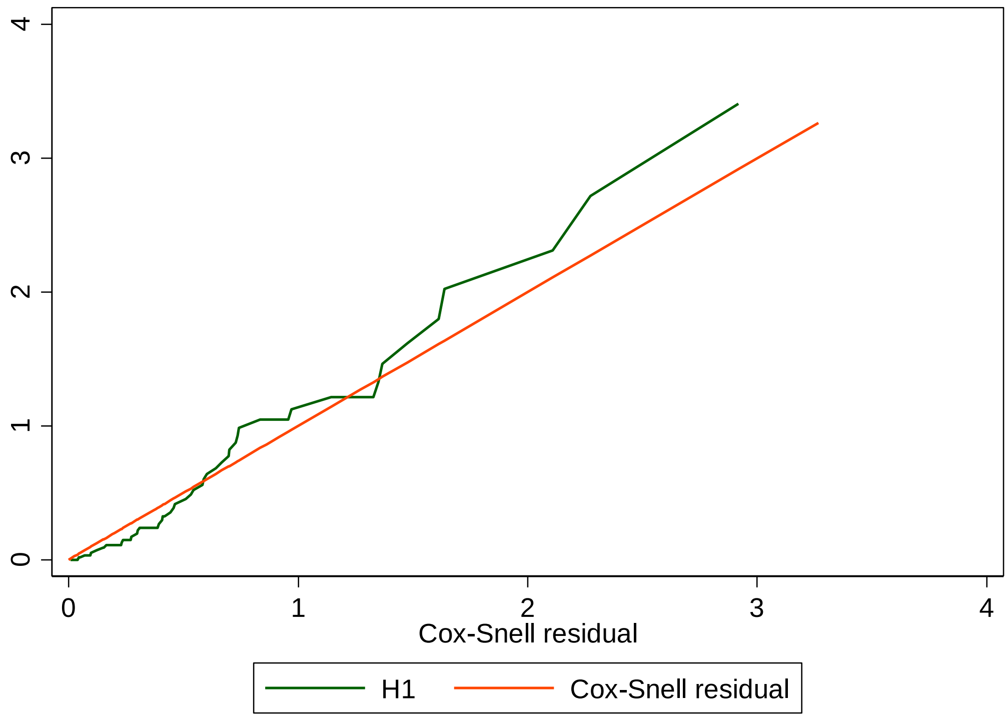
The employed covariates are constructed as follows:

- Budget deficit / GDP: operating budget deficit divided by GDP (current prices).
- Capital account / GDP: capital account balance divided by GDP (current prices).
- Current account / GDP: current account balance divided by GDP (current prices).
- Financial account / GDP: financial account balance divided by GDP (current prices).
- Financial linkages: the "Consolidated Banking Statistics" data set of BIS is used to build the financial weights as explained in Appendix A. However, complete data on consolidated bank loan statistics to most of the sample countries are only available after 1998. Semi-annual data are available for Australia, Greece, Iceland, New Zealand, Portugal, and South Africa starting from 1983.
- GDP growth rate: percent of changes in Growth Domestic Product (constant prices) with respect to the previous period.
- Inflation: percent of changes in Consumer Price Index with respect to the previous period.
- Inflation volatility: the whole period standard deviation of one-year window standard deviation of inflation rate.
- Macroeconomic similarities: the weights are constructed as explained in Appendix A.
- Money growth: percent of changes in money plus quasi money (M2) with respect to the previous period.
- Previous Crises: equals one if there is at least one crisis in the last four quarters; zero, otherwise.
- Real effective exchange rate: CPI based real effective exchange rate.
- Share price index growth: percent of changes in Share Price Index with respect to the previous period.
- Size of economy: based on the magnitude of GDP, countries are divided into three categories: small, medium, and large. Greece, Iceland, Ireland, New Zealand, Portugal, and South Africa are in the first category. Austria, Belgium, Denmark, the Netherlands, Norway, Spain, Sweden, and Switzerland lie in the second category. Australia, Canada, France, Italy, Japan, and the United Kingdom constitute the third category.

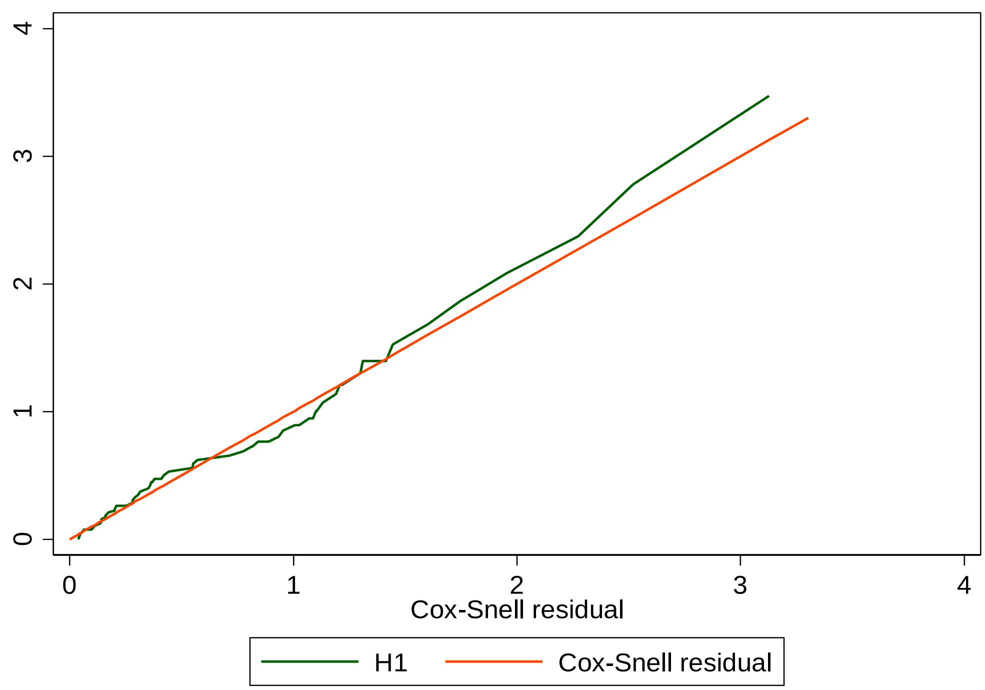
- Trade linkages: the relevant data are taken from the IMF's DOTS to construct the weights for international trade as explained in Appendix A.
- Trade openness: export plus import divided by GDP.
- Unemployment rate: unemployed individuals divided by the labour force (expressed in percentages).
- Unemployment volatility: the whole period standard deviation of one-year window standard deviation of unemployment rate.
- Whole period GDP growth: percent of changes in GDP (constant prices) at the fourth quarter 1998 from the GDP (constant prices) at the first quarter 1970.

Appendix C

1. Goodness of fit for Model 1 (monthly-type)

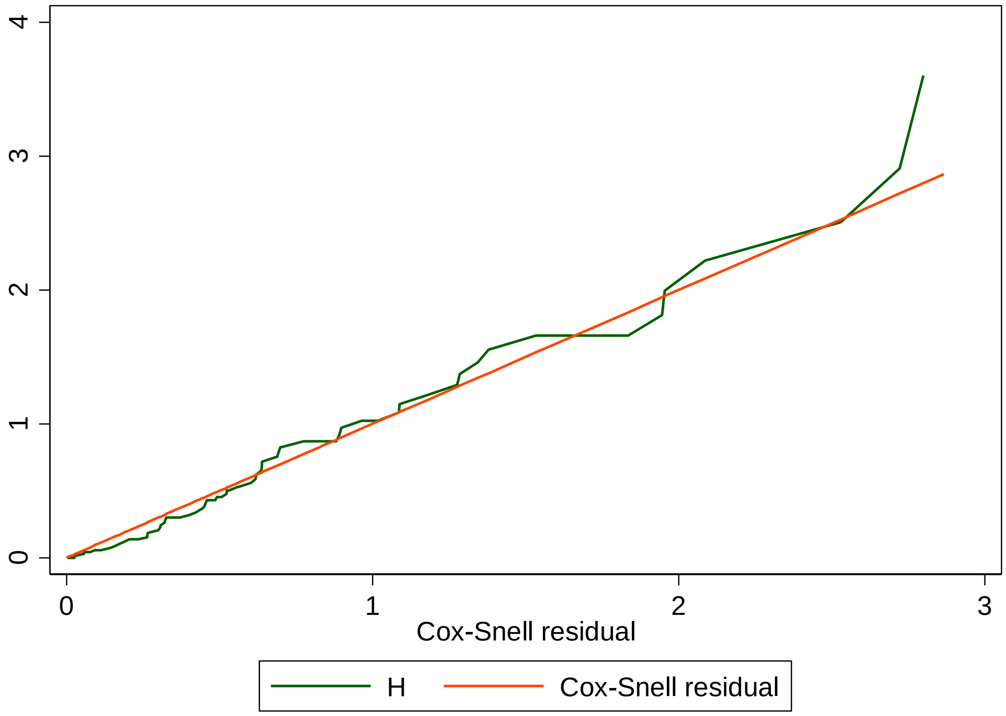


2. Goodness of fit for Model 2 (monthly-

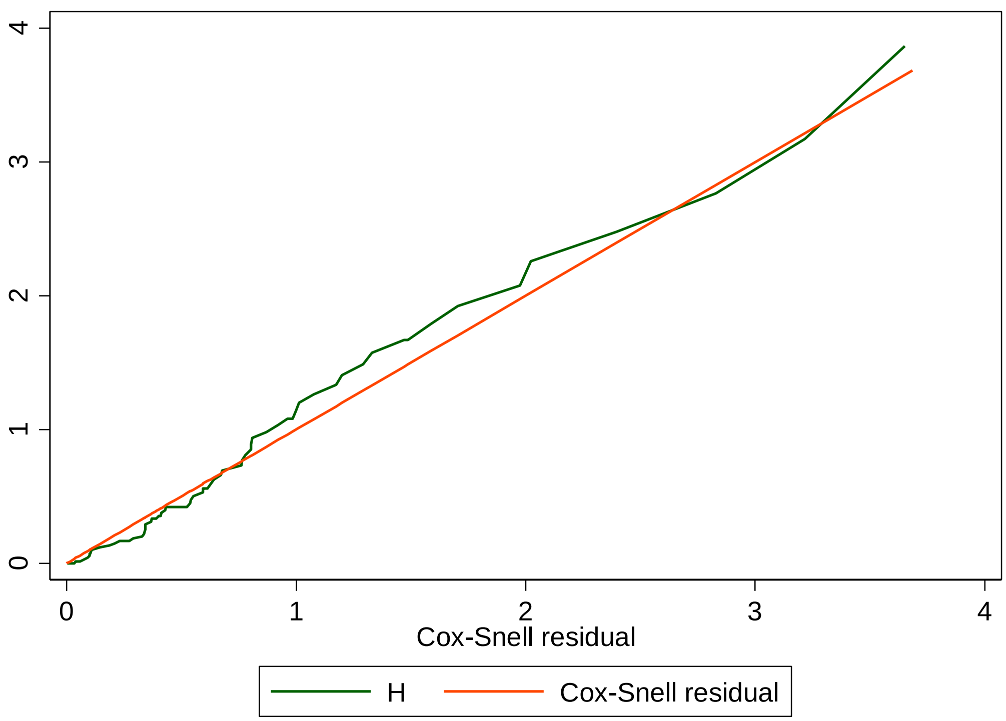


type)

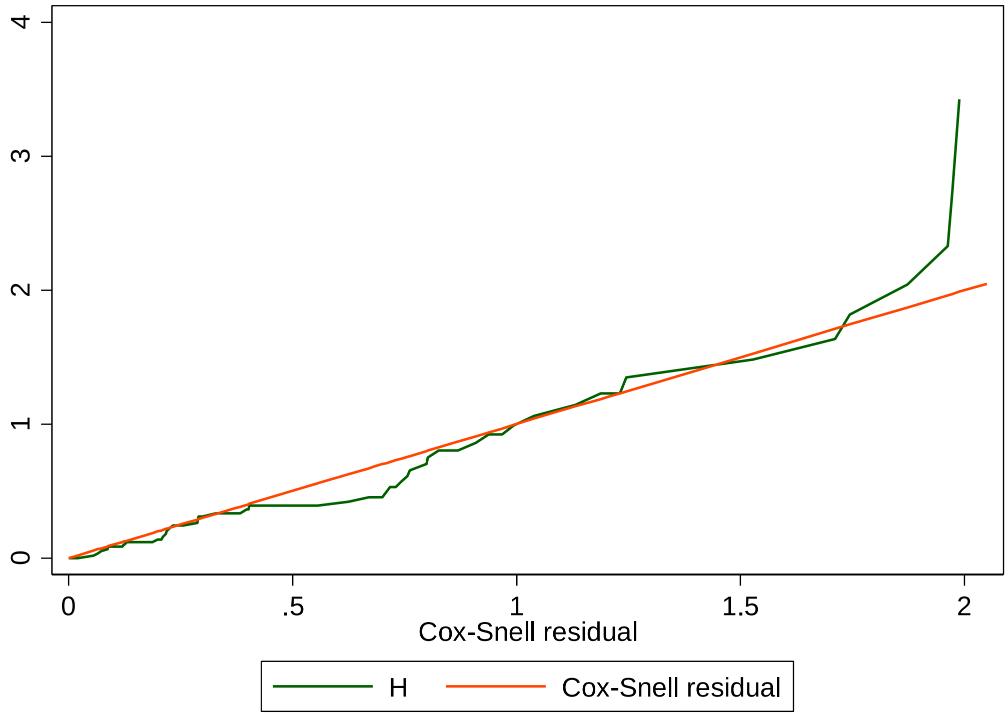
3. Goodness of fit for Model 3 (monthly-type)



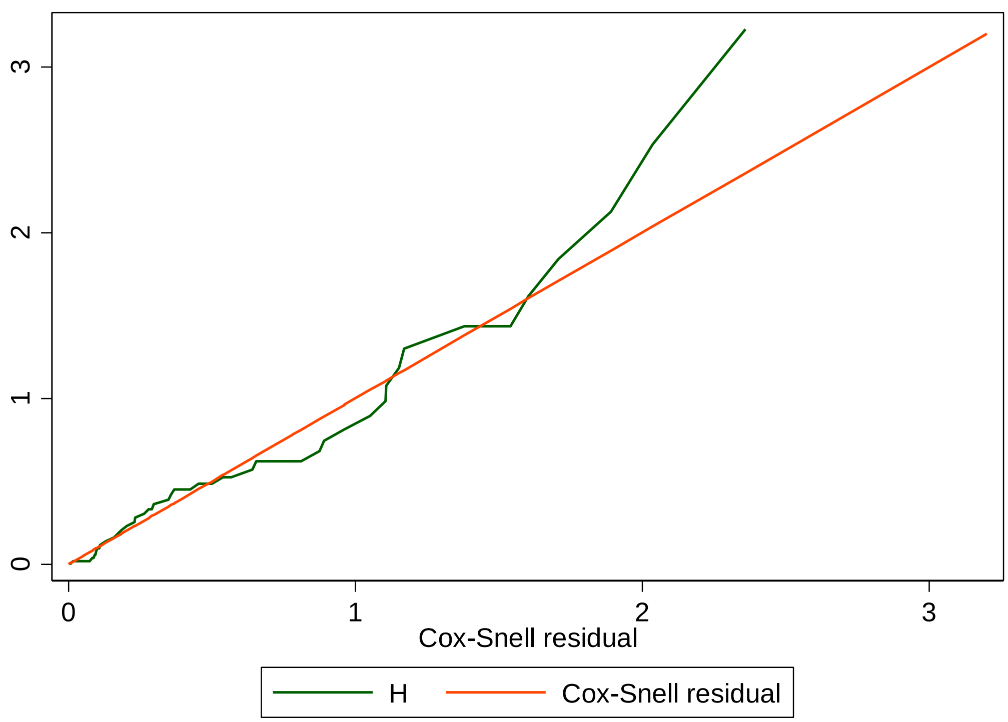
4. Goodness of fit for Model 4 (monthly-type)



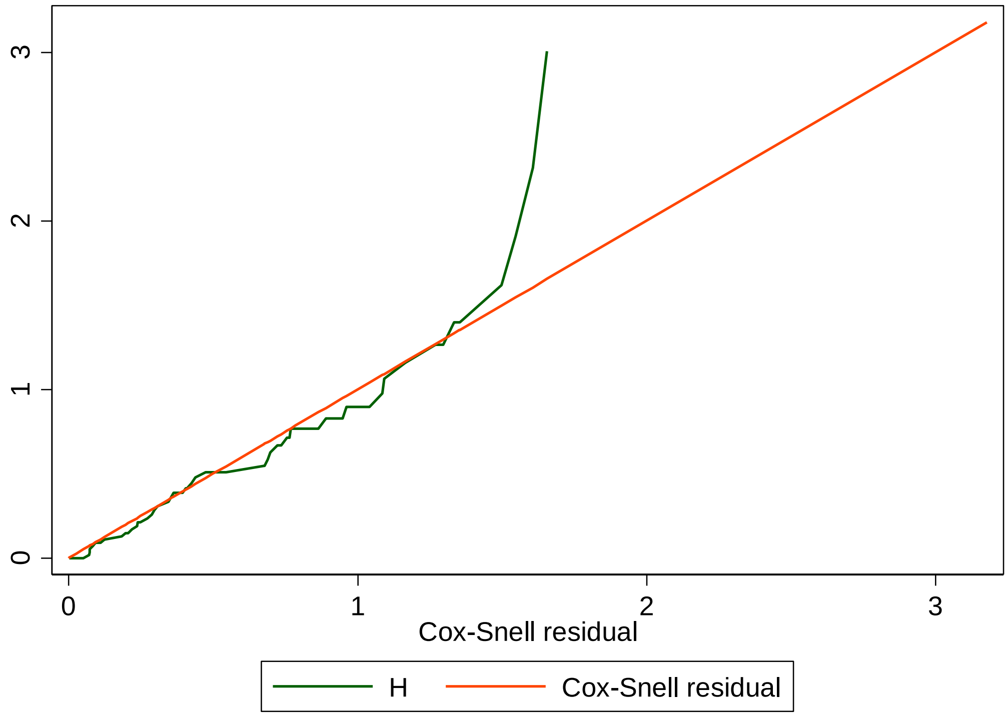
5. Goodness of fit for Model 1 (quarterly-type)



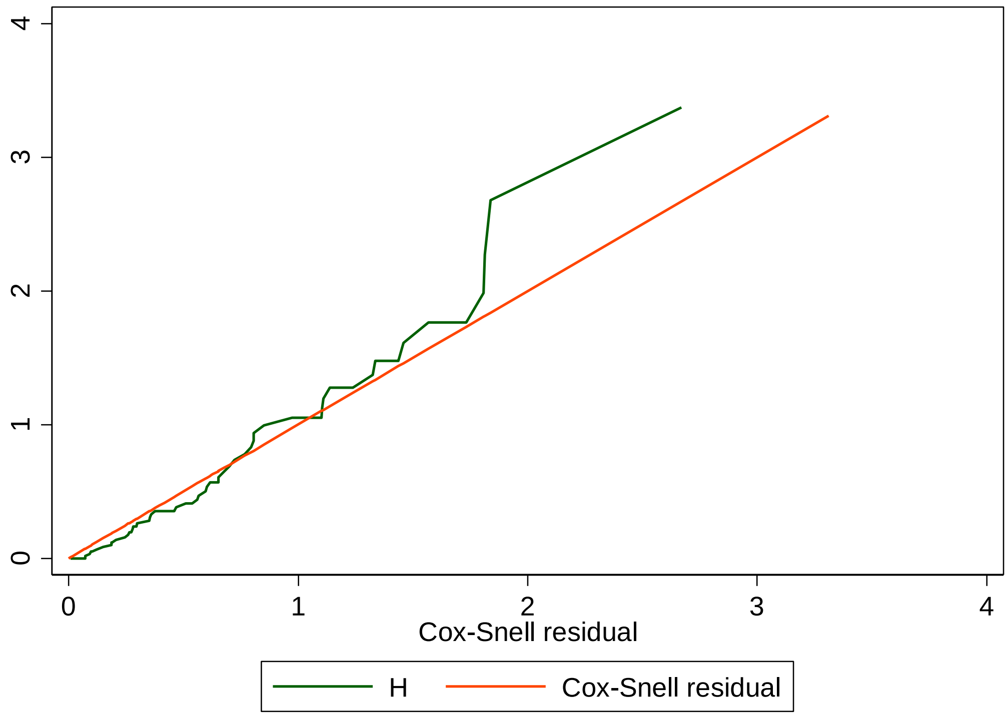
6. Goodness of fit for Model 2 (quarterly-type)



7. Goodness of fit for Model 3 (quarterly-type)



8. Goodness of fit for Model 4 (quarterly-type)



1. Test of proportional-hazard assumption for Model 1 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	0.04752	0.13	1	0.72
econsize	0.11928	0.71	1	0.4001
newGDPg	0.00091	0	1	0.9931
newreer	0.10701	0.62	1	0.4303
newUnempR	0.03708	0.11	1	0.7451
newCPI1	-0.00534	0	1	0.9717
newcShareP	-0.06327	0.25	1	0.6156
newMQMg	-0.10289	1.27	1	0.2596
newOPs	-0.21787	2.29	1	0.1298
newCAGDP	-0.07901	0.05	1	0.8255
newCPGDP	-0.01172	0.01	1	0.935
newFAGDP	-0.04213	0.16	1	0.6907
newBDGDP	-0.07003	0.47	1	0.4908
newcompeti~n	-0.02444	0.04	1	0.8493
newfinance	-0.20393	3.32	1	0.0685
newmacsimi~P	0.03181	0.07	1	0.786
global test		10.78	16	0.8231

2. Test of proportional-hazard assumption for Model 2 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	-0.00268	0	1	0.9824
econsize	0.1577	1.3	1	0.255
newGDPg	0.00961	0.01	1	0.9378
newreer	0.14722	0.91	1	0.3411
newUnempR	0.04637	0.16	1	0.6853
newCPI1	0.12563	1.17	1	0.2785
newcShareP	-0.07358	0.17	1	0.6777
newMQMg	-0.16991	2.24	1	0.1343
newOPs	-0.02592	0.04	1	0.8493
newCAGDP	0.08566	0.18	1	0.6732
newCPGDP	-0.01621	0	1	0.9466
newFAGDP	0.08679	0.49	1	0.484
newBDGDP	-0.0765	0.4	1	0.5287
newcompeti~n	-0.00529	0	1	0.971
newfinance	-0.14226	1.02	1	0.3135
newmacsimi~P	0.05237	0.15	1	0.7025
global test		6.67	16	0.9791

3. Test of proportional-hazard assumption for Model 3 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	-0.03535	0.07	1	0.7965
infstdtime	0.00102	0	1	0.9941
econsize	-0.03135	0.06	1	0.8029
newGDPg	0.20828	2.91	1	0.0882
newreer	-0.0067	0	1	0.9511
newUnempR	0.06943	0.46	1	0.4962
newCPI1	0.01534	0.02	1	0.885
newcSharep	-0.01747	0.02	1	0.8776
newMQMg	-0.07727	0.49	1	0.4831
newOPs	-0.16628	2.09	1	0.1487
newCAGDP	0.10441	0.95	1	0.3291
newCPGDP	0.16429	1.5	1	0.2206
newFAGDP	0.11064	0.67	1	0.4147
newBDGDP	-0.06382	0.27	1	0.6045
newcompeti~n	-0.08597	0.48	1	0.4864
newfinance	-0.19523	2.42	1	0.1202
newtmacsim~g	0.09533	0.63	1	0.4262
global test		10.2	17	0.8948

4. Test of proportional-hazard assumption for Model 4 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	0.00749	0	1	0.9554
infstdtime	0.0709	0.21	1	0.6504
tgdpg	-0.03116	0.05	1	0.8295
econsize	0.06312	0.21	1	0.649
newlGDPg	0.01669	0.02	1	0.8997
newcREER	-0.07001	0.28	1	0.5987
newlUnempR	0.03361	0.07	1	0.7896
newlCPI1	-0.13361	0.53	1	0.4666
newlcShareP	-0.00537	0	1	0.971
newlMQMg	0.06297	0.2	1	0.6519
newlOPs	-0.07387	0.25	1	0.6196
newlCAGDP	-0.0641	0.26	1	0.6123
newlCPGDP	0.06232	0.21	1	0.6446
newlFAGDP	0.07645	0.26	1	0.6107
newlBDGDP	0.01177	0.01	1	0.9317
newcompeti~n	0.01048	0.01	1	0.9371
newfinance	-0.1973	2.2	1	0.138
newtmacsim~g	0.00845	0	1	0.9485
global test		12.6	18	0.8146

5. Test of proportional-hazard assumption for Model 1 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	-0.05423	0.14	1	0.7112
infstdtime	0.08399	0.23	1	0.629
tgdpg	0.0675	0.24	1	0.6227
econsize	0.00927	0	1	0.947
PCris	0.12015	0.72	1	0.395
newGDPg	-0.1213	1.06	1	0.3039
newreer	0.09037	0.38	1	0.539
newUnempR	-0.02124	0.03	1	0.8533
newCPI1	-0.10485	0.76	1	0.3847
newcSharep	0.11104	0.54	1	0.4626
newMQMg	-0.02667	0.07	1	0.7877
newOPs	-0.02352	0.02	1	0.8898
newCAGDP	0.07961	0.08	1	0.775
newCPGDP	-0.07977	0.56	1	0.4558
newFAGDP	-0.02628	0.01	1	0.9074
newBDGDP	-0.16299	1.05	1	0.3055
newcompeti~n	-0.06745	0.33	1	0.5656
newfinance	-0.06187	0.22	1	0.6382
newtmacsim~g	0.06089	0.26	1	0.6119
global test		5.07	19	0.9994

6. Test of proportional-hazard assumption for Model 2 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	-0.13693	0.67	1	0.4136
infstdtime	0.05648	0.12	1	0.7329
PCris	0.04593	0.09	1	0.7583
newGDPg	-0.09974	0.66	1	0.4181
newreer	0.04374	0.06	1	0.8007
newUnempR	-0.00311	0	1	0.9796
newCPI1	-0.05349	0.31	1	0.5783
newcSharep	0.04999	0.08	1	0.7781
newMQMg	0.05778	0.16	1	0.6892
newOPs	-0.15521	1.29	1	0.2558
newCAGDP	-0.01198	0.01	1	0.9165
newCPGDP	-0.0723	0.04	1	0.8427
newFAGDP	-0.11866	0.57	1	0.4487
newBDGDP	-0.01717	0.01	1	0.9279
newcompeti~n	-0.11402	0.63	1	0.4278
newfinance	0.01224	0.01	1	0.9076
newtmacsim~g	0.0724	0.21	1	0.6488
global test		4.84	17	0.9982

7. Test of proportional-hazard assumption for Model 3 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	-0.03484	0.05	1	0.8226
infstdtime	-0.04011	0.06	1	0.8099
tgdpg	0.07148	0.21	1	0.6468
econsize	-0.0668	0.26	1	0.6084
newlGDPg	0.15435	1.27	1	0.2605
newlreer	0.06435	0.18	1	0.6673
newlUnempR	0.03398	0.05	1	0.8238
newlCPI1	0.10539	0.55	1	0.4572
newlcShareP	0.02292	0.02	1	0.886
newlMQMg	0.02639	0.06	1	0.8136
newlOPs	-0.0102	0	1	0.9512
newlCAGDP	0.07599	0.13	1	0.7185
newlCPGDP	0.12592	0.46	1	0.4975
newlFAGDP	-0.02112	0.03	1	0.8736
newlBDGDP	-0.01854	0.01	1	0.9256
newcompeti~n	-0.06576	0.21	1	0.6482
newfinance	-0.08319	0.36	1	0.5509
newtmacsim~g	0.11471	0.62	1	0.4324
global test		5.34	18	0.9982

8. Test of proportional-hazard assumption for Model 4 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
UnempgStdt~e	-0.13137	0.64	1	0.4247
econsize	0.10506	0.37	1	0.5429
PCris	0.04462	0.08	1	0.7725
newldGDPg	0.22157	1.9	1	0.1683
newldreer	0.03768	0.05	1	0.8251
newldUnempR	0.00843	0	1	0.9537
newldCPI1	0.14079	0.7	1	0.4031
newldcShareP	-0.13531	0.41	1	0.5244
newldMQMg	0.03484	0.06	1	0.8024
newldOPs	-0.0377	0.08	1	0.7757
newldCAGDP	-0.00649	0	1	0.9811
newldCPGDP	0.00698	0	1	0.9748
newFAGDP	-0.06034	0.07	1	0.7869
newldBDGDP	0.15554	0.22	1	0.6418
newcompeti~n	0.06275	0.11	1	0.7374
newfinance	0.02881	0.02	1	0.8799
newtmacsim~1	-0.04478	0.05	1	0.8175
global test		5.9	17	0.9939

Chapter 3

Currency Crises, Exchange Rate Regimes, and Capital Account Liberalization: A Duration Analysis Approach

3.1 Introduction

The links between the incidence of currency crises and the choice of exchange rate regimes as well as the impact of capital market liberalization policies on the occurrence of currency crises have been subject of considerable debates in recent years. It is of great interest to assess how exchange rate arrangements and financial liberalization will affect episodes of crisis. Policy makers also seek to know what type of exchange rate regime is more sustainable and whether controlling capital flows in fact contributes to the stability of currencies.

Yet, the literature is not clear on these issues and presents mixed views. Many economists argue that fixed exchange rates are a cause of currency crises while others find that the intermediate and/or flexible exchange regimes are more crisis prone. The role of capital market liberalization is even more controversial. The common view in the literature blames high capital mobility as an underlying cause of currency crises, especially when combined with fixed exchange rates. However, several studies hold that capital mobility restrictions are responsible for crises – as a contributing factor behind the crises – and advocate financial liberalization. It is evident that, for the time being, there is no consensus on these topics and more research is required before the controversies can be settled.

The main purpose of this paper is to systematically examine what type of exchange rate regimes are more susceptible to currency crises by investigating the data from twenty OECD countries and South Africa over the period of 1970-1998. We adapt the empirical models of the determinants of currency crises, which were presented in our previous paper, as the benchmark models and examine how the likelihood of currency crises is influenced by *de jure* and *de facto* exchange rate regimes. We also study the role of capital mobility and test for currency stability under free and restricted capital flows. We examine whether the hazard of speculative attack changes under the different combinations of exchange rate regimes and the presence or absence of capital controls.

We employ two prominent *de facto* exchange rate regime classifications in the literature, those of Reinhart and Rogoff (2004), and Levy-Yeyati and Sturzenegger (2005), to identify the actual exchange rate arrangements. Our index for *de jure* exchange rate regimes is the IMF exchange rate classification. We also categorize capital mobility policies into restricted and open policies with the help of Chinn and Ito's (2005) index of financial openness.

As in our previous paper, duration analysis is our methodology to study the probability of a currency crisis occurrence under different exchange rate regimes and capital mobility policies. Duration models rigorously incorporate the time factor into the likelihood functions and allow us to investigate how the amount of time that a currency has already spent in the tranquil state affects the stability of the currency. This feature helps us to capture the unobservable determinants of currency stability that are embodied in the baseline hazard functions. We apply semi-parametric duration models to estimate the unrestricted baseline hazard of a currency exiting a tranquil state into a turbulence state. These models do not require any distribution assumptions about the timing of failures and can capably deal with both monotonic and non-monotonic duration dependence. Compared to other duration models, they are more realistic and can produce estimations that are more efficient.

The nonlinear nature of duration specification lets us investigate how the different exchange rate regimes or the presence and absence of capital controls can change the sensitivity of currency crises with respect to changes in a set of macroeconomic fundamentals and contagion channels. Furthermore, we use crisis episodes that are identified by extreme value theory to minimize the concerns regarding the accuracy of crisis episodes dating. We apply several robustness checks, including running our models on two different crisis episodes sets that are based on monthly and quarterly-type spells, to verify the reliability of our estimation results.

We find that there is a significant link between the choice of exchange rate regime and the incidence of currency crises in our sample. Nevertheless, the results are sensitive to the choice of the *de facto* exchange rate system. When we use Reinhart and Rogoff's (2004) *de facto* classification to categorize the exchange rate regimes, fixed exchange rate arrangements are least susceptible to speculative attacks. However, when we rely on Levy-Yeyati and Sturzenegger's (2005) *de facto* classification, intermediate exchange rate regimes will experience the smallest number of currency crisis incidences. On the other hand, we find that the impact of capital account policies on the occurrence of currency crises, in our sample, demonstrates different results. While the baseline hazard of open-type capital accounts is lower than the baseline hazard of restricted-type capital accounts, when we enter our set of control variables to the models, the hazard of open-type capital accounts appears to be higher than the hazard of restricted-type capital accounts. This relation is more significant at the low duration crisis episodes.

For the remainder of the paper we proceed as follows. Section 2 looks at the exchange rate regimes classifications and briefly introduces the two *de facto* exchange rate regime classifications that we use in this paper. It also quickly reviews the empirical literature on the links between exchange rate regimes and the occurrence of currency crises. Section 3 reviews the empirical literature and presents the links between capital control policies and occurrences of currency crises. Section 4 describes the empirical methodology and data. Section 5 presents the main empirical results and robustness tests. Section 6 discusses the results and concludes. Some detailed technical results are presented in the appendix.

3.2 Classification of exchange rate regimes and currency crises

3.2.1 Classifications

Since the collapse of the Bretton Woods system, a large empirical literature has developed to assess the performance of exchange rate regimes. The early literature – *e.g.* the influential work of Baxter and Stockman (1989) – compared the performance of key macroeconomic variables with fixed and flexible exchange rate arrangements. However, they found little significant differences across fixed and flexible regimes. There was a drawback in the way that they characterized the exchange rate regimes and this shortcoming affected negatively the early literature.

For many years, empirical studies relied on the International Monetary Fund's *de jure* classification of exchange rate regimes to measure the impact of exchange rate arrangements on economic performance.[1] This classification is a countries' self-declared index, which was published in the Fund's *Annual Report on Exchange Rate Arrangements and Exchange Restrictions*.[2] However, in a pioneering paper, Calvo and Reinhart (2002) noticed that in practice there is a substantial deviation between the officially reported and the actually prevailing exchange rate arrangements.[3] Therefore, the empirical results of those analyses based on the *de jure* classification could be misleading. This problem motivated researchers to devise alternative classifications to identify the *de facto* exchange rate regimes and categorize countries more accurately according to their actual practice rather than official statement.[4]

In this subsection, we briefly introduce two prominent alternative classifications in the literature: Reinhart and Rogoff (2004) and Levy-Yeyati and Sturzenegger (2005).[5] Reinhart and Rogoff (hereafter RR) rely on the IMF classification as their starting point and develop their own classification system based on a statistical analysis of the *ex post* behavior of exchange rates in the official, dual and/or parallel markets. For countries with only official rates they apply a broad variety of descriptive statistics (mostly exchange rate variability, variability with respect to the officially announced bands, and inflation) to verify whether the *de jure* classification is accurate. If not, they reclassify the exchange rate into the alternative

1. Ideally, the exchange-rate system classification ought to be based on the degree to which a system in a particular category constrains domestic monetary policy independence (Tavlas *et al.*; 2008).
2. The *de jure* classification roughly distinguished between three broad categories: pegged, limited flexibility, and more flexible. These three coarse categories could be extended into fifteen fine subcategories that cover a continuum of exchange rates regimes from hard fixes to free floats.
3. For example, several economies officially reported their currencies as pegs but often underwent frequent devaluations and, hence, in practice their regimes resembled a flexible more than a fixed. Alternatively, other countries officially committed to the flexible exchange rates, however, exhibited "fear of floating" and acted differently.
4. To address this and a few other shortcomings, the IMF has adopted a modified classification system based on the Fund's members' *de facto* regimes since 1999. Bubula and Ötker-Robe (2002) provide more details.
5. Tavlas *et al.* (2008) review the main methodologies that have been used to construct the *de facto* exchange rate regimes. They also survey the empirical literature that has been generated by the *de facto* classifications.

categories. For countries with dual and/or parallel rates, they classify the exchange rate based on the market-determined rates, which they argue are important indicators of the underlying monetary policy.

RR classify the exchange rates regimes into fourteen fine categories. Nevertheless, these categories can be aggregated into three coarse branches: fixed, intermediate, and float. The fixed branch includes: (1) regimes with no separate legal tender, (2) regimes with a pre-announced peg or currency board arrangements, (3) regimes with a pre-announced horizontal band that is narrower than or equal to plus/minus two percent, and, (4) regimes with a *de facto* peg. The intermediate branch contains: (5) pre-announced crawling pegs, (6) regimes with a pre-announced crawling band that is narrower than or equal to plus/minus two percent, (7) *de facto* crawling pegs, (8) regimes with a pre-announced crawling band that is wider than or equal to plus/minus two percent, (9) regimes with a *de facto* crawling band that is narrower than or equal to plus/minus two percent, (10) regimes with a *de facto* crawling band that is narrower than or equal to plus/minus five percent, (11) regimes with a moving band that is narrower than or equal to plus/minus two percent, and, (12) managed floating arrangements. Finally, the float branch includes: (13) freely floating exchange rates. The last category, (14) free falling regimes, can be reclassified into fixed, intermediate, or float on the basis of the provided chronologies.[6]

Levy-Yeyati and Sturzenegger (hereafter LYS) use cluster analysis and construct their alternative classification exclusively based on the official exchange rate and the evolution of foreign exchange reserves. They adopt the classic textbook definition of fixed and flexible exchange rates to classify the regimes. They categorize the exchange rate arrangements that are associated with low volatility in (1) nominal exchange rate level (σ_{e}) and, (2) changes in nominal exchange rate ($\sigma_{\Delta e}$) but high volatility in international reserves (σ_{R}) as fixed exchange rate regimes, while arrangements with high volatility exchange rate levels and exchange rate movements but stable international reserves are defined as flexible exchange rate regimes.

LYS fine classification distinguishes five different regimes: (1) fixed regimes, 2) crawling pegs, (3) dirty floats, (4) floats, and, (5) inconclusive.[7] However, their coarse classification collapses into three categories: (1) fixed, (2) intermediate, and, (3) float. LYS purely rely on statistical methodology, hence, almost one third of the observations in their sample cannot be classified by their algorithm due to missing data or because the exchange rate was pegged to an undisclosed basket.

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6. RR classify an exchange rate arrangement as a free falling regime if the 12-month inflation rate is equal to or exceeds 40 percent per annum. The regime is also considered to be free falling during the six months immediately following a currency crisis and there is a transition from a peg or a quasi-peg regime to a managed or independent float regime. See the Appendix in Reinhart and Rogoff (2004) for more details.
7. Inconclusive regimes include those exchange rates that experience low volatility with respect to all three characteristics or for which there is no information about the classifying variables. Nearly two percent of the regimes were classified as inconclusive in the latest update of LYS.

RR and LYS's *de facto* exchange rate regimes are very popular among alternative classifications and the series that they provide have been widely used in the empirical literature. The latest update of RR dataset provides monthly *de facto* exchange rate regimes for 227 countries from January 1940 through December 2007, while the latest update of LYS dataset provides annual *de facto* exchange rate regimes for 183 countries from 1974 through 2004.

Both RR and LYS classifications have made a significant contribution to the *de facto* exchange regimes literature. Nevertheless, there are two concerns regarding the alternative classification. First, there is no empirical evidence on how to choose among the existing alternative systems. Second, there is no commonly accepted test – indeed few studies have been performed – to verify the reliability of these classifications and accordingly the studies that use them. In a recent paper, Eichengreen and Razo-Garcia (2011) investigate the disagreement between *de facto* exchange rate regimes.[8] They find that there is a good amount of agreement across the classifications; however, the disagreements are not negligible. Their results show that the disagreement is more pronounced in the case of emerging and developing countries.

3.2.2 Exchange rate regimes and currency crises

The wave of currency crisis incidences in the 1990's and early 2000's has stimulated the debates on the potential links between the choice of an exchange rate regime and the occurrence of crises. Fischer (2001) and Williamson (2002), among others, view fixed exchange rate regimes as crisis prone and argue that, in a world of integrated financial markets, rigid exchange rates are more susceptible to speculative attacks.

Yet, during the major currency crisis events, intermediate exchange rate regimes (soft pegs and tightly managed floats) have been the main targets of speculative attacks. Therefore, some researchers suggest that such regimes are not viable and support for the "bipolar view" of exchange rate regimes. The proponents of the bipolar view claim that the intermediate regimes suffer from a lack of verification and transparency. Moreover, they argue that high capital mobility leaves little room for the governments to follow inconsistent internal and external policies. Thus, in a world of free international capital mobility, countries will be forced to abandon the intermediate regimes and choose between the two extreme exchange rate regimes: either hard pegs or freely floating regimes (see *e.g.*, Eichengreen, 1994; and Fischer, 2001).

Nevertheless, many economists have challenged the bipolar view. Calvo and Reinhart (2002) demonstrated empirically that many intermediate regimes have not vanished and have maintained their

8. They use data from three popular classification schemes: RR, LYS, and Bubula and Ötker-Robe (2002), which has been extended by Anderson (2009).

existence. They pointed out that the bipolar systems do not necessarily enhance the credibility of monetary-exchange rate policies and can even destabilize the financial system. Williamson (2000 and 2002) advocates intermediate regimes and proposes certain types of them (*i.e.* band, basket, and crawl) as the arrangements that can stabilize the real effective exchange rate and improve the sustainability of the exchange system. He argues these regimes can help preventing misalignments and provide greater flexibility to cope with shocks, whereas hard pegs and free floats can cause misalignments and damage the sustainability of the system.

Some researchers have empirically studied the links between the exchange rate regimes and the occurrence of currency crises. Ghosh *et al.* (2003) statistically examine the impact of exchange rate regimes on currency crises for the IMF country members from 1972 to 1999. Using the IMF's *du jure* exchange rate regimes and their own constructed *de facto* classification, they find that crises are more likely under floating regimes.

Bubula and Ötker-Robe (2003) investigate the links between the exchange rate regime and the incidence of currency crises among IMF country members from 1990 to 2001. Their logit model estimation results, obtained on the basis of the *de facto* exchange rate regimes of Bubula and Ötker-Robe (2002), provide some support for the bipolar view. During their sample period, the likelihood of crises for the intermediate regimes was significantly higher than that of hard pegs and floating regimes.

Rogoff *et al.* (2004) and Husain *et al.* (2005), using the *de facto* classification of Reinhart and Rogoff (2004), estimate the probability of currency crises for IMF country members. According to their results, over the 1970 to 2000 period, currency crises tended to occur more frequently in the intermediate regimes. Applying an alternative measure of currency crises, they find floating regimes have a significantly lower risk of entering into a crisis compared to pegs and intermediate regimes.

Haile and Pozo (2006) apply probit models to test whether the exchange regime in place has an impact on the vulnerability of countries to currency crises. Their sample includes 18 developed countries from 1974 to 1998. When they use Levy-Yeyati and Sturzenegger's (2005) *de facto* exchange rate regimes, their results show that the *de facto* exchange arrangements play no role in determining crisis periods. However, when they use the IMF *de jure* classification, they find that the probability of currency crises is higher for the declared pegged regimes than for intermediate or floating regimes.

Esaka (2010a, b) examines how *de facto* exchange rate regimes affect the occurrence of currency crises in 84 countries from 1980 to 2001. His probit model estimation results, obtained by employing the *de facto* classification of Reinhart and Rogoff (2004), demonstrate no significant increase in the likelihood of currency crises for the intermediate regimes compared with the hard pegs and free floating regimes (Esaka, 2010a). He finds pegged regimes significantly decrease the likelihood of currency crises compared with floating regimes (Esaka, 2010b). He also found that hard pegs with liberalized capital account significantly decrease the probability of currency crises compared to the floating and intermediate regimes with capital control.

3.3 Capital markets liberalization and currency stability

The link between capital markets liberalization and macroeconomic instability is one of the key topics in international economics. Many economists and policymakers believe that large and volatile capital flows make the international financial system unstable and cause currency crises. In their view, the liberalization of international capital flows, especially when combined with fixed exchange rates, will lead to financial disruptions (see *e.g.*, Radelet and Sachs, 2000; Stiglitz, 2002).

On the other hand, capital mobility restrictions may also undermine the stability of financial system and contribute to the occurrence of crises. Imposing capital controls will induce investment irreversibility, result in a net capital outflow, and worsen financial instability (Dooley and Isard, 1980). Moreover, restricted capital accounts can create distortions, signify inconsistent policies, and exhibit the potential vulnerabilities of the financial system, which may induce capital flight and trigger currency crises (Bartolini and Drazen, 1997).

In addition to the lack of consensus on the links between capital market liberalization and the occurrence of currency crises, the potential interdependence of capital account policies with the choice of exchange rate regime makes the issue at stake even more complicated. It is widely recognized that under high capital mobility, monetary policies cannot easily focus on both maintaining fixed exchange rates and accommodating with real shocks effectively. This is usually referred to as the "impossible trinity".[9] It points to the argument that policymakers in open economies may concentrate only on two of three conflicting objectives: capital mobility, monetary independence, and the stable fixed exchange rate.[10] This argument implies there could be interdependence between the choices of exchange rate regimes and capital account policies.

As a direct implication of the impossible trinity, one can expect, due to the current trend of financial liberalization, monetary policies will increasingly become inconsistent with the sustainability of fixed

9. However, Lavoie (2001) counters the impossible trinity claim and argues that even under capital mobility can maintain their monetary policy autonomy. Partially based on his argument, Frenkel and Rapetti (2007) analyze the macroeconomic evolution of Argentina during the (2001) crisis and question the validity of impossible trinity.
10. Obstfeld and Taylor (2005) elaborate the role of impossible trinity on the evolution of the international financial system.

exchange rates and make this type of exchange rate arrangement more crises prone (this conclusion is incompatible with the bipolar view). Furthermore, wide financial and trade integration, rapid financial innovations, and deep financial developments have gradually reduced the effectiveness of capital controls and consequently the monetary policy-exchange rate stability dilemma is now evident even in the countries that are willing to impose capital controls.

Several studies empirically investigate the impact of capital control policies on insulating countries from the macroeconomic instability and currency crises. Edwards (1989) investigates the role of capital controls in 39 devaluation episodes for 24 developing countries from 1961 to 1982. His findings show that these countries typically employed intensified capital controls programs in the year before the devaluation to slow down the unavoidable balance of payment crises. Demirgüç-Kunt and Detragiache (1997) estimate the probability of a systemic crisis for both industrial and developing countries over the period of 1980-1994. Their results indicate that capital account liberalization can contribute to the macroeconomic instability and the occurrence of banking crises.

On the other hand, Glick and Hutchison (2005) study the link between capital controls and currency stability for 69 emerging and developing countries from 1975 to 1997. Their probit estimation results show that restrictions on capital flows are unable to efficiently protect countries from currency crises. Their findings provide no evidence that countries with high capital mobility are more prone to speculative attacks. Glick, Guo, and Hutchison (2006) address concerns about self-selection bias and attempt to revise their earlier work accordingly.[11] The outcome of their analysis suggests that even after controlling for the sample selection bias, countries with liberalized capital accounts experience a lower likelihood of speculative attacks. Glick and Hutchison (2010) present a new version of their earlier study. They expand the time coverage from 1975 to 2004 and apply duration-adjusted measures of capital control intensity to allow for changes in control programs over time. Their results re-emphasize their previous findings and assert that countries with less restrictive capital controls and more liberalized financial markets appear to be less vulnerable to speculative pressures.

A possible cause of these mixed empirical results could be attributed to the complexity of properly measuring the degree of openness or restrictions in cross-border financial transactions. The underlying source of data for conventional measures of quantifying financial openness is based upon the IMF's *de jure* classifications, which are published in the *Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER)*. However, this information is overly aggregated to fully capture the dynamics of

11. Self-selection bias points to the non-random choice of capital control programs. Countries that are facing considerable amount of pressure in their exchange markets are more likely to impose capital control programs and accordingly a positive correlation between capital controls and speculative attacks will be observed.

actual capital controls. Moreover, it is almost impossible to distinguish between *de jure* and *de facto* controls on capital account transactions. Consequently, the indices that are constructed to quantify the capital account restrictions, especially those that are dichotomous, fail to account for the intensity of capital controls. It is well known that measuring the extent of openness on capital account transactions is very complicated.

Nonetheless, many studies rely on the IMF's *AREAER* attempt to quantify the degree of financial openness and measure the impact or determinants of capital controls. Chinn and Ito (2005) present an index for measuring the degree of capital account openness. The Chinn-Ito index is based on a five-year moving average of the *de jure* binary dummy variables that codify the tabulation of restriction on cross-border transactions. This index attempts to measure the intensity of capital controls. The latest update of this index covers 182 countries for the period of 1970-2009. The index is constructed in such a way that the series has a mean of zero and country values range from -1.844 to 2.478, where the higher values indicate a greater intensity of restrictions on capital account transactions. Chinn and Ito (2008) provide details on how their index is constructed and compare it with other existing measures in the literature.

3.4 Data and methodology

This paper analyzes the incidence of currency crises for 21 countries with the help of an unbalanced panel of quarterly data over the period of 1970 through 1998. The countries in our sample includes: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, and the UK. These countries share common similarities and provide higher frequency data for our empirical models.

Episodes of currency crises come from our first paper; "*Identifying Extreme Values of Exchange Market Pressure*". These episodes correspond to the extreme values of exchange market pressure indices. The indices are constructed on the basis of monthly and quarterly data. Accordingly, two different types of crisis episodes are obtained: monthly-type and quarterly-type.[12]

We employ the empirical models of the determinants of currency crises, which are presented in our previous paper – "*Empirics of Currency Crises: A Duration Analysis Approach*" – as the benchmark and examine how the likelihood of currency crises change under *de jure* and *de facto* exchange rate regimes. We also study the role of capital mobility and test for currency stability under free and restricted capital flows. In particular, we investigate the impact of different combinations of exchange rate arrangements

12. Since little monthly data is available to run our empirical models, the monthly incidences of crisis are expanded to contain the relevant quarters. Hence, the monthly-type crisis episodes suggest that at least one month within that quarter is recognized as the incidence of a crisis.

and capital controls on the hazard of speculative attacks. The continuous semi-parametric Cox proportional hazard models are our main methodology in pursuing these objectives.

Our index for *de jure* exchange rate regimes is the same as the IMF's classification. For the choice of a *de facto* regimes index, we have some options available. However, there is no systemic methodology to choose and/or evaluate the existing alternative systems. Moreover, as Eichengreen and Razo-Garcia (2011) point out, during periods of currency volatility, different *de facto* classifications tend to produce different results. Hence, they advise investigators to be particularly careful when attempting to link *de facto* regimes to financial crises. Thus, considering the time coverage of the *de facto* regimes, we employ both RR and LYS classifications in an attempt to capture the probable discrepancies. We adopt the coarse classification of RR and LYS and divide the exchange rate arrangements into three categories: (1) fixed, (2) intermediate, and; (3) floating regimes.[13] On this ground, we construct the categorical variables of exchange rate regimes: $Fix_{i,t}$, $Intermediate_{i,t}$, and $Float_{i,t}$.[14] Each country (i) at time t is assigned to one of these categories based on RR or LYS classifications.

We utilize the Chin-Ito index as our measure of capital account restrictions. This index, to some extent, can capture the intensity of capital mobility restrictions and enjoys a wide coverage across counties and time. On the basis of this index, we construct a dummy variable for capital controls ($CapControls_{i,t}$). A capital account is classified as open – $CapControls_{i,t}$ takes the value of one – if the value of the Chinn-Ito index is more than the average of similar countries during that period of time.[15] Otherwise, it is classified as restricted and $CapControls_{i,t}$ takes the value of zero.[16]

To examine the impact of different exchange rate regimes under the presence or absence of capital controls, we combine the exchange rate classifications with the capital account policies and categorize our sample into six different regimes (three different exchange rate classifications with two capital account choices). Consequently, we construct two series of six categorical variables (one for RR-based and the other for LYS-based classifications), which are introduced in the following section.

Before we move on to our empirical results, we should point out that we are fully aware of the problems of reverse causation. This paper deals with the impact of exchange rate regimes and capital account

13. RR and LYS datasets are respectively available at:
http://www.carmenreinhart.com/research/publications-by-topic/exchange-rates-and-dollarization/, and:
http://www.utdt.edu/ver_contenido.php?id_contenido=4643&id_item_menu=8006.

14. Since we have two indexes for exchange rate regimes, RR and LYS, we construct two series of categorical variables.

15. All countries in our sample are categorized as advanced economies except for South Africa and some years in case of Greece and Portugal, which are categorized as emerging economies. The average value of the Chinn-Ito index for industrialized countries equals 0.257, 0.804, and 2.152 over the periods of 1970-79, 1980-89, and 1990-99, respectively.

16. The Chinn-Ito index dataset is available at http://web.pdx.edu/~ito/Chinn-Ito_website.htm.

policies on the occurrence of currency crises, not the other way around. To mitigate the potential problem of reverse causality (the impact of crises on exchange rate and capital regimes), we use lagged variables. Hence, the exchange rate regimes and capital account openness variables enter into the models with at least a one-period lag. This remedy to the potential problem of reverse causality is also useful to treat the potential interdependence between the choice of exchange rate regimes and capital account liberalization policies. In order to deal with this concern, we recognize and control for the duration of the policy mix composed of the exchange rate regimes and capital control programs. It is in line with the recent studies in the literature.

3.5 Empirical results

In this section, first, we empirically investigate the links between the probability of a currency crisis and the choice of exchange rate regimes. Then, we evaluate the impact of capital mobility on the stability of exchange rates. Finally, we examine how the likelihood of currency crises changes under different combinations of exchange rate regimes and capital controls.

3. 5.1 Exchange rate regimes and currency crises

As a first step, we find how the incidences of different exchange rate regimes are distributed across our sample. As Table 1 presents, the IMF *de jure* system classifies major portion of the sample as the intermediate regimes compared to the fixed and floating arrangements. The same pattern is even more pronounced under the RR *de facto* classification (it should not be surprising knowing that RR relies on the IMF classification). However, LYS *de facto* system assigns more quarters to the corner regimes – fixed or floats –than the intermediate regimes.

In the next step, we figure out how the monthly and quarterly-type of currency crisis episodes are jointly scattered with the exchange rate arrangements and calculate the unconditional probability of currency crisis under different exchange rate regimes. From the reported results in Table 2, it is evident that when the regimes are categorized based upon *de jure* classification the differences between the calculated probabilities for currency crisis incidences under different exchange rate regimes are negligible. Yet, the probabilities that are calculated under *de facto* classifications show significant results, but different according to the chosen classification. When regimes are categorized by the LYS classification, the intermediate exchange rate arrangements are the least susceptible regime to the speculative attacks. However, when regimes are categorized by the RR classification, the fixed arrangements are the most sustainable exchange rates. To verify that the results are statistically significant and not random or due to differences in sample sizes, we run Chi-square independence test (not reported) and log-rank test. Both

Table 1. Incidence of Exchange Rate Regimes under different classifications

	de jure (IMF)		*de facto (LYS* [❦]*)*		*de facto (RR)*	
	quarters	*share* (%)	*quarters*	*share* (%)	*Quarters*	*share* (%)
Fix	696	28.57	796	45.64	615	25.25
Intermediate	1040	42.69	344	19.72	1654	67.90
Float	700	28.74	604	34.63	167	6.86
Total	2436	100.00	1744	100.00	2436	100.00

❦LYS classification starts from 1974 and contains several unclassified observations.

Table 2. Unconditional probability of crisis under different Exchange Rate Regime classifications

	monthly-type			*quarterly-type*		
	IMF	*LYS*	*RR*	*IMF*	*LYS*	*RR*
Fix (t-1)	9.91	9.57	5.63	7.18	5.87	4.03
Intermediate (t-1)	10.14	7.87	12.11	6.24	4.37	8.3
Float (t-1)	10.39	12.69	6.10	7.79	10.02	4.27
Log-rank test[❦]	1.36	5.81	18.63	1.39	11.70	11.25
P-value	0.51	0.06	0.00	0.50	0.00	0.00

Probabilities are calculated by dividing the number of crises under a particular regime to the total number of regime-quarters. All numbers are in percent, except for the Long-rank test results.

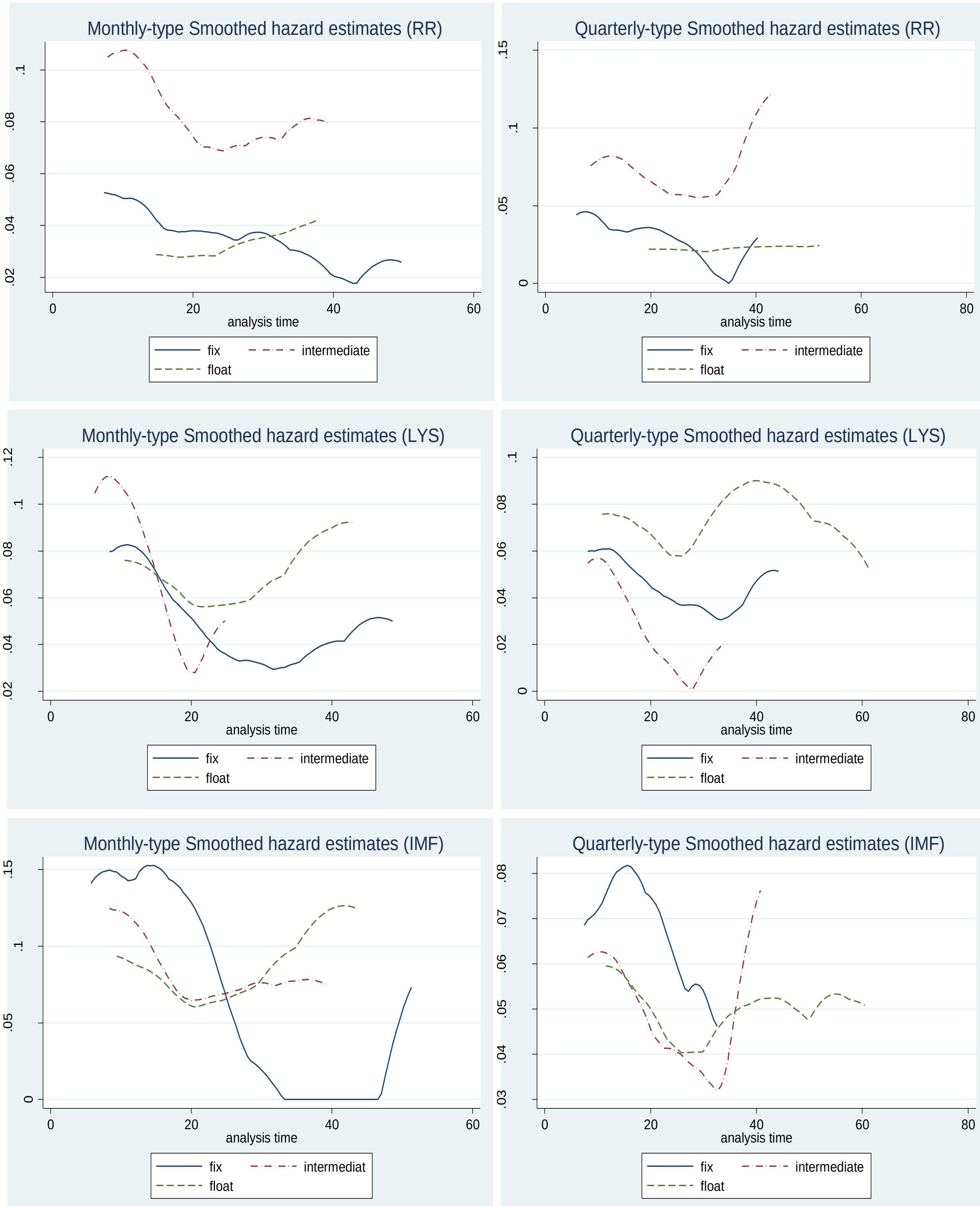
❦The null hypothesis of log-rank test is whether the hazard functions are equal across different groups.

tests produce similar results and confirm our findings. The same structure is observable for both of the monthly and quarterly-type spells.

In addition, to obtain a visual understanding of the dynamics of the hazards under different exchange rate regimes, we present the smoothed estimations of the non-parametric hazards in Figure 1. In the diagrams of this figure, the vertical axis measures the probability that a currency exits a tranquil state and enters into a crisis state, while the horizontal axis represents the successive number of quarters spent in tranquility. The presented diagrams reconfirm the pattern that we observed in Table 2. When regimes are categorized based on the RR classification, the hazard of crises is at the highest level for the intermediate regimes. However, when regimes are classified under the LYS alternative system, the outcomes inverted and the intermediate regimes enjoy the lowest probability of attack (especially for the quarterly-type spells). Similar to the Table 2 results, the hazards that are built upon the IMF classification do not show a clear pattern. It should also be useful to mention that the observed non-monotonic nature of the hazards in Figure 1 validates our choice of semi-parametric Cox models.

Now, we apply the Cox proportional hazard models to evaluate formally the contribution of the choice of exchange rate regimes to the occurrence of currency crises. We adapt the models that are used in our

Figure 1. Monthly and quarterly-type smoothed hazards under different exchange rate regimes



previous paper by entering the exchange rate regime categorical variables. As in our previous paper, we run four different models for each monthly and quarterly-type spells. Variables in models 1 and 2 are contemporaneous while in models 3 and 4 they are lagged by one quarter. In models 1 and 3 the variables of each country are measured on their own, while all time-varying variables in models 2 and 3 are measured relative to the reference countries – Germany or the U.S. The results related to the RR and LYS classifications are presented in tables 3 through 6.[17] The results related to the IMF classification are not statistically significant whether monthly or quarterly-type models are being used, and hence are not reported here.

Tables 3 and 4 present the estimation results for monthly-type models of RR and LYS classifications.[18] An examination of the reported results in Table 3 reveals that the hazard of fixed exchange rate regimes is significantly lower than the hazard of intermediate exchange rate regimes in all of the four RR-based monthly-type models. The hazard of fixed regimes is also lower than the hazard of float regimes; however, in two of these models the difference is statistically significant. On the other hand, the results of Table 4 show that the hazard of intermediate exchange rate regimes is significantly lower than the hazard of fixed exchange rate regimes in two of the four LYS-based monthly-type models. Furthermore, in three of these models, the hazard of intermediate regimes is significantly lower than the hazard of float regimes. In both Tables 3 and 4, some control variables (trade linkages, inflation, unemployment volatility, and the financial account ratio to GDP) are repeatedly significant in all models and have the expected sign.

Tables 5 and 6 provide the estimation results for quarterly-type models of RR and LYS classifications. The results that they present are similar to those reported in Tables 3 and 4. Table 5 shows that when the episodes of currency crisis are identified with lower frequency data, the hazard of fixed exchange rate regimes is significantly lower than the hazard of intermediate exchange rate regimes in three of the four RR-based models. However, in all LYS-based quarterly-type models, the hazard of intermediate regimes is significantly lower than that of fixed and floating exchange regimes. Among the control variables, inflation is statistically significant in most of the models.

It is clear that in our sample there is a statistically significant link between the choice of an exchange rate regime and the occurrence of currency crises. Nevertheless, the results are sensitive to the choice of *de facto* exchange rate system. Fixed exchange rate regimes are the least susceptible exchange arrangement to speculative attacks, if the exchange rate regimes are determined by the RR classification, while

17. From what we perceived in Figure 1, the Fix exchange rate regimes are chosen as the base in our RR-based categorical variables while the Intermediate exchange rate regimes are assigned as the base for LYS-based categorical variables.
18. The models are interacted with different linear and non-linear time functions. The presented estimation results are the outcome of the interaction with a logarithmic form of time.

Table 3. Cox proportional hazard estimation (monthly-type spells) under RR de facto classifications

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Fix is the base				
Intermediate	1.37*	1.5*	1.11*	1.15*
	(1.9)	(1.79)	(1.65)	(1.71)
Float	1.69*	2.15**	0.68	1.22
	(1.91)	(2.27)	(078)	(1.28)
Unemployment volatility	0.03	0.04**	0.05**	0.07**
	(1.38)	(2.22)	(2.03)	(2.45)
Previous crises				0.4*
				(1.68)
Size of economy	0.83**		0.76**	1.04**
	(2.39)		(2.1)	(2.52)
Whole period GDP growth		0.02**	0.02	0.01
		(2.1)	(1.38)	(1.25)
GDP growth rate	0.00	-0.01	-0.06	-0.07
	(-0.05)	(-0.17)	(-0.79)	(-0.87)
Inflation	0.26***	0.23**	0.04	0.2**
	(3.21)	(2.3)	(0.45)	(2.24)
Unemployment rate	0.00	-0.02	-0.01	-0.03
	(0.11)	(-0.98)	(-0.4)	(-1.15)
Share price index growth	-0.03***	-0.01	-0.01	0.01
	(-3.34)	(-0.64)	(-0.62)	(0.7)
Real effective exchange rate	0.00	0.01	0.01*	0.01**
	(-0.17)	(0.31)	(1.71)	(2.53)
Money growth	-0.03**	-0.05***	0.01	-0.01
	(-2.44)	(-3.4)	(0.48)	(-0.61)
Real domestic credit growth	0.04***	0.05***	0.02	0.02*
	(3.61)	(3.6)	(1.23)	(1.68)
Trade openness	0.29	0.04**	0.13	0.03
	(0.69)	(2.59)	(0.28)	(1.58)
Current account / GDP	-0.02	0.00	-0.09*	0.00
	(-0.46)	(-1.63)	(-1.96)	(-0.61)
Capital account / GDP	0.28	0.00	-0.74	0.00
	(0.84)	(-0.42)	(-0.85)	(-0.51)
Financial account / GDP	0.07**	0.00**	-0.11*	0.00***
	(2.3)	(-2.08)	(-1.92)	(-2.88)
Budget deficit / GDP	0.02**	0.00	0.02	0.00
	(2.54)	(0.16)	(1.38)	(-0.13)
Trade linkages	0.11**	0.14**	0.12**	0.14*
	(2.43)	(2.47)	(2.28)	(1.88)
Financial linkages	-0.02	-0.02	0.00	0.00
	(-0.93)	(-0.88)	(-0.1)	(-0.13)
Macroeconomic similarities	0.05	0.06	0.01	-0.03
	(1.03)	(1.00)	(0.11)	(-0.38)
Log likelihood	-184.78	-136.55	-185.68	-132.83

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 4. Cox proportional hazard estimation (monthly-type spells) under LYS de facto classifications

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Intermediate is the base				
Fix	1.45**	0.89	1.15	1.82**
	(2.19)	(1.16)	(1.64)	(2.3)
Float	1.03*	0.83	1.3**	1.39*
	(1.66)	(1.1)	(1.97)	(1.72)
Unemployment volatility	0.07**	0.03	0.06**	0.09**
	(2.51)	(1.44)	(2.27)	(2.52)
Previous crises				-0.04
				(-0.21)
Size of economy	1.44**		0.92*	1.34**
	(2.47)		(1.71)	(2.4)
Whole period GDP growth		0.01	-0.00	-0.01
		(0.48)	(-0.06)	(-0.35)
GDP growth rate	-0.05	-0.15	0.04	-0.03
	(-0.44)	(-1.41)	(0.32)	(-0.31)
Inflation	0.48***	0.13	0.3**	0.44***
	(4.06)	(0.87)	(2.28)	(2.78)
Unemployment rate	0.03	0.01	0.03	0.03
	(1.17)	(0.36)	(1.05)	(0.92)
Share price index growth	-0.03**	0.00	-0.02	0.02
	(-2.65)	(0.2)	(-1.16)	(1.08)
Real effective exchange rate	0.01	0.00	0.02**	0.03***
	(1.27)	(-0.01)	(2.16)	(3.33)
Money growth	-0.03**	-0.04**	-0.04	-0.03
	(2.39)	(-2.46)	(-0.94)	(-1.17)
Real domestic credit growth	0.04***	0.05***	0.02	0.03*
	(3.41)	(3.04)	(1.01)	(2.14)
Trade openness	0.3	0.07***	0.36	0.04
	(0.58)	(3.3)	(0.61)	(1.09)
Current account / GDP	0.01	0.00	-0.1*	0.00
	(0.13)	(-1.41)	(-1.66)	(-0.73)
Capital account / GDP	0.12	0.00	-1.82	0.00
	(0.38)	(0.26)	(-1.22)	(-0.86)
Financial account / GDP	0.06*	0.00*	-0.12**	0.00**
	(1.7)	(-1.79)	(-2.04)	(-2.46)
Budget deficit / GDP	0.02**	0.00	0.01	0.00
	(2.37)	(0.05)	(0.89)	(-1.45)
Trade linkages	0.12**	0.14**	0.18**	0.21***
	(2.32)	(2.07)	(2.18)	(3.4)
Financial linkages	-0.01	0.01	0.01	0.01
	(-0.25)	(0.48)	(0.59)	(0.5)
Macroeconomic similarities	0.05	0.08	-0.06	-0.08
	(1.16)	(1.18)	(-0.76)	(-1.6)
Log likelihood	-118.28	-91.9	-124.01	-95.29

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 5. Cox proportional hazard estimation (quarterly-type spells) under RR de facto classifications

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Fix is the base				
Intermediate	1.2*	1.95*	1.45*	0.43
	(1.7)	(1.95)	(1.75)	(0.47)
Float	1.27	1.99*	1.51	0.17
	(1.52)	(1.87)	(1.5)	(0.16)
Unemployment volatility	0.01	0.00	0.00	0.02
	(0.26)	(-0.18)	(0.04)	(0.64)
Previous crises				-0.4
				(-1.21)
Size of economy	0.39		0.44	0.36
	(1.1)		(1.11)	(0.83)
Whole period GDP growth		0.00	0.00	0.01
		(0.33)	(-0.02)	(0.49)
GDP growth rate	-0.04	0.02	0.07	0.06
	(-0.41)	(0.2)	(0.81)	(0.6)
Inflation	0.2**	0.16*	0.1	0.21*
	(2.04)	(1.85)	(1.15)	(1.66)
Unemployment rate	0.01	0.1	0.03	0.04
	(0.39)	(0.49)	(1.23)	(1.45)
Share price index growth	-0.01	0.00	-0.02*	0.00
	(-1.62)	(-0.34)	(-1.68)	(-0.51)
Real effective exchange rate	0.00	-0.01	0.01	0.01*
	(-0.41)	(-0.24)	(1.44)	(1.74)
Money growth	-0.02	-0.04***	-0.01	0.00
	(-1.43)	(-2.61)	(-0.45)	(-0.02)
Real domestic credit growth	0.03*	0.01	0.04	0.04
	(1.92)	(0.02)	(1.54)	(1.35)
Trade openness	0.01	0.02	0.18	0.04*
	(0.31)	(0.83)	(0.4)	(1.9)
Current account / GDP	0.02	0.00	0.02	0.00
	(0.72)	(0.43)	(0.36)	(0.05)
Capital account / GDP	0.19	0.00	-2.28**	0.00
	(0.39)	(0.8)	(-2.19)	(0.8)
Financial account / GDP	-0.01	0.00	-0.02	-0.02
	(-0.39)	(0.24)	(-0.32)	(-0.71)
Budget deficit / GDP	0.01	0.00	0.00	0.00
	(1.19)	(0.73)	(0.45)	(0.49)
Trade linkages	0.1	0.15	0.13	0.22
	(0.84)	(1.55)	(1.25)	(1.35)
Financial linkages	0.00	0.00	0.00	0.00
	(-1.41)	(-0.95)	(-1.46)	(-0.84)
Macroeconomic similarities	0.05	-0.15	0.05	-0.09
	(0.43)	(-0.16)	(0.43)	(-0.56)
Log likelihood	-124.79	-106.2	-114.47	-95.74

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 6. Cox proportional hazard estimation (quarterly-type spells) under LYS de facto classifications

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Intermediate is the base				
Fix	3.14***	2.57***	-2.89**	3.53***
	(3.17)	(3.21)	(-2.09)	(-3.56)
Float	2.8***	2.8***	3.33**	2.74***
	(2.94)	(3.82)	(2.48)	(3.34)
Unemployment volatility	0.04	0.01	0.03	0.02
	(1.46)	(0.41)	(0.9)	(0.83)
Previous crises				-0.76**
				(-2.18)
Size of economy	0.74*		0.76	0.68
	(1.68)		(1.15)	(1.5)
Whole period GDP growth		-0.01	-0.04	-0.02
		(-0.63)	(-1.61)	(-0.96)
GDP growth rate	0.04	0.05	0.08	0.17*
	(0.36)	(0.48)	(0.65)	(1.95)
Inflation	0.49***	0.3***	0.42**	0.27**
	(4.05)	(2.8)	(2.7)	(2.06)
Unemployment rate	0.04	0.03	0.12***	0.6**
	(1.44)	(1.07)	(3.067)	(2.27)
Share price index growth	-0.01	0.01	-0.02**	-0.02
	(-1.26)	(0.44)	(-2.09)	(-1.39)
Real effective exchange rate	0.02	0.01	0.02**	0.02**
	(1.47)	(0.98)	(2.27)	(2.23)
Money growth	-0.05*	-0.05***	-0.01	-0.02
	(-1.79)	(-2.9)	(-0.25)	(-0.9)
Real domestic credit growth	-0.01	0.00	0.06**	0.05*
	(-0.19)	(-0.03)	(2.04)	(1.85)
Trade openness	0.03*	0.02	1.11	0.03
	(1.79)	(0.81)	(1.15)	(1.14)
Current account / GDP	-0.01	0.00	-0.02	0.00
	(-0.15)	(1.02)	(-0.24)	(-0.36)
Capital account / GDP	0.16	0.00	-3.06**	0.00
	(0.51)	(1.02)	(-2.27)	(0.55)
Financial account / GDP	-0.01	0.00	-0.03	0.00
	(-0.56)	(0.38)	(-0.46)	(0.95)
Budget deficit / GDP	0.01	0.00	0.00	0.00
	(0.81)	(0.86)	(0.81)	(-0.98)
Trade linkages	0.19	0.35***	0.19	0.09
	(1.02)	(2.9)	(1.33)	(0.84)
Financial linkages	0.00	0.00	0.00	0.00
	(-0.6)	(0.01)	(-1.07)	(-0.76)
Macroeconomic similarities	-0.02	-0.12	0.08	0.11
	(-0.13)	(-1.08)	(0.62)	(1.02)
Log likelihood	-76.1	-75.9	-67.35	-66.49

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

intermediate exchange rate regimes will experience the least number of currency crisis incidences, if the exchange rate regimes are determined with the help of the LYS classification. The Akaike Information Criterion (AIC) indicates a better fitness of data for all LYS-based models compared to RR-based models. However, determining the outcome of which *de facto* system is more appropriate, definitely, requires a methodology that is more comprehensive and, ideally, looks to determine how close these systems are to the “true” regimes.

We run several robustness tests to verify whether our adopted methodology is appropriate and the obtained results are consistent. In the first step, we run four different models on each of monthly and quarterly-type spells. The observed consistency of the results is a sign of the stability of the models and the reliability of their results. Then, we run Schoenfeld residual test to check whether the hazards are truly proportional and, hence, if applying Cox models is appropriate. The test results (not reported) show that almost in all monthly and quarterly-type models (both RR-based and LYS-based) all covariates are proportional and, thus, confirm that it is appropriate to apply the Cox models to be applied to our sample. We also checked the sensitivity of our results with respect to the tied spells and ran our models with two alternative methods: the Efron and marginal calculations. The obtained results (not reported) from both methods are similar and do not indicate any significant issue related to the tied spells. Finally, we examined our results for the existence of unobservable heterogeneity. The test results did not show any unobservable heterogeneity between the countries in our sample.

3.5.2 Capital mobility and currency crises

We start our investigation by examining the types of capital accounts, which are categorized with the help of the Chinn-Ito index, and figuring how the restricted and open-type of capital accounts have been distributed across our sample. As Table 7 presents, open and restricted-type of capital accounts have almost an equal share in our sample. However, the unconditional probability of currency crisis episodes with different types of capital accounts shows that more incidences of speculative attack have taken place during the periods of time that are categorized as restricted-type of capital accounts. We also run log rank test and Chi-square independence test (not reported) and verify that observed differences between the calculated probabilities of currency crises for different types of capital accounts are statistically significant. Table 7 reports the results.

Figure 2 visualizes the hazards of currency crises for different types of capital accounts. The presented diagrams confirm the observed pattern in Table 7 for both monthly and quarterly-type spells. We also run the Cox proportional hazard models (the restricted-type model being chosen as the base) without any control variables. The results (reported in Table 7) are in line with our previous findings and indicate that

Table 7. Distribution of Capital Account Type and incidences of currency crisis

	Chinn-Ito index		*monthly-type spells*		*quarterly-type spells*	
	quarters	*share* (%)	*probability*	*stcox*	*probability*	*stcox*
Restricted	1116	48.69	0.12		0.08	
Open	1176	51.31	0.08	-0.32**	0.06	-0.28*
				(-2.34)		(-1.73)
Log-rank test ❦			6.42		3	
P-value			0.01		0.08	

❦*The null hypothesis of log-rank test is whether the hazard functions are equal across different groups.*
For the Cox proportional hazard estimations, the restricted-type is the base.
The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

the baseline hazards of open-type capital accounts are lower than the baseline hazards of restricted-type. However, when we apply the Cox proportional hazard models with our set of control variables, strikingly, the obtained results will be different from what we found in Table 7 and Figure 2. According to the results presented in Tables 8 and 9, the hazards of open-type capital accounts are higher than the hazards of restricted-type capital accounts, although this relation is statistically significant only in the monthly-type spells (models 1, 2, and 3). Similar to our previous estimation results, some control variables such as inflation, trade linkages, unemployment volatility, and financial account ratio to GDP, are repeatedly significant and have the expected sign.

The impact of capital account policies on the occurrence of currency crises demonstrates different results in our sample. While baseline hazard of open-type capital accounts are lower than the baseline hazard of

Figure 2. Monthly and quarterly-type smoothed hazards under different exchange rate regimes

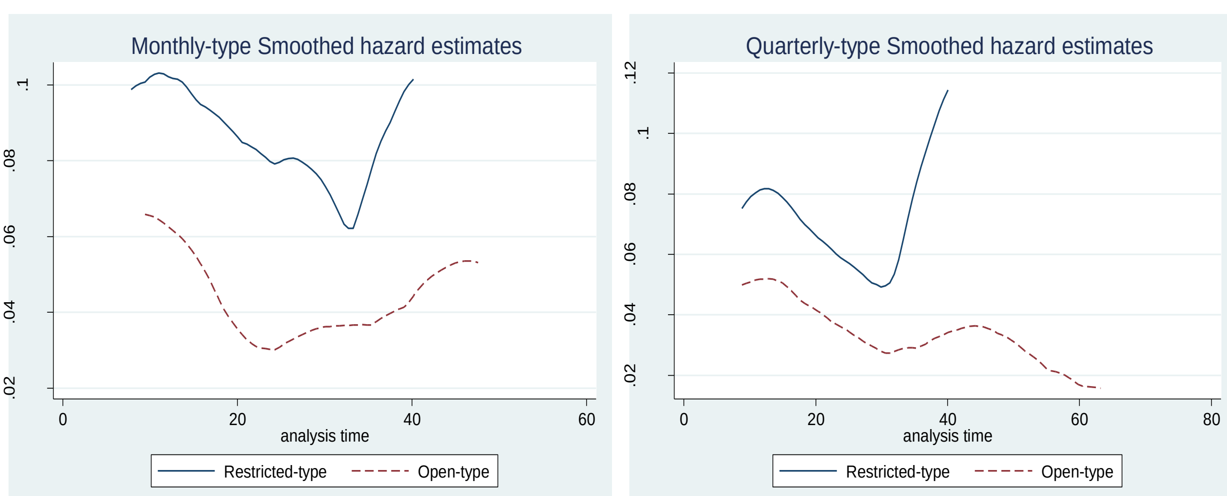


Table 8. Cox proportional hazard estimation (monthly-type spells) under capital mobility

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Restricted-type is the base				
Open-type	0.87*	0.89*	0.77**	0.46
	(1.67)	(1.82)	(1.9)	(1.02)
Unemployment volatility	0.04**	0.04**	0.05***	0.07***
	(1.65)	(2.33)	(2.79)	(2.88)
Previous crises				0.19
				(1.08)
Size of economy	0.72**		0.59*	0.9**
	(1.97)		(1.77)	(2.29)
Whole period GDP growth	0.02	0.03***	0.02*	0.02
	(1.15)	(2.66)	(1.76)	(1.47)
GDP growth rate	0.03	-0.04	-0.04	-0.09
	(0.4)	(-0.53)	(-0.62)	(-1.11)
Inflation	0.33***	0.4***	0.09	0.24***
	(3.9)	(3.27)	(1.25)	(2.64)
Unemployment rate	0.00	-0.01	0.01	-0.01
	(-0.38)	(-0.36)	(0.23)	(-0.44)
Share price index growth	-0.03***	-0.01	-0.01	0.001
	(-3.41)	(-0.61)	(-0.9)	(0.51)
Real effective exchange rate	0.01	0.04	0.02**	0.02***
	(0.94)	(0.94)	(2.59)	(3.38)
Money growth	-0.01	-0.05***	0.01	-0.01
	(-0.95)	(-2.89)	(0.56)	(-0.6)
Real domestic credit growth	0.03**	0.05***	0.02	0.03*
	(2.09)	(3.33)	(1.32)	(1.98)
Trade openness	-0.12	0.04**	-0.04	0.03*
	(-0.27)	(2.5)	(-0.1)	(1.65)
Current account / GDP	-0.03	0.00*	-0.1***	0.00
	(-0.62)	(-1.94)	(-3.28)	(-0.45)
Capital account / GDP	0.14	0.00	-0.72	0.00
	(0.43)	(-0.14)	(-1.37)	(-0.48)
Financial account / GDP	0.09*	0.00**	-0.12*	0.00**
	(1.79)	(-2.24)	(-1.81)	(2.46)
Budget deficit / GDP	0.01	0.00	0.01	0.00
	(1.62)	(0.2)	(0.66)	(0.24)
Trade linkages	0.12**	0.16***	0.14**	0.14*
	(2.3)	(3.05)	(2.15)	(1.84)
Financial linkages	0.01	0.00	0.01	0.01
	(-0.32)	(-0.05)	(0.19)	(0.25)
Macroeconomic similarities	0.03	0.04	0.02	-0.03
	(0.61)	(0.76)	(0.45)	(-0.45)
Log likelihood	-152.25	-136.67	-152.02	-131.22

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 9. Cox proportional hazard estimation (quarterly-type spells) under capital mobility

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Restricted-type is the base				
Open-type	0.21	0.61	0.44	0.72
	(0.41)	(1.23)	(0.77)	(1.47)
Unemployment volatility	0.05*	0.03	0.5*	0.05
	(1.92)	(1.08)	(1.8)	(1.46)
Previous crises	-0.26		-0.5*	-0.45
	(-1.12)		(-1.9)	(-1.28)
Size of economy	0.51	0.23	0.44	0.32
	(1.38)	(0.63)	(1.15)	(0.9)
Whole period GDP growth		0.01		0.01
		(0.6)		(0.61)
GDP growth rate	0.02	0.04	0.08	0.05
	(0.17)	(0.57)	(0.95)	(0.61)
Inflation	0.23***	0.25**	0.2**	0.31**
	(2.85)	(2.32)	(2.1)	(2.44)
Unemployment rate	0.02	0.02	0.6**	0.04**
	(1.09)	(0.76)	(2.29)	(1.98)
Share price index growth	-0.01	0.00	-0.01	-0.01
	(-1.19)	(-0.34)	(-1.31)	(-0.58)
Real effective exchange rate	0.01	0.00	0.02**	0.01***
	(0.81)	(0.15)	(2.32)	(3.63)
Money growth	-0.01	-0.02*	-0.02	-0.03
	(-1.02)	(-1.76)	(-0.88)	(-1.56)
Real domestic credit growth	0.03*	-0.01	0.06***	0.07***
	(1.71)	(0.34)	(2.81)	(3.84)
Trade openness	0.24	0.02	0.3	0.04*
	(0.66)	(1.25)	(0.06)	(1.93)
Current account / GDP	0.00	0.00	0.02	0.00
	(0.1)	(0.07)	(0.28)	(0.18)
Capital account / GDP	0.08	0.00	-2.21**	0.00
	(0.21)	(1.2)	(-2.05)	(0.97)
Financial account / GDP	-0.01	0.00	0.00	0.00
	(-0.27)	(0.45)	(-0.05)	(0.27)
Budget deficit / GDP	0.01	0.00	0.01	0.00
	(0.96)	(0.4)	(0.74)	(1.02)
Trade linkages	0.13	0.19**	0.17*	0.19*
	(1.11)	(2.24)	(1.73)	(1.71)
Financial linkages	0.00	0.00	0.00	0.00
	(-0.78)	(-0.17)	(-1.59)	(-1.37)
Macroeconomic similarities	0.03	-0.06	0.05	-0.07
	(0.25)	(-0.55)	(0.47)	(-0.61)
Log likelihood	-132.42	-112.35	-117.76	-98.29

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

restricted-type capital accounts, when we enter the set of control variables to our models, the hazard of open-type capital accounts appear to be higher than the hazard of restricted-type capital accounts. This relation is often statistically significant when the episodes of currency crises are identified with higher frequency – monthly – data. It can be interpreted as a sign that capital control policies could help in preventing low duration crises. The obtained results are robust to a variety of samples and models. We ran different models and received consistent results for both monthly and quarterly-type models. The results of Schoenfeld residual test (reported in Appendix A) show that a few covariates in some models do not individually pass the proportionality test; however, all models jointly pass the proportionality test. We also did sensitivity checks for the tied spells and found no significant differences between the results of the Efron and the marginal calculations. Finally, we tested our results for the existence of unobservable heterogeneity. The test results did not show any unobservable heterogeneity at the country level in our sample.

3.5.3 Exchange rate regimes, capital mobility, and currency crises

As the last step in our study, we examine how the hazard of speculative attack may change under different combinations of exchange rate regimes and capital account liberalization policies. We combine the exchange rate classifications with the capital control policies to construct two series of different categorical variables. The first series of categorical variables is based on RR and the second series is based on LYS classifications.

In the first series, the categorical variables are constructed as: (1) Regime 1 (fixed with capital controls), (2) Regime 2 (fixed with no capital controls), (3) Regime 3 (intermediate with capital controls), (4) Regime 4 (intermediate with no capital controls), and, (5) Regime 5 (float with capital no controls).[19] While in the second series, the categorical variables are constructed as: (1) Regime 1 (intermediate with capital controls), (2) Regime 2 (intermediate with no capital controls), (3) Regime 3 (fixed with capital controls), (4) Regime 4 (fixed with no capital controls), (5) Regime 5 (float with capital controls), and, (6) Regime 6 (float with no capital controls).

Tables 10 through 12 report the estimation results of the Cox proportional hazard models. According to the presented results in Tables 10 and 12 for the monthly and quarterly-type spells of the first and second series, the hazard of Regime 1is lower than the hazard of Regime 3 and this relation is often statistically significant. Regime 1 has also often a lower hazard compared to Regimes 4 and 5; however, these

19. Since the total observations for the “float with capital controls” combination in the first series are less than one percent of the sample, this combination is dropped from our categorical variables in the first series.

Table 10. Cox proportional hazard (monthly-type spells) under RR classification & capital policies

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Regime 1 is the base				
Regime 2	omitted	omitted	omitted	omitted
Regime 3	1.58*	1.47*	1.33*	1.27
	(1.86)	(1.77)	(1.78)	(1.57)
Regime 4	0.49	0.00	-0.10	0.64
	(0.51)	(0.01)	(-0.11)	(0.66)
Regime 5	1.54	1.74*	-0.03	0.86
	(1.47)	(1.79)	(-0.04)	(1.1)
Unemployment volatility	0.04	0.05**	0.06**	0.07**
	(1.49)	(2.33)	(2.26)	(2.46)
Previous crises				0.41*
				(1.7)
Size of economy	0.98**		0.90**	1.12**
	(2.47)		(2.18)	(2.45)
Whole period GDP growth		0.03***	0.03**	0.02
		(2.67)	(2.34)	(1.39)
GDP growth rate	-0.02	-0.03	-0.07	-0.10
	(-0.28)	(-0.4)	(-0.97)	(-1.1)
Inflation	0.38***	0.43***	0.04	0.21*
	(3.67)	(3.15)	(0.43)	(1.88)
Unemployment rate	0.02	-0.02	0.00	-0.02
	(0.91)	(-0.8)	(-0.15)	(-0.7)
Share price index growth	-0.03***	0.00	-0.01	0.01
	(-3.32)	(0.01)	(-0.87)	(0.85)
Real effective exchange rate	0.00	0.02	0.02**	0.02**
	(-0.26)	(0.49)	(2.35)	(2.42)
Money growth	-0.04	-0.11***	0.02	-0.01
	(-1.53)	(-3.18)	(0.63)	(-0.4)
Real domestic credit growth	0.06**	0.09***	0.02	0.03
	(2.01)	(3.28)	(0.9)	(1.21)
Trade openness	0.06	0.04**	-0.66	0.03*
	(0.13)	(2.42)	(-1.04)	(1.65)
Current account / GDP	-0.03	0.00	-0.12**	0.00
	(-0.56)	(-1.19)	(-2.23)	(-0.27)
Capital account / GDP	0.36	0.00	-1.08	0.00
	(1.08)	(-0.64)	(-0.99)	(-0.49)
Financial account / GDP	0.07*	0.00*	-0.11	0.00**
	(1.84)	(-1.79)	(-1.54)	(-2.16)
Budget deficit / GDP	0.02**	0.00	0.01	0.00
	(2.32)	(0.34)	(0.83)	(-0.05)
Trade linkages	0.14**	0.18**	0.14**	0.16
	(2.32)	(2.54)	(2.14)	(0.27)
Log likelihood	-112.01	-86.06	-116.06	-90.83

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 11. Cox proportional hazard (monthly-type spells) under LYS classification & capital policies

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Regime 1 is the base				
Regime 2	-1.08	-0.98	-0.86	-1.16
	(-0.76)	(-0.57)	(-0.5)	(-0.69)
Regime 3	1.44*	0.5	1.35	1.38
	(1.67)	(0.45)	(1.39)	(1.21)
Regime 4	omitted	omitted	omitted	omitted
Regime 5	0.94	0.62	1.43	0.87
	(1.14)	(0.578)	(1.53)	(0.79)
Regime 6	-0.49	-0.77	0.79	0.7
	(-0.42)	(-.53)	(0.59)	(0.52)
Unemployment volatility	0.06**	0.03	0.06**	0.08**
	(1.98)	(1.36)	(1.97)	(2.31)
Previous crises				0.04
				(0.16)
Size of economy	1.35**		1.04	1.3**
	(2.07)		(1.59)	(2.09)
Whole period GDP growth		0.00	-0.01	-0.01
		(0.19)	(-0.39)	(-0.53)
GDP growth rate	-0.08	-0.15	0.07	-0.08
	(-0.64)	(-1.27)	(0.52)	(-0.64)
Inflation	0.54***	0.16	0.28**	0.48***
	(3.99)	(0.74)	(2.05)	(2.72)
Unemployment rate	0.04*	0.02	0.04	0.03
	(1.68)	(0.54)	(1.32)	(0.84)
Share price index growth	-0.03**	0.00	-0.01	0.02
	(-2.39)	(0.1)	(-0.96)	(1.3)
Real effective exchange rate	0.1	0.00	0.03***	0.03***
	(1.34)	(0.05)	(2.6)	(2.88)
Money growth	-0.03**	-0.09**	-0.04	-0.04
	(-2.03)	(-2.53)	(-0.99)	(-1.05)
Real domestic credit growth	0.04***	0.09***	0.3	0.04
	(3.34)	(3.1)	(1.00)	(1.38)
Trade openness	0.26	0.11***	0.22	0.04
	(0.47)	(3.18)	(0.32)	(1.31)
Current account / GDP	-0.02	0.00	-0.19**	0.00
	(-0.33)	(-0.78)	(-2.05)	(-0.15)
Capital account / GDP	0.11	0.00	-3.55*	0.00
	(0.34)	(0.21)	(-1.73)	(-0.75)
Financial account / GDP	0.05	0.00*	-0.16**	0.00*
	(1.42)	(-1.94)	(-2.3)	(-1.7)
Trade linkages	0.12**	0.18**	0.24*	0.19**
	(2.21)	(2.17)	(1.84)	(2.13)
Log likelihood	-114.94	-55.49	-76.26	-63.74

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

Table 12. Cox proportional hazard (quarterly-type spells) under RR classification & capital policies

Variable	*Contemporaneous*		*Lagged*	
	Model (I)	*Model (II)*	*Model (III)*	*Model (IV)*
Regime 1 is the base				
Regime 2	omitted	omitted	omitted	omitted
Regime 3	1.48*	2.16**	1.27	0.49
	(1.72)	(2.14)	(1.52)	(0.53)
Regime 4	0.61	0.85	0.48	-0.42
	(0.58)	(0.77)	(0.45)	(-0.42)
Regime 5	0.43	1.86*	1.06	0.05
	(1.35)	(1.7)	(0.99)	(0.5)
Unemployment volatility	0.03	0.01	0.03	0.05
	(1.06)	(0.4)	(1.21)	(1.58)
Previous crises				-0.45
				(-1.35)
Size of economy	0.46		0.51	0.38
	(1.13)		(1.16)	(0.81)
Whole period GDP growth		0.01	0.01	0.01
		(0.85)	(0.41)	(0.76)
GDP growth rate	-0.02	-0.03	0.04	0.03
	(-0.26)	(-0.4)	(0.43)	(0.35)
Inflation	0.22***	0.24**	0.15*	0.31**
	(2.67)	(2.57)	(1.89)	(2.34)
Unemployment rate	0.02	0.02	0.04	0.04
	(0.86)	(0.85)	(1.48)	(1.57)
Share price index growth	-0.01	0.00	-0.01	-0.01
	(-1.2)	(0.01)	(-1.3)	(-0.48)
Real effective exchange rate	0.00	-0.01	0.01*	0.01
	(0.01)	(0.85)	(1.79)	(1.64)
Money growth	-0.02	-0.04**	-0.03	-0.03
	(-1.01)	(-2.03)	(-1.04)	(-0.93)
Real domestic credit growth	0.02	0.00	0.07**	0.08**
	(1.39)	(-0.08)	(2.39)	(2.54)
Trade openness	0.26	0.02	-0.13	0.03*
	(0.59)	(1.29)	(-0.23)	(1.74)
Current account / GDP	0.00	0.00	0.02	0.00
	(0.05)	(0.07)	(0.31)	(0.29)
Capital account / GDP	0.18	0.00	-2.35**	0.00
	(0.45)	(0.55)	(-2.02)	(0.85)
Financial account / GDP	-0.01	0.00	-0.01	-0.01
	(-0.29)	(0.5)	(-0.1)	(-0.46)
Budget deficit / GDP	0.01	0.00	0.02	0.00
	(0.62)	(0.46)	(0.22)	(0.67)
Trade linkages	0.10	0.16	0.17	0.21
	(0.81)	(1.34)	(1.44)	(1.4)
Log likelihood	-102.84	-85.11	-92.31	-77.95

The values in parentheses below estimates are the corresponding z-statistics.
***, (**), [*] imply estimates are significant at 1, (5), and [10] percent.

relations are scarcely statistically significant. The relation between Regime 1 and Regime 2 is problematic and omitted. These results are in line with our previous findings for the RR-based exchange rate regimes.

Table 11 presents the results for the monthly-type spells of the second series. The results show that the hazard of Regime 1 is lower than the hazard of Regime 2 although the relation is not statistically significant. It implies that for the LYS-based models, the intermediate regimes may demonstrate lower hazard while there is less capital control. The hazard of Regime 1 is lower than the hazards of Regimes 3 and 5 although scarcely statistically significant. The hazard of Regime 1 does not show a clear relation compared to the hazard of Regime 6. In general, these results are in line with our previous findings. The relation between Regime 1 and Regime 4 is problematic and omitted. The estimation of quarterly-type spells of the second series models are often not converging and not reported.

3.6 Conclusion

In this paper, we investigated whether there is a link between the choice of exchange rate regimes and the occurrence of currency crises. Our adopted methodology is duration analysis and the incidences of currency crisis come from 21 countries over the period 1970-1998. With the help of Cox proportional models, we tested how the likelihood of currency crises changes under the *de jure* and *de facto* exchange rate classifications. We also examined the role of capital mobility on the sustainability of the currencies.

Our data indicates that there exists a meaningful link between the choice of exchange rate regime and the occurrence of currency crises. Nevertheless, the results are sensitive to the choice of the *de facto* exchange rate classification. While RR-based models show that fixed exchange rate arrangements are least susceptible to speculative attacks, LYS-based models point to the intermediate exchange rate regimes as the least crisis prone. Until a reliable methodology or empirical test is devised to evaluate in a systematic way the current *de facto* classifications, it remains difficult to determine objectively which *de facto* classification is most appropriate. In the meantime, researchers can rely on the characteristics of individual countries and scrutinize the monetary system of the countries under surveillance to determine more precisely the classification of their exchange rate regimes.

The data also shows that the impact of capital account policies on the occurrence of currency crises takes different directions. While the baseline hazard of open-type capital accounts is lower than the baseline hazard of restricted-type capital accounts, when we enter our set of control variables into the models, the hazard of open-type capital accounts appears to be higher than the hazard of restricted-type capital accounts. This relation is more significant for low duration crisis episodes and can be interpreted as a sign that capital control policies could help preventing currency crises.

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Appendix: Schoenfeld residual test results for Capital Mobility models

1. Test of proportional-hazard assumption for Model 1 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	-0.00663	0	1	0.9593
UnempgStdt~e	0.07839	0.45	1	0.5001
tgdpg	-0.01001	0.01	1	0.9352
econsize	0.14409	1.1	1	0.2943
newGDPg	0.00205	0	1	0.9848
newreer	0.1657	1.53	1	0.2163
newUnempR	0.014	0.02	1	0.8994
newCPI1	-0.02943	0.05	1	0.8262
newcShareP	-0.05446	0.17	1	0.6763
newMQMg	0.02345	0.05	1	0.831
newRDMCRg	-0.00685	0	1	0.9538
newOPs	-0.21498	1.98	1	0.1591
newCAGDP	-0.05256	0.06	1	0.8046
newCPGDP	-0.00232	0	1	0.987
newFAGDP	0.05039	0.11	1	0.7411
newBDGDP	-0.0182	0.02	1	0.9
newcompeti~n	-0.09666	0.69	1	0.4067
newfinance	-0.12236	1.48	1	0.2237
newmacsimi~P	0.09018	0.65	1	0.4211
global test		8.15	19	0.985

2. Test of proportional-hazard assumption for Model 2 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	-0.05859	0.27	1	0.6011
UnempgStdt~e	0.00957	0.01	1	0.9314
tgdpg	0.00891	0.01	1	0.9233
newdGDPg	0.04962	0.5	1	0.4816
newdreervol	0.12546	1.25	1	0.2629
newdUnempR	-0.04184	0.12	1	0.7318
newdCPI1	0.00559	0	1	0.9485
newdcShareP	0.02742	0.11	1	0.7401
newdMQMg	0.0418	0.28	1	0.5973
newdRDMCRg	-0.01431	0.03	1	0.8641
newdOPsg	-0.00156	0	1	0.9873
newdCAGDP	-0.00536	0	1	0.9719
newdCPGDP	-0.08228	0.19	1	0.666
newdFAGDP	0.02259	0.05	1	0.8261
newdBDGDP	-0.02044	0.06	1	0.8085
newcompeti~n	0.03663	0.06	1	0.8085
newfinance	-0.14868	2.91	1	0.0879
newmacsimi~P	0.02337	0.04	1	0.8447
global test		10.65	18	0.9087

3. Test of proportional-hazard assumption for Model 3 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	0.06161	1.05	1	0.3059
UnempgStdt~e	-0.11276	4.51	1	0.0337
tgdpg	-0.01546	0.03	1	0.8552
econsize	-0.09165	0.76	1	0.3831
newlGDPg	0.02367	0.06	1	0.8081
newlreer	0.13003	2.74	1	0.0977
newlUnempR	0.02933	0.09	1	0.7583
newlCPI1	-0.10371	0.95	1	0.3307
newlcShareP	-0.1288	2.84	1	0.0919
newlMQMg	-0.04661	0.58	1	0.4454
newlRDMCRg	0.06423	2.47	1	0.1163
newlOPs	-0.20579	3.13	1	0.0768
newlCAGDP	0.03758	0.74	1	0.3913
newlCPGDP	-0.00734	0.01	1	0.9402
newlFAGDP	-0.06897	0.8	1	0.3698
newlBDGDP	-0.0554	1.68	1	0.1949
newcompeti~n	-0.17811	6.66	1	0.0099
newfinance	-0.08823	2.44	1	0.118
newtmacsim~g	0.18251	7.06	1	0.0079
global test		14.2	19	0.7718

4. Test of proportional-hazard assumption for Model 4 (monthly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.finop	.	.	1	.
1.finop	-0.12775	0.63	1	0.4287
UnempgStdt~e	-0.01059	0.01	1	0.9289
tgdpg	-0.06641	0.22	1	0.6355
PCris	-0.00593	0	1	0.9699
econsize	0.07831	0.32	1	0.5709
newldGDPg	0.06657	0.2	1	0.656
newldreer	0.11689	0.5	1	0.4792
newldUnempR	0.08418	0.31	1	0.5787
newldCPI1	-0.11895	0.44	1	0.5047
newldcShareP	0.03233	0.07	1	0.7861
newldMQMg	0.02466	0.03	1	0.858
newldRDMCRg	0.04577	0.2	1	0.6508
newldOPs	-0.06564	0.29	1	0.5896
newldCAGDP	-0.10531	0.38	1	0.5394
newldCPGDP	0.04185	0.05	1	0.821
newldFAGDP	0.057	0.09	1	0.7669
newldBDGDP	-0.01488	0	1	0.951
newcompeti~n	-0.10164	0.84	1	0.3582
newfinance	-0.19402	3.4	1	0.0652
newtmacsim~g	0.09867	0.81	1	0.3687
global test		9.43	20	0.9774

5. Test of proportional-hazard assumption for Model 1 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	-0.10148	0.6	1	0.4401
UnempgStdt~e	-0.16607	1.45	1	0.2279
econsize	0.03504	0.07	1	0.7968
PCris	0.09942	0.56	1	0.4526
newGDPg	-0.10848	0.86	1	0.355
newreer	0.06815	0.22	1	0.6424
newUnempR	-0.05109	0.19	1	0.6622
newCPI1	-0.09154	0.61	1	0.4356
newcSharep	0.05064	0.12	1	0.7273
newMQMg	0.01251	0.01	1	0.9184
newRDMCRg	-0.03257	0.05	1	0.8231
newOPs	-0.06036	0.15	1	0.7002
newCAGDP	0.1138	0.16	1	0.6937
newCPGDP	-0.06437	0.31	1	0.5798
newFAGDP	-0.02114	0.01	1	0.9292
newBDGDP	-0.07772	0.28	1	0.5988
newcompeti~n	-0.04177	0.12	1	0.7332
newfinance	-0.03494	0.09	1	0.7677
newtmacsim~g	0.02876	0.05	1	0.8195
global test		7.56	19	0.9906

6. Test of proportional-hazard assumption for Model 2 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	-0.04808	0.2	1	0.6551
UnempgStdt~e	-0.19967	2.6	1	0.1066
tgdpg	0.04942	0.39	1	0.5331
econsize	-0.08683	0.53	1	0.4649
newdGDPg	-0.06373	0.57	1	0.45
newdreer	0.16446	2.46	1	0.1165
newdUnempR	0.0168	0.05	1	0.83
newCPI1	-0.02341	0.18	1	0.6753
newdcShareP	0.00635	0	1	0.9617
newdMQMg	0.0767	0.41	1	0.5228
newdRDMCRg	-0.09718	0.87	1	0.3522
newdOPsg	-0.02585	0.07	1	0.788
newCAGDPg	-0.11329	2.42	1	0.1196
newCPGDPg	-0.13149	0.51	1	0.474
newFAGDPg	-0.06994	0.76	1	0.3821
newBDGDPg	0.09508	0.39	1	0.5336
newcompeti~n	-0.16364	4.04	1	0.0443
newfinance	-0.10802	2.74	1	0.0977
newtmacsim~g	0.15968	3.31	1	0.0687
global test		19.8	19	0.4067

7. Test of proportional-hazard assumption for Model 3 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	-0.08482	0.34	1	0.5577
UnempgStdt~e	-0.18905	1.8	1	0.18
PCris	-0.02733	0.04	1	0.8323
econsize	0.02727	0.03	1	0.8574
newlGDPg	0.12993	0.95	1	0.3286
newlreer	0.03209	0.05	1	0.8153
newlUnempR	-0.0192	0.02	1	0.8988
newlCPI1	0.10181	0.45	1	0.5028
newlcShareP	-0.03724	0.07	1	0.7874
newlMQMg	0.01769	0.02	1	0.8998
newlRDMCRg	-0.00493	0	1	0.9762
newlOPs	0.00214	0	1	0.9892
newlCAGDP	0.09937	0.25	1	0.6157
newlCPGDP	0.13228	0.53	1	0.4648
newlFAGDP	-0.03229	0.07	1	0.7984
newlBDGDP	0.03348	0.04	1	0.8438
newcompeti~n	-0.05931	0.16	1	0.6924
newfinance	-0.02355	0.03	1	0.8743
newtmacsim~g	0.1006	0.4	1	0.5257
global test		9.75	19	0.9589

8. Test of proportional-hazard assumption for Model 4 (quarterly-type)

Time: Rank(t)

	rho	chi2	df	Prob>chi2
0b.lfinop	.	.	1	.
1.lfinop	0.00828	0	1	0.9495
UnempgStdt~e	-0.12568	0.61	1	0.4346
tgdpg	0.07189	0.53	1	0.4685
PCris	0.04561	0.15	1	0.701
econsize	0.13618	1.22	1	0.2697
newldGDPg	0.16044	2.56	1	0.1094
newldreer	-0.05449	0.37	1	0.5438
newldUnempR	-0.09925	1.25	1	0.2638
newldCPI1	0.13574	0.96	1	0.3282
newldcShareP	-0.12434	1.46	1	0.2269
newldMQMg	0.08314	0.3	1	0.5853
newldRDMCRg	0.01289	0.02	1	0.8927
newldOPs	-0.06854	0.65	1	0.421
newldCAGDP	-0.01401	0.02	1	0.8824
newldCPGDP	-0.02698	0.12	1	0.7275
newFAGDP	-0.01647	0.05	1	0.8299
newldBDGDP	0.16969	1.3	1	0.2537
newcompeti~n	0.08466	0.58	1	0.446
newfinance	-0.04696	0.24	1	0.6236
newtmacsim~1	-0.07016	0.34	1	0.5582
global test		15.57	20	0.743