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Empirics of Currency Crises: A Duration Analysis Approach

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Abstract: This paper 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, 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. Our findings show that high values of volatility of unemployment rates, inflation rates, unemployment rates, real effective exchange rate, trade openness, and size of economy, and contagion factors (which mostly work through trade channels) increases the hazard of a crisis.

Keywords: International finance, exchange rate, crises.

JEL classification: F31, G01.

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 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. 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 to remove the risk of a biased coefficient and provide 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 the 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. 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.

2.1 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.

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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 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]

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.

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.

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.

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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.

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.

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.

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 Kalbeisch 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:

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

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:

$$h_j(t) = \phi(x(t), \beta, h_0(t)), \tag{2}$$

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 (.) 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 $t_1, \dots, t_n$) is:

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

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 ith 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.

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

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

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 rise 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

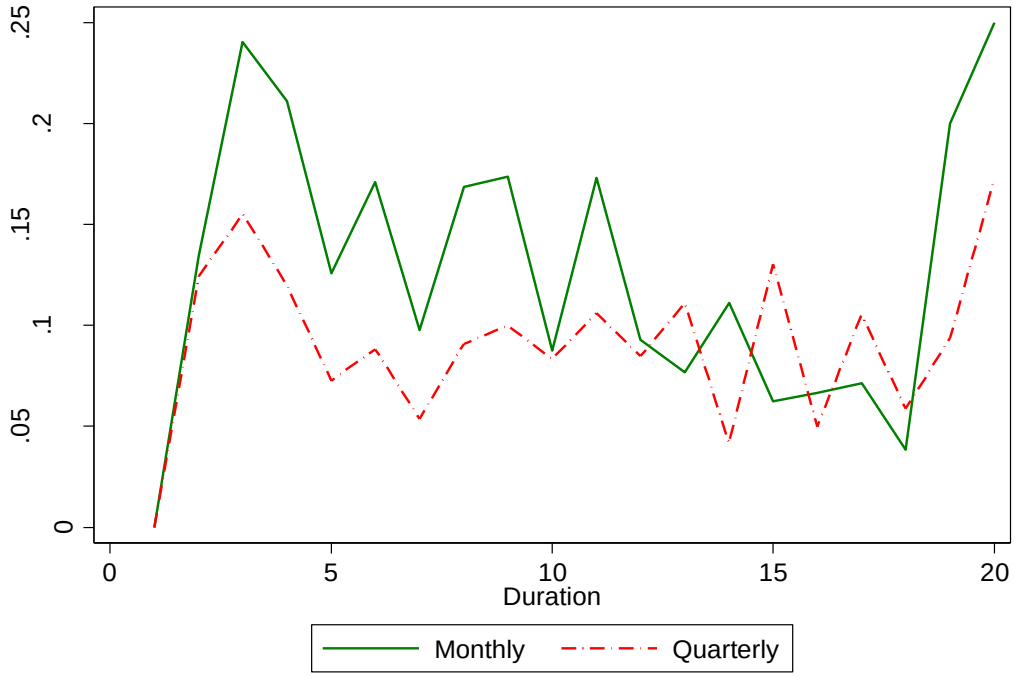


Figure 2. Estimated hazard for monthly-type spells by Gompetrz model

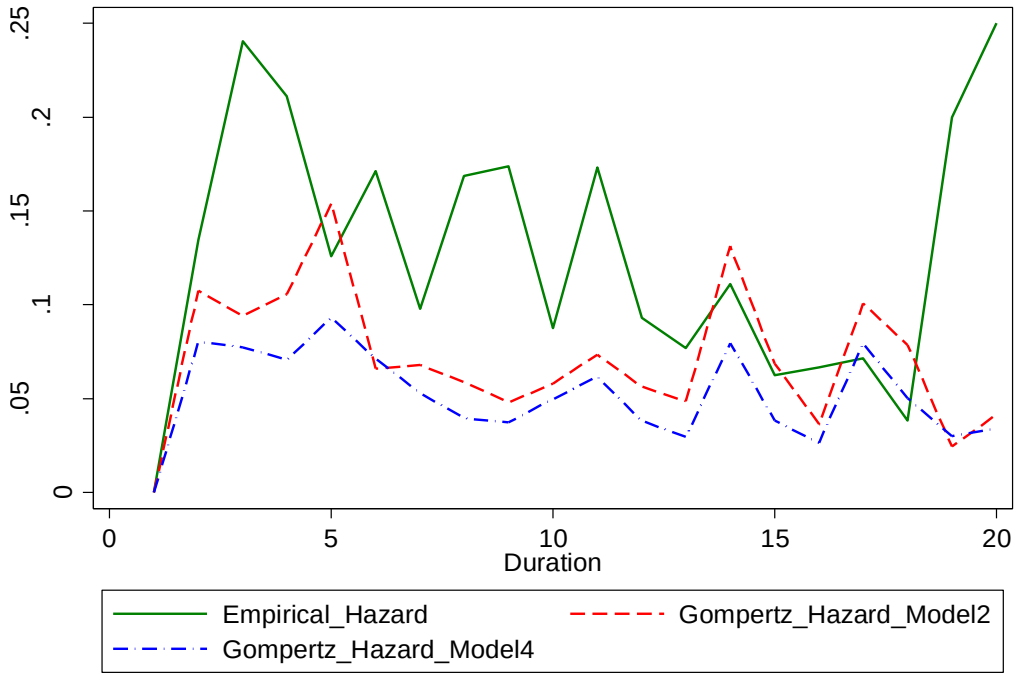
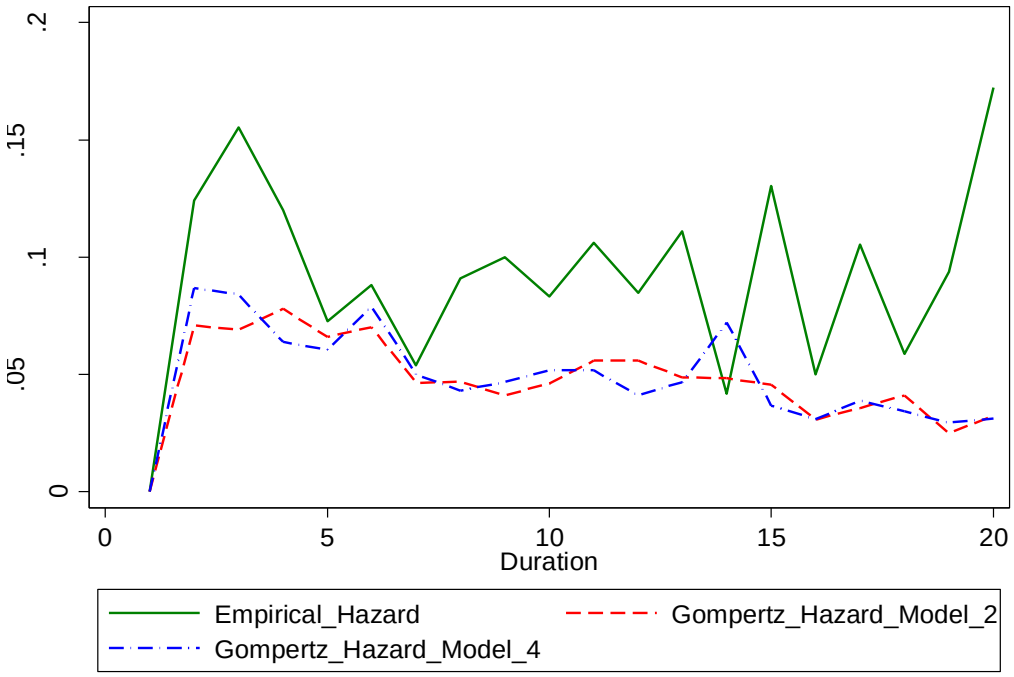


Figure 3. Estimated hazard quarterly-type spells by Gompetrz model



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 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:

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

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 (9) 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 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 $\gamma_1$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 $\gamma_2$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 $\gamma_3$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.

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) that 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 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.

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.

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 outcome, 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 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 ration of financial account to GDP will decline the likelihood of speculative attack. Model 4 produces similar results to those that are built by model 4. 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 one 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.

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 compare to the alternative models.

A more formal test of overall fit can be performed with 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 will. 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)

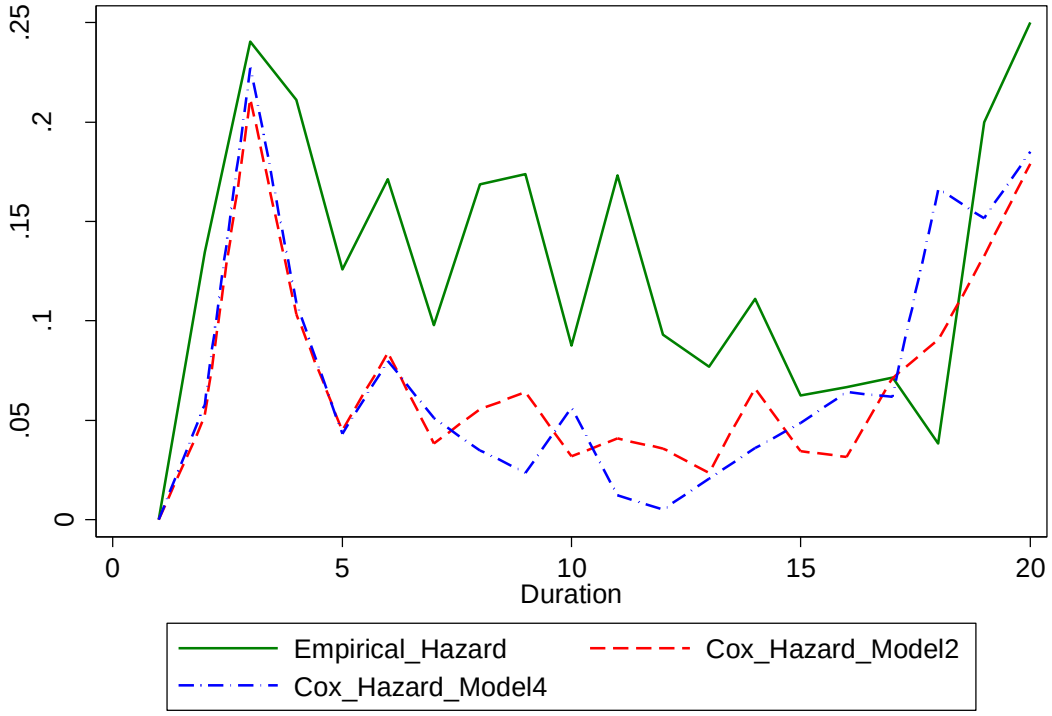


Figure 5. Estimated hazard by Cox continuous model (quarterly-type spells)

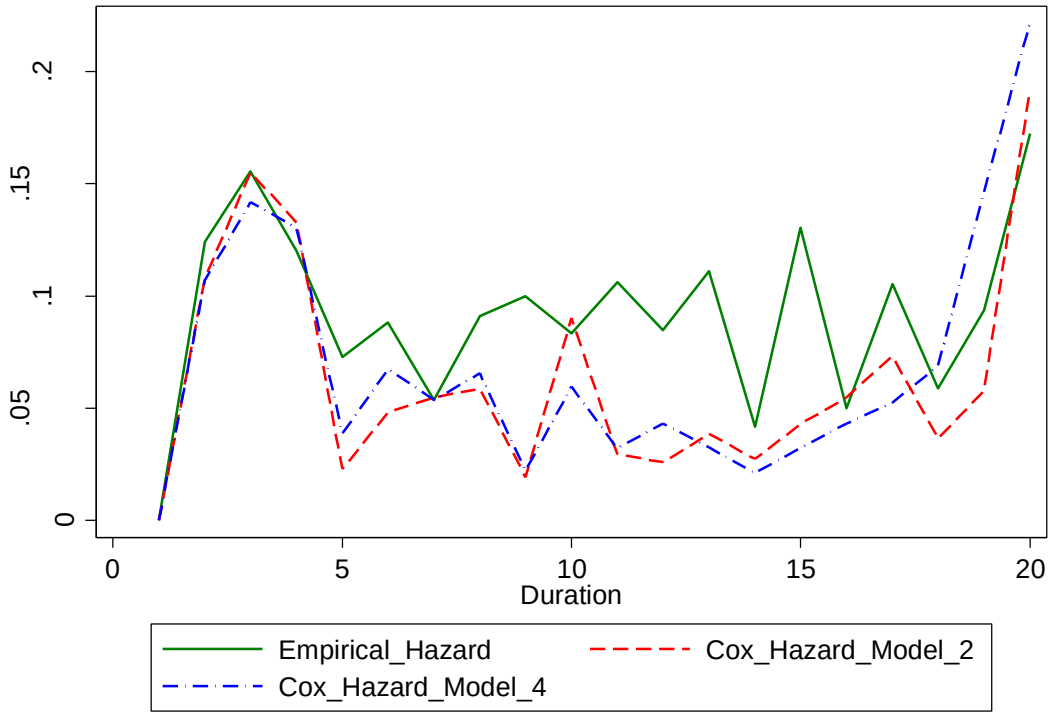


Figure 6. Estimated hazard by discrete semi-parametric model (monthly-type spells)

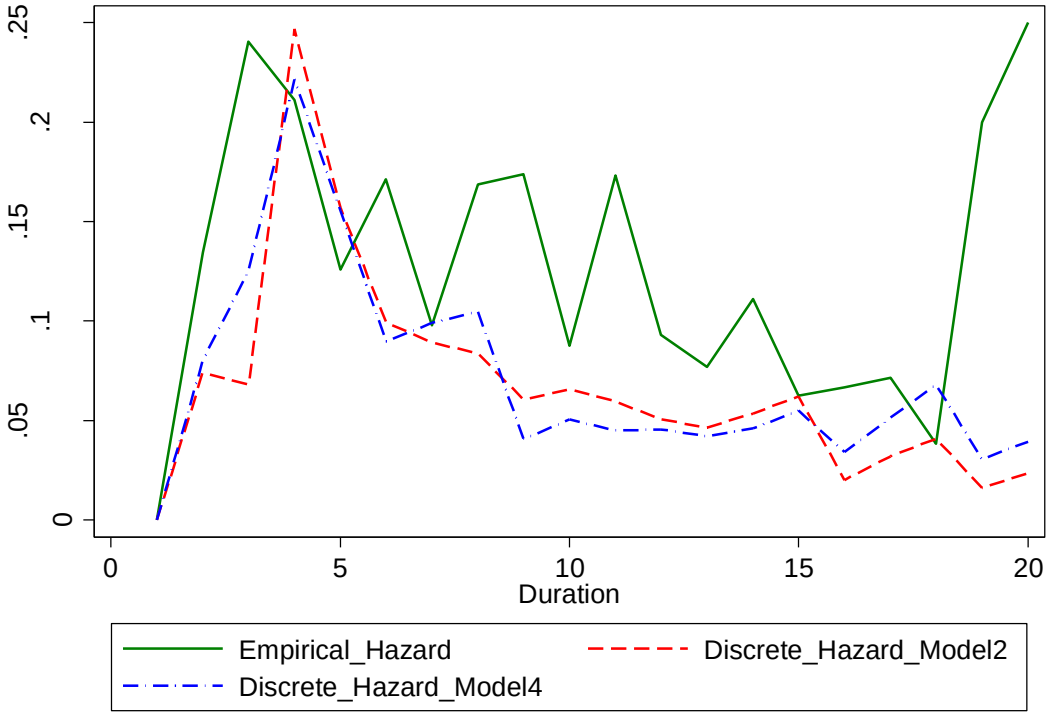
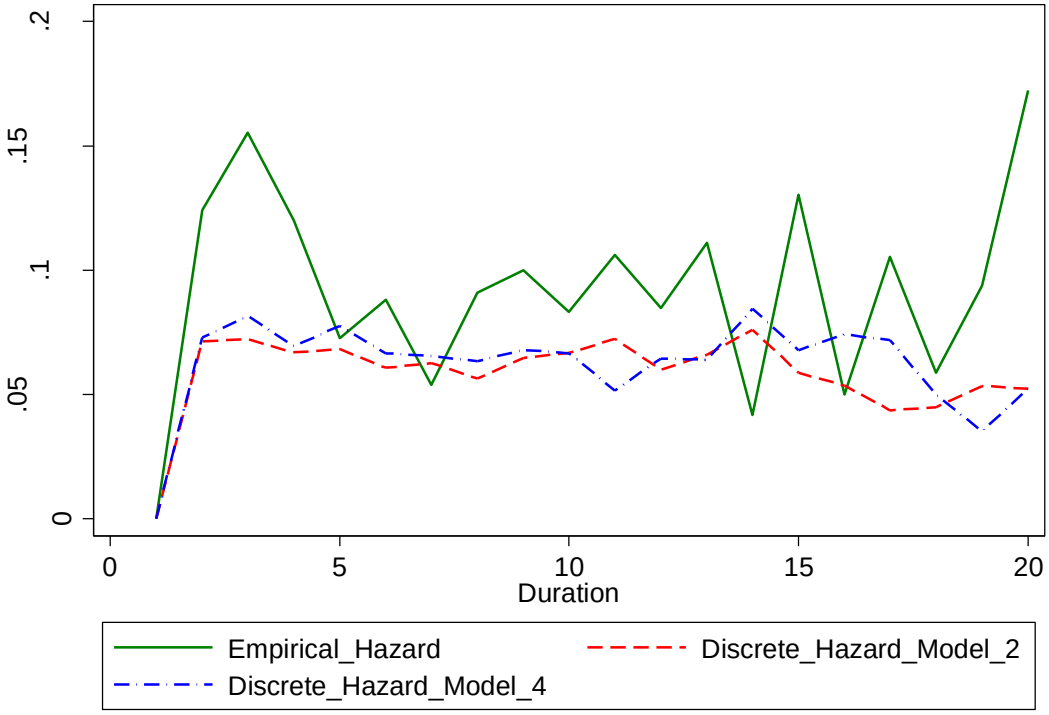


Figure 7. Estimated hazard by discrete semi-parametric model (quarterly-type spells)



thechinques 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 present the estimation results for our prefferd models. The similiraties of the estimated coefficient implies that ties are not a significant issue in our tests.

Another ground for 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.

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

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.

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

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 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 20th 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 estimations. It also appeared 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 policy makers to fix their exchange rates with their major trade partners and/or even constitute currency union to avoid currency crises. Yet, current Euro zone crisis showed those recommendations might prevent currency crisis incidents but 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:

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

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

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.

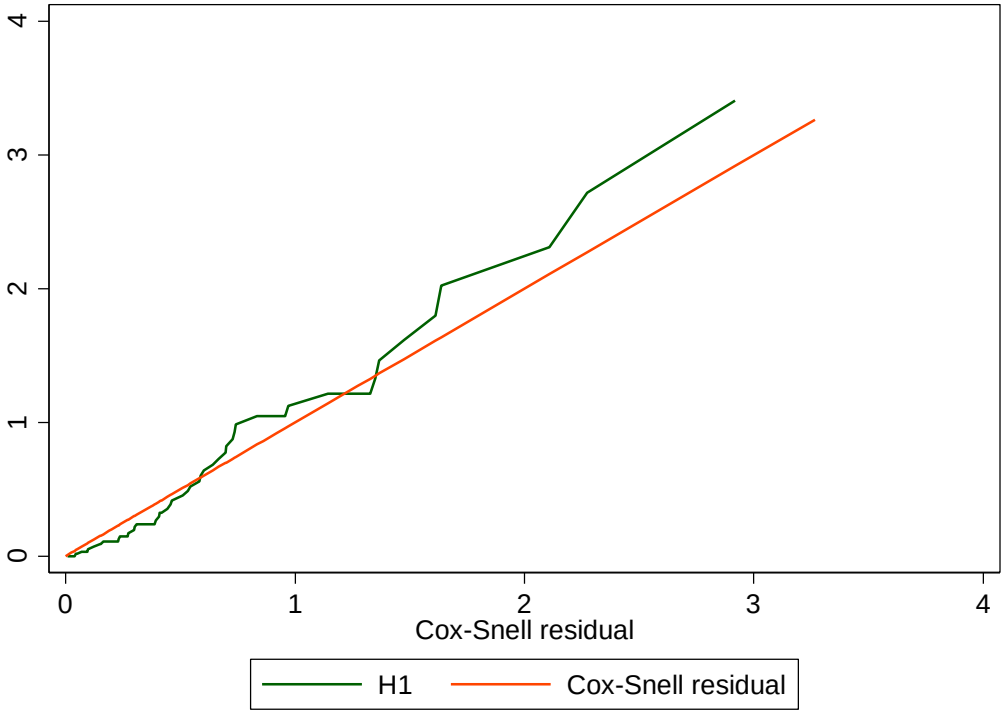
The employed covariates are constructed as follows:

- 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) 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 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.

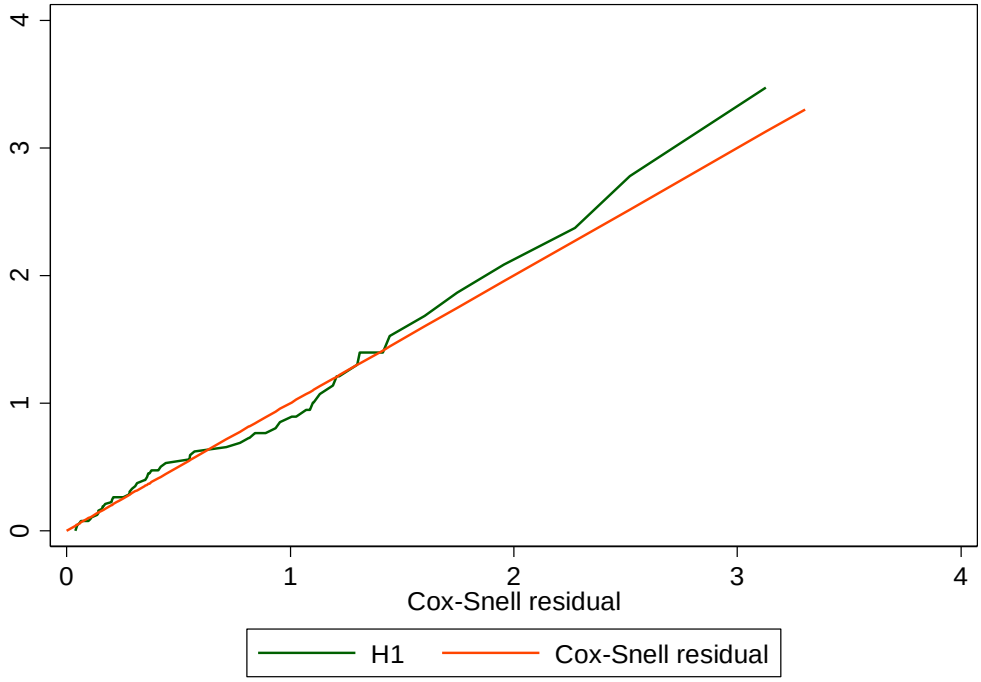
- Trade openness: export plus import divided GDP.
- Unemployment rate: unemployed individuals divided by the labour force (expressed in percentages).
- Unemployment volatility: the whole period standard deviation of one-year window standard deviation of unemployment rate.
- Whole period GDP growth: percent of changes in GDP (constant prices) at the fourth quarter 1998 from the GDP (constant prices) at the first quarter 1970.

Appendix C

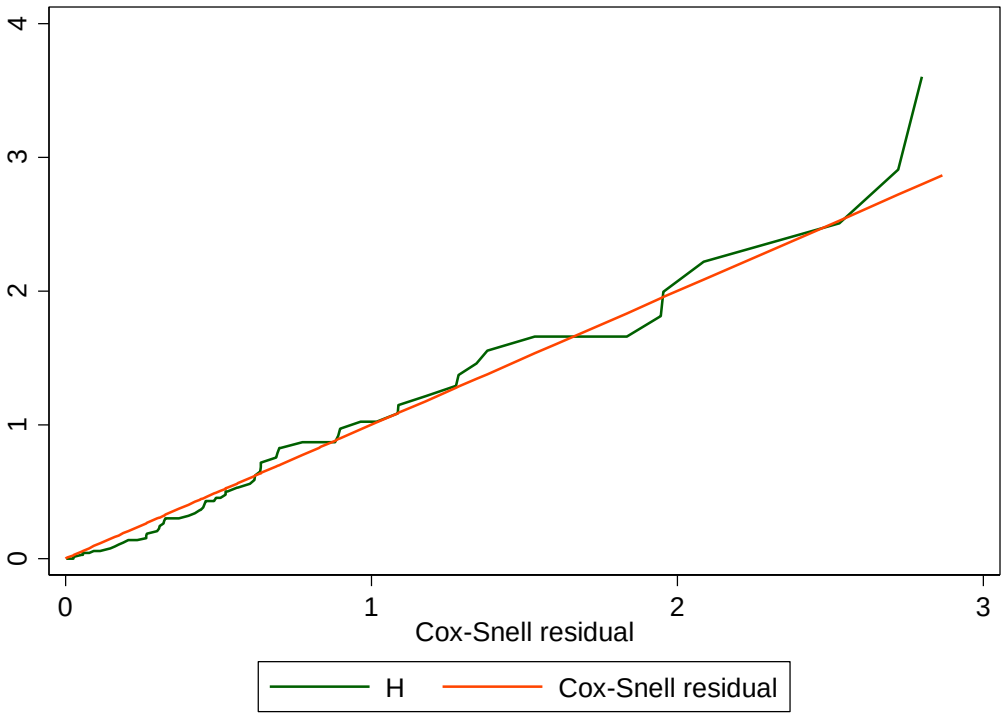
1. Goodness of fit for Model 1 (monthly-type)



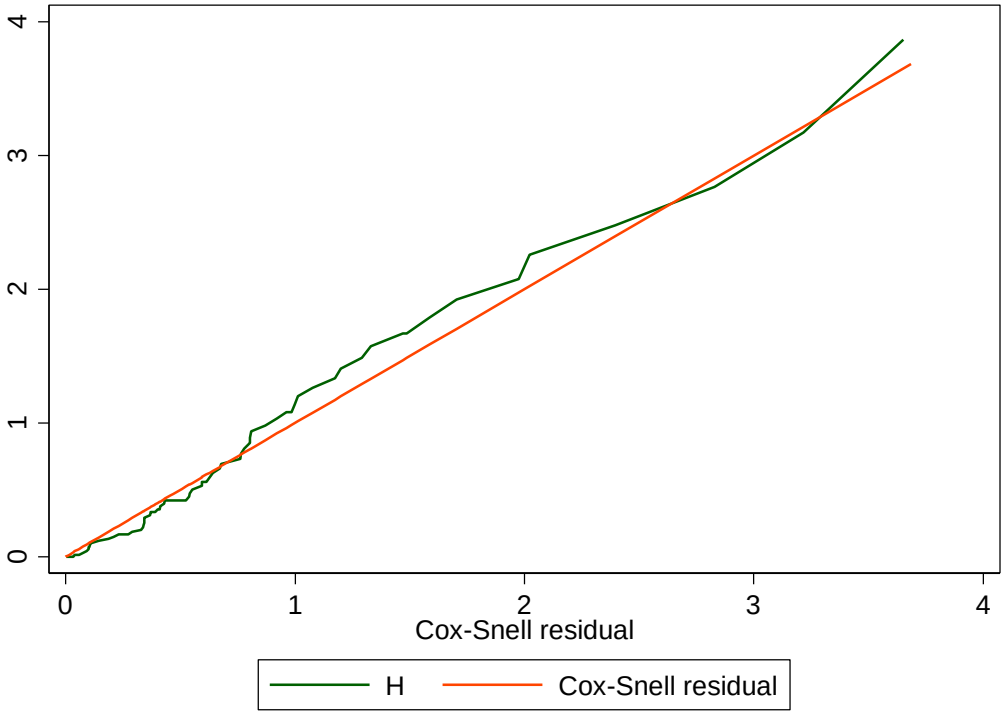
2. Goodness of fit for Model 2 (monthly-type)



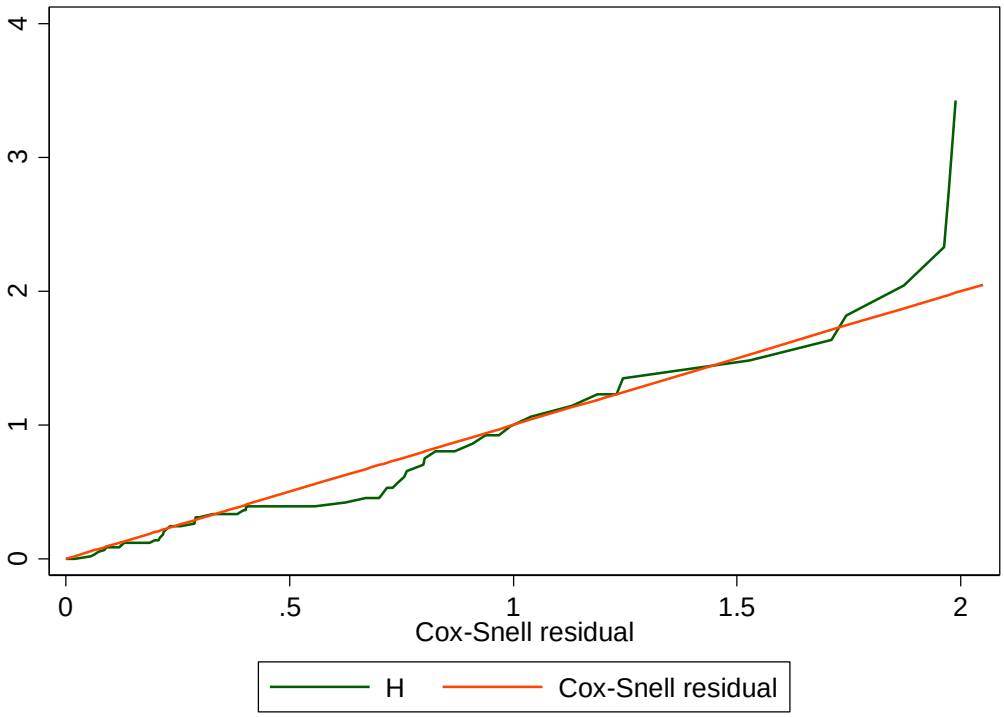
3. Goodness of fit for Model 3 (monthly-type)



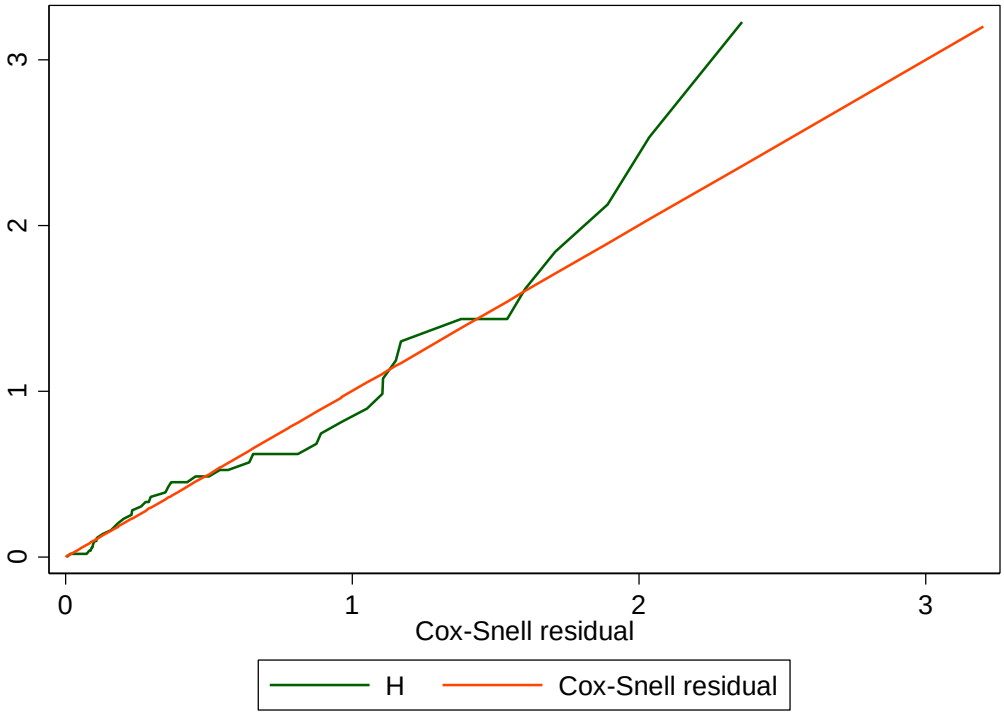
4. Goodness of fit for Model 4 (monthly-type)



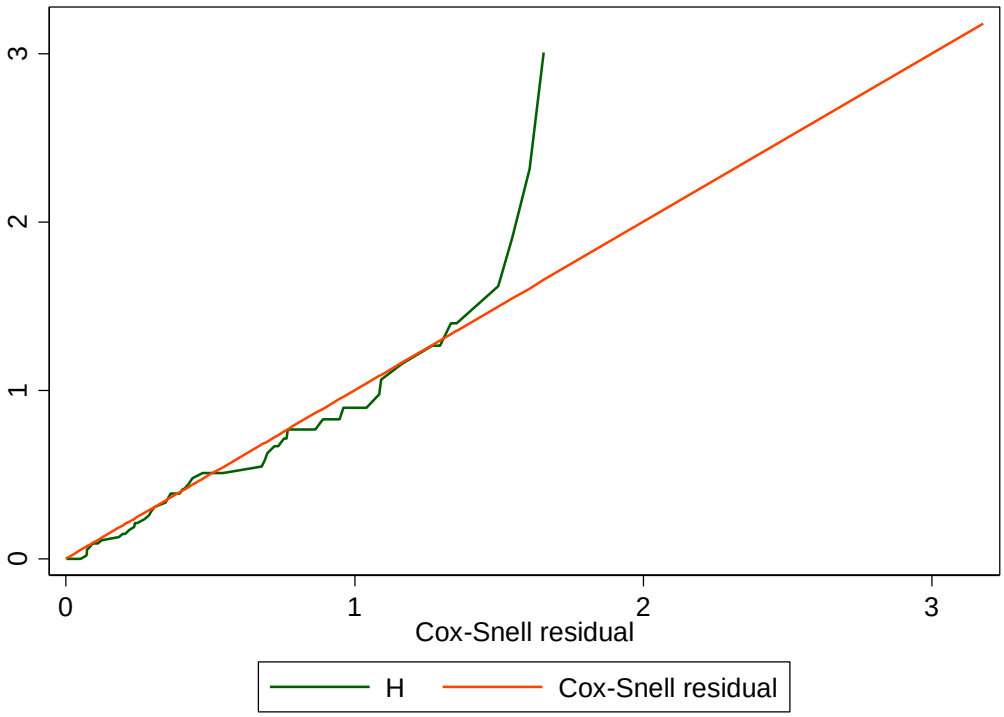
5. Goodness of fit for Model 1 (quarterly-type)



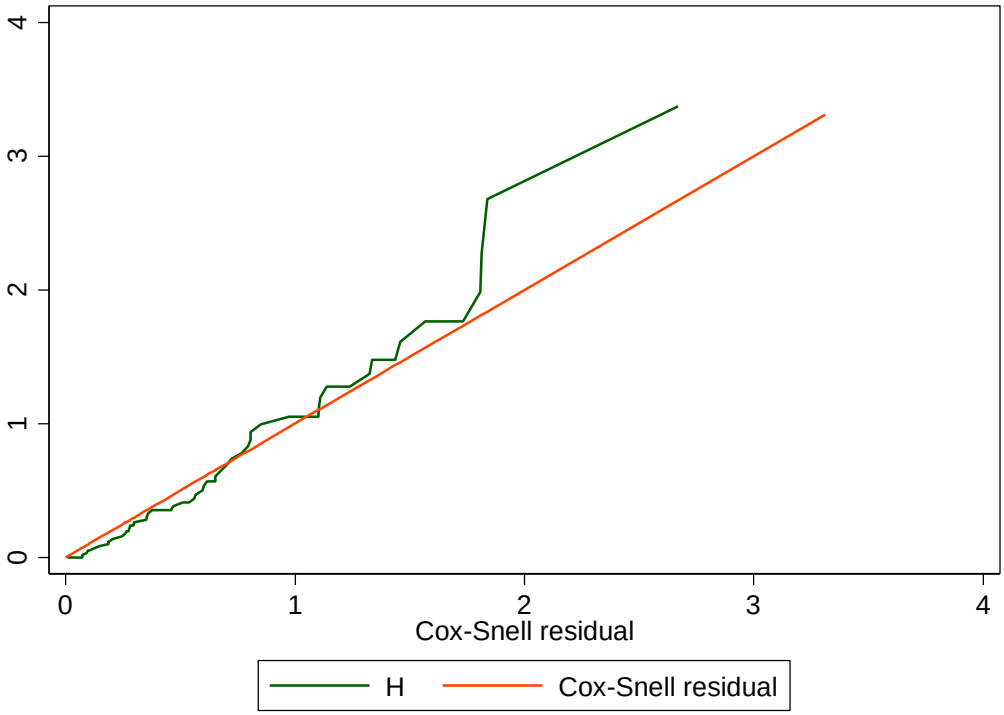
6. Goodness of fit for Model 2 (quarterly-type)



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