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Essays on Financial Crises Dynamics: Contagion and Interaction Effects

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Biography

Filipe Macedo Pinto Grilo was born on December 12, 1989, in Vila Nova de Gaia, Portugal.

Filipe concluded his undergraduate studies in Economics in 2010, at the School of Economics and Management of the University of Porto (FEP), with the final grade of 16 out of 20. During his undergraduate studies, he was awarded two Integration to Research Grants (BII) financed by the Foundation for Science and Technology (FCT). From these two grants, he presented his work in several conferences and published an article at *Papers in Regional Science*. He also won the 2nd Research Contest FEP/AEFEP with the research project: "A Corrupção nas Autarquias: Breve Análise Teórica e Modelo Explicativo".

After graduation, Filipe enrolled in the Doctoral Programme in Economics of the School of Economics and Management of the University of Porto, with a research grant by the FCT. After completing the scholar component of the PhD program with a grade of 16 out 20, he started his thesis under the supervision of Manuel Duarte da Silva Rocha and José Manuel Peres Jorge. During his PhD, he presented his work in several seminars. He also contributed to a project for the Ministry of Economy on active employment policies, and co-authored a Policy Paper at *Observatório da Qualidade da Democracia*, a paper at *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology* and a paper at *Motriz, Journal of Physical Education*. From 2016 to 2020, he joined the Faculty of Economics and Management of the University of Porto as a teaching assistant, lecturing the courses of Macroeconomics I, Macroeconomics II, and Monetary Economics.

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Abstract

The thesis is composed of three essays. The first essay identifies contagion effects in the Global Financial Crisis (GFC). In particular, I assess the causality interactions between global stock and sovereign bond markets, considering that any market can transmit contagion effects in response to the initial shock from the ground-zero market (the US stock market). With a VAR-DCC-GARCH model, I identify contagion effects stemming directly from the US as well as contagion effects stemming from a broad set of 34 countries worldwide. I find that the US transmitted very few contagion effects, suggesting that the contagion effects stemmed indirectly via other markets. I also find that the southern European sovereign bond markets contaminated several central and northern European sovereign bond markets, during the GFC. Finally, I find that Emerging Markets Economies transmitted on average more contagion effects than Advanced Economies in the GFC.

The second essay studies the role of a banking system in the context of contagion effects to its domestic sovereign bond market. I develop a global game, where a banking system increases its holdings of domestic sovereign debt – and thus offsets the effects predicted by the common lender hypothesis – when it has a strong balance sheet and it is highly exposed to domestic sovereign debt. I then discuss how these results offer a new explanation for the contagion process from the Greek to the Portuguese sovereign bond markets during the Eurozone Sovereign Debt Crisis (ESDC). In particular, I highlight the role of the Portuguese banking system in offsetting these contagion effects in the beginning of the ESDC.

Finally, the third essay examines the role of the channels of interaction that run from banking to currency crises (and vice-versa) in signaling these two types of crisis. I propose a unified Early Warning System (EWS) for banking and currency crises, jointly estimating the likelihood of both types of crisis using a system of two dynamic probit equations. For each equation, I add multiplicative terms between the leading indicators and the interaction effects from the other type of crisis to assess empirically the channels of crises interaction. I find several of these channels to be leading indicators. I also find that including channels of crises interaction improves substantially the predictability power of the EWS.

Keywords: Financial Crises, Contagion Effects, Crises interaction Effects, Global Financial Crisis, Eurozone Sovereign Debt Crisis, Emerging Markets, Advanced Economies.

JEL Classification Codes: C73, F30, F47, G01, G21, H63

Resumo

A tese é composta por três ensaios. O primeiro ensaio identifica efeitos de contágio na Crise Financeira Global (CFG). Particularmente, eu afiro as interações de causalidade entre mercados globais de ações e obrigações soberanas, considerando que qualquer mercado pode transmitir efeitos de contágio em resposta ao choque inicial vindo do mercado onde a crise originou (o mercado de ações americano). Com um modelo VAR-DCC-GARCH, eu identifico efeitos de contágio vindos diretamente dos Estados Unidos e também vindos de um conjunto de 34 países ao longo do globo. Eu encontro que os Estados Unidos transmitiram muito poucos efeitos de contágio, o que sugere que os efeitos de contágio possam ter sido transmitidos indiretamente por via de outros mercados. Eu também encontro que os mercados de obrigações soberanas dos países do sul da Europa contaminaram os mercados de obrigações soberanas dos países do centro e do norte da Europa, durante a CFG. Finalmente, eu encontro que os países Emergentes transmitiram em média mais efeitos de contágio do que os Países Avançados na CFG.

O segundo ensaio estuda o papel de um sistema bancário no contexto de efeitos de contágio para o seu mercado doméstico de obrigações soberanas. Eu desenvolvo um jogo global, onde um sistema bancário aumenta a sua participação de dívida soberana doméstica – e, por consequência, anula os efeitos previstos pela hipótese do credor comum – quando tem uma situação patrimonial sólida e quando está altamente exposto à dívida soberana doméstica. Eu posteriormente discuto como estes resultados oferecem uma nova explicação sobre o processo de contágio que aconteceu do mercado de obrigações soberanas gregas para o mercado de obrigações soberanas portuguesas durante a Crise da Dívida Pública da Zona Euro (CDPZE). Particularmente, eu realço o papel que o sistema bancário português teve em anular os efeitos de contágio no início da CDPZE.

Finalmente, o terceiro ensaio examina o papel dos canais de interação que ocorrem entre crises bancárias e cambiais em sinalizar estes dois tipos de crise. Eu proponho um sistema de sinalização unificado para crises bancárias e cambiais, estimando conjuntamente a probabilidade de ambos tipos de crise usando um sistema de duas equações probit dinâmicas. Para cada equação, eu adiciono termos multiplicativos entre os indicadores prévios e os efeitos de interação do outro tipo de crise para medir empiricamente os canais de interação entre crises. Eu encontro que estes canais são indicadores prévios de crise.

Eu também encontro que incluir canais de interação entre crises melhora substancialmente o poder preditivo do sistema de sinalização.
Palavras-Chave: Crises Financeiras, Efeitos de Contágio, Efeitos de Interação entre Crises, Crise Financeira Global, Crise da Dívida Pública da Zona Euro, Mercados Emergentes, Economias Avançadas.
Códigos de Classificação JEL: C73, F30, F47, G01, G21, H63

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Chapter 1

Introduction

Financial crises are highly disruptive events that provoke massive contractions in economic activity and threaten prosperity. Besides their severity, these crises are complex and dynamic labyrinths that can make markets tumble like domino tiles. Because of their complexity and danger, financial crises are one of the most critical subjects in economics' research.

The Global Financial Crisis (GFC) is a clear example of a complex and dynamic crisis. In broad terms, this crisis has evolved via two distinct directions. On the one hand, it quickly transmitted to the rest of the world, despite starting in a segment of the American banking sector. On the other hand, besides causing several banking crises throughout the globe, several authors argue that the GFC may have provoked vulnerabilities leading to the Euro Area Sovereign Debt Crisis (ESDC) (e.g. Mody, 2009). Thus, the GFC may have mutated into a sovereign debt crisis.

In this thesis, I focus on those two crisis dynamics. The first dynamics – contagion – may be broadly defined as the transmissions of a crisis in one country to other countries. The second dynamics – crises interaction – may be defined as the effects of a crisis on vulnerabilities leading to different types of crises in the same country.

The goal of this thesis is to contribute to the literature on financial crises, explicitly analyzing these two dynamics. In the three essays presented in this thesis, I examine these dynamics to improve our understanding of the causes of financial crises and how to prevent them.

Chapter 2 focuses exclusively on contagion effects in the GFC. In particular, I identify the causality interactions between global stock and sovereign bond markets, considering that any market can transmit contagion effects in response to the initial shock from the ground-zero market (the US stock market).

Using a VAR-DCC-GARCH model, I assess contagion effects arising directly from the US as well as contagion effects stemming from a broad set of 34 countries worldwide. The main contribution of this chapter arises from considering additional sources of contagion other than the US. In this respect, this chapter is more comprehensive than the existing research on the GFC because the analysis carried out allows disentangling the directions of causality of contagion effects, from transmitter to receiver. Consequently, I assess which markets transmitted more contagion effects and I discern if the contagion effects identified by the standard approach in the literature stemmed directly from the US or indirectly via other markets.

This chapter is relevant to the literature on financial crises because knowing the origin of contagion effects allows policymakers to design appropriate policy responses and prepare contingency plans to guarantee financial stability.

In Chapter 3, I address the two crisis dynamics in the context of the ESDC. In particular, I study how banks may influence contagion effects within the sovereign bond market. Thus, on the one hand, I analyse the transmission of contagion effects from a sovereign debt crisis to other countries. On the other hand, I show how banking problems can create vulnerabilities that enable contagion effects within the sovereign bond market and, ultimately, precipitate a sovereign debt crisis.

In this essay, I develop a global game, where a banking system increases its holdings of domestic sovereign debt – and thus offsets contagion effects stemming from other markets – when it has a strong balance sheet and it is highly exposed to domestic sovereign debt. I then discuss how these results shed a light on the ESDC, taking the example of the contagion dynamics from Greece to Portugal during the beginning of the ESDC. In particular, I highlight the role of the Portuguese banking system in offsetting these contagion effects.

This chapter has important policy implications. By showing that the stability of the sovereign bond market may be compromised after a negative shock to the capital of the national banking system, the findings in this essay recommend a more coordinated policy response between monetary and fiscal authorities.

Chapter 4 focuses on crises interaction effects. More specifically, this essay examines the role of the channels of interaction that run from banking to currency crises (and vice-versa) in signaling these two types of crisis.

To do so, I first develop a unified Early Warning System for banking and currency crises, jointly estimating the likelihood of both types of crisis. I then include multiplicative terms between the leading indicators and the interaction effects from the other type of crisis. These terms allow us to assess if some vulnerabilities may gain relevance to signal a crisis if and only if the other type of crisis occurs.

This chapter is relevant for policymakers because I show that the policymaker should be vigilant of both types of crises in order to predict more successfully both banking and currency crises. Moreover, some policies may actually have unwanted results if the policymaker does not consider the channels of crises interaction.

Finally, Chapter 5 summarises the results of this thesis, offering a brief discussion.

References

[1] Mody, M. A. (2009). “From Bear Stearns to Anglo Irish: how eurozone sovereign spreads related to financial sector vulnerability”. International Monetary Fund Working Papers, 09-108.

Chapter 2

Stock and Bond Markets Contagion in the Global Financial Crisis: Identifying Multiple Sources of Contagion at a Global Level

Abstract: We identify contagion effects during the Global Financial Crisis (GFC). In particular, we assess the causality interactions between global stock and sovereign bond markets, considering that any market can transmit contagion effects in response to the initial shock from the ground-zero market (the US stock market). With a VAR-DCC-GARCH model, we identify contagion effects stemming directly from the US as well as contagion effects arising from a broad set of 34 countries worldwide. We find that the US transmitted very few contagion effects, suggesting that the contagion effects stemmed indirectly via other markets. We also find that the southern European sovereign bond markets contaminated several central and northern European sovereign bond markets, during the GFC. Finally, we find that Emerging Markets Economies transmitted on average more contagion effects than Advanced Economies in the GFC.

KEYWORDS: Contagion, Global Financial Crisis, VAR-GARCH, Cross-Asset, Emerging Markets, Advanced Economies

JEL CODES: F30, G01, G15

2.1. Introduction

The Global Financial Crisis (GFC) was the severest financial crisis since the Great Depression. Starting in a segment of the American banking sector, the subprime crisis mutated into a global financial crisis.[1] With the spreading of the crisis throughout countries and assets, several authors started to test whether the American stock market contaminated other stock markets (e.g., Horta, Mendes, and Vieira, 2010; Yiu, Alex Ho, and Choi, 2010; Aloui, Aïssa, and Nguyen, 2011), other American asset markets (Longstaff, 2010; Guo, Chen, and Huang, 2011), and other countries' asset markets (Chudik and Fratzscher, 2011; Beirne and Gieck, 2014).

Besides the severity of the GFC, various findings in the literature on contagion suggest that this crisis had complex contagion dynamics. First, according to Beirne and Gieck (2014), the GFC has been associated with turbulences in asset markets across Advanced Economies (AEs) and Emerging Market Economies (EMEs). Second, several authors argue that the GFC changed investors' risk perception in the Euro Area sovereign bond market, which may have led to the Euro Area Sovereign Debt Crisis (ESDC) (e.g. Mody, 2009). Since the GFC started in the stock market, the change in the behaviour of investors in the sovereign bond market motivates the need to test whether there was both cross-country and stock-bond contagion effects in the GFC.

Third, although the GFC undoubtedly started in the US, a couple of studies calls into question the extension of contagion effects stemming directly from the US: (*i*) Bekaert, Ehrmann, Fratzscher, and Mehl (2014) test if contagion effects in the GFC have arisen from the US, the global financial sector, or country-specific shocks, and conclude that the US had a lower impact than country-specific shocks; (*ii*) Kamin and DeMarco (2012) find evidence that suggests that the US sub-prime crisis may have been just a trigger, instead of being a fundamental driver of the global crisis,. Thus, if contagion effects stemming directly from the US were limited, it may be the case that other markets transmitted contagion effects in the GFC. Fourth, various studies indicate that EMEs had a decoupling-recoupling dynamic in the GFC, i.e. there was an initial decoupling of EMEs from AEs, but in the first half of 2009, global financial markets became highly synchronized (e.g.

[1] Adrian and Shin (2008) estimate that, in the worst scenario, total losses with subprime lending would be roughly about USD 100-200 billion, which is infinitesimal compared to USD 58 trillion of the net worth of households.

Dooley and Hutchinson, 2009; Chudik and Fratzscher, 2011). These dynamics may imply that EMEs have been affected afterwards, which may have been caused by other mature markets in reaction to the initial shock from the US stock market. Finally, various contagion studies do not find evidence of contagion effects from the US stock market to Emerging Asian markets (for example, Lee, 2012; Morales and Andreosso-O'Callaghan, 2012). Despite this, there is evidence of capital outflows from these markets (Kawai, Lamberte, and Park, 2012) and these markets suffered sharp losses in the GFC.[2] Thus, these facts point to the possibility of other markets to be important in exacerbating the effects of the GFC to Emerging Asian markets.

Based on the previous evidence, we hypothesize that assuming the US as the only source of contagion may compromise the contagion identification in the GFC and may ignore contagion effects stemming from other markets that may have been critical in exacerbating the crisis. This argument motivates our paper.

The goal of the present paper is to identify and study both cross-country and cross-asset contagion effects in the GFC. In particular, we identify contagion effects between stock and sovereign bond markets, by considering that any market can transmit contagion effects in response to the initial shock from the ground-zero market (the US stock market). To this end, we use a VAR-DCC-GARCH model, which enables us to identify contagion effects stemming directly from the US as well as contagion effects arising from a broad set of 34 countries worldwide.

This study mainly contributes to the literature on contagion in the GFC by considering additional sources of contagion other than the US. In particular, we assume the US being the ground-zero country and, at the same time, we allow other markets to transmit contagion effects in reaction to the shock stemming from the ground-zero country. To the best of our knowledge, this is the first study to consider these two effects simultaneously in the GFC. In this respect, this study is more comprehensive than the existing research on the GFC because this framework allows us to disentangle the directions of causality of contagion effects, from transmitters to receivers. Besides, considering several sources of contagion enables us to assess which markets transmitted more contagion effects, as

[2] For instance, according to our calculations and using Datastream data, the stock market capitalization of Singapore and Thailand decreased by about 25% and 28% during the GFC, respectively.

well as, to discern if the contagion effects identified by the literature stemmed directly from the US or indirectly via other markets.

Besides analysing which markets transmitted and received more contagion effects, this study also contributes to three debates in the literature on contagion in the GFC. First, we analyse contagion effects within the Euro Area sovereign bond market and contribute to the research that links the GFC to the ESDC. Second, we focus on the contagion effects transmitted to Emerging Asian markets and document if these markets were isolated from the GFC. Finally, we analyse contagion effects within and across EMEs and AEs, and shed light on the behaviour of EMEs during the GFC.

Our main findings are as follows. First, we find that the US directly transmitted very few contagion effects during the GFC. More specifically, we suggest that some contagion effects, which were identified by the literature as coming from the US, may have stemmed indirectly via other markets.

Second, we find an abnormally high number of contagion effects within the Euro Area sovereign bond market during the GFC. In particular, we find that the sovereign bond markets of southern European countries (Greece, Italy, Portugal, and Spain) contaminated several central and northern European sovereign bond markets during the GFC. Third, we find very few contagion effects from advanced markets to Emerging Asian stock markets. Finally, EMEs transmitted, on average, more contagion effects than AEs, suggesting that EMEs were also responsible for exacerbating the crisis, despite the initial decoupling dynamic.

We consider our results to be of relevance to the various agents in the financial markets. Knowing the origin of contagion effects allows policymakers to design appropriate policy responses and prepare contingency plans to guarantee financial stability.

The rest of the article is structured as follows. Section 2.2 reviews the empirical literature on contagion. Section 2.3 outlines the empirical methodology, providing details on the methodology used. Section 2.4 describes the various data series and sources. Section 2.5 presents and discusses the main empirical results. Section 2.6 summarises the main points and concludes.

2.2. Literature Review

This study relates to two strands of literature in the empirical studies of contagion. This first strand analyses cross-country contagion, whereas the second strand analyses cross-asset contagion.

The first strand of literature appeared when researchers started testing the existence of contagion across countries in late-1990s financial crises, such as the Tequila Crisis (1994), the Asian Financial Crisis (1997), and the Long-Term Capital Management (LTCM) Crisis (1998) (for example, Glick and Rose, 1999; Van Rijckeghem and Weder, 2001; Forbes and Rigobon, 2002). One key issue of cross-country contagion literature is that it identifies contagion effects commonly assuming that these effects stem only from the ground-zero country. This practice frequently occurs because financial crises traditionally start in a specific country. For example, the Tequila Crisis arose in Mexico, the LTCM crisis in Russia, and the Global Financial Crisis in the United States. By assuming a unique source of contagion, the goal of these studies is to understand which countries were contaminated by the ground-zero country (e.g. Glick and Rose, 1999; Forbes and Rigobon, 2002; Aloui *et al.,* 2011). Thus, the focus of the analysis is to identify the receivers of contagion effects.

Despite the common practice of assuming a unique source of contagion, a small number of studies considers multiple sources/transmitters of contagion effects (e.g. Baig and Goldfajn, 1999; Masih and Masih, 1999; Sander and Kleimeier, 2003). This change in approach occurred because of the Asian Financial Crisis since, as indicated by Baig and Goldfajn (1999), no single event acted as a clear catalyst. Thus, assuming a ground-zero country in this crisis (instead of several countries) could misidentify the contagion sources and could compromise the contagion identification.

By considering various contagion sources, the goal of these cross-country contagion studies changes. Since multiple countries can be sources of contagion, the purpose of these studies is also to identify which countries transmit contagion effects. Thus, instead of only focusing on the receivers of contagion effects, these studies introduce more comprehensiveness to the contagion analysis because they allow disentangling the directions of causality of contagion effects, from transmitters to receivers (Sander and Kleimeier, 2003).

Turning our discussion to the GFC, given its impact on the global economy and its rapid spreading, this crisis has been widely addressed in the cross-country contagion literature (e.g. Naoui, Liouane, and Brahim, 2010; Yiu *et al*., 2010; and Aloui *et al*., 2011). Besides, since the GFC undoubtedly started in the US financial sector, the literature on contagion in the GFC commonly assumes the US as the ground-zero country and the unique source of contagion (e.g. Naoui *et al.*, 2010; Yiu *et al*., 2010; and Aloui *et al*., 2011).

Despite the facts mentioned above, we highlight three results in the literature of contagion in the GFC that may put into question that the US was the only contagion source in the GFC. First, a couple of studies that analyse contagion effects in the GFC but consider the possibility of other contagion sources than just the US find that contagion effects from the US were limited (Bekaert *et al*., 2014; Kamin and DeMarco, 2012). We argue that these findings raise the possibility that, despite the evident existence of a ground-zero country, there might be other markets that transmitted contagion effects in the GFC. Second, several studies argue that Emerging financial markets had a decoupling-recoupling dynamic in the GFC, i.e. there was an initial de-coupling of EMEs from AEs, but global financial markets became highly synchronized in the first half of 2009 (e.g., Dooley and Hutchison, 2009; Chudik and Fratzscher, 2011). These dynamics may imply that EMEs were only affected afterwards, which might have been caused by other markets in reaction to the initial shock from the US. Third, various studies of cross-country contagion in the GFC that address Emerging Asian countries do not find contagion effects from the ground-zero country (the US) to the majority of these countries (for example, Morales and Andreosso-O'Callaghan, 2012; Lee, 2012; Wang, 2014). However, at the same time, there is evidence of capital outflows from these markets (Kawai *et al*., 2012) and these Asian markets also suffered sharp losses. These facts together may motivate for the possibility of other countries to be important in contaminating Emerging Asian countries.

Given the above discussion, we contribute to the cross-country contagion literature by considering additional sources of contagion other than the US in the GFC. In particular, we combine the two approaches in the literature, i.e. *(i)* we assume the US being the ground-zero country, but *(ii)* we also study contagion effects stemming from other countries in the presence of the ground-zero country. To the best of our knowledge, this is the first work to identify these two types of contagion effects in the GFC.

The second strand of literature, regarding cross-asset contagion studies, started to appear in the aftermath of the Asian Financial Crisis. Focusing on the contagion links between stock and currency markets, these contagion studies find which asset markets were responsible for the contagion effects (Baig and Goldfajn, 1999; Granger, Huangb, and Yang, 2000; Khalid and Kawai, 2003; Dungey and Martin, 2007). After the Asian Financial Crisis, a small number of studies appeared to study contagion between stock and sovereign bond markets in several periods of financial distress (e.g., Hartmann, Straetmans, and De Vries, 2004; Baur and Lucey, 2009).

Turning to the GFC, due to the cross-asset nature of this crisis, the literature on cross-asset contagion literature in the GFC had room to grow. Still, this topic remained almost absent, as Dua and Tuteja (2016) stated. In fact, to the best of our knowledge, very few works have studied cross-asset contagion in the GFC, analysing both cross-asset and cross-country contagion (Chudik and Fratzscher, 2012; Beirne and Gieck, 2014; Petmezas and Santamaria, 2014; Dua and Tuteja, 2016).

Petmezas and Santamaria (2014) exclusively study stock-bond contagion effects in the GFC and ESDC between the US and five European countries. They find some evidence of stock-bond contagion during the GFC. Because they exclusively focus on stock-bond contagion, Petmezas and Santamaria (2014) do not analyse within-asset contagion (i.e., cross-country contagion). Dua and Tuteja (2016) examine the existence of financial contagion between India, Euro Area, Japan and US stock and currency markets during the GFC and the ESDC. They find evidence of significant contagion effects both across and within asset classes. Despite their contribution, both Petmezas and Santamaria (2014) and Dua and Tuteja (2016) limit their analysis to a small number of countries. Since the GFC was a global crisis, concentrating on a relatively small number of countries restricts the broadness of their studies, and consequently, their conclusions.

Chudik and Fratzscher (2012) and Beirne and Gieck (2014) study cross-asset contagion in a large sample of countries (60 and 26, respectively). While the former analyses cross-asset contagion (between bonds, stocks and currencies) in some financial distress episodes over the period 1998 to 2011, the latter compares cross-asset contagion effects (stocks, bonds, and currencies) in the GFC with the effects in the ESDC. Despite the large samples of countries, both studies use a GVAR methodology, which means that they aggregate several countries into a global variable. In their case, they only consider two possible sources of contagion: contagion from the US and a global variable. By doing so, they do not explicitly analyse cross-country contagion, restricting the comprehensiveness of their analysis.

Given the above discussion, we contribute to the cross-asset contagion literature in the GFC by explicitly investigating both cross-country and cross-asset contagion using a large sample of AEs and EMEs (34 countries). Besides, by considering that all markets (countries and assets) can be potential sources of contagion, we can disentangle both cross-country and cross-asset contagion effects (from transmitters to receivers), simultaneously testing the existence of contagion effects stemming from the ground-zero market.

2.3. Econometric Methodology

This section has five subsections and discusses different features of the methodology applied in this study. Subsection 2.3.1 presents the definition of contagion used in this paper. Subsection 2.3.2 discusses and reviews the empirical frameworks used in the contagion literature. Subsection 2.3.3 presents the model specification. Subsection 2.3.4 introduces the contagion tests used in this work. Subsection 2.3.5 presents the approach used to identify the crisis period.

2.3.1. Contagion Definition

The definitions of financial contagion have been surveyed by, for example, Pericoli and Sbracia (2003) and Forbes (2013). These studies are examples of a strand of literature that underlines the importance of choosing the definition of contagion. Selecting the definition of contagion is pivotal because there are several definitions available and because the core debate in this literature arises from the fact that the conclusions depend on the definition of contagion and the methodology used. Even between prevailing studies, we encounter a substantial disparity regarding definitions: Forbes and Rigobon (2002), Kodres and Pritsker (2002), Dungey, Fry, González-Hermosillo, and Martin

(2010), and Bekaert *et al*. (2014). Given the diversity of options, the results sometimes go in opposite directions, as Forbes and Rigobon (2002) show in their study.

We follow the seminal definition of Forbes and Rigobon (2002), which is the most adopted definition in the literature. Forbes and Rigobon (2002) define contagion as a significant increase in market comovement in the crisis period, compared to a tranquil period. By looking at contagion in this perspective, Forbes and Rigobon (2002) separate contagion effects from normal spillovers. In this sense, spillovers are normal comovements between two markets during tranquil periods, whereas contagion effects are excessive comovements between two markets during crisis periods.

2.3.2. Empirical Frameworks

This section reviews the empirical frameworks used in financial contagion literature. This subject has been recently surveyed in Forbes (2013). We divide this section into two parts: (i) we discuss the role of fundamentals in explaining contagion; and (ii) we review the econometric methodologies that assume more than one contagion source.

First, there is a debate in the empirical contagion literature about the role of fundamentals in explaining contagion.[3] On the one hand, several studies assume that fundamentals cannot explain contagion (see, for example, Forbes and Rigobon, 2002; Bekaert, Harvey, and Ng, 2005). On the other hand, recent studies have been pointing out several methodological problems associated with assuming that fundamentals cannot explain contagion, and consider the opposite to avoid these problems (see, for example, Baur, 2012; Beirne and Gieck, 2014).

Assuming that fundamentals cannot explain contagion implies that contagion has to be estimated in two phases. The first phase separates the return component that can be explained by fundamentals from the unexpected return component.[4] Consider the case of two markets, market A and B. To test for contagion effects from market B to market A,

[3] By fundamentals, we mean macroeconomic or financial variables that can explain the behaviour of a market during normal times. For instance, the return of a global stock portfolio can be used as a fundamental variable.
[4] The use of the term "unexpected" is in line with the literature, and in particular with Baur (2012).

one first estimates the impact of a fundamental variable (in our example, the returns of a global stock portfolio) on markets A and B, as it is shown in Equations (2.1) and (2.2).

$$R_{A,t} = a + bR_{W,t} + e_{A,t} \tag{2.1}$$

$$R_{B,t} = c + dR_{W,t} + e_{B,t} \tag{2.2}$$

where $R_{A,t}$ ($R_{B,t}$) the returns of market A (B); $R_{W,t}$ the returns of a global stock portfolio; $e_{A,t}$ and $e_{B,t}$ the error-terms, i.e. the return components (of markets A and B, respectively) that are not explained by $R_{W,t}$ (i.e. the fundamentals).

After the first phase, the estimation of contagion effects comes in a second-phase equation (traditionally the volatility equation of a GARCH model), using the error-terms, $e_{A,t}$ and $e_{B,t}$, as it is shown in Equation (2.3).

$$e_{A,t} = c_0 + c_1 e_{B,t} + c_2 e_{B,t} D_{crisis} + \eta_t \tag{2.3}$$

where D_{crisis} is a dummy variable which takes the value 1 in the crisis period and 0 elsewhere. Contagion effects from market B to market A occur if the parameter c_2 is significantly positive.

Despite its influence in the literature, this approach may bias the identification of contagion effects mainly in two ways. First, according to Baur (2012) and Forbes (2013), the model specified in Equations (2.1) to (2.3) (and consequently its results) is sensitive to the specification of the first-phase equations – Equations (2.1) and (2.2). Since contagion is identified using model error-terms, this raises some questions about what is being captured in the error-terms and whether any contagion could be caused by omitted variables not captured by Equations (2.1) and (2.2). Second, according to Baur (2012), controlling the first-phase regression for financial or macroeconomic variables (which usually also change in the crisis period) can turn unexpected shocks into expected, underestimating the impact of unexpected shocks on the error-terms, and, consequently in the identification of contagion effects.

Given the above discussion, we follow the practice of more recent studies and assume that contagion can be identified from increasing comovements that can be explained by fundamentals (e.g. Baur, 2012; Beirne and Gieck, 2014; Bekaert *et al*., 2014).

We now review the econometric methodologies that assume more than one contagion source. Since assuming more than one contagion source raises problems of endogeneity, the literature that considers more than one contagion source has developed frameworks to take into account the issue of endogeneity that might exist between contagion sources. We divide this literature into three groups, according to their empirical approach: factor models, VAR models (in particular, the global VAR) and VAR-GARCH models.[5]

First, a factor model is identical to a two-stage least squares, which is a method to handle the problem of endogeneity. This type of model firstly estimates factors using instrumental variables and, secondly uses these factors' estimations to identify contagion. This model is proposed, for example, by Bekaert *et al.* (2014) and Tola and Wälti (2015). For example, Bekaert *et al*. (2014) study contagion in the GFC and use a US factor, a global financial factor and a domestic market factor. Even though this type of models are traditionally used to prevent the presence of endogeneity, according to West, Wong, and Anatolyev (2009), a two stage-least squares is not efficient when there is conditional heteroscedasticity in the data. Thus, in the presence of conditional heteroscedasticity – which is common in financial time series – the problem of endogeneity might not be adequately tackled by this method.

In the second group, studies use VAR models to handle the problem of endogeneity. These models can be found, for example, in Baig and Goldfajn (1999), Chudik and Fratzscher (2011, 2012), and Beirne and Gieck (2014). Despite the popularity of VAR models in econometrics, these models have two caveats, when estimating financial contagion.

The first caveat is the curse of dimensionality, referred to by Sims (1980). To deal with the curse of dimensionality, several authors have proposed the Global VAR as a solution (e.g. Chudik and Fratzscher, 2011, 2012; Beirne and Gieck, 2014). The Global VAR consists of a VAR representation in which source countries – except the ground-

[5] Other studies use Multivariate GARCH models, estimating contagion in the second-phase equation. Because these models have the same problems that were discussed above, we do not review them.

zero country – are aggregated depending on the weight of the commercial and financial relations with the estimated country.[6] Thus, instead of having n parameters to estimate, each equation has two parameters – contagion from the global variable and the ground-zero country. Despite its ability to deal with the curse of dimensionality, Global VARs are not suited to our research question because aggregating all sources would not allow us to identify the contagion effects transmitted by each country. Also, the aggregation method may have some cautions since it assumes that contagion effects come from countries with significant commercial and/or financial relations, excluding *a priori* cases of contagion with no fundamental relationship. There are, however, examples of contagion between countries with similar vulnerabilities but without any trade or financial linkages (Lane and Milesi-Ferretti, 2011).

The second caveat of VAR models is that they are not immune to conditional heteroscedasticity since they do not adjust for the heteroscedasticity in returns. Moreover, according to Forbes (2013), attempts to correct posteriorly for heteroscedasticity generate fragile results. As we analyse two completely different periods regarding volatility, not taking into account the increase in the residual's variances and covariances – which is common in financial turmoil periods – might overestimate the identification of contagion effects.

The third group of studies has emerged in the literature on contagion by using VAR-GARCH models (for example, Khalid and Rajaguru, 2007; Hammoudeh, Yuan, and McAleer, 2009; Muñoz, Márquez, and Sánchez, 2011). The VAR-GARCH models share the same ability of VAR models to prevent the problem of endogeneity, but they are immune to conditional heteroscedasticity (the second caveat of VAR models). This immunity comes from the fact that VAR-GARCH models can design the structure of the variance-covariance matrix.

There are two common methodologies to model the structure of the variance-covariance matrix in the literature on financial contagion. On the one hand, a few studies use the Dynamic Conditional Correlation (DCC) model of Engle (2002) (e.g., Muñoz *et al.*, 2011). The essential advantage of the DCC model is that it allows a dynamic structure to the variance-covariance matrix. By assuming the DCC specification, the VAR-GARCH model is flexible enough to accommodate the change in the volatility dynamics

[6] Countries with more commercial and financial relations have more weight.

(variances and covariances) in a crisis period. This flexibility is pivotal to identify contagion since the variances and covariances dynamics may be different in tranquil periods from in crisis periods. Thus, the DCC specification is more conservative in identifying contagion effects than a VAR model with adjustments for heteroscedasticity because it endogenously accommodates for non-linear correlations between residuals.

On the other hand, a few works use the BEKK specification of Engle and Kroner (1995). This specification has the drawback of requiring a large number of parameters to estimate and, at the same time, cannot consider dynamic correlations in the variance-covariance matrix. Ergo, assuming the BEKK specification implies breaking the sample into pre, during, and post-crisis periods, as Khalid and Rajaguru (2007) have done. However, by doing this, the contagion inference becomes more difficult because the model cannot endogenously recognize the increase in the correlations. Adding to this discussion, Şerban, Brockwell, Lehoczky, and Srivastava (2007) compare the BEKK model to the DCC model and their implications in portfolio management. They find that the latter model outperforms the former, which highlights the benefits of addressing non-linear correlations for portfolio management.

Given the above discussion, we choose to use the VAR-DCC-GARCH model to identify contagion effects in the GFC. Recall that there is still a caveat of the VAR models that the VAR-GARCH models do not handle, i.e. the curse of dimensionality.[7] As stated above, since our research question requires identifying each transmitter and receiver of contagion effects, a solution a la Global VAR is not suited. Another possible way to handle this problem would be limiting our sample to a handful of countries. However, we would risk losing some essential dynamics for the understanding of the spreading of the crisis because this crisis was global, as discussed above.

Thus, we opt to limit the number of contagion sources in each regression, i.e. we identify contagion effects between each pair of countries, studying all possible combinations. Hence, our model has four endogenous variables: two markets (stock and sovereign bond) for each country. For instance, the stock market of country A is explained by its past information, the past information of country's A sovereign bond market, and the past

[7] There have been some efforts to tackle this problem, but the existing alternatives focus on the correlation parameters in the second moments (Carnero and Eratalay, 2014). There is not any way to overcome this problem in the first phase of the estimation (VAR), where we test the contagion effects.

information of country's B stock and sovereign bond markets. Besides, as discussed earlier, and since the GFC undoubtedly started in the US, we include the exogenous presence of the US stock market (the ground-zero market). This inclusion means that the US stock market is an exogenous variable in the system, i.e. its past information explains countries A and B's markets but not vice-versa.

We acknowledge that the decision of limiting the number of contagion sources in each regression is critical to this study. On the one hand, it allows us to consider a comprehensive sample, avoiding the curse of dimensionality. On the other hand, it may be a shortcoming because it omits variables (such as the returns of other countries that are not present in the regression). We argue, however, that the exogenous presence of the US stock market may restrict the impact of this drawback. Since all endogenous contagion effects result from the initial shock by the ground-zero market, the presence of the ground-zero in the regression will function as a common shock. Thus, when identifying contagion effects between pairs of countries, the exogenous variable controls for possible endogenous contagion effects from other countries that are not considered in the regression, reducing the potential bias arising from omitted variables.

The model's specification will be presented in the following subsection.

2.3.3. Model Specification

The econometric model is specified as follows:

$$R_t = \alpha + \mathrm{B}R_{t-1} + \Phi R_{t-1}D_{crisis} + \delta R_{US,t-1} + \gamma R_{US,t-1}D_{crisis} + \varepsilon_t \qquad (2.4)$$

with R_t a 4x1 vector of returns: country A's stock and sovereign bond markets, and country B's stock and sovereign bond markets; R_{t-1} a corresponding vector of lagged returns; D_{crisis} the crisis period dummy scalar; $R_{US,t-1}$ a scalar of lagged returns of the US stock market (the ground-zero market); and $\varepsilon_t = (e_{As,t}; e_{Ab,t}; e_{Bs,t}; e_{Bb,t})$ an error-term vector.

Following the common practice of the literature that uses a VAR structure to identify contagion, we restrict the number of lags in the empirical analysis to one (e.g. Chudik and Fratzscher, 2011; Muñoz *et al.*, 2011; Dua and Tuteja, 2016). The choice of the literature is motivated by the fact that contagion is considered to be a "fast and furious" event

(Kaminsky, Reinhart, and Vegh, 2003).[8] The parameters of the mean return Eq. (2.4) comprise the constant terms $\alpha = (\alpha_{As}; \alpha_{Ab}; \alpha_{Bs}; \alpha_{Bb})$, the parameters of the autoregressive terms B, a 4x4 matrix of β_{ij} parameters, the parameters of contagion

$$\Phi = \begin{bmatrix} 0 & \varphi_{AbAs} & \varphi_{BeAs} & \varphi_{BbAs} \\ \varphi_{AsAb} & 0 & \varphi_{BsAb} & \varphi_{BbAb} \\ \varphi_{AsBs} & \varphi_{AbBs} & 0 & \varphi_{BbBs} \\ \varphi_{AsBb} & \varphi_{AbBb} & \varphi_{BsBb} & 0 \end{bmatrix},$$

the parameters of interdependence with the US, $\delta = (\delta_{As}; \delta_{Ab}; \delta_{Bs}; \delta_{Bb})$, and the contagion parameters from the US, $\gamma = (\gamma_{As}; \gamma_{Ab}; \gamma_{Bs}; \gamma_{Bb})$.

The error-term vector ε_t is multivariate and normally distributed $\varepsilon_t |\, \mathrm{I}_{t-1} \sim (0, \mathrm{H}_t)$ with its corresponding conditional variance-covariance matrix given by:

$$\mathrm{H}_t = \begin{bmatrix} h_{As,t} & h_{AsAb,t} & h_{AsBs,t} & h_{AsBb,t} \\ h_{AbAs,t} & h_{Ab,t} & h_{AbBs,t} & h_{AbBb,t} \\ h_{BsAs,t} & h_{BsAb,t} & h_{Bs,t} & h_{BsBb,t} \\ h_{BbAs,t} & h_{BbAb,t} & h_{BbBs,t} & h_{Bb,t} \end{bmatrix} \tag{2.5}$$

In the multivariate GARCH(1,1)-DCC representation proposed by Engle (2002), H_t takes the following form:

$$\mathrm{H}_t = D_t P_t D_t \tag{2.6}$$

Where $D_t = diag\left(\sqrt{h_{As,t}}, \sqrt{h_{Ab,t}}, \sqrt{h_{Bs,t}}, \sqrt{h_{Bb,t}}\right)$, and the conditional correlation matrix, P_t, which varies over time, is given by:

$$P_t = \left(diag(Q_t)\right)^{-\frac{1}{2}} Q_t \left(diag(Q_t)\right)^{-\frac{1}{2}} \tag{2.7}$$

Where the (4x4) symmetric positive definite matrix $Q_t = (q_{ij,t})$ is define as follows:

[8] The literature on contagion that uses a univariate methodology considers contagion as a contemporaneous event (for example, Baur, 2012).

$$Q_t = (1 - \alpha_q - \beta_q)\bar{Q} + \alpha_q \eta_{t-1}\eta'_{t-1} + \beta_q Q_{t-1} \tag{2.8}$$

In Eq. (2.8), α_q and β_q are non-negative scalar such that $\alpha_q + \beta_q < 1$, $\bar{Q}$ is the (4x4) matrix of unconditional correlations of the standardized errors η_t. Additionally, Q_0 has to be positive definite.

The conditional variances $h_{As,t}$, $h_{Ab,t}$, $h_{Bs,t}$, and $h_{Bb,t}$ follow a multivariate GARCH (1,1) specification as:

$$\begin{bmatrix} h_{As,t} & 0 & 0 & 0 \\ 0 & h_{Ab,t} & 0 & 0 \\ 0 & 0 & h_{Bs,t} & 0 \\ 0 & 0 & 0 & h_{Bb,t} \end{bmatrix} = \begin{bmatrix} c_{As} & 0 & 0 & 0 \\ 0 & c_{Ab} & 0 & 0 \\ 0 & 0 & c_{Bs} & 0 \\ 0 & 0 & 0 & c_{Bb} \end{bmatrix} +$$

$$+ \begin{bmatrix} a_{As} & 0 & 0 & 0 \\ 0 & a_{Ab} & 0 & 0 \\ 0 & 0 & a_{Bs} & 0 \\ 0 & 0 & 0 & a_{Bb} \end{bmatrix} \begin{bmatrix} {e_{As,t}}^2 & 0 & 0 & 0 \\ 0 & {e_{Ab,t}}^2 & 0 & 0 \\ 0 & 0 & {e_{Bs,t}}^2 & 0 \\ 0 & 0 & 0 & {e_{Bb,t}}^2 \end{bmatrix} +$$

$$+ \begin{bmatrix} b_{As} & 0 & 0 & 0 \\ 0 & b_{Ab} & 0 & 0 \\ 0 & 0 & b_{Bs} & 0 \\ 0 & 0 & 0 & b_{Bb} \end{bmatrix} \begin{bmatrix} h_{As,t-1} & 0 & 0 & 0 \\ 0 & h_{Ab,t-1} & 0 & 0 \\ 0 & 0 & h_{Bs,t-1} & 0 \\ 0 & 0 & 0 & h_{Bb,t-1} \end{bmatrix} \tag{2.9}$$

The parameters of Eq. (2.9) comprise the constant terms $c = (c_{As}; c_{Ab}; c_{Bs}; c_{Bb})$, the ARCH parameters $a = (a_{As}; a_{Ab}; a_{Bs}; a_{Bb})$, and the GARCH parameters $b = (b_{As}; b_{Ab}; b_{Bs}; b_{Bb})$. As standard in the GARCH specification, to ensure positive variances, all parameters must be positive.

And the conditional covariances are given by:

$$h_{ij,t} = p_{ij,t}\sqrt{h_{i,t}h_{j,t}} \tag{2.10}$$

2.3.4. Contagion Tests

We follow the common practice of the studies that use a VAR structure to analyse contagion effects, and we identify contagion effects using Granger causality tests (e.g.

Chudik and Fraztscher, 2011; Beirne and Gieck, 2014). In light of the definition of contagion presented in Subsection 2.3.1, endogenous contagion effects between markets occur when the parameter of contagion φ_{ij} in Equation (2.4) is significantly positive. For instance, if $\varphi_{BsAs} > 0$, there is contagion from country B's stock market to country A's stock market.

The identification of exogenous contagion effects from the US stock market is slightly different from the identification of endogenous contagion effects. As we consider the US stock market to be an exogenous variable, the US stock market is included in all regressions. This means that for each country, there are 33 estimates (N-1) for the US contagion parameter. Given the multiplicity of estimates of the US stock market contagion variable to each market, we only consider contagion, when, for each market, the parameter γ is significantly positive across all estimations.

2.3.5. Crisis Period Identification

One of the main concerns in the literature on contagion is the identification of the crisis period, since several studies have demonstrated that the identification of contagion effects depends on the crisis period (see, for example, Baur, 2012). Thus, several authors have proposed strategies to identify crisis periods (for example, Baig and Goldfajn, 1999; Forbes and Rigobon, 2002; Dungey *et al*., 2010).

In this study, we adopt the approach proposed by Baur (2012). This approach has the advantage of combining the two principal methodologies of identifying crisis periods used in the literature. First, the approach defines a relatively long crisis period, using several timelines, which include all major financial and economic news events representing the crisis under analysis (in our case, the GFC). Second, the approach uses volatility estimates from the ground-zero market (in our case, the US stock market) to identify regimes of excess volatility. Finally, the crisis period results from combining both approaches, being the period that is common to both methodologies. The implementation of this approach is presented in Subsection 2.4.2.

2.4. Empirical Aspects

This section has two subsections. Subsection 2.4.1 describes the dataset used and discusses several measurement issues. Subsection 2.4.2 implements the methodology described in section 2.3.5 to identify the crisis period, presenting the various data series and sources.

2.4.1. Data

We use a dataset that includes daily observations from 1993 to 2013 on a set of 36 economies, of which 21 AEs and 15 EMEs.[9] These countries represent 80% of the world GDP and include relatively open and financially developed economies. The economies in our sample are in line with other cross-asset contagion studies, as for example, Chudik and Fratzscher (2011) and Beirne and Gieck (2014).[10] The data is obtained from Thomson Datastream. For government bond yields, we use longer maturities (10 years, for the UK, we use nine years). For stock markets, we use Datastream country indices denominated in local currency. Adopting the local currency denomination follows the standard practice in the literature. It is motivated by the fact that expressing the indices in their national currencies restricts their changes to the movements in the stock prices only, avoiding distortions induced by changes in the exchange rates. Our sample starts on the 23rd of August 1993 and ends on the 23rd of August 2013. The span of our sample is comparable with others in the literature.[11]

Regarding the frequency of the data, the literature on contagion commonly uses daily or weekly data (for daily data, e.g. Caporale, Pittis, and Spagnolo, 2006; Dungey and Gajurel, 2014; for weekly data, e.g. Chudik and Fratzscher, 2011; Beirne and Gieck, 2014). We choose to analyse daily prices rather than weekly, mainly for two reasons.

[9] Australia, Austria, Belgium, Brazil, Canada, China, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sweden, Thailand, Taiwan, United Kingdom, and the United States. We later exclude Sweden from the results since models did not converge.
[10] We used the countries that are common in these two studies. Since Chudik and Fratzscher (2011) considered the Euro Area as a whole, we considered the Euro Area countries used in Beirne and Gieck, (2014).
[11] For example, Beirne and Gieck (2014) start their sample in 1998.

First, according to Baig and Goldfajn (1999) and Aït-Sahalia, Cacho-Diaz, and Laeven (2015), most correlations tend to disappear in five days or even less. Second, Nagayasu (2002) and Armada, Leitão, and Lobão (2011) show that contagion effects are less detectable when using less frequent data.

Besides analysing each country individually, we are also interested in detecting trends and results across some groups of countries. Therefore, in line with Chudik and Fratzscher (2011) and Beirne and Gieck (2014), we also analyse groups of countries, in particular, the Euro Area (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain), Other Advanced Economies (Australia, Canada, Denmark, Japan, New Zealand, Norway, South Africa, UK, and the US), and emerging market regions – Emerging Asia (China, Hong Kong, India, Indonesia, Malaysia, Singapore, Taiwan, and Thailand), Emerging Europe (Czech Republic, Hungary, Poland, and Russia), and Latin America (Brazil, Colombia, and Mexico).[12] The definition of the groups follows the common practice of this literature (Chudik and Fratzscher, 2011; Beirne and Gieck, 2014).

Table 2.1 presents some descriptive statistics for the different data series, distinguishing between the normal and the crisis periods. The statistics in Table 2.1 show significant differences in mean returns across markets. When comparing the returns in the normal period with the returns in the crisis period, all groups (except the sovereign bond markets of EME Europe) decreased its mean and increased its standard deviation, implying an increase in the uncertainty.

2.4.2. GFC Period Identification

In this section, we implement the methodology described in Subsection 2.3.5 to identify the GFC period. As stated earlier, this methodology consists of combining two approaches to identifying the crisis period. First, we use economic news events representing the GFC to define a relatively long crisis period. Second, we use volatility estimates from the US stock market (the ground-zero market) to identify regimes of excess volatility. The crisis period is thus the period when the results of the two methodologies overlap.

[12] This group does not include all the economies in the Euro Area.

Starting by the first approach, we follow the common practice of the literature and use the timelines provided by the Federal Reserve Board of St. Louis (2009) and Gorton and Metrick (2012).[13] According to these studies, the GFC can be confined from August 2007 until March 2009. The crisis start is justified by the deterioration of liquidity in the money market and the run on US subprime originator Countrywide on the 17th of August 2007 (Federal Reserve Board of St. Louis, 2009; Gorton and Metrick, 2012). The month assumed to be the end date is characterized by the absence of adverse news events and a stock market recovery (Federal Reserve Board of St. Louis, 2009; Gorton and Metrick, 2012).

Table 2.1 – Descriptive Statistics

	Normal Period				Crisis Period			
	Avg (%)	Min (%)	Max (%)	Std dev	Avg (%)	Min (%)	Max (%)	Std Dev
US stock market	0.038	-6.799	5.367	0.011	-0.129	-9.377	3.246	0.097
Stock market indices								
Advanced	0.031	-20.254	16.470	0.013	-0.274	-13.536	16.262	0.028
of which:								
Euro Area	0.029	-20.254	16.470	0.015	-0.310	-10.357	16.262	0.028
Other Advanced	0.034	-14.485	9.153	0.011	-0.258	-13.861	12.292	0.030
Emerging markets	0.053	-65.969	28.123	0.016	-0.169	-15.316	24.610	0.029
of which:								
EME Asia	0.052	-22.773	19.836	0.015	-0.159	-12.116	15.712	0.026
EME Europe	0.032	-65.969	28.123	0.021	-0.263	-15.316	24.610	0.037
EME Latin America	0.086	-10.482	19.527	0.013	-0.069	-9.940	9.241	0.024
Sovereign Bonds								
Advanced	-0.013	-25.251	26.544	0.014	-0.123	-19.203	13.927	0.021
of which:								
Euro Area	-0.015	-25.251	16.939	0.012	-0.133	-10.061	11.159	0.019
Other Advanced	-0.010	-21.468	26.544	0.017	-0.120	-19.203	13.927	0.025
Emerging markets	-0.029	-32.316	31.594	0.030	-0.056	-23.195	26.136	0.031
of which:								
EME Asia	-0.014	-26.970	27.307	0.028	-0.152	-17.654	16.346	0.028
EME Europe	-0.053	-19.733	19.375	0.042	0.174	-23.195	26.136	0.037
EME Latin America	-0.037	-32.316	31.594	0.021	-0.105	-13.884	19.956	0.028

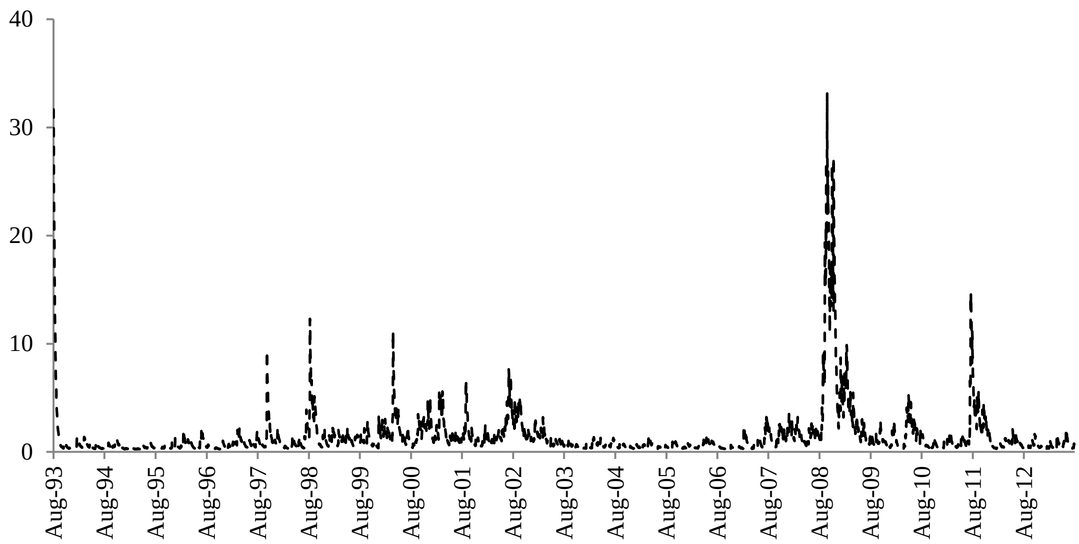
This table displays summary statistics for daily returns for each group of countries, separated by asset class and by normal and crisis period. Source: Author's calculations based on data from DataStream

[13] See, for example, Baur (2012).

Turning to the second approach, we estimate a time-varying conditional volatility, defining the crisis period when the conditional volatility continuously exceeds a threshold. As stated earlier, we use the volatility of the US stock market returns to identify the GFC period because we assume that this crisis originated in the US financial sector. The conditional volatility is estimated with an asymmetric GARCH model (Glosten, Jagannathan, and Runkle, 1993), as it is common in the literature. We then follow Baur (2012) and choose the 95% quantile based on the pre-crisis distribution of return volatility, as the threshold to define excess volatility. Figure 2.1 plots the conditional volatility estimates of the US daily returns for the period from 23rd of August 1993 to 23rd of August 2013. The resulting period in which the volatility of US stock returns continuously exceeds the threshold (i.e. the 95% quantile) is from September 2008 until March 2009.

Overlapping both periods, we define the GFC period from September 2008 until March 2009. We will use later this period for the crisis period dummy variable (variable D_{crisis} in Equation 2.4).

Figure 2.1 – Conditional Volatility: US Stock Returns



The figure plots conditional volatility estimates (asymmetric GJR-GARCH(1,1)) of the US stock market index.

2.5. Empirical Results

This section has two subsections. In Subsection 2.5.1, we focus on the contagion effects stemming directly from the United States, i.e. exogenous contagion effects (captured by parameter γ in Equation 2.4). In particular, we compare the occurrences of contagion effects stemming directly from the US when considering the US as the unique source of contagion with those occurrences when considering the possibility of endogenous contagion effects arising from other countries. Thus, from this exercise, we assess whether the contagion effects identified using the approach followed in the literature were directly transmitted by the US or were indirectly transmitted by other countries in reaction to the normal spillovers from the US.

In Subsection 2.5.2, we analyse endogenous contagion effects, i.e. contagion effects stemming from countries other than the US (parameter φ_{ij} in Equation 2.4). As stated earlier, these endogenous contagion effects are identified in the presence of the exogenous shock from the US. In particular, we study which countries transmitted and received more endogenous contagion effects; we examine cross-asset and within-asset contagion effects; and, we also contribute to three debates in the literature on contagion in the GFC.

2.5.1. Contagion Effects from the United States

Table 2.2 summarizes our results regarding contagion effects stemming directly from the US (parameter γ in Equation (2.4) presented in Subsection 2.3.3). A positive and statistically significant coefficient identifies contagion.

Table 2.2 – Contagion Effects from the United States

	Contagion from US		Number of regressions in which the US contagion loses significance (out of 33)	Number of regressions in Column (3) that have other significant contagion sources (% of the regressions in Column (3) in brackets)
	Standard Approach (1)	Our Approach (2)	(3)	(4)
Euro Area				
Austria	C^{***}	C^{***}	0	-
Belgium	C^{***}		7	2 (29)
Finland			-	-
France	C^{*}		21	11 (52)
Germany			-	-
Greece			-	-
Ireland	C^{***}		3	2 (66)
Italy	C^{***}		2	1 (50)
Netherlands	C^{**}		17	9 (53)
Portugal	C^{***}		4	4 (100)
Spain	C^{**}		11	7 (63)
Other Advanced Economies				
Australia	C^{*}		32	9 (28)
Canada	C^{***}		1	1 (100)
Denmark			-	-
Japan			-	-
New Zealand	C^{**}		23	15 (65)
Norway	C^{***}		3	3 (100)
South Africa	C^{***}	C^{***}	0	-
United Kingdom			-	-
Emerging Asia				
China			-	-
Hong Kong			-	-
India			-	-
Indonesia			-	-
Malaysia			-	-
Singapore			-	-
Thailand			-	-
Taiwan			-	-
Emerging Europe				
Czech Republic	C^{***}		1	1 (100)
Hungary	C^{**}		5	4 (80)
Poland			-	-
Russia	C^{***}		5	5 (100)
Latin America				
Brazil	C^{**}		7	3 (43)
Colombia	C^{***}	C^{***}	0	-
Mexico			-	-
Total	18	3	-	-

The table shows the estimation results of a model testing for exogenous contagion effects stemming directly from the US stock market. C denotes contagion, i.e. the parameter γ specified in Eq.(2.4) is positive and statistically significant. *** Denotes statistical significance at 1%. ** Denotes statistical significance at 5%. * Denotes statistical significance at 10%. - Denotes not applicable.

Columns (1) and (2) focus on the contagion effects stemming from the US. Column (1) considers the US as the unique source of contagion (i.e. the approach in the literature), whereas Column (2) considers that other countries may be additional endogenous sources of contagion (our approach and key contribution).[14] We compare the results in Column (1) with the results in Column (2) to assess the impact of our approach in identifying contagion effects stemming directly from the US.

Column (1) of Table 2.2 presents the estimates for the standard approach, suggesting that (i) the US contaminated a large share of countries in our sample (18 out of 34), and (ii) the US did not contaminate Emerging Asian markets. These two results are broadly in line with the literature (e.g., Horta *et al.*, 2010; Naoui *et al.*, 2010; Morales and Andreosso-O'Callaghan, 2012).

Column (2) adds the possibility of multiple contagion sources, thus allowing contagion effects to stem from other countries in reaction to the exogenous shock from the US. The estimates of the contagion effects arising directly from the US in Column (2) suggest that the US only contaminated Austria, Colombia, and South Africa. Thus, the number of contagion effects stemming directly from the US identified by our approach is substantially lower than the number of contagion effects identified by the standard method (three vs 18), suggesting that the literature may have overidentified the contagion effects stemming directly from the US.

Columns (3) and (4) of Table 2.2 give more insight into why our approach substantially reduces the identification of cases of contagion effects stemming directly from the US. As stated in Subsection 2.3.2, our approach requires identifying contagion effects between each pair of countries, studying *all* possible combinations. Thus, our approach introduces two major changes to the method used in the literature. On the one hand, it adds potential sources of contagion. On the other hand, it requires estimating 33 (i.e., N-1) regressions for each country (instead of just one regression). Thus, as stated in Subsection 2.3.4, there are 33 estimates for the US contagion parameter (parameter γ specified in Equation 2.4) for each market, and we only consider contagion when the parameter is significantly positive across all regressions. Columns (3) and (4) allow disentangling the impact of these two changes on the identification of contagion effects stemming directly from the US.

[14] Given the cross-asset dimension of our study, in Column (1) we also consider that a country's stock market can contaminate its sovereign bond market and vice-versa.

Column (3) presents, for each country, the number of regressions (out of 33) in which the US loses significance as a contagion source. Thus, this column allows analysing how frequent the presence of additional possible sources of contagion dismisses the US as a contagion source. For instance, the US contagion parameter for Belgium is insignificant in seven regressions, suggesting that in seven cases, the presence of another potential source of contagion dismisses the US as a direct contagion source to Belgium. The results in Column (3) show that in the majority of countries (for example, Australia, France, and New Zealand) the US loses significance as a contagion source in numerous regressions. Only in Canada and the Czech Republic, the significance of the US contagion parameter is eliminated by a single regression. These results imply that even if we relax the definition of contagion from the US and consider that the US contagion parameter must be significantly positive in at least 95% of the 33 cases, i.e. more than 31 regressions (for example, to minimize the possibility of spurious regressions impacting the results), we still find a substantial reduction in the identification of contagion effects from the US. In this case, instead of three countries, we would consider that the US had directly contaminated five countries (Austria, Canada, Czech Republic, and South Africa), which is still much lower than the 18 countries identified by the standard methodology.

Column (4) of Table 2.2 shows how frequent the contagion parameter from an additional source is significant when the US loses significance as a contagion source. For instance, two of the seven regressions (i.e. 29%) in which the US contagion parameter for Belgium is insignificant suggest that contagion effects were stemming from other countries. The results in Column (4) show that, most of the times, the presence of significant contagion effects from other countries dismisses contagion effects directly from the US: in 12 countries (out of 15), there are other significant contagion sources in at least 50% of the cases when the US contagion parameter loses significance. [15] These results suggest that, in these cases, the contagion effects stemmed from other countries, rather than directly from the US. Also, the majority of the percentages presented in Column (4) is under 100%, i.e. there are some regressions where there are no contagion effects from other countries, but the US contagion parameter still loses significance. This result suggests that the normal spillover from another country is enough to deny the existence of contagion effects stemming directly from the US.

[15] Only Australia, Belgium, and Brazil show a percentage lower than 50% in Column (4) of Table 2.2.

Given the discussion above, the results presented on Table 2.2 suggest that despite contagion effects, the spreading of the GFC directly from the US may have majorly occurred from normal spillovers, which were amplified by other markets in reaction to these spillovers. These results draw emphasis on the motivation for this study because they are only possible to find when we do not focus exclusively on the contagion effects transmitted by the US.

Even though these results differ from the majority of the literature on contagion in the GFC, they are broadly in line with a few studies that also find evidence suggesting that contagion effects stemming directly from the US may have been more limited than implied by the standard literature (e.g., Kamin and DeMarco, 2012; Bekaert *et al*., 2014). While Bekaert *et al.* (2014) find that domestic shocks were more relevant than shocks stemming from the US, Kamin and DeMarco (2012) find little evidence of contagion from the US to abroad and suggest that indirect contagion may have played a more significant role in spreading the crisis. Our study goes beyond this suggestion by identifying which markets were also responsible for exacerbating the GFC in response to the initial shock directly transmitted by the US. In the next subsection, we analyse these endogenous contagion effects thoroughly.

2.5.2. Endogenous Contagion Effects in the GFC

This subsection has three subsections. In Subsection 2.5.2.1, we exclusively focus on the cross-country dimension of our study. In particular, we analyse the groups of countries identified in Subsection 2.4.1 in terms of transmitters and receivers of contagion effects. In Subsection 2.5.2.2, we turn to the asset-dimension of our study. This subsection first analyses and compares cross-asset contagion effects with within-asset contagion effects in the GFC. Afterwards, this subsection provides with a more in-depth cross-country analysis, focusing on the cross-country contagion effects that occurred in each asset combination. In Subsection 2.5.2.3, we also contribute to three debates that exist in the literature on contagion effects in the GFC, mainly the links from the GFC to the ESDC, contagion effects to Emerging Asian markets, and contagion effects between AEs and EMEs.

2.5.2.1. The Largest Transmitters and Receivers of Contagion Effects in the GFC

Table 2.3 summarizes our results regarding the existence of contagion effects stemming from countries other than the US (parameters Φ in Equation 2.4).[16] The table allows the identification of the number of endogenous contagion effects transmitted and received by each country. Thus, this section exclusively focuses on the cross-country dimension of the contagion effects. As referred above, these endogenous contagion effects are identified in the presence of the exogenous shock from the US.

Column (1) of Table 2.3 shows that Latin America (42.67) stands out as the largest transmitter of contagion effects, followed by Emerging Asia (30.75). The other three regions do not substantially differ between each other regarding the average number of contagion effects transmitted. These results suggest that Latin America and Emerging Asia – two emerging market regions – were critical to exacerbate the GFC. These results may be surprising because it implies that investors have become more reactive/concerned with the developments in these two emerging market regions during the GFC than with the events in AEs, even though the GFC started in an advanced economy and AEs were more exposed to subprime assets.

Column (1) and (2) present the number of contagion effects transmitted and received by each country, respectively. Column (3) displays the net effect, i.e. the difference between contagion effects transmitted and contagion effects received by each country; this column allows identifying countries that were net transmitters and net receivers of contagion effects during the GFC. For instance, Austria transmitted 17 contagion effects and received 30 contagion effects, which means that Austria was a net receiver of contagion effects (17 – 30 = -13). To ease the interpretation of results and to detect trends across groups of countries, Table 2.3 also presents the average of contagion effects (transmitted, received, and the net effect) in each group of countries presented in Subsection 2.4.1. For instance, on average, each Euro Area country transmitted 25.36 contagion effects and received 27.82 contagion effects, which means that the Euro Area was a net receiver group of contagion effects.

[16] A positive and statistically significant positive coefficient implies contagion.

Table 2.3 – Transmitters and Receivers of Contagion Effects

	Transmitter	Receiver	Net effect
	(1)	(2)	(3) = (1) – (2)
Euro Area	(25.36)	(27.82)	(-2.45)
Austria	17	30	-13
Belgium	27	31	-4
Finland	23	35	-12
France	23	31	-8
Germany	32	24	8
Greece	43	28	15
Ireland	19	28	-9
Italy	28	24	4
Netherlands	27	27	0
Portugal	21	25	-4
Spain	19	23	-4
Other Advanced Economies	(22.63)	(28.75)	(-6.13)
Australia	14	12	2
Canada	20	43	-23
Denmark	38	23	15
Japan	18	22	-4
New Zealand	11	28	-17
Norway	23	22	1
South Africa	29	41	-12
UK	28	39	-11
Emerging Asia	(30.75)	(23.38)	(7.38)
China	47	10	37
Hong Kong	38	21	17
India	29	36	-7
Indonesia	28	9	19
Malaysia	19	44	-25
Singapore	34	26	8
Thailand	28	27	1
Taiwan	23	14	9
Emerging Europe	(18.25)	(27.00)	(-8.75)
Czech Rep.	17	19	-2
Hungary	14	25	-11
Poland	20	17	3
Russia	22	47	-25
Latin America	(42.67)	(25.33)	(17.33)
Brazil	48	41	7
Colombia	38	12	26
Mexico	42	23	19

This table presents the number of occurrences of endogenous contagion effects (transmitted, received, and the net-effect) by country

Column (2) shows that, on average, there are almost no substantial differences regarding the number of contagion effects received by each group of countries, suggesting that contagion effects were uniformly received across the globe. Only Emerging Asia slightly emerges as the region with the lowest average number of contagion effects received (23.38), suggesting that this region was better prepared for this crisis. This lower number is mainly because of Indonesia (9) and China (10), which appear to be the least vulnerable countries to contagion effects. Regarding the receivers of contagion, these results are comparable to those we find in Column (1) of Table 2.2. Namely, using the standard approach (Column (1) of Table 2.2), we find that the majority of the countries in the sample received contagion effects, with the apparent exception of Emerging Asian countries. Thus, these results are broadly in line with the cross-country contagion literature in the GFC (e.g., Horta *et al*., 2010; Naoui *et al*., 2010; Morales and Andreosso-O'Callaghan, 2012). The major difference with those studies is that we find that these receivers of contagion, instead of being directly contaminated by the US, were contaminated via other countries.

Column (3) shows a clear distinction between net receivers and net transmitters. On the one hand, Advanced Economies (Euro Area and Other Advanced Economies) and Emerging Europe were net receivers of contagion effects. On the other hand, Latin America and Emerging Asia were net transmitters of contagion effects. These results reinforce the result found above, suggesting that these emerging markets have exacerbated the impact of the GFC, which started in an advanced economy.

The results above justify the approach of this study and contribute to the literature on cross-country contagion in the GFC (e.g. Naoui *et al.*, 2010; Yiu *et al*., 2010; and Aloui *et al*., 2011). By analysing multiple sources of contagion, we find that, even considering the presence of the US stock market as a contagion source, the two emerging regions identified above were important in exacerbating the GFC. To the best of our knowledge, these results have not been uncovered before. Based on these results, we argue that the GFC was a complex crisis regarding the dynamics of contagion effects, therefore corroborating our approach of considering multiple sources of contagion.

2.5.2.2. Within-asset and Cross-asset Contagion Effects

Tables 2.4 to 2.6 present the number of endogenous contagion effects, while focusing on the asset class of the transmitter and receiver of contagion effects. Table 2.4 displays the contagion effects aggregated by asset class, whereas Tables 2.5 and 2.6 present the number of contagion effects transmitted and received by each country in each asset combination. Thus, in Table 2.4, we exclusively focus on the asset-dimension of our study. In contrast, in Tables 2.5 and 2.6, we focus on the two dimensions of our research, i.e. cross-country and asset dimensions.

Table 2.4 presents the estimation results for contagion effects aggregated by asset class. In particular, the table displays the occurrences of within-asset contagion (diagonal values) and the occurrences of cross-asset contagion (off-diagonal values). For instance, there were 241 contagion effects identified within the stock market (that is, contagion effects from a stock market to another stock market). To ease the interpretation of results, Table 2.4 presents the total of contagion effects *transmitted* by each class of assets in Row (3), and the total of contagion effects *received* by each class of assets in Column (3). The table also displays, in square brackets, the standard deviations of the occurrences of contagion effects in each asset combination.

Table 2.4 – Within-asset and Cross-asset Contagion Effects by Asset Class

		Transmitters		
		Stock Market (1)	Bond Market (2)	Total (1) + (2) = (3)
Receivers	Stock Market (1)	241	210	451
		[4.88]	[5.07]	[8.16]
	Bond Market (2)	234	222	456
		[3.44]	[2.79]	[4.22]
	Total (1) + (2) = (3)	475	432	907
		[6.49]	[5.46]	[9.48]

The table presents contagion effects aggregated by asset class. In columns, the table identifies contagion effects transmitted by each asset class; in rows, the table identifies contagion effects received by each asset class. In square brackets, the table presents the standard deviation.

We highlight two key results from Table 2.4. First, Row (3) shows that there is no substantial difference between the occurrences of contagion effects transmitted by stock markets and by sovereign bond markets (475 vs 432). [17] These results may be surprising

[17] The statistical test for the difference between the two means has a p-value of 0.38.

because the GFC started as a banking crisis and has spread through the financial system. It was thus expectable that investors reacted more to losses in the stock market, exacerbating the GFC from the stock market. These results, however, suggest that investors may have also adjusted their portfolios in sovereign bond markets, leading to numerous contagion effects stemming from these markets. To the best of our knowledge, the identification of multiple contagion effects arising from the sovereign bond market in the GFC has not been uncovered, justifying our choice of including the sovereign bond market in our analysis.

Second, comparing the off-diagonal values (234 + 210 = 444) with the diagonal values (241 + 222 = 463) of Table 2.4, the results show that there is no substantial difference between the occurrences of cross-asset contagion and the number of occurrences of within-asset contagion (444 vs 463, respectively). [18] The extensive identification of cross-asset contagion effects is in line with the findings of Petmezas and Santamaria (2014) and Dua and Tuteja (2016).

Even though we identify numerous cross-asset contagion effects, a small number of works has found that before the GFC stock-bond correlations tended to decrease during crisis periods, i.e. cross-asset contagion was a rare phenomenon before the GFC (see, for example, Baur and Lucey, 2009; Baur, 2010). For instance, based on an increase in diversification and a more frequent portfolio rebalancing of investors, Baur (2010) explains that the decline of stock-bond correlations during crisis periods (and, consequently, the absence of cross-asset contagion) occurs because agents react mostly to cross-country information. This implies that, during crisis periods, agents tend to adjust their portfolio within the same asset class across countries (i.e., within-asset contagion).

However, the existence of cross-asset contagion can be explained by investor induced contagion caused by wealth effects. As argued by Petmezas and Santamaria (2014), adverse shocks to investors' wealth increase the risk of reaching capital limits, which encourage a liquidation of positions, causing a liquidity spiral between markets. The decline in liquidity in both markets increases volatility in both asset classes, increasing stock-bond comovements during a financial crisis (i.e., cross-asset contagion).

Our results, thus, point to the possibility that the GFC had different cross-asset contagion dynamics than before. In country-specific crises (where wealth effects may be residual), the increase in portfolio diversification (through different asset classes) may

[18] The statistical test for the difference between the two means has a p-value of 0.70.

lead to an absence of cross-asset contagion effects. In contrast, our results suggest that in the GFC (which was a systemic crisis) severe financial constraints to investors may have reduced the possibilities to avoid the crash across assets.

Tables 2.5 and 2.6 present the estimations for endogenous contagion effects by each asset combination. Table 2.5 (2.6) shows the number of within-asset (cross-asset) contagion effects transmitted and received by each country.

Table 2.5 presents the number of contagion effects transmitted and received by each country (and the net effect) within the stock market in Columns (1) to (3), and within the sovereign bond market in Columns (4) to (6). For instance, the Austrian stock market transmitted five contagion effects to other stock markets and received eight contagion effects from other stock markets, which means that the Austrian stock market is a net receiver of contagion effects within the stock market (5 – 8 = -3). As before, to detect trends across groups of countries, Table 2.5 also presents the average of contagion effects (transmitted, received, and the net effect) in each group of countries presented in Subsection 2.4.1.

Columns (1) to (3) show that Latin American stock markets stand out as the largest net transmitters of contagion effects within the stock market (8.67). In fact, Latin American stock markets are, on average, the largest transmitters and the lowest receivers of contagion effects within the stock market (13.33 and 4.66, respectively). The soundness of Latin American stock markets has been explained by significant improvements in external balance sheets during the preceding boom, which weakened financial contagion channels to that region, according to Ocampo (2009). However, to the best of our knowledge, the fact that Latin American stocks transmitted extensive contagion effects, playing an important role in exacerbating the GFC to other stock markets, has not been uncovered before.

Columns (4) to (6) of Table 2.5 display the number of occurrences of contagion effects within the sovereign bond market and show that the Euro Area sovereign bond markets stand out as the largest transmitters and receivers of contagion effects (8.00 and 7.64, respectively). These results suggest that the GFC was a turbulent period for the Euro Area sovereign bond markets. Recall that the GFC occurred one year before the beginning of the Euro Area Sovereign Debt Crisis. Thus, these results motivate the need to analyse contagion effects within the Euro Area sovereign bond market, assessing if there are links between these two crises. This particular market will be further investigated in Subsection 2.5.2.3.1.

Table 2.5 – Within-asset Contagion Effects

	Stock			Bond		
	Transmitter (1)	Receiver (2)	Net effect (3) = (1) – (2)	Transmitter (4)	Receiver (5)	Net effect (6) = (4) – (5)
Euro Area	(6.36)	(6.09)	(0.27)	(8.00)	(7.64)	(0.36)
Austria	5	8	-3	4	6	-2
Belgium	7	9	-2	8	6	2
Finland	5	4	1	3	21	-18
France	7	8	-1	7	4	3
Germany	15	3	12	7	9	-2
Greece	9	9	0	11	10	1
Ireland	3	5	-2	3	10	-7
Italy	6	5	1	11	3	8
Netherlands	5	8	-3	12	3	9
Portugal	2	3	-1	12	7	5
Spain	6	5	1	10	5	5
Other Advanced Economies	(4.75)	(9.50)	(-4.75)	(5.13)	(5.25)	(-0.13)
Australia	1	3	-2	2	5	-3
Canada	2	8	-6	7	9	-2
Denmark	11	5	6	6	5	1
Japan	5	13	-8	8	1	7
New Zealand	2	10	-8	1	2	-1
Norway	4	12	-8	4	1	3
South Africa	6	13	-7	7	13	-6
UK	7	12	-5	6	6	0
Emerging Asia	(9.50)	(7.25)	(2.25)	(5.75)	(7.13)	(-1.38)
China	15	3	12	4	2	2
Hong Kong	21	7	14	8	9	-1
India	13	4	9	7	12	-5
Indonesia	5	4	1	7	2	5
Malaysia	2	12	-10	7	14	-7
Singapore	10	18	-8	6	3	3
Thailand	8	2	6	1	14	-13
Taiwan	2	8	-6	6	1	5
Emerging Europe	(4.25)	(6.50)	(-2.25)	(6.25)	(6.00)	(0.25)
Czech Rep.	1	4	-3	8	4	4
Hungary	4	8	-4	5	4	1
Poland	6	5	1	7	3	4
Russia	6	9	-3	5	13	-8
Latin America	(13.33)	(4.66)	(8.67)	(7.33)	(5.00)	(2.33)
Brazil	15	12	3	9	7	2
Colombia	8	0	8	5	0	5
Mexico	17	2	15	8	8	0

The table presents the number of within-asset contagion effects transmitted and received by stock and sovereign bond markets.

Table 2.6 presents the number of cross-asset contagion effects transmitted and received (and the net effect) by each country's stock market in Columns (1) to (3) and by each country's sovereign bond market in Columns (4) to (6). For instance, the Austrian stock market transmitted two contagion effects to sovereign bond markets and received eight contagion effects from sovereign bond markets (2 – 8 = -6). Table 2.6 also displays the average of contagion effects in each group of countries.

Table 2.6 – Cross-asset Contagion Effects

	Stock			Bond		
	Transmitter (1)	Receiver (2)	Net effect (3) = (1) – (2)	Transmitter (4)	Receiver (5)	Net effect (6) = (4) – (5)
Euro Area	(5.91)	(7.09)	(-1.18)	(5.09)	(7.00)	(-1.91)
Austria	2	8	-6	6	8	-2
Belgium	6	10	-4	6	6	0
Finland	8	3	5	7	7	0
France	6	8	-2	3	11	-8
Germany	5	6	-1	5	6	-1
Greece	10	4	6	13	5	8
Ireland	8	8	0	5	5	0
Italy	6	5	1	5	11	-6
Netherlands	7	9	-2	3	7	-4
Portugal	4	10	-6	3	5	-2
Spain	3	7	-4	0	6	-6
Other Advanced Economies	(9.00)	(7.75)	(1.25)	(3.75)	(6.25)	(-2.50)
Australia	4	0	4	7	4	3
Canada	5	18	-13	6	8	-2
Denmark	18	8	10	3	5	-2
Japan	3	5	-2	2	3	-1
New Zealand	6	7	-1	2	9	-7
Norway	14	8	6	1	1	0
South Africa	7	5	2	9	10	-1
UK	15	11	4	0	10	-10
Emerging Asia	(5.88)	(2.00)	(3.88)	(9.63)	(7.00)	(2.63)
China	7	3	4	21	2	18
Hong Kong	8	2	6	1	3	-2
India	3	2	1	6	18	-12
Indonesia	7	2	5	9	1	8
Malaysia	4	2	2	6	16	-10
Singapore	5	2	3	13	3	9
Thailand	7	3	4	12	8	4
Taiwan	6	0	6	9	5	4
Emerging Europe	(6.25)	(7.75)	(-1.50)	(1.50)	(6.75)	(-5.25)
Czech Rep.	8	8	0	0	3	-3
Hungary	3	8	-5	2	5	-3
Poland	4	8	-4	3	1	2
Russia	10	7	3	1	18	-17
Latin America	(8.33)	(7.67)	(0.67)	(13.67)	(8.00)	(5.67)
Brazil	8	10	-2	16	12	4
Colombia	9	5	4	16	7	9
Mexico	8	8	0	9	5	4

The table presents the number of cross-asset contagion effects transmitted and received by stock and sovereign bond markets.

Columns (1) and (2) present the results for the cross-asset contagion effects transmitted and received by stock markets, respectively. Column (1) shows that the Other Advanced Economies and Latin American stock markets emerge as the most active transmitters of contagion effects to sovereign bond markets (9.00 and 8.33, respectively). These results suggest that these two groups of stock markets may have provoked severe funding constraints to investors, which may have encouraged investors to liquidate their positions in other asset markets, thus increasing the comovements between sovereign bond markets and these two groups of stock markets.

Column (2) shows that Emerging Asian stock markets stand out as the lowest receiver of contagion effects stemming from sovereign bond markets (2.00), which suggests that Emerging Asian stock markets were more shielded from investor-induced contagion caused by wealth effects than the other stock markets.

Column (4) to (6) display the number of cross-asset contagion effects transmitted and received (and the net effect) by sovereign bond markets and show two key results. First, Latin American sovereign bond markets stand out as the most active transmitters and receivers of cross-asset contagion effects (13.67 and 8.00, respectively). These results suggest that investors in Latin American sovereign bond markets may have faced severe liquidity constraints, which were caused by stock markets (because these sovereign bond markets were primary receivers of cross-asset contagion effects) and have caused contagion to other stock markets (because these sovereign bond markets were major transmitters of cross-asset contagion effects). Second, Emerging Europe sovereign bond markets (especially Russia) emerge as the major net receivers of cross-asset contagion effects (-5.25), which suggests that these sovereign bond markets may have been particularly vulnerable from wealth induced contagion effects.

Overall, the cross-asset contagion results presented above contribute to the literature on cross-asset contagion in the GFC, such as Petmezas and Santamaria (2014) and Dua and Tuteja (2016). These studies tend to use small samples of mostly Advanced Economies to study cross-asset contagion in the GFC.[19] Our results show, however, that there were cross-asset contagion effects that were majorly transmitted or received by

[19] Petmezas and Santamaria (2014) study cross-asset contagion in the UK, US, France, Germany, Spain and Italy, while Dua and Tuteja (2016) study within and cross-asset contagion in China, Eurozone, India, Japan and US.

Emerging Market Economies. These results suggest that, even if a crisis starts in an advanced economy, the focus of the analysis on contagion effects should not be restricted to Advanced Economies.

2.5.2.3. Current debates in the Literature on Contagion Effects in the GFC

This subsection presents results that contribute to three debates in the literature on contagion effects in the GFC. In Subsection 2.5.2.3.1, we focus on the contagion effects within the Euro Area sovereign bond market. This subsection analyses if there were contagion effects within these bond markets and contributes to the literature that links the GFC to the ESDC (e.g. Mody, 2009). Subsection 2.5.2.3.2 focuses on the contagion effects to Emerging Asian markets. In particular, this subsection analyses which group of countries transmitted more contagion effects to Emerging Asian markets and contributes to the literature that studies the impact of the GFC on Emerging Asian markets (e.g. Lee, 2012). In Subsection 2.5.2.3.3, we analyse contagion effects within and across Advanced and Emerging countries. We also examine if EMEs were more isolated than AEs from contagion effects in the GFC, contributing to the literature that examines the impact of the GFC in EMEs (e.g. Dooley and Hutchinson, 2009; Dimitriou, Kenourgios, and Simos, 2013).

2.5.2.3.1. Contagion Effects within the Euro Area Sovereign Bond Market

Table 2.7 presents the estimation results for contagion effects within the Euro Area sovereign bond market during the GFC. The table gives a picture of how investors reacted in the Euro Area sovereign bond market during the GFC, thus contributing to the debate in the literature that examines the links from the GFC to the ESDC.

Table 2.7 – Contagion Effects within the Euro Area Sovereign Bond Market

		Transmitters											
		Aus	Bel	Fin	Fra	Ger	Gre	Ire	Ita	Net	Por	Spa	Total (12)
Receivers	Austria	-					C^{***}		C^{***}	C^{***}	C^{***}	C^{***}	5
	Belgium		-				C^{**}		C^{***}	C^{***}	C^{***}	C^{***}	5
	Finland		C^{***}	-	C^{***}	C^{***}	C^{***}			C^{***}	C^{***}	C^{***}	7
	France				-		C^{*}			C^{**}		C^{*}	3
	Germany				C^{***}	-	C^{*}		C^{***}	C^{***}	C^{***}	C^{***}	6
	Greece	C^{***}	C^{**}		C^{**}		-		C^{***}	C^{***}	C^{***}		6
	Ireland		C^{***}		C^{**}		C^{***}	-	C^{***}	C^{***}	C^{***}	C^{***}	7
	Italy						C^{***}		-				1
	Netherlands						C^{***}			-	C^{**}	C^{**}	3
	Portugal		C^{**}				C^{***}	C^{**}		C^{**}	-	C^{*}	5
	Spain		C^{**}				C^{***}			C^{*}		-	3
	Total (12)	1	5	0	4	1	10	1	5	9	7	8	51
	Net effect (13): Row (12) – Column (12)	-4	0	-7	1	-5	4	-6	4	6	2	5	0

The table shows the estimation results of a model testing for endogenous contagion effects within the Euro Area sovereign bond market. C denotes contagion if φ_{ij} is positive and significant. The transmitters of contagion are displayed in columns, whereas the receivers of contagion are displayed in rows. Model: Equation (2.4). In this case, countries A and B belong to the Euro Area sovereign bond market. *** Denotes statistical significance 1%, ** Denotes statistical significance 5%, * Denotes statistical significance 10%.

Each column in Table 2.7 presents the results for the contagion effects *transmitted* by each sovereign bond market; each row displays the results for the contagion effects *received* by each sovereign bond market. For instance, the Austrian sovereign bond market (1) transmitted contagion effects to the Greek sovereign bond market; and (2) received contagion effects from the sovereign bond markets of Greece, Italy, the Netherlands, Portugal, and Spain. To ease the interpretation of the results, the table also presents the total of contagion effects *received* by each sovereign bond market in Column (12) and the total of contagion effects *transmitted* by each sovereign bond market in Row (12).

We also present the net effect in Row (13), which is given by the difference between the contagion effects transmitted and the contagion effects received by each sovereign bond market. The main advantage of this measure is that, by aggregating several countries into groups, the contagion effects transmitted within the group are cancelled out: the effect transmitted by a country (which counts positively to the net effect) is cancelled by the same effect received by the other country in the same group (which counts negatively to the net effect). Thus, if contagion effects transmitted within the group are cancelled out, this measure allows identifying the global direction of contagion effects across groups, i.e. if a group received/transmitted more contagion effects from/to other groups of countries. This measure is particularly relevant in this section because we divide the Euro Area into the southern European countries and the central and northern European countries to analyse if there was a clear direction of contagion effects within the Euro Area and across these two groups of countries.[20]

We highlight three key results from Table 2.7. First, the overall results in Column (12) show an abnormally high number of contagion effects within the Euro Area sovereign bond market during the GFC (51 out of 110 possible contagion effects).[21] These results suggest intensive portfolio rebalancing effects, increasing the comovements within the Euro Area sovereign bond market.

Second, Row (12) presents the total of contagion effects transmitted by each sovereign bond market, suggesting that the sovereign bond markets of Greece (10), Netherlands (9), Spain (8), and Portugal (7) were the most active sources of contagion within the Euro Area sovereign bond market. These results suggest that investors became more reactive to changes in the yields of these sovereign bonds during the GFC.

Finally, the results in Row (13) of Table 2.7 allow us to identify the global net direction of contagion effects within the Euro Area sovereign bond market. In this sense, dividing this region into the southern European countries (Greece, Italy, Portugal, and Spain) and the central and northern European countries, the sum of the net effect shows that the former region was a major net transmitter of contagion effects, whereas the latter region is a major net receiver of contagion effects (15 vs -15).[22] Thus, in aggregate terms, the net direction of contagion effects within the Euro Area sovereign bond market is from

[20] The choice of dividing the Euro Area into these two groups of countries is motivated by the fact that, during the ESDC, various European policymakers used this division, as stated by Matthijs and McNamara (2015).
[21] We identify 51 contagion effects out of 110 possible situations (11 x 10). For instance, in the whole sample, we identify 940 contagion effects out of 4488 possible situations (34 x 2 x 33 x 2). From this, we conclude that the incidence of contagion effects within the Euro Area sovereign bond market is 46%, which is substantially higher than the incidence in the whole sample (20%).
[22] If we consider the Netherlands as an outlier and not include it in the group of central and northern European sovereign bond markets, the net direction of contagion effects becomes even more pronounced since the total net effect of this group becomes equal to -21.

southern Europe to central and northern Europe. These results suggest that investors overall recognized that the central and northern European countries were exposed to potential problems in the southern European countries and adjusted their portfolios accordingly, increasing the comovements between these two groups of countries.

Overall, the results presented above contribute to the debate that links the GFC to the ESDC, as for example Mody (2009), Pappas, Ingham, Izzeldin, and Steele (2016), and Wu, Erdem, Kalotychou, and Remolona (2016). These studies argue that the GFC changed the investor's risk perceptions. For instance, Wu *et al*. (2016) state that from late 2008, the investors' concern switched to macroeconomic news regarding the health of the EU and that this change in perceived risk in the Euro Area led to a divergence of the bond yields and CDS spreads. In this sense, Pappas *et al*. (2016) argue that Greece was the most affected by the change in the risk perception. Our results go a step further beyond these results, suggesting that investors early recognized that, if problems in Greece or another Euro Area sovereign would arise – most probably in some Southern European country – they would affect the Euro Area as a whole, instead of being limited to a single country. Thus, our results suggest that by late 2008 – one year before the beginning of the ESDC – investors became aware of the potential fragilities of the Euro Area sovereign bond market as a whole, increasing the comovements within this market. The implication of these results is even more relevant because, in mid-2010, political leaders still thought that problems in Greece would be limited to Greece, as can be seen in Wyplosz (2017).

2.5.2.3.2. Contagion Effects to Emerging Asian Markets

The impact of the GFC on Emerging Asian markets has been widely debated in the literature. On the one hand, several studies find that the US did not contaminate Emerging Asian markets (see, for example, Lee, 2012; Wang, 2014; Wu, Meng, and Xu, 2015). Our results in Column (1) in Table 2.2 are in line with these studies, suggesting that the US did not contaminate Emerging Asia, even considering the US as the unique source of contagion. Several reasons have been put forward to explain the perseverance of these markets. First, according to Lai and Ravenhill (2012), Asian banks had minimal exposure to subprime and related assets. For instance, IMF (2009) estimates that Asia's (excluding Japan) exposure to those assets were less than 10% of bank capital. Second, Morales and Andreosso-O'Callaghan (2012) argue that Asian markets have adopted several policy instruments, as for example the Chian Mai Initiative, which made these markets better prepared for coping with the external financial turmoil.[23]

On the other hand, several reasons question the actual resilience of Emerging Asian markets during the GFC. First, Kawai *et al*. (2012) present evidence of capital outflows from Asia during the GFC. Second, as can be seen in Table 2.1, the stock markets of this region had also worse average returns (0.05 vs -0.16) and increased volatility (0.015 vs 0.026) when comparing normal periods with the GFC period.[24] Finally, while our results in Table 2.3 suggest that Emerging Asian markets have received fewer contagion effects than other regions, we still find evidence of contagion effects to this region. In this section, we contribute to the debate on the impact of the GFC on Emerging Asian markets by looking at the sources of contagion effects to this particular region.

Table 2.8 presents contagion effects transmitted to Emerging Asian markets that were identified using our approach. Column (1) and (2) display the number of contagion effects (per country) transmitted to Emerging Asian stock and sovereign bond markets, respectively. To ease the interpretation of the results, Column (3) presents the total of contagion effects transmitted by each country to Emerging Asian markets. The table also shows the mean of contagion effects in each group of countries. For instance, on average, each Euro Area country transmitted 1.64 contagion effects to Emerging Asian stock markets. Row (31) displays the total of contagion effects received by each Emerging Asian asset class (stock and sovereign bond).

[23] The Chiang Mai Initiative consists of a network of bilateral swaps and repurchase agreements through which countries can obtain emergency assistance.

[24] Emerging Asian sovereign bond markets also had worse average returns (-0.014 vs -0.152), but the volatility did not increase (it was 0.028 in both periods).

Table 2.8 – Contagion Effects to Emerging Asia (EA) Markets

	Contagion To EA Stock Markets (1)	Contagion To EA Bond Markets (2)	Total (3) = (1) + (2)
Euro Area	(1.64)	(3.64)	(5.27)
Austria	2	2	4
Belgium	1	3	4
Finland	3	1	4
France	3	3	6
Germany	1	4	5
Greece	3	4	7
Ireland	0	5	5
Italy	2	5	7
Netherlands	1	5	6
Portugal	1	5	6
Spain	1	3	4
Other Advanced Economies	(1.50)	(3.00)	(4.50)
Australia	0	0	0
Canada	0	2	2
Denmark	6	5	11
Japan	1	3	4
New Zealand	1	3	4
Norway	2	3	5
South Africa	1	4	5
UK	1	4	5
Emerging Europe	(1.75)	(3.25)	(5.00)
Czech Rep.	0	5	5
Hungary	2	4	6
Poland	3	3	6
Russia	2	1	3
Latin America	(5.66)	(4.33)	(10.00)
Brazil	6	3	9
Colombia	4	7	11
Mexico	7	3	10
Total (31)	54	90	144

The table presents the number of occurrences of contagion effects transmitted by each country to Emerging Asian stock markets in Column (1), to Emerging Asian sovereign bond markets in Column (2), and to Emerging Asian markets (in general) in Column (3).

We highlight three key results from Table 2.8. First, Row (31) shows that Emerging Asian sovereign bond markets received substantially more contagion effects than stock markets (90 vs 54). This result suggests that Emerging Asian markets were more vulnerable to contagion effects through the sovereign bond market. As Lai and Ravenhill (2012) states, Emerging Asian sovereign bond markets have significantly expanded in the last decade, becoming much more prominent sources of finance relative to bank credit. Since these markets are less established/developed than the Emerging Asian stock markets, our result suggests that the fast expansion of the sovereign bond market may have increased the vulnerability of this market to contagion effects. Also, Column (2) shows that the Southern European countries (Greece, Italy, Portugal, and Spain) – that were identified as critical transmitters of contagion within the Euro Area sovereign bond market in Subsection 2.5.3.1 – were also active sources of contagion effects to Emerging Asian sovereign bond markets. These results are broadly in line with Azis, Mitra, Baluga, and Dime (2013), who conclude that the rise in the yields of the Euro Area sovereign bond markets worsened market sentiment and led to capital outflows from Asian local bond markets.

Second, Column (1) shows that Latin American markets stand out as the largest transmitters of contagion effects to Emerging Asian stock markets. The financial links between these two groups of countries can be dated at least until the Asian Financial Crisis of 1997 when Asian stock markets transmitted contagion effects to Latin American stock markets (see, for example, Fujii, 2005). Now, during the GFC, our results suggest the reverse direction and that the connections between these two regions still exist.

Finally, Column (1) also shows that Advanced Economies (Euro Area and Other Advanced Economies) had, on average, scarce contagion effects to Emerging Asian stock markets, suggesting that Emerging Asian stock markets were well shielded from contagion effects from advanced markets. These results may also shed light on why the US stock market did not contaminate Emerging Asian stock markets.

2.5.2.3.3. Advanced Economies vs EMEs Analysis

During the GFC, EMEs have shown a different reaction than AEs. According to Dooley and Hutchinson (2009), there was a decoupling-recoupling dynamic in EMEs in particular for 11 CDS spreads. Adding to the fact that the GFC started in an advanced economy, these decoupling-recoupling dynamics may suggest that some contagion effects occurred afterwards, in reaction to the first shock stemming from the US. Thus, in this subsection, we contribute to this issue by analysing contagion effects between (i.e., within and across) AEs and EMEs.

Besides this distinct reaction of the EMEs in the GFC, other motivate an analysis of the contagion effects between these two groups of countries. According to Edison and Warnock (2008), EMEs have not only higher transaction costs and a greater likelihood of failed trades than AEs, but also potentially poor financial information that reflects varied accounting practices, disclosure requirements, and enforcement. Despite these frictions, EMEs have increased their share in the global financial market because of the recent trend of financial globalization and due to the reduction of restrictions on cross-border transactions (Elson, 2011). Thus, even though the GFC started in an advanced economy, the expanded share of markets with various financial frictions, such as EMEs, might have helped to exacerbate the GFC.

Table 2.9 displays the average number of endogenous contagion effects transmitted and received by AEs and by EMEs. Columns (1) and (2) present the average number of contagion effects transmitted to AEs and EMEs, respectively. The table also displays the average number of contagion effects transmitted by each group of countries (AEs and EMEs) in Column (3). Columns (4) and (5) present the average number of contagion effects received from AEs and EMEs, respectively. Column (6) displays the average number of contagion effects received by each group of countries. For instance, on average, each advanced economy transmitted 9.68 contagion effects to EMEs and received 13.68 contagion effects from EMEs.

To ease the interpretation of the results, the table also presents (in brackets) the relative number of contagion effects: for contagion effects transmitted, the table displays the average number of contagion effects relative to the number of possible receivers; for contagion effects received, the table presents the average number of contagion effects relative to the number of potential transmitters. For instance, each advanced economy transmitted, on average, 14.53 contagion effects to the other 18 AEs, which represents 0.81 contagion effects relative to the total number of possible receivers (14.53/18 = 0.81). These relative contagion effects are essential to compare fairly the two groups of countries because these groups have different sizes in our sample (there are 19 AEs and 15 EMEs). The table also displays, in square brackets, the standard deviations of the relative number of contagion effects.

Table 2.9 – Advanced Economies vs Emerging Market Economies Analysis

	Contagion effects transmitted to			Contagion effects received from		
	AEs (1)	EMEs (2)	Total (1) + (2) = (3)	AEs (1)	EMEs (2)	Total (1) + (2) = (3)
	14.53	9.68	24.21	14.53	13.68	28.21
AEs	(0.81)	(0.65)	(0.73)	(0.81)	(0.91)	(0.85)
	[0.34]	[0.39]	[0.23]	[0.29]	[0.25]	[0.22]
	17.33	12.47	29.80	12.26	12.47	24.73
EMEs	(0.91)	(0.89)	(0.90)	(0.65)	(0.89)	(0.75)
	[0.39]	[0.32]	[0.32]	[0.45]	[0.31]	[0.36]

The table shows the average number of contagion effects transmitted and received by AEs and EMEs. In brackets, the table presents the number of contagion effects transmitted relative to the number of possible receivers, and the number of contagion effects received relative to the number of possible transmitters. In square brackets, the table displays the standard deviation for the relative numbers.

We highlight three key results from Table 2.9. First, Column (6) shows the average number of contagion effects received by each group of countries (relative to the number of possible transmitters) and suggests that there is no statistically significant difference between the number of contagion effects received by AEs and by EMEs (0.85 vs 0.75).[25] This result suggests that EMEs were similarly contaminated despite the initial financial decoupling stated, for example, by Dooley and Hutchinson (2009) and Dimitriou *et al.* (2013).

Second, Column (3) presents the average number of contagion effects transmitted by each group of countries (relative to the number of possible receivers) and suggests that EMEs transmitted on average more contagion effects than AEs (0.90 vs 0.73).[26] Even though the GFC started in an advanced economy, this finding indicates that EMEs contributed more to exacerbate the crisis than AEs. This result further motivates the need to use an approach that allows the possibility to have multiple contagion sources as ours since this result can only be uncovered with this approach.

[25] The statistical test for the difference between these two means has a p-value of 0.32.
[26] The statistical test for the difference between these two means has a p-value of 0.09.

Finally, comparing the values in Row (1), Column (2) with the values in Row (2), Column (1) of Table 2.9, the results shows that, in relative terms, EMEs transmitted more contagion effects to AEs than the opposite (0.91 vs 0.65).[27] Thus, this result suggests that EMEs have provoked more instability to AEs in the GFC than the opposite. We call attention to this result because the literature on EMEs in the GFC has analysed how Advanced Economies (mainly, the US) destabilized EMEs (e.g. Dimitriou *et al.*, 2013; Celik, 2012), but we suggest that the opposite direction of instability should also be assessed. This result, thus, draws emphasis on the motivation for this study because it is only possible to find it when one considers multiple sources of contagion.

2.6. Concluding Remarks

In this study, we undertook a comprehensive analysis of financial contagion in the GFC. Instead of just considering the contagion effects from the ground-zero market, we hypothesised that any market might contaminate others in reaction to the initial shock stemming from the ground-zero country. With this approach, we aimed to analyse relevant contagion dynamics beyond the effects directly arising from the US.

We used a VAR-DCC-GARCH model to estimate contagion effects between the stock and sovereign bond markets of a broad set of 34 countries worldwide. In particular, we do not deny the US as the ground-zero country, but we also allow other countries to be sources of contagion. Thus, *(i)* we let the US being the ground-zero country, as an exogenous variable; and, at the same time, *(ii)* we allow other countries to transmit contagion effects in reaction to the shock stemming from the ground-zero country, as endogenous variables. To the best of our knowledge, this is the first study to consider these two effects simultaneously in the GFC.

Our findings are as follows. First, the United States directly transmitted very few contagion effects during the GFC. This result contrasts to the majority findings in the literature, suggesting that the spreading of the GFC directly from the US may have majorly occurred from normal spillovers. Also, our results indicate that the normal spillovers from the US may have been amplified by other markets in reaction to these spillovers. Thus, these results suggest that some contagion effects, identified by the literature as

[27] The statistical test for the difference between these two means has a p-value of 0.05.

coming directly from the US, may have come indirectly via other markets. These results strengthen the motivation of our approach since they indicate that some crucial dynamics occurred in markets other than the United States.

Second, Latin American and Emerging Asian markets were found to be the largest transmitters of endogenous contagion effects in the GFC. These results suggest that investors became more reactive with the developments in these two emerging market regions than with the events in AEs, despite the facts that (1) the GFC started in an advanced economy and (2) AEs were more exposed to subprime assets.

Third, we found that there is no substantial difference between the number of occurrences of cross-asset contagion and the number of occurrences of within-asset contagion during the GFC. This result contrasts to the findings in the literature of stock-bond correlations before the GFC and points to the possibility that the GFC had different cross-asset contagion dynamics than before.

Fourth, we found an abnormally high number of contagion effects within the Euro Area sovereign bond market during the GFC, i.e. several months before the beginning of the ESDC. In addition, we found that the sovereign bond markets of southern European countries (Greece, Italy, Portugal, and Spain) contaminated various central and northern European sovereign bond markets. These results suggest that investors generally recognize that the central and northern European countries were exposed to potential problems in the southern European countries.

Fifth, we found that Emerging Asian stock markets received very few contagion effects from advanced markets. This result might shed light on why several studies that consider the US as the unique source of contagion do not find contagion effects to these markets. Despite the immunity to contagion effects from more mature markets, we found that Latin American markets transmitted numerous contagion effects to Emerging Asian stock markets. In addition, we also found that Emerging Asian markets received more contagion effects via the sovereign bond market than via the stock market.

Finally, our results indicate that EMEs transmitted on average more contagion effects than AEs. These results reinforce the idea that EMEs are becoming non-passive in the global financial network. We argue this is an essential issue because these markets still have some limitations and can threaten the stability of the global financial market, as we found during the GFC.

We argue that our findings are crucial to almost everyone who deals with financial markets: policymakers, investors, regulators, and academics. First, knowing the origin of contagion effects allows the policymaker to design appropriate policy responses. With this study, we indicated that even if the policymaker had isolated the connections to the United States and its toxic assets, the domestic economy might have been affected by other markets. From another perspective, this paper matters to regulators and investors because it allows them to understand more about the international financial architecture. More so, given that our study provides for a broader sample of potential contagion sources, our work is crucial to understand the relationship between stock and bond markets during crisis periods. Since stocks and bonds have very different risk-return characteristics, these two asset classes are often in every portfolio. In this sense, our work was crucial to understanding their relationship during crisis periods, and consequently to the literature on portfolio management in crisis periods. Last, by unravelling contagion effects throughout the globe, this article provides results that may be of use to other studies aiming to understand which factors determine the direction of the transmissions.

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Appendix 2.A

In this appendix, we present some examples of our contagion estimations. Since we estimate contagion effects between each pair of countries, it would be infeasible to present all estimations. Thus, we randomly selected three countries to present some examples of our estimations. The three countries are Canada, Hungary and Malaysia.

Estimations of Model in Equations 2.4-2.10: Canada and Hungary[a,b]

Variables	**Canada Stock**		**Canada Bond**		**Hungary Stock**		**Hungary Bond**	
Equation 2.4								
$R_{CANs,t-1}$	0.0054	(0.22)	0.0330	(1.60)	0.0503	(1.57)	-0.0770***	(-2.95)
$R_{CANb,t-1}$	-0.0166	(-0.99)	0.0347	(1.30)	-0.0383*	(-1.68)	0.0572***	(3.10)
$R_{HUNs,t-1}$	-0.0435***	(-2.91)	0.0133	(0.93)	0.0239	(1.16)	-0.0711***	(-4.52)
$R_{HUNb,t-1}$	0.0105	(0.72)	0.0247	(1.43)	-0.0082	(-0.41)	-0.0172	(-0.80)
$R_{CANs,t-1} * D_{crisis}$	-		-0.0851	(-1.05)	-0.5693	(-7.19)	-0.2053***	(-3.16)
$R_{CANb,t-1} * D_{crisis}$	0.1276**	(2.13)	-		0.2066***	(2.99)	0.0005	(0.01)
$R_{HUNs,t-1} * D_{crisis}$	-0.1677***	(-3.49)	0.0086	(0.16)	-		-0.0249	(-0.34)
$R_{HUNb,t-1} * D_{crisis}$	-0.1647**	(-2.40)	-0.0350	(-0.60)	-0.1309*	(-1.75)	-	
$R_{US,t-1}$	0.2011***	(7.93)	-0.0962***	(-3.45)	0.3200***	(9.22)	-0.1353***	(-4.98)
$R_{US,t-1} * D_{crisis}$	0.3517***	(7.52)	0.0647	(0.87)	0.7204***	(8.03)	-0.1870***	(-2.77)
Constant	0.0006***	(3.31)	-0.0001	(-0.24)	0.0004	(1.57)	-0.0006***	(-2.77)

(Continued)

Estimations of Model in Equations 2.4-2.10: Canada and Hungary[a,b] (Continued)

Variables	Canada Stock		Canada Bond		Hungary Stock		Hungary Bond	
Equation 2.9								
ARCH	0.3082***	(8.84)	0.2360***	(7.51)	0.3382***	(10.75)	0.5296***	(11.58)
GARCH	0.4837***	(4.02)	0.4978**	(2.46)	0.3215***	(3.50)	0.3850***	(4.23)
Constant	0.0001	(1.59)	0.0001	(1.48)	0.0001***	(4.00)	0.0001**	(2.30)
Equation 2.7 (Conditional Quasicorrelations)								
R_{CANs}	1							
R_{CANb}	0.1060***	(3.36)	1					
R_{HUNs}	0.2921***	(11.29)	0.1288***	(4.73)	1			
R_{HUNb}	-0.0868***	(-3.22)	-0.0280	(-1.00)	-0.1343***	(-5.02)	1	
Equation 2.8								
α_q	0.0059***	(4.79)						
β_q	0.9783***	(30.46)						
Statistics								
Log-Likelihood	36827.12							
Chi-Square	797.38							
Sample Size	3132							

[a]Robust z-statistics in brackets.

[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

R_{CANs} (Returns of Canada Stock market), R_{CANb} (Returns of Canada Bond market), R_{HUNs} (Returns of Hungary Stock market), R_{HUNb} (Returns of Hungary Bond market), and D_{crisis} (crisis dummy variable).

Estimations of Model in Equations 2.4-2.10: Canada and Malaysia[a,b]

Variables	Canada Stock		Canada Bond		Malaysia Stock		Malaysia Bond	
Equation 2.4								
$R_{CANs,t-1}$	-0.0141	(-0.58)	0.0391	(1.50)	0.1093***	(5.35)	-0.0361	(-1.31)
$R_{CANb,t-1}$	-0.0216	(-1.31)	0.0340	(1.67)	-0.0289**	(-2.14)	0.1338***	(6.36)
$R_{MALs,t-1}$	0.0279*	(1.92)	-0.0006	(-0.04)	0.0255	(1.57)	0.0162	(0.82)
$R_{MALb,t-1}$	-0.0085	(-0.74)	0.0022	(0.17)	-0.0124	(-1.19)	-0.1982***	(-9.59)
$R_{CANs,t-1} * D_{crisis}$	-		-0.0933	(-1.38)	-0.0993**	(-2.27)	0.2659***	(3.02)
$R_{CANb,t-1} * D_{crisis}$	0.0445	(0.86)	-		-0.0129	(-0.28)	-0.0766	(-0.78)
$R_{MALs,t-1} * D_{crisis}$	-0.5530***	(-3.76)	0.1087	(0.72)	-		-0.1020	(-0.32)
$R_{MALb,t-1} * D_{crisis}$	0.1073*	(1.66)	0.0006	(0.01)	0.0804*	(1.84)	-	
$R_{US,t-1}$	0.1916***	(7.67)	-0.0945***	(-3.42)	0.1995***	(9.31)	-0.0143	(-0.47)
$R_{US,t-1} * D_{crisis}$	0.2792***	(5.98)	0.0761	(1.07)	-0.0507	(-0.98)	-0.2214***	(-2.07)
Constant	0.0005***	(2.93)	-0.0001	(-0.33)	0.0006***	(3.81)	-0.0004	(-1.57)
Equation 2.9								
ARCH	0.3360***	(8.72)	0.2392***	(7.60)	0.4346***	(9.36)	0.5592***	(12.37)
GARCH	0.5742***	(4.44)	0.4601**	(2.38)	0.4719***	(4.45)	0.3076***	(3.08)
Constant	0.0001	(0.58)	0.0001*	(1.74)	0.0001	(0.82)	0.0001	(1.23)

(Continued)

Estimations of Model in Equations 2.4-2.10: Canada and Malaysia[a,b] (Continued)

Variables	Canada Stock		Canada Bond		Malaysia Stock		Malaysia Bond
Equation 2.7 (Conditional Quasicorrelations)							
R_{CANs}	1						
R_{CANb}	0.0450	(1.01)	1				
R_{MALs}	0.0964**	(2.56)	0.0001	(0.00)	1		
R_{MALb}	-0.0389	(-1.06)	-0.0260	(-0.73)	-0.0725	(-1.38)	1
Equation 2.8							
α_q	0.0095***	(5.72)					
β_q	0.9771***	(34.49)					
Statistics							
Log-Likelihood	37517.87						
Chi-Square	802.41						
Sample Size	3132						

[a]Robust z-statistics in brackets.

[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

R_{CANs} (Returns of Canada Stock market), R_{CANb} (Returns of Canada Bond market), R_{MALs} (Returns of Malaysia Stock market), R_{MALb} (Returns of Malaysia Bond market), and D_{crisis} (crisis dummy variable).

Estimations of Model in Equations 2.4-2.10: Hungary and Malaysia[a,b]

Variables	Hungary Stock		Hungary Bond		Malaysia Stock		Malaysia Bond	
Equation 2.4								
$R_{HUNs,t-1}$	0.0316	(1.53)	-0.0771***	(-4.81)	0.0543***	(4.48)	0.0027	(0.17)
$R_{HUNb,t-1}$	-0.0176	(-0.87)	-0.0149	(-0.70)	0.0250**	(2.06)	0.0565***	(3.21)
$R_{MALs,t-1}$	-0.0333	(-1.61)	0.0370**	(2.18)	0.0318*	(1.93)	0.0133	(0.69)
$R_{MALb,t-1}$	-0.0088	(-0.54)	0.0013	(0.10)	-0.0156	(-1.47)	-0.2094***	(-9.82)
$R_{HUNs,t-1} * D_{crisis}$	-		-0.1242***	(-2.29)	0.0069	(0.20)	0.1453***	(3.15)
$R_{HUNb,t-1} * D_{crisis}$	-0.0845	(-0.96)	-		0.0160	(0.39)	-0.2100***	(-2.87)
$R_{MALs,t-1} * D_{crisis}$	-0.6054**	(-2.41)	0.0708	(0.36)	-		-0.3214*	(-1.82)
$R_{MALb,t-1} * D_{crisis}$	-0.1325	(-1.60)	0.0575	(0.78)	0.0706	(1.63)	-	
$R_{US,t-1}$	0.3345***	(12.09)	-0.1633***	(-7.64)	0.2526***	(15.48)	0.0073	(0.32)
$R_{US,t-1} * D_{crisis}$	0.1798***	(2.97)	-0.1795***	(-2.74)	-0.1442***	(-3.98)	-0.0990*	(-1.81)
Constant	0.0006**	(2.20)	-0.0006**	(-2.54)	0.0006***	(3.79)	-0.0004	(-1.50)
Equation 2.9								
ARCH	0.3556***	(10.45)	0.5126***	(11.37)	0.4210***	(9.40)	0.5434***	(12.26)
GARCH	0.3457***	(3.43)	0.3939***	(4.08)	0.4791***	(4.66)	0.3649***	(3.10)
Constant	0.0001***	(3.33)	0.0001**	(2.17)	0.0001	(0.43)	0.0001	(0.96)

(Continued)

Estimations of Model in Equations 2.4-2.10: Canada and Malaysia[a,b] (Continued)

Variables	Hungary Stock		Hungary Bond		Malaysia Stock		Malaysia Bond
Equation 2.7 (Conditional Quasicorrelations)							
R_{HUNs}	1						
R_{HUNb}	-0.1290***	(-6.31)	1				
R_{MALs}	0.1176***	(5.49)	-0.0318	(-1.50)	1		
R_{MALb}	-0.0288	(-1.37)	0.0906***	(4.17)	-0.0165	(-0.71)	1
Equation 2.8							
α_q	0.0070***	(2.76)					
β_q	0.9149***	(31.66)					
Statistics							
Log-Likelihood	36303.85						
Chi-Square	886.00						
Sample Size	3132						

[a]Robust z-statistics in brackets.

[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

R_{HUNs} (Returns of Hungary Stock market), R_{HUNb} (Returns of Hungary Bond market), R_{MALs} (Returns of Malaysia Stock market), R_{MALb} (Returns of Malaysia Bond market), and D_{crisis} (crisis dummy variable).

Chapter 3

The role of banks in Financial Contagion between Sovereigns: An interpretation of the contagion from Greece to Portugal

Abstract: We study the role of a banking system in the context of contagion effects to its domestic sovereign bond market. We develop a global game, where a banking system increases its holdings of domestic sovereign debt – and thus offsets the effects predicted by the common lender hypothesis – when it has a strong balance sheet, and it is highly exposed to domestic sovereign debt. We then discuss how these results offer a new explanation for the contagion process from the Greek to the Portuguese sovereign bond markets during the Eurozone Sovereign Debt Crisis (ESDC). In particular, we highlight the role of the Portuguese banking system in offsetting these contagion effects at the beginning of the ESDC.

KEYWORDS: Contagion, Global Games, Eurozone Sovereign Debt Crisis, Sovereign Default, Bank Failures

JEL CODES: C73, G01, G21, H63

3.1. Introduction

According to the common lender hypothesis, contagion among countries arises when common lenders reduce their exposure to a country as a response to a crisis in another country (see, for example, Kaminsky and Reinhart, 2000). In the case of sovereign debt, though, this hypothesis may overlook other key players. In particular, banks with a strong domestic base may increase their holdings of government debt to protect their sovereign. They may thus offset the reduction in the exposure of common lenders.

Banks with a strong domestic base do much of their borrowing and lending within national borders and thereby are highly exposed to the destabilizing effects of domestic shocks on their local operations. Since a destabilization of the sovereign bond market may have strong adverse effects on local activities, it may be in the best interest of "domestic banks" to neutralize an attack on their government bonds. In this paper, we hypothesize that these banks may be willing to increase their holdings of domestic public debt, so as to compensate for the reduced lending from international lenders to the domestic government.

Besides the exposure to the destabilizing effects of a domestic sovereign bond market successful attack, we point out that banks' balance sheets play a pivotal role in the decision of banks to increase their holdings of domestic sovereign debt. Depending on their strength, banks may protect their domestic sovereign from contagion effects deriving from the common lender channel. Thus, since a stronger banking system is better able to stop a speculative attack, it has more incentives to protect its sovereign than a weaker banking system. International speculators will take into account the strength of the banking system when deciding whether to launch a speculative attack on the government bond market or not. This mechanism will imply that the market for sovereign debt may become unstable after large negative shocks to the capital of the domestic banking system.

Building on the main insights of the literature on global games, this paper contributes to understanding the role of a domestic banking system in the context of contagion through common lenders. We model the domestic banking system as a large player whose behaviour is endogenously determined in equilibrium. More specifically, we model a banking system that may be interested in assisting its domestic government in the secondary bond market, weighting the benefits of buying domestic government bonds and thereby acting as a backstop against speculative attacks, against the costs associated to the possible collapse in the value of these bonds.

The strategic interaction between domestic banks and international speculators depends on two key elements: (i) the size of the exposure of domestic banks to national sovereign debt, and (ii) the strength of domestic banks' balance sheets (in our case, measured by their exposure to international shocks). First, the domestic sovereign debt held by the domestic banking system serves as a commitment device: the more the domestic bank holds its sovereign debt, the more the bank will lose with the successful attack on the sovereign bond market. As a result, the bank is more committed to protecting its sovereign and speculators recognize this commitment and are less willing to attack the sovereign bond market.

Second, the strength of domestic bank's balance sheets also influences the strategic interaction between the two classes of players. On the one hand, when the domestic banks have strong balance sheets, they are better able to shield their sovereign against speculative attacks. International speculators anticipate the incentives of domestic banks and are less prone to speculative attacks. In this case, there is a backstop.

On the other hand, when the domestic banking system is weak, international speculators perceive and incorporate this limitation of domestic banks into their decisions to attack the domestic sovereign. For example, a strong negative shock to the capital of the national banking system may trigger a speculative attack, as international speculators perceive weaker domestic banks. The attack is likely to be successful since domestic banks anticipate their own limitations and do not defend their sovereign.

We use the model's results to shed light on the Eurozone Sovereign Debt Crisis (ESDC). Take the case of Portugal, a country that was considered the next in line after the Greek sovereign debt crisis. In particular, we study the role of the Portuguese banking system in offsetting the contagion effects from the Greek to the Portuguese sovereign bond market at the beginning of the ESDC. We start by studying the contagion dynamics from the Greek sovereign bond market to the Portuguese sovereign bond market during late 2009 until the Portuguese request for assistance (May 2011). The aim of this study is twofold. First, we empirically test for contagion effects from the Greek to the Portuguese sovereign bond market, focusing explicitly on the timing of the contagion effects. We find that the significant increase in the comovements between the Greek sovereign bond yields and the Portuguese yields is only detectable after the Greek official request for assistance in April 2010. Second, we document the behaviour of international lenders regarding their exposure to the Portuguese economy and the Portuguese sovereign debt.

We find an apparent contradiction between the contagion effects identified in the Portuguese sovereign bond market and the behaviour of international lenders because these agents appear to start reducing their exposure to Portugal several months before the Greek official request for assistance.

Our model offers a possible explanation to reconcile these two apparently contradictory facts, focusing on the role played by the Portuguese banking system. We document the behaviour of the Portuguese banking system regarding their claims to its domestic sovereign at the beginning of the ESDC, noticing two substantial changes in the conduct of the Portuguese banks. First, Portuguese banks appear to increase substantially their net claims on their government months before April 2010, which is in sharp contrast with the behaviour of other European banks. This evolution suggests that Portuguese banks backed up their government until April 2010, offsetting the reduction in the exposure of international investors, and limiting the pressure on Portuguese government bond yields. Second, after the Greek official request for assistance, Portuguese banks appear to reduce substantially their net claims on their government. Our model provides a possible explanation to support the changes in bank behaviour, focusing on the Portuguese banks' exposure to Portuguese debt and the Greek economy.

The structure of the paper is as follows. Section 3.2 reviews the literature. Section 3.3 introduces the model. Section 3.4 presents our main results regarding the effects of an increase in the amount of domestic public debt held by the banking system and of a negative capital shock to the banking system. Section 3.5 shows an overview of the beginning of the ESDC, focusing on the contagion effects from the Greek to the Portuguese sovereign bond market and on the behaviour of international lenders, and gives an interpretation of the evidence in light of our model. Section 3.6 concludes.

3.2. Literature review

This paper is related to three strands of literature. The first strand of literature studies the behaviour of governments and banks in managing sovereign debt in times of stress. On the one hand, Bolton and Jeanne (2011) focus on government behaviour. More particularly, they show that the riskiest sovereigns issue too much debt, as they do not take into account the costs of contagion.

On the other hand, the propensity of domestic banks to increase domestic debt in times of stress has attracted attention in the literature. First, the moral suasion hypothesis states that vulnerable governments induce domestic banks to hold domestic public debt (see, for example, Battistini, Pagano, and Simonelli, 2013; Uhlig, 2014). Second, Acharya and Steffen (2015) suggest that domestic banks engaged in a form of "carry trade" during the Eurozone Sovereign Debt Crisis (ESDC), increasing their holdings of long-term domestic public debt and using short-term unsecured funding in wholesale markets or loans from the ECB. Third, Broner, Erce, Martin, and Ventura (2014) point out that sovereign debt offers a higher expected return to domestic creditors than to foreign ones, thus justifying the increased exposure of domestic banks to domestic public debt. Finally, Sosa-Padilla (2018) uses endogenous costs of default to explaining why commercial banks have substantial holdings of sovereign debt.

We contribute to this literature by explaining the increased exposure of domestic banks because of their lack of diversification in their operations. Moreover, unlike this strand of literature, our focus is on the consequences of the behaviour of domestic banks in stopping contagion effects to their sovereign.

The second strand of literature focuses on the links between sovereign distress and banking crises. Regarding the links from government default to banking distress, Alessandro (2011) proposes a mechanism by which a government default negatively influences the relation between domestic and foreign investors. The mechanism is rooted in information asymmetry since domestic investors have superior verification capabilities. In our case, domestic investors (banks) play a prominent role because their lack of diversification gives them a strategic motive to hold domestic government debt. Also, Gennaioli, Martin, and Rossi (2014) study the link from government default to financial fragility by building a model where a government default has a negative impact on the balance sheet of domestic banks. Our paper, though, contributes to the literature by addressing the inverse link – how bank problems expose domestic government distress.

Regarding the links going from weak banks to financially stressed governments, some papers have studied how bank bailouts aggravate problems in their sovereigns, but the channels described in these papers are completely different from ours (see, for example, Gray, 2009; Gerlach, Schulz, and Wolff, 2010; Pisani-Ferry, 2012). In these papers, implicit or explicit government guarantees to banks undermine the ability of sovereigns to pay their debt. In contrast, in our case, weak banks (which have not been bailed out yet) are unable to help their domestic government.

In the third strand of the literature, global games have been frequently applied to study contagion. Despite the wide variety of models, most models focus on the role of information acquisition to explain contagion.[1] Ahnert and Kakhbod (2017) examine the consequences of private information acquisition and demonstrate that endogenous information acquisition after adverse news (either on the bank or on the solvency of the sovereign) increases the probability of a bank run or a debt crisis. In a different direction, Ho and Wu (2012) highlight the psychological component of financial contagion in a global game, whereas Ahnert and Bertsch (2015) highlight the role of strategic uncertainty among speculators. Our paper has a distinct view, as none of the global game approaches considers the interaction between domestic banks and domestic government debt.

3.3. The Model

Consider an economy – country P – populated by a unit continuum of risk-neutral agents, the speculators, indexed by $i \in [0,1]$. As in Cappelletti and Esposito (2013), the game occurs in the secondary market, where speculators will bet on the reduction of sovereign bond prices of a country with weak fundamentals, selling to repurchase them when the price is lower.

There exists one bank in country P, which may provide funds to the domestic sovereign up to m^*.[2] The bank is as an additional large player that has previously loaned funds to the sovereign in country P and a sovereign in a foreign country (country G), amounting to m_P and to m_G respectively.

The sovereign in country P is characterised by the underlying economic fundamental θ that measures the difficulty of a successful attack. For example, a sovereign's fundamental represents its financial health, i.e. its capacity to generate income. The fundamental θ is drawn from an improper uniform distribution over the real line and it is not known with certainty (by speculators and by the bank) when the decisions to attack and to defend are made.

[1] Several papers also focus on learning to explain contagion. See, for example, Steiner and Stewart (2008), Manz (2010), and Trevino (2019).

[2] For the sake of simplicity, we assume the existence of only one bank in country P. This bank represents the banking system as a whole.

We assume that there was a successful attack on country G's sovereign bond market that led to a downfall in its value, resulting in unexpected losses for the bank in country P equal to m_G. From this point on, we will see how the game evolves.

Speculators play a simultaneous-move game with binary action space $a_i \in \{0,1\}$: each speculator either attacks ($a_i = 1$) or does not attack ($a_i = 0$). Simultaneously, the bank decides its intervention $m \in [0, m^*]$: the bank either defends the attack with its loanable resources up to m^* or does not defend the attack ($m = 0$). The bank's loanable resources, m^*, depend both on the bank's dimension ($\overline{m}$) and the losses in Country G (m_G):

$$m^* = \overline{m} - m_G. \tag{3.1}$$

We let m^* be common knowledge in the economy.

The success of the attack depends on the economic fundamental θ, on the proportion of attacking speculators (denoted by $A = \int_0^1 a_i di$), and on the bank's intervention: a speculative attack is successful if the fraction of acting speculators weakly exceeds the strength of the fundamental and the amount financed by the bank ($A \geq \theta + m$). This means that when a large enough number of speculators attack, the aggregate action destabilizes the sovereign bond market, puts powerful pressure on bond prices and delivers a profit to the speculators that correctly anticipated the actions of the others.

The payoff of a speculator from not attacking is normalized to zero. The payoff from attacking is $1 - c$ if the attack is successful and $-c$ otherwise, where $c \in (0,1)$ parametrizes the cost of attacking. Thus, the payoff of a speculator is given by:

$$v_{inv}(\theta, m) = \begin{cases} 1 - c & if\ a_i = 1\ \ and\ A \geq \theta + m \\ -c & if\ a_i = 1\ \ and\ A < \theta + m \\ 0 & if\ a_i = 0 \end{cases} \tag{3.2}$$

We now study the payoff of the bank. As stated earlier, the bank decides to disburse m. The benefit of the bank from successfully defending the attack is given by the net profit from the increase in the bond prices $r(m_P + m)$, where $r \in [0,1]$ is a constant representing the rate of return from the investment in domestic sovereign bonds. If, however, the bank fails to defend the attack – consequently, the national sovereign bonds' price collapses –, the bank will have a loss that is a percentage of the amount $m_P + m$, since the bank had previously loaned m_P to the sovereign of Country P. For the sake of simplicity, we assume that the percentage is equal to one, which means that the bank will not get any of the invested amount $m_P + m$.[3] The bank will defend the attack if there is an expectation of recovering that money.

The bank's decision to disburse m is thus conditional on the fundamental of the country θ, and on how much the bank has previously loaned to country P, m_P. The payoff of the bank is given by:

$$v_{bank}(\theta, m, m_P) = \begin{cases} r(m_P + m) & A < \theta + m \\ -m_P - m & A \geq \theta + m \end{cases} \tag{3.3}$$

Given the linear nature of the bank's problem, the bank ultimately chooses if it defends using its full financing capacity ($m = m^*$) or does not defend at all ($m = 0$). The decision of the bank becomes a binary choice (defend or not) because (i) the marginal profit from a successful action is constant (and independent from m), and (ii) the probability of a successful action depends positively on m. Thus, if the bank intervenes, it maximizes the probability of a successful action, i.e. it intervenes with its full financing capacity.

Following the global games literature pioneered by Carlsson and Van Damme (1993), all agents (speculators and the bank) receive a public signal $\tilde{s}_P$ about the economic fundamental of the sovereign in country P:

$$\tilde{s}_p = \theta + \gamma \tag{3.4}$$

where the noise γ is normally distributed with zero mean and precision ρ. Moreover, each speculator i receives a private signal $\tilde{s}_{inv,i}$ about country P's fundamental before deciding whether to attack or not:

$$\tilde{s}_{inv,i} = \theta + \varepsilon_i \tag{3.5}$$

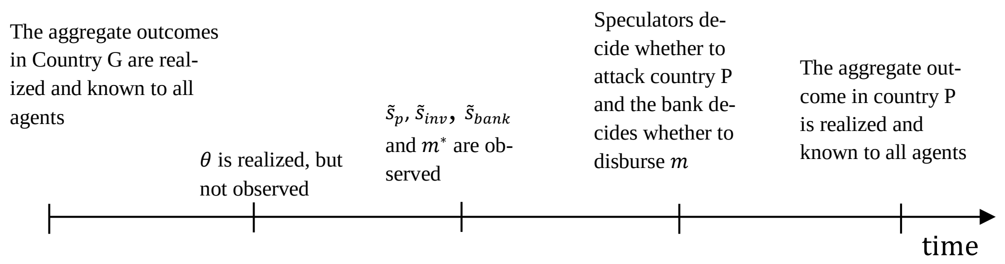
[3] The amount m_P corresponds to the bank's losses (regardless of the bank's intervention) provoked by a successful attack on the sovereign bond market. We argue that these losses can be significant even if the bank does not hold large amounts of its sovereign debt because m_P can also be interpreted as indirect costs from a destabilized sovereign bond market. For instance, if a bank mainly operates within national borders, a sovereign bond market collapse can increase uncertainty in the domestic economy, which may lead to a contraction in the economic activity and consequently a reduction in the bank's operations and profits.

where the idiosyncratic noise ε_i is identically and independently normally distributed across speculators with zero mean, precision α and its cumulative distribution function is denoted by H(.). The bank also receives a private signal $\tilde{s}_{bank}$ about its sovereign's fundamental before deciding whether to disburse m:

$$\tilde{s}_{bank} = \theta + \eta \tag{3.6}$$

where the idiosyncratic noise η is also independent and normally distributed with zero mean, precision β and its cumulative distribution function is denoted by K(.). All distributions are common knowledge. Figure 3.1 illustrates the timing of the game.

Figure 3.1 – The sequence of events



This figure draw the sequence of events in the global game.

3.3.1. Speculative attacks and funds provision in equilibrium

We now turn to the characterization of the equilibrium in our economy. The bank and the speculators take their decisions simultaneously. Speculators know that the bank may not want to defend the attack, and they correctly compute the likelihood of the bank's intervention. As mentioned above, the bank refrains from lending if there is no prospect to recover its loans m and m_P fully.

There is a coordination problem faced by speculators. Each speculator is uncertain about the information reaching all other speculators and the bank, and therefore faces strategic uncertainty – the expected payoff of each speculator from attacking the sovereign in country P depends positively on the fraction of speculators also attacking, and negatively on the bank's willingness to provide funds. The bank's expected payoff from providing funds, in turn, depends positively on the fraction of speculators who do not attack country P. Clearly, the decisions by the speculators and the bank are strategic complements.

There is a unique equilibrium in which agents employ trigger strategies: a speculator will attack if and only if her private signal on the sovereign's fundamental is below some critical value s_{inv}^*, identical for all speculators.[4] Analogously, the bank will defend the sovereign in country P if and only if its own private signal is above some critical value s_{bank}^*. Appendix 3.A shows that the focus on trigger strategies is without loss of generality, as there is no equilibrium in other type of strategies.

For the sake of simplicity, we assume that the private signals are arbitrarily more accurate than the public signal (i.e., ρ/α, $\rho/\beta \to 0$) and the posteriors will coincide with private signals, i.e. we can disregard public information in building our equilibrium.[5]

From now on, we express the signals and thresholds of speculators and the bank in terms of these agents' posteriors, denoted without tilde (i.e., s_{inv}, s_{bank}, s_{inv}^* and s_{bank}^*).

Proposition 1. *There is a unique equilibrium. Speculator i attacks iff $s_{inv,i} < s_{inv}^*$ and the bank defends iff $s_{bank}^* < s_{bank}$; the speculative attack always succeeds when $\theta < \underline{\theta}$, succeeds if the bank does not defend and if $\underline{\theta} \leq \theta < \overline{\theta}$, does not succeed if the bank defends and if $\underline{\theta} \leq \theta < \overline{\theta}$, and never succeeds when $\theta \geq \overline{\theta}$; where s_{inv}^*, s_{bank}^*, $\underline{\theta}$ and $\overline{\theta}$ are joint solutions to:*

$$\overline{\theta} = H\left(s_{inv}^* - \overline{\theta}\right) \tag{3.7}$$

$$\underline{\theta} + m^* = H\left(s_{inv}^* - \underline{\theta}\right) \Leftrightarrow \underline{\theta} = H\left(s_{inv}^* - \underline{\theta}\right) - m^* \tag{3.8}$$

$$(m^* + m_P)K\left(\underline{\theta} - s_{bank}^*\right) - m_P K\left(\overline{\theta} - s_{bank}^*\right) = \frac{rm^*}{1+r} \tag{3.9}$$

$$H\left(\underline{\theta} - s_{inv}^*\right) + \int_{\underline{\theta}}^{\overline{\theta}} h(\theta - s_{inv}^*)\, K(s_{bank}^* - \theta) d\theta = c \tag{3.10}$$

Proof. See Appendix 3.B.

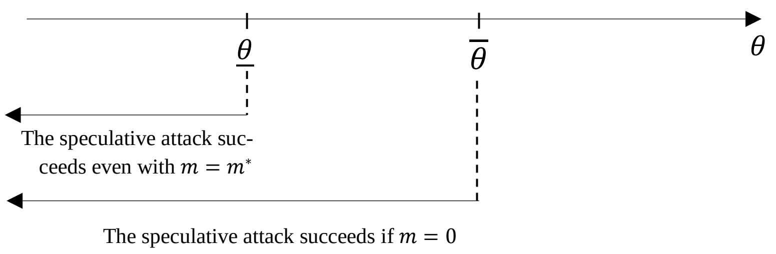
[4] When solving the game, we consider a global game with a large player, in line with Corsetti, Guimaraes, and Roubini (2006).

[5] This assumption is commonly used in the literature on global games. See, for example, Corsetti *et al*. (2006).

The four equations (3.7), (3.8), (3.9), and (3.10) in four endogenous variables ($\overline{\theta}$, $\underline{\theta}$, s_{bank}^* and s_{inv}^*) completely characterize the equilibrium. The equilibrium is characterized by four critical thresholds. The first two thresholds are critical values for the fundamental θ below which the attack always succeed – one threshold $\overline{\theta}$ conditional on no help from the bank and the other threshold $\underline{\theta}$ conditional on the bank's intervention. The other two thresholds are s_{inv}^* and s_{bank}^* for the private signals reaching the speculators and the bank, respectively. Speculator i attacks the sovereign bond market iff $s_{inv,i} < s_{inv}^*$ and the bank defends the attack iff $s_{bank} > s_{bank}^*$.

Figure 3.2 plots the two thresholds for the success of the speculative attack. As it was stated earlier, the fundamental θ is drawn from an improper uniform distribution over the real line and it is not known with certainty. If θ is drawn below $\underline{\theta}$, the speculative attack succeeds regardless of the bank's intervention. If θ is drawn above $\overline{\theta}$, the speculative attack does not succeed even if the bank does not intervene. If θ is drawn between $\underline{\theta}$ and $\overline{\theta}$, the speculative attack succeeds if and only if the bank does not intervene.

Figure 3.2 – Thresholds for the collapse of the sovereign bond market



This figure draws the two thresholds for the attack's success.

3.4. The role of the bank in defending its domestic sovereign

In this section, we examine the behaviour of the bank and its implications in the sovereign bond market. More specifically, we address the following two questions:

1. How do the bank's holdings of its sovereign debt (m_P) affect the behaviour of the bank (and speculators) and ultimately the likelihood of a successful attack on the sovereign bond market?
2. How do the bank's capital losses from an international shock (m_G) affect the actions of the bank (and speculators) and consequently the likelihood of a successful attack on country P's sovereign bond market?

3.4.1. The impact of the bank's holdings of its sovereign debt ($\boldsymbol{m_P}$)

To answer the first question, we summarize our comparative static exercise by means of the following proposition.

Proposition 2. *The thresholds s^*_{bank}, s^*_{inv}, $\underline{\theta}$, and $\overline{\theta}$ are decreasing in the amount of the previously loaned debt to country P,m_P.*
Proof. See Appendix 3.D.

As stated earlier, m_P not only can be interpreted as the amount of its sovereign debt held by the bank, but it also can be understood as indirect exposure to the sovereign bond market. If the government is an essential player in the economy (which can be measured by the weight of its expenditures on the GDP), a significant downfall in the sovereign bond prices can increase uncertainty in the domestic economy and can lead to a contraction in the economic activity. Thus, the less diversified is the banking system (i.e. operating more within national borders), the more exposed its operations and profits are to the domestic sovereign bond market and the higher m_P.

The increase in m_P has a direct effect on the bank's decision, since it amplifies the pay-offs of the two scenarios: (i) if the attack on the sovereign bond market succeeds, the bank has more to lose (because the bank will not get any of the invested amount $m_P + m$); (ii) if the attack does not succeed, the bank has more to win (because the bank will get net profit from the increase in the bond prices $r(m_P + m)$). As the bank has more "skin in the game", the bank becomes more interested in intervening, decreasing s^*_{bank}. Thus, the increase in m_P translates into a higher commitment from the bank.

Since s^*_{bank} decreases and the bank's intervention is more likely to occur, speculators recognize that the attack is less likely to succeed if θ is between $\underline{\theta}$ and $\overline{\theta}$ because the probability that the bank does not defend the attack, given by $K(s^*_{bank} - \theta)$, decreases. Thus, fewer speculators are willing to attack the sovereign bond market, decreasing s^*_{inv}.

The decrease in s^*_{inv} negatively impacts the two thresholds $\underline{\theta}$ and $\overline{\theta}$. Because fewer speculators are willing to attack the sovereign bond market, the less likely is a successful attack on that market. Since a successful attack is less likely to happen, due to the decrease in both thresholds, the bank becomes even more interested in intervening, decreasing s^*_{bank}. The reduction in s^*_{bank} will once more trigger less speculators to attack, and so on and so forth, until a new equilibrium is reached.

Given the above discussion, Proposition 2 shows that the domestic banking system has a clear role in preventing contagion effects from another country if the destabilization of the domestic sovereign bond market has critical implications for the banking system's operations.

3.4.2. The impact of the bank's capital losses from an international shock (m_G)

To answer the second question, we summarize our comparative statics exercise by means of the following proposition.

Proposition 3. *The thresholds s^*_{bank}, s^*_{inv}, $\underline{\theta}$, and $\overline{\theta}$ are increasing in the capital losses of the national banking system in the foreign country, m_G.*
Proof. See Appendix 3.E.

The bank's capital losses from an international shock translate into a reduction in the amount of the bank's intervention capacity, m^*. The decline in m^* has a direct effect increasing $\underline{\theta}$, meaning that an attack is more likely to cause destabilising effects in the sovereign bond market despite the bank's intervention since the bank's intervention capacity is smaller.

The increase in $\underline{\theta}$ impacts the triggers of the two classes of agents. On the one hand, the bank first recognises that there is a higher risk of losing all of its money because the probability of a successful attack on the sovereign bond market despite its intervention – given by $K(\underline{\theta} - s_{bank})$ – increases. Hence, the bank becomes less interested in intervening, increasing s^*_{bank}.

On the other hand, speculators realise that the attack's success despite the bank's intervention – given by $H(\underline{\theta} - s_{inv})$ – is more likely. Moreover, since the bank becomes less interested in intervening (i.e., s^*_{bank} increases) and the intervention is less likely to occur, speculators recognise that the attack is more likely to be successful even if θ is between $\underline{\theta}$ and $\overline{\theta}$ because the probability that the bank does not defend the attack, given by $K(s^*_{bank} - \theta)$, increases. Thus, more speculators are willing to attack the sovereign bond market, increasing s^*_{inv}.

The increase in s^*_{inv} positively impacts the two thresholds $\underline{\theta}$ and $\overline{\theta}$. Because more speculators are willing to attack the sovereign bond market, an attack on that market is more likely to succeed. Since the likelihood of a successful attack increases, due to the rise in both thresholds, the bank becomes even less interested in intervening, increasing s^*_{bank}. The rise in s^*_{bank} will once more trigger more speculators to attack, and so on and so forth, until a new equilibrium is reached.

Given the above discussion, Proposition 3 shows that adverse shocks to the domestic banking system's balance sheets may compromise the banking system's capacity in preventing contagion effects from another country.

3.5. An interpretation of the contagion process from Greece to Portugal

This section has two subsections. In Subsection 3.5.1, we present an overview of the beginning of the ESDC. In particular, we study the contagion dynamics from the Greek sovereign bond market to the Portuguese sovereign bond market during late 2009 until the Portuguese request for assistance (May 2011). The aim of this subsection is twofold. First, we empirically test for contagion effects from the Greek to the Portuguese sovereign bond market, focusing explicitly on the timing of the contagion effects. We find that the contagion effects to the Portuguese sovereign bond market are only detectable after the Greek official request for assistance. Second, we document the behaviour of international lenders regarding their exposure to the Portuguese economy and the Portuguese sovereign debt. We find an apparent contradiction between the timing of identifying contagion effects in the Portuguese sovereign bond market and the behaviour of international lenders because these agents appear to start reducing their exposure to Portugal several months before the Greek official request for assistance.

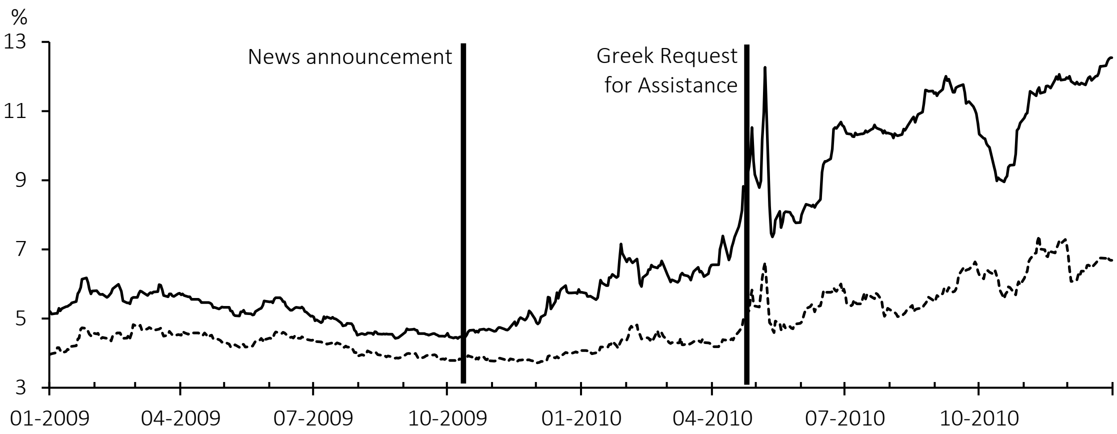
In Subsection 3.5.2, we use the model's results to offer a possible explanation to reconcile those two apparently contradictory facts. In particular, we focus on the role played by the Portuguese banking system in offsetting the contagion effects to the Portuguese sovereign bond market. To this end, we document the behaviour of the Portuguese banking system regarding their claims to its domestic sovereign at the beginning of the ESDC. We notice two substantial changes in the behaviour of the Portuguese banks. First, Portuguese banks appear to increase substantially their net claims on their government months before April 2010, which is in sharp contrast with the behaviour of other European banks. This increase suggests that Portuguese banks backed up their government until April 2010, offsetting the reduction in the exposure of international investors, and limiting the pressure on Portuguese government bond yields. Second, after the Greek official request for assistance, Portuguese banks appear to reduce substantially their net claims on their government. Our model provides a possible explanation to support the changes in the behaviour, focusing on the Portuguese banks' exposure to Portuguese debt and the Greek economy.

3.5.1. An overview of the beginning of the ESDC

Figure 3.3 plots the 10-year government bond yields for Greece and Portugal. Following the announcement of an unexpected large public budget deficit in October 2009, tensions in the Greek sovereign bond market reached a height after the Greek prime minister requested official assistance on 23 April 2010. Still, Portuguese government bond yields remained relatively stable until April 2010, thus suggesting that contagion effects were contained until this date.

The behaviour of Portuguese bond yields is consistent with the naïve view that the Greek official request for assistance caused a shift in expectations, leading international investors to anticipate the possibility of other sovereign defaults in the Eurozone. Since Portugal also had weak fundamentals, it was perceived as a natural candidate for the next in line for sovereign default.

Figure 3.3 – 10-year Government Bond Yields for Greece (solid line) and Portugal (dashed line) from 2009 to 2010



This figure plots the 10-year government bond yields for Greece and Portugal from 2009 to 2010. This two-year window is enough to encompass the key events in the Greek crisis. The recently elected Greek prime minister revealed an unexpected large deficit in government accounts on 18 October 2009 (indicated by the left vertical line); the Greek prime minister requested official assistance on 23 April 2010 (indicated by the right vertical line). Source: Datastream.

To examine the authenticity of this popular view, (i) we test the existence of contagion effects from the Greek to the Portuguese sovereign bond market, and (ii) we analyse the evolution of international lenders' exposure to Portuguese debt and economy. More particularly, we focus on the timing of the contagion effects and the change of the behaviour of international lenders. According to the naïve view, contagion effects from the Greek to the Portuguese sovereign bond market should start after April 2010, and international lenders should start withdrawing their funds from Portugal immediately after April 2010.

Fact 1: *Contagion effects from the Greek to the Portuguese sovereign bond market are only detectable after the Greek official request for assistance (April 2010).*

We start by testing the existence of contagion effects from the Greek to the Portuguese sovereign bond market. More specifically, we focus on the timing of the contagion effects, testing whether contagion effects from the Greek to the Portuguese sovereign bond market occurred after October 2009 and/or after April 2010.

We follow the seminal definition of Forbes and Rigobon (2002) to define contagion. Forbes and Rigobon (2002) denote contagion as a significant increase in market comovement in crisis periods when compared to tranquil periods. From this definition, the authors disentangle spillovers from contagion effects: spillovers are comovements that two assets have during normal periods, whereas contagion effects are excessive comovements during crisis periods.

Since our goal is to test contagion effects in two separate periods, we use historical events to subdivide the crisis period into two phases.[6] The first phase starts when the Greek prime minister revealed an unexpected large public budget deficit (18 October 2009) and ends on 22 April 2010; the second phase begins on the date when Greece requested official assistance (23 April 2010) and ends when Portugal requested official assistance (6 April 2011). The starting dates of the two phases are broadly in line with the empirical literature of contagion in the ESDC (e.g. Kalbaska and Gatkowski, 2012; Claeys and Vasicek, 2014).

We assume the Greek sovereign bond market to be the ground-zero and the only source of contagion to test the existence of contagion effects from Greece to Portugal. This assumption implies that contagion effects occur from Greece to Portugal, and not the other way around. Moreover, since our focus is only on the contagion effects from Greece to Portugal and is not on the contagion effects within the Euro Area, the effect of other potential sources of contagion to Portugal would be irrelevant to our analysis.[7]

[6] We choose only to use ad-hoc definitions (based on news events) to identify the crisis periods because an endogenous statistical approach would not be able to differentiate these two crisis periods. An endogenous statistical approach only looks for high volatility phases. Since these two periods are periods of high volatility, the statistical approach would consider these two periods together as a unique crisis period.

[7] To check the robustness of our results, we have augmented the model to include a second source of contagion. We tested the effects of Greece together with the effects of countries such as Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Spain and Switzerland. We obtained similar results, suggesting that contagion effects did not happen through a third country. The results are available upon request.

Regarding the econometric model, we augmented Baur (2012)'s model to account for two crisis periods[8]. To sum up, our econometric model is the following:

$$R_{PT,t} = a + b_1 R_{GR,t} + b_2 R_{GR,t} D1_{crisis} + b_3 R_{GR,t} D2_{crisis} + e_{PT,t} \tag{3.11}$$

where $R_{PT,t}$ ($R_{GR,t}$) is the first differences of Portuguese (Greek) Sovereign yields[9]; $e_{PT,t}$ the error term; and $D1_{crisis}$ ($D2_{crisis}$) a dummy variable which takes the value 1 in the first (second) crisis period and 0 elsewhere. From Equation (3.11), if coefficients b_2 and/or b_3 are positive and significant, it means that there is contagion in the respective crisis period.

We model the conditional variance by fitting an EGARCH model (Nelson, 1991) to control for heteroscedasticity in the data. We choose the EGARCH over the standard GARCH model because by modelling the log variance rather than the variance, the EGARCH model does not require the imposition of parameter constraints. Moreover, after detecting a positive trend in the conditional variance, we decide to include a linear trend variable in the variance model to control for the positive trend. The rest of the econometric model is as follows:

$$e_{PT,t} \,|\, \mathrm{I}_{t-1} \sim N\left(0, \mathrm{h}_{PT,t}\right) \tag{3.12}$$

$$\log\left(\mathrm{h}_{PT,t}\right) = \alpha + \beta \frac{e_{PT,t-1}}{\sqrt{\mathrm{h}_{PT,t-1}}} + \delta \frac{|e_{PT,t-1}|}{\sqrt{\mathrm{h}_{PT,t-1}}} + \gamma \log\left(\mathrm{h}_{PT,t-1}\right) + \varphi t + \eta_{PT,t} \tag{3.13}$$

where $e_{PT,t}$ is the error term as defined in Equation (3.11), $\mathrm{h}_{PT,t}$ is the variance of $e_{PT,t}$ conditionally to the information at time t-1, and t is the linear trend variable.

Data was obtained from Thomson Datastream. We use 10-year government bonds yields of Portugal and Greece. Our sample starts in January 2009 and ends in August 2013. We start our sample in January 2009 to minimize the influence of the Global Financial Crisis and to have a relatively long tranquil period before the crisis periods.[10] To

[8] As discussed in Chapter 2, Baur (2012) considers that contagion effects may be identified from increasing contemporaneous comovements that can be explained by fundamentals. Thus, Baur (2012) does not introduce any control variable in the regression.

[9] The use of first differences in government bond yields follows the common practice in the literature. See, for example, Chudik and Fratzscher (2012) and Beirne and Gieck (2014).

[10] We also tested the possibility of starting our sample in 2007 and augmenting the model with a dummy for the GFC. We obtain similar results.

balance between tranquil and turbulent periods, we choose to end our sample in August 2013.

Table 3.1 presents the estimates for our econometric model, specified in Equations (3.11) to (3.13). The table suggests that contagion effects from the Greek to the Portuguese sovereign bond market occurred after April 2010 (b_3 coefficient), but contagion effects were absent during the first phase (b_2 coefficient). This result indicates that the contagion effects from the Greek to the Portuguese sovereign bond market appear to start occurring after the Greek official request for assistance.

Table 3.1 – Contagion Estimation Results from the Greek to the Portuguese Sovereign Bond Markets

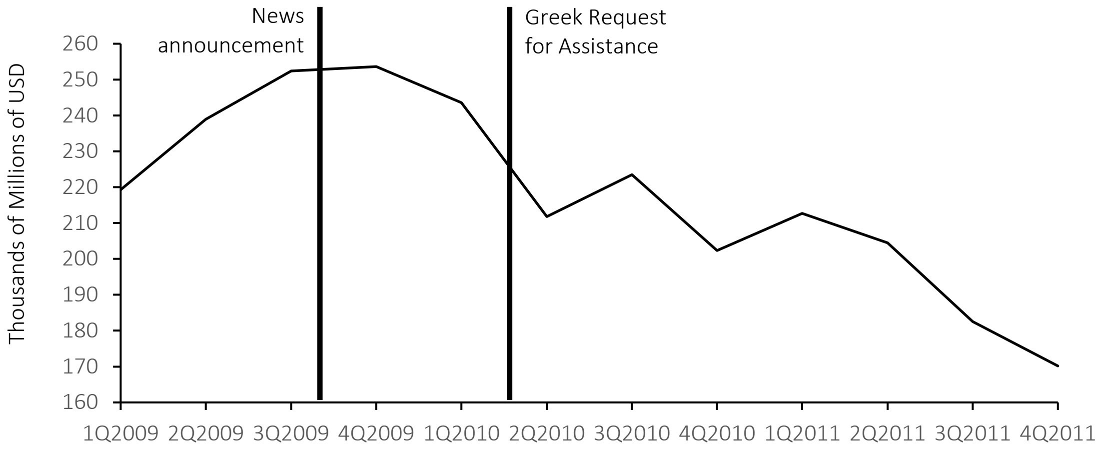
	Coefficients			
	a	b_1	b_2	b_3
Portugal	0.00011	0.21904***	0.13556	0.25646***

The table shows the estimation results of a model testing for contagion effects from the Greek to the Portuguese sovereign bond markets. The model is the one presented in Equations (3.11) to (3.13). Note: Coefficient estimates of the EGARCH model and robust z-statistics are reported in Appendix 3.F. *** Denotes statistical significance 1%. ** Denotes statistical significance 5%. * Denotes statistical significance 10%.

Fact 2. *International lenders started reducing their exposure to Portugal months before the Greek official request for assistance.*

We now analyse the evolution of international lenders' exposure to Portuguese debt and economy. Figure 3.4 plots the evolution of claims of foreign banks on the Portuguese economy between 2009 and 2011. The figure shows a clear reduction of the exposure to the Portuguese economy before April 2010, thus suggesting that foreign banks anticipated the possibility of a Greek default, as well as its consequences for Portugal.

Figure 3.4 – Total Foreign Claims on Portugal

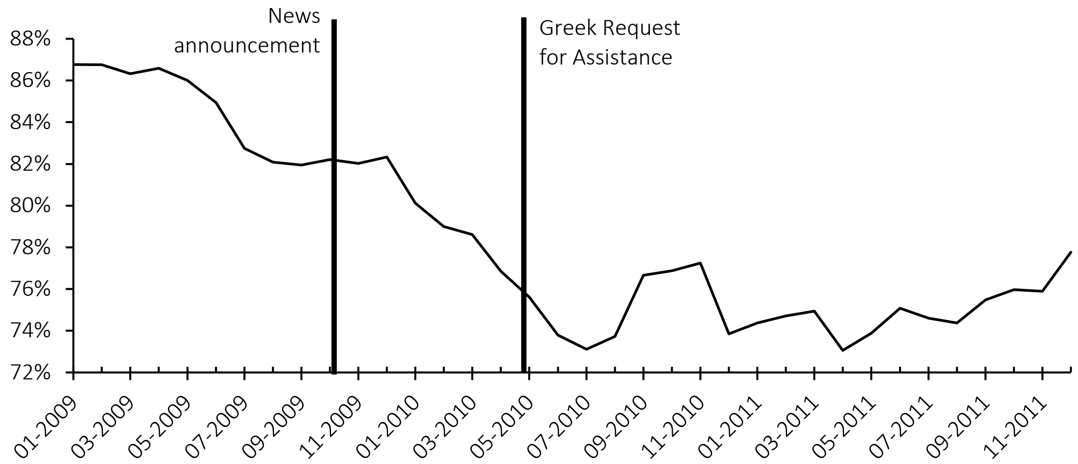


This figure plots the evolution of total foreign claims on Portugal. Source: Table 9D of BIS Quarterly Review – Detailed Tables. The recently elected Greek prime minister revealed an unexpected large deficit in government accounts on 18 October 2009 (indicated by the left vertical line); the Greek prime minister requested official assistance on 23 April 2010 (indicated by the right vertical line).

The evolution of the composition of Portuguese sovereign debt holders is also consistent with the trend in Figure 3.4. Figure 3.5 illustrates the dynamics of the share of Portuguese sovereign debt held by all agents except Portuguese domestic banks. There is a clear reduction in the weight of these agents after December 2009, suggesting international capital outflows from Portugal months before the Greek official request for assistance.

There is an apparent contradiction between Fact 1 (contagion effects from the Greek to the Portuguese sovereign bond market were only detectable after April 2010) and Fact 2 (the evolution of the foreign claims and the holdings of Portuguese sovereign debt depicted in Figures 3.4 and 3.5). One would expect that the sharp reduction in the exposure to the Portuguese economy and the negative evolution of the composition of Portuguese sovereign debt holders led to an increase in government bond yields. Yet, bond yields remained relatively stable until April 2010, which seems to conform with the more naïve view.

Figure 3.5 – Share of Portuguese sovereign debt held by all agents except Portuguese domestic banks



This figure plots the evolution of the share of Portuguese sovereign debt held by all agents except Portuguese domestic banks. Source: Banco de Portugal. The recently elected Greek prime minister revealed an unexpected large deficit in government accounts on 18 October 2009 (indicated by the left vertical line); the Greek prime minister requested official assistance on 23 April 2010 (indicated by the right vertical line).

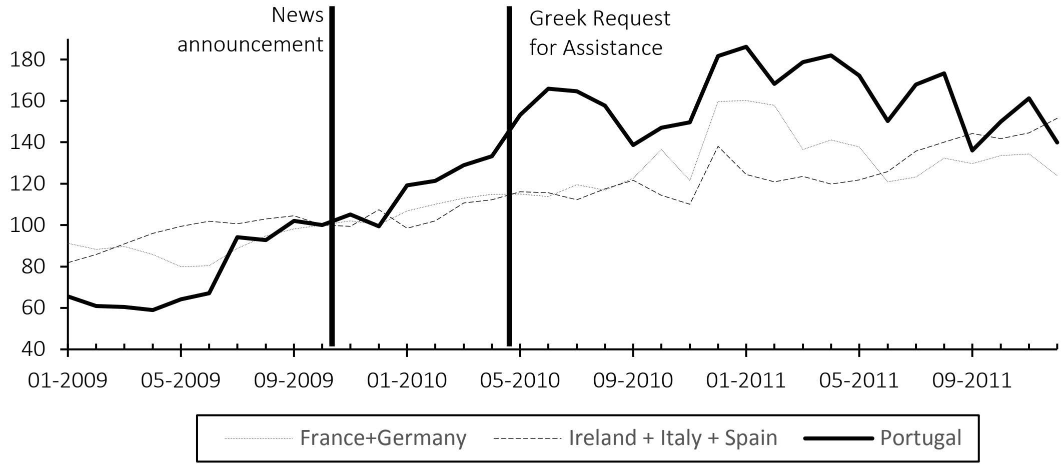
3.5.2. Our interpretation of the contagion process from Greece to Portugal

Our model reconciles the apparent contradiction between Fact 1 and Fact 2. In our view, Portuguese banks backed up their government until April 2010, offsetting the reduction in the exposure of international investors, and limiting the pressure on Portuguese government bond yields.

To investigate our view, it is useful to look at the behaviour of Portuguese banks before April 2010. Figure 3.6 depicts the evolution of banks' net claims on their domestic central government in several European countries, and shows that Portuguese banks increased their net claims on their government by 50% between October 2009 and April 2010.[11] This behaviour, which is in sharp contrast with the practice of other European banks, contributed to stabilizing Portuguese sovereign yields in the period before the Greek request for official assistance.

[11] Banks' net claims on their domestic central government are the claims that banks have on their government minus the deposits that the government has on the banks.

Figure 3.6 – Banks' Net Claims to its Domestic Central Government, Index (October 2009 = 100)



This figure plots the evolution of banks' net claims to its domestic central government for several European countries. Sources: IMF International Financial Statistics. The recently elected Greek prime minister revealed an unexpected large deficit in government accounts on 18 October 2009 (indicated by the left vertical line); the Greek prime minister requested official assistance on 23 April 2010 (indicated by the right vertical line).

According to our model, the 18% of the Portuguese sovereign debt held by Portuguese banks (related with m_P in our model) – illustrated in Figure 3.5 – may have been more than enough to signal the domestic banking system's commitment. This commitment maintained the two thresholds ($\underline{\theta}$ and $\overline{\theta}$) to a lower level, limiting the possibility of a successful speculative attack on the sovereign bond market. Moreover, before April 2010, the more Portuguese sovereign debt the banking system was buying, the more incentives the banking system had to commit to defending their government. Thus, the Portuguese sovereign bonds yields remained almost unaltered.

Nevertheless, at this point, it remains to explain why the Portuguese government bond yields started to increase after April 2010. The more naïve view suggests that this increase was due to a shift in the behaviour of international investors (because they perceived Portugal as the "next in line"). In contrast, we argue that Portuguese banks stopped helping their sovereign, thus leaving their sovereign exposed to the usual common lender channel. Taken together, Figures 3.4 to 3.6 support our view. On the one hand, Figures 3.4 and 3.5 show that the evolution of the foreign claims and the holdings of Portuguese sovereign debt by other agents except domestic banks did not dramatically worsen after the request for official assistance. On the other hand, Figure 3.6 indicates that Portuguese banks reduced their net claims on the central government shortly after the Greek request for official assistance, thus suggesting that Portuguese banks changed their behaviour.

According to our model, balance-sheet effects can be responsible for the reduction of Portuguese banks' net claims on their central government after April 2010. Capital losses after the Greek bailout (m_G in our model) reduced the ability of Portuguese banks to continue increasing their lending to their sovereign. We argue that capital losses led the Portuguese banking system to stop supporting their government shortly after April 2010, as suggested by Figure 3.6.

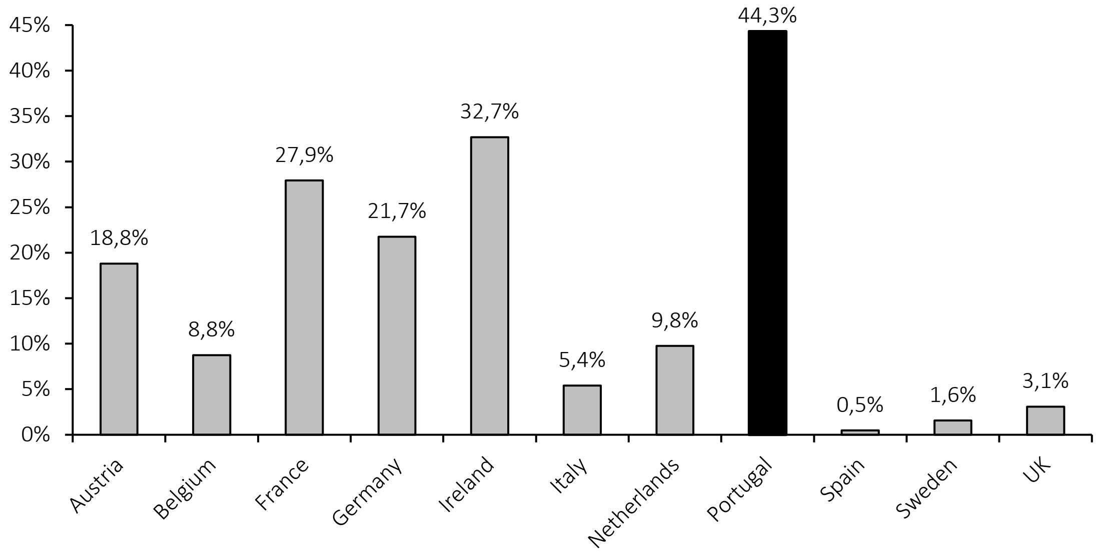
Portuguese banks were heavily exposed to the Greek economy and suffered a large negative capital shock after April 2010. Figure 3.7 plots the claims on Greece by European banks as a proportion of their Capital Tier 1 near the date of the sharp increase in Greek sovereign yields. The Portuguese banking system was among the most exposed to the Greek economy in terms of its own capital (when compared with other national banking systems). The Greek program for official assistance and the evolution of the Greek sovereign yields are likely to have had a negative impact on the balance sheets of Portuguese banks. On the one hand, Portuguese banks suffered immediate losses on tradable Greek debt that was being marked-to-market. On the other hand, banks anticipated losses when they perceived the increased risk of default of the Greek government.[12] These losses reduced the ability of Portuguese banks to shield their sovereign.

According to our model, the large negative capital shock constrained the Portuguese banking system. This shock led the Portuguese banking system to become less interested in intervening, increasing the thresholds ($\underline{\theta}$ and $\overline{\theta}$) substantially, and consequently the probability of a successful attack on the sovereign bond market. After a certain point, the Portuguese banking system chose not to defend their sovereign.

As a result of the reduced ability to protect their sovereign, Portuguese banks were no longer able to offset the effects of the common lender after the Greek request for official assistance. This event marks the moment when the Greek sovereign crisis started to contaminate the Portuguese sovereign debt market, with the Portuguese sovereign bond yields increasing substantially.

[12] For example, in their 2011 financial report, BPI bank recognized an impairment corresponding to 77% of their exposure to Greek sovereign bonds (BPI, 2012).

Figure 3.7 – European Banks' Claims on Greece Relative to their Capital Tier 1 at the end of March 2010



This figure shows the European banks' claims on Greece relative to their Capital Tier 1 at the end of March 2010. Source: Table 9D of BIS (2010), and EBA (2010). The European countries in our sample were chosen due to data availability.

3.6. Concluding Remarks

This paper contributes to the understanding of the role of a domestic banking system in the context of contagion through common lenders. We model a global game, in which the domestic banking system is a large player interested in assisting its domestic government in the secondary bond market. In its decision to assist its domestic government, the banking system weighs the benefits of buying domestic government bonds and thereby acting as a backstop against speculative attacks, against the costs associated to the possible collapse in the value of those bonds.

The strategic interaction between the domestic banking system and international speculators depends on two key elements: (i) the exposure of domestic banks to national sovereign debt, and (ii) the strength of domestic banks' balance sheets, measured by their exposure to international shocks.

The amount of domestic sovereign debt held by the domestic banking system serves as a commitment device: the more the domestic bank holds its sovereign debt, the more at stake the bank has with a successful attack on the sovereign bond market. As a result, the domestic banking system is more committed to protecting its sovereign and speculators recognize this commitment and are less willing to attack the sovereign bond market. Thus, the attack is less likely to succeed, the more the domestic banking system holds its sovereign debt.

The strength of the domestic bank's balance sheets also influences the strategic interaction between the two classes of players. On the one hand, when the domestic banks are sound, they have incentives to protect their sovereign against speculative attacks. International speculators anticipate the incentives of domestic banks and are less prone to speculative attacks. In this case, there is a backstop.

On the other hand, when the domestic banking system is weak, international speculators perceive and incorporate this limitation of domestic banks into their decisions to attack the domestic sovereign bond market. For example, a strong negative shock to the capital of the national banking system may trigger a speculative attack, as international speculators perceive weaker domestic banks. The attack is likely to be successful since domestic banks anticipate their own limitations and do not defend their sovereign.

We use the model's results to shed light on the Eurozone Sovereign Debt Crisis (ESDC). We take the example of the contagion dynamics from Greece to Portugal during the beginning of the Eurozone Sovereign Debt Crisis (ESDC) to show the role played by the Portuguese banking system. In particular, we first test for contagion effects from the Greek to the Portuguese sovereign bond market, focusing explicitly on the timing of the contagion effects. Then, we document the behaviour of international lenders' exposure to Portuguese debt and economy. We find an apparent contradiction: contagion effects from the Greek to the Portuguese sovereign bond market can only be traced after the Greek official request for assistance, whereas international lenders started reducing their exposure to Portugal several months before.

Our model reconciles these two apparently contradictory facts. In our view, Portuguese banks backed up their government until April 2010, increasing the net claims on their government by 50%, which offset the reduction in the exposure of international investors, and limited the pressure on Portuguese government bond yields. According to our model, since the Portuguese banks were highly exposed to its sovereign debt, they protected their sovereign.

Shortly after the Greek request for official assistance, Portuguese banks changed their behaviour, reducing their net claims on the central government. According to our model, balance-sheet effects can be responsible for this reduction. Because the Portuguese banking system was among the most exposed to the Greek economy in terms of its own capital (when compared with other national banking systems), capital losses after the Greek bailout reduced the ability of Portuguese banks to continue increasing their lending to their sovereign. As a result of the reduced ability to protect their sovereign, Portuguese banks were no longer able to offset the effects of the common lender after the Greek request for official assistance. This event marks the moment when contagion effects from the Greek to the Portuguese sovereign bond market start to be detectable, with the Portuguese sovereign bond yields increasing substantially.

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Appendix 3.A

In this Appendix, we prove that there is a unique equilibrium and the focus in switching strategies is without any loss of generality. This can be obtained by the iterated deletion of strictly dominated strategies, as in Corsetti *et al.* (2004).

First, we consider the expected payoff of a speculator to attacking the sovereign in country P conditional on s_{inv}^{i} when all other speculators follow the switching strategy around s_{inv}^{*} and when the bank plays his best response against this switching strategy (which is to switch at s_{bank}^{*}). Using Equation (3.10), this expected payoff, $W_{inv}(s_{inv}^{i}, s_{inv}^{*})$, is given by:

$$H\left(\underline{\theta}(s_{inv}^{*}) - s_{inv}^{i}\right) + \int_{\underline{\theta}(s_{inv}^{*})}^{\overline{\theta}(s_{inv}^{*})} h\left(\theta - s_{inv}^{i}\right) K\left(s_{bank}^{*}(s_{inv}^{*}) - \underline{\theta}(s_{inv}^{*})\right) d\theta \qquad (3.A.1)$$

where $\underline{\theta}(s_{inv}^{*})$ indicates the value of $\underline{\theta}$ when speculators follow the s_{inv}^{*}-switching strategy. $\overline{\theta}(s_{inv}^{*})$ is defined analogously. Moreover, note that $W_{inv}(.,.)$ is decreasing in its first argument and increasing in its second. This means that, for sufficiently low values of s_{inv}^{i}, the speculator attacks, independently of the actions of the other speculators and the bank.

Second, we now denote by s_{inv}^{0} the threshold value of s_{inv}^{i} below which it is a dominant action for a speculator to attack the sovereign in country P. All agents (speculators and the bank), realizing this, ignore any strategy for the speculator which prevent him from attacking below s_{inv}^{0}.

Third, if there is signal below s_{inv}^{1} where s_{inv}^{1} solves

$$W_{inv}(s_{inv}^{1}, s_{inv}^{0}) = c, \qquad (3.A.2)$$

preventing the speculator from attacking cannot be rational for him because the switching strategy around s_{inv}^{1} is the best reply to the switching strategy around s_{inv}^{0}. In this case, even the most pessimistic speculator believes that the incidence of attack is higher than that implied by the switching strategy around s_{inv}^{0} and the bank's best reply

$s^*_{bank}(s^0_{inv})$. Since the payoff to attacking is increasing in the incidence of attack by the other speculators, any strategy that prevents from attacking for signals lower than s^1_{inv} is dominated. Thus, after two rounds of deletion of dominated strategies, any strategy for a speculator that prevents from attack for signals lower than s^1_{inv} is eliminated. Proceeding in this way, one generates the increasing sequence

$$s^0_{inv} < s^1_{inv} < \cdots < s^n_{inv} < \cdots \qquad (3.A.3)$$

where any strategy that prevents from attacking for signal $s^i_{inv} < s^n_{inv}$ does not survive n + 1 rounds of deletion of dominated strategies. The sequence is increasing since $W_{inv}(.,.)$ is decreasing in its first argument, and increasing in its second. The smallest solution s^i_{inv} to the equation

$$W_{inv}\left(s^i_{inv}, s^i_{inv}\right) = c \qquad (3.A.4)$$

is the least upper bound of this sequence, and hence its limit. Any strategy that prevents from attacking for signal lower than s^i_{inv} does not survive iterated dominance. On the other hand, if s^i_{inv} is the largest solution to Eq. (3.A.4), there is an exactly analogous argument from "above", which demonstrates that a strategy that attacks for signals larger than s^i_{inv} does not survive iterated dominance. Consequently, there is a unique solution to Eq. (3.A.4), that remains after eliminating all iteratively dominated strategies. This strategy is the only equilibrium strategy. This completes the proof.

Appendix 3.B

In this appendix, we give proof of Proposition 1.

Let us first derive the equations determining $\overline{\theta}$ and $\underline{\theta}$. If the fundamental is θ and speculators attack only if they observed a signal below s_{inv}^{*}, the probability that any particular speculator receives a signal below this level and hence the proportion of speculators that attack is:

$$prob\left[s_{inv}^{i} \leq s_{inv}^{*} \middle| \theta\right] = H(s_{inv}^{*} - \theta) \qquad (3.B.1)$$

Proof. See Appendix 3.C.

Moreover, we define the conditional probability of a successful attack given a private signal for a speculator equal to s_{inv}^{*}, as follows:

$$prob\left[\theta^{i} \leq \theta^{*} \middle| s_{inv}^{*}\right] = H(\theta^{*} - s_{inv}^{*}) \qquad (3.B.2)$$

Using our definition of the threshold for failure $\overline{\theta}$, if the bank does not help, the attack succeeds for any θ such that $\theta \leq \overline{\theta}$. Then, at $\theta = \overline{\theta}$ the mass A of speculators that attack is just enough for succeeding. By the law of large numbers, this mass A corresponds to the probability $H\left(s_{inv}^{*} - \overline{\theta}\right)$. We can write the first equilibrium condition, which defines $\overline{\theta}$, as follows:

$$\overline{\theta} = H\left(s_{inv}^{*} - \overline{\theta}\right) \qquad (3.B.3)$$

If the bank helps, a successful attack happens for any θ such that $\theta \leq \underline{\theta}$. As above, at $\underline{\theta}$, the critical mass of speculators to cause a collapse in the bonds' price is $A = H(s_{inv}^{*} - \underline{\theta})$. The threshold for failure conditional on the bank's intervention $\underline{\theta}$ is:

$$\underline{\theta} + m^{*} = H\left(s_{inv}^{*} - \underline{\theta}\right) \Leftrightarrow \underline{\theta} = H\left(s_{inv}^{*} - \underline{\theta}\right) - m^{*} \qquad (3.B.4)$$

This is the second equilibrium condition – defining $\underline{\theta}$. Note that m^* can be decomposed in $\overline{m} - m_G$, the capacity of the bank and the losses from country G, respectively. Conditional on $m^* > 0$, we have that $\overline{\theta} > \underline{\theta}$.

We now turn to the equations determining the triggers s_{inv}^* and s_{bank}^*, starting from the latter. After receiving the signal $\tilde{s}_{bank}$, the bank assigns the probability $K(\underline{\theta} - s_{bank})$ to the attack's success despite its intervention, where s_{bank} is the posterior associated to the signal $\tilde{s}_{bank}$. Using Eq.(3.10), the bank's expected payoff (denoted by W_{bank}) is therefore:

$$W_{bank}(m, m_P, \theta, s_{bank}) = r(m + m_P) * \left(1 - K(\theta - s_{bank})\right) + \\ +(-m - m_P) * K(\theta - s_{bank}) \qquad (3.B.5)$$

which is increasing in s_{bank}. As said earlier, given the linear nature of the problem, the bank has only two choices: it defends using its full financing capacity ($m = m^*$) or does not defend at all ($m = 0$). Therefore, the optimal strategy consists of defending the sovereign if and only if his expected payoff, $W_{bank}(m^*, m_P, \underline{\theta}, s_{bank})$, is at least equal to $W_{bank}(0, m_P, \overline{\theta}, s_{bank})$. That is, if and only if $s_{bank} \geq s_{bank}^*$, where s_{bank}^* is implicitly defined by the zero-profit condition below:

$$(m^* + m_P)K(\underline{\theta} - s_{bank}^*) - m_P K(\overline{\theta} - s_{bank}^*) = \frac{rm^*}{1+r} \qquad (3.B.6)$$

We now turn to the speculators' problem. Whether or not the bank intervenes, the attack succeeds for $\theta \leq \underline{\theta}$. So, a speculator receiving a signal $\tilde{s}_{inv}$ will assign probability $H(\underline{\theta} - s_{inv})$ to the attack's success regardless of the bank's action.

However, for θ comprised between $\underline{\theta}$ and $\overline{\theta}$, the attack succeeds only if the bank does not defend. So, the speculators' expected payoff (denoted W_{inv}) from attacking the sovereign includes a term accounting for the conditional probability that the bank does not defend the attack, given by $K(s_{bank}^* - \theta)$:

$$W_{inv} = (1-c)\left(H(\underline{\theta} - s_{inv}) + \int_{\underline{\theta}}^{\overline{\theta}} h(\theta - s_{inv})\, K(s_{bank}^* - \theta) d\theta\right) +$$

$$+(-c)\left[1-\left(H\left(\underline{\theta}-s_{inv}\right)+\int_{\underline{\theta}}^{\overline{\theta}}h(\theta-s_{inv})\,K(s_{bank}^{*}-\theta)d\theta\right)\right] \qquad (3.B.7)$$

where h is the probability density function of H. The optimal trigger s_{inv}^{*} for speculators is implicitly defined by the zero-profit condition (in expected terms) below:

$$H\left(\underline{\theta}-s_{inv}^{*}\right)+\int_{\underline{\theta}}^{\overline{\theta}}h(\theta-s_{inv})\,K(s_{bank}^{*}-\theta)d\theta=c \qquad (3.B.8)$$

As shown in Appendix 3.A, there is a unique value s_{inv}^{*} that solves this equation. This completes the proof.

Appendix 3.C

In this appendix, we give proof of Equation (3.B.1).

In this game, there is public information about the sovereign's ability to pay their debt:

$$\theta = \theta + \gamma \tag{3.C.1}$$

According to our assumptions the private signals for investors are:

$$s_{inv} = \theta + \varepsilon_i \tag{3.C.2}$$

According to Jorge and Rocha (2015), the posterior signals for investors are the following:

$$E(\theta | s_{inv}) = \frac{\rho\theta + \alpha s_{inv}}{\rho + \alpha} \tag{3.C.3}$$

From here, we can now compute the $prob\left[s_{inv}^i \leq s_{inv}^* \middle| \underline{\theta}\right]$. First, we begin with the posteriors, $prob\left[p_{inv}^i \leq p_{inv}^* \middle| \underline{\theta}\right]$.

Using Equation (3.C.3), we get:

$$p_{inv}^* = E\left(\underline{\theta} \middle| s_{inv}^*\right) = \frac{\rho\underline{\theta} + \alpha s_{inv}^*}{\rho + \alpha} \tag{3.C.4}$$

From Equation (3.C.4), we can now compute the $prob\left[p_{inv}^i \leq p_{inv}^* \middle| \underline{\theta}\right]$ to get the $prob\left[s_{inv}^i \leq s_{inv}^* \middle| \underline{\theta}\right]$:

$$p_{inv}^i \leq p_{inv}^* \Leftrightarrow \frac{\rho\underline{\theta} + \alpha s_{inv}^i}{\rho + \alpha} < p_{inv}^* \Leftrightarrow s_{inv}^i < p_{inv}^* + \frac{\rho}{\alpha}\left(p_{inv}^* - \underline{\theta}\right) \tag{3.C.5}$$

Using Equation (3.C.5), we can derive:

$$prob\left[p_{inv}^i \leq p_{inv}^* \middle| \underline{\theta}\right] = prob\left[s_{inv}^i \leq p_{inv}^* + \frac{\rho}{\alpha}(p_{inv}^* - \underline{\theta}) \middle| \underline{\theta}\right] \tag{3.C.6}$$

Since $E(s_{inv}^i | \underline{\theta}) = \underline{\theta}$, using Equation (3.C.6) and normalizing the probability, we can get:

$$prob\left[\frac{s_{inv}^{i}-\underline{\theta}}{\frac{1}{\sqrt{\alpha}}}\leq\frac{p_{inv}^{*}+\frac{\rho}{\alpha}\left(p_{inv}^{*}-\underline{\theta}\right)-\underline{\theta}}{\frac{1}{\sqrt{\alpha}}}\middle|\underline{\theta}\right]=$$

$$=\Phi\left(\frac{p_{inv}^{*}+\frac{\rho}{\alpha}\left(p_{inv}^{*}-\underline{\theta}\right)-\underline{\theta}}{\frac{1}{\sqrt{\alpha}}}\right) \qquad (3.C.7)$$

With the assumption that the private signals are arbitrarily more accurate than the public signal, i.e. $\frac{\rho}{\alpha}\to 0$, we get:

$$\Phi\left(\frac{s_{inv}^{*}-\underline{\theta}}{\frac{1}{\sqrt{\alpha}}}\right)=G\left(s_{inv}^{*}-\underline{\theta}\right) \qquad (3.C.8)$$

Which completes the proof.

Appendix 3.D

This appendix proves Proposition 2. As in Corsetti *et al.* (2006), we define new variables:

$$\underline{w} = \underline{\theta} - s_{inv}^{*} \quad (3.D.1)$$

$$\overline{w} = \overline{\theta} - s_{inv}^{*} \quad (3.D.2)$$

In order to prove Proposition 2, we differentiate the four equations in our model. Starting with Eq.(3.7), we get:

$$\overline{\theta} = H\left(s_{inv}^{*} - \overline{\theta}\right) \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial \overline{\theta}}{\partial m_P} = -h(\overline{w})\left[\frac{\partial \overline{\theta}}{\partial m_P} - \frac{\partial s_{inv}^{*}}{\partial m_P}\right] \Leftrightarrow \frac{\partial \overline{\theta}}{\partial m_P}$$

$$= \frac{h(\overline{w})}{1 + h(\overline{w})}\frac{\partial s_{inv}^{*}}{\partial m_P} \quad (3.D.3)$$

$$\frac{\partial \overline{w}}{\partial m_P} = -\frac{1}{1 + h(\overline{w})}\frac{\partial s_{inv}^{*}}{\partial m_P} \quad (3.D.4)$$

Differentiating Eq.(3.8), we have:

$$\underline{\theta} = H\left(s_{inv}^{*} - \underline{\theta}\right) - (\overline{m} - m_G) \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial \underline{\theta}}{\partial m_P} = -h\left(\underline{w}\right)\left[\frac{\partial \underline{\theta}}{\partial m_P} - \frac{\partial s_{inv}^{*}}{\partial m_P}\right] \Leftrightarrow \frac{\partial \underline{\theta}}{\partial m_P} = \frac{h\left(\underline{w}\right)}{1 + h\left(\underline{w}\right)}\frac{\partial s_{inv}^{*}}{\partial m_P} \quad (3.D.5)$$

$$\frac{\partial \underline{w}}{\partial m_P} = -\frac{1}{1 + h\left(\underline{w}\right)}\frac{\partial s_{inv}^{*}}{\partial m_P} \quad (3.D.6)$$

From Eq.(3.9), we have:

$$(m^{*} + m_P)K\left(\underline{\theta} - s_{bank}^{*}\right) - m_P K\left(\overline{\theta} - s_{bank}^{*}\right) = \frac{rm^{*}}{1 + r}$$

Differentiating it, we get:

$$\frac{\partial s_{bank}^{*}}{\partial m_P} = Z_1 + Z_2\frac{\partial \overline{\theta}}{\partial m_P} + Z_3\frac{\partial \underline{\theta}}{\partial m_P} \quad (3.D.7)$$

Where

$$Z_1 = \frac{K(\overline{\theta} - s^*_{bank}) - K(\underline{\theta} - s^*_{bank})}{m_P k(\overline{\theta} - s^*_{bank}) - (m^* + m_P)k(\underline{\theta} - s^*_{bank})} < 0, \tag{3.D.8}$$

$$Z_2 = \frac{1}{1 - \frac{m^* + m_P}{m_P} \frac{k(\underline{\theta} - s^*_{bank})}{k(\overline{\theta} - s^*_{bank})}} < 0, \tag{3.D.9}$$

$$Z_3 = \frac{1}{1 - \frac{m_P}{m^* + m_P} \frac{k(\overline{\theta} - s^*_{bank})}{k(\underline{\theta} - s^*_{bank})}} > 0, \tag{3.D.10}$$

Differentiating Eq.(3.10), we get:

$$H(\underline{\theta} - s^*_{inv}) + \int_{\underline{\theta}}^{\overline{\theta}} h(\theta - s^*_{inv})\, K(\theta - s^*_{bank}) d\theta = c \Leftrightarrow$$

$$\Leftrightarrow H(\underline{w}) + \int_{\underline{w}}^{\overline{w}} h(w) K(w + s^*_{inv} - s^*_{bank}) dw = c \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial H(\underline{w})}{\partial m_P} + \frac{\partial}{\partial m_P}\left[\int_{\underline{w}}^{\overline{w}} h(w) K(w + s^*_{inv} - s^*_{bank}) dw\right] = 0 \Leftrightarrow$$

$$\Leftrightarrow \varphi_1 \frac{\partial \overline{w}}{\partial m_P} + \varphi_2 \frac{\partial \underline{w}}{\partial m_P} + \varphi_3 = 0 \tag{3.D.11}$$

Where,

$$\varphi_1 = h(\overline{w}) K(\overline{w} + s^*_{inv} - s^*_{bank}) - Z_2 z > 0, \tag{3.D.12}$$

$$\varphi_2 = h(\underline{w}) \left(1 - K(\underline{w} + s^*_{inv} - s^*_{bank})\right) - Z_3 z > 0, \tag{3.D.13}$$

$$\varphi_3 = Z_1 z < 0, \tag{3.D.14}$$

$$z = \int_{\underline{w}}^{\overline{w}} h(w) k(w + s^*_{inv} - s^*_{bank})\, dw. \tag{3.D.15}$$

Combining equations (3.D.4), (3.D.6), and (3.D.11), this yields:

$$-\varphi_1 \frac{1}{1+h(\overline{w})} \frac{\partial s_{inv}^*}{\partial m_P} - \varphi_2 \frac{1}{1+h(\underline{w})} \frac{\partial s_{inv}^*}{\partial m_P} + \varphi_3 = 0 \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial s_{inv}^*}{\partial m_P} = \frac{\varphi_3}{\frac{\varphi_1}{1+h(\overline{w})} + \frac{\varphi_2}{1+h(\underline{w})}} < 0 \qquad (3.D.16)$$

Using Eq.(3.D.3):

$$\frac{\partial \overline{\theta}}{\partial m_P} = \frac{h(\overline{w})}{1+h(\overline{w})} \frac{\partial s_{inv}^*}{\partial m_P} < 0 \qquad (3.D.17)$$

And Eq.(3.D.5):

$$\frac{\partial \underline{\theta}}{\partial m_P} = \frac{h(\underline{w})}{1+h(\underline{w})} \frac{\partial s_{inv}^*}{\partial m_P} < 0 \qquad (3.D.18)$$

From Eq.(3.D.7), we have:

$$\frac{\partial s_{bank}^*}{\partial m_P} = Z_1 + Z_2 \frac{\partial \overline{\theta}}{\partial m_P} + Z_3 \frac{\partial \underline{\theta}}{\partial m_P} < 0 \qquad (3.D.19)$$

Which completes the proof.

Appendix 3.E

In this appendix, we give a proof of Proposition 3. In order to prove Proposition 3, we differentiate the four equations in our model. Using the new variables defined in Appendix 3.D and starting with Eq.(3.7):

$$\frac{\partial\overline{\theta}}{\partial m_G} = -h(\overline{w})\left[\frac{\partial s_{inv}^*}{\partial m_G} - \frac{\partial\overline{\theta}}{\partial m_G}\right] \Leftrightarrow \frac{\partial\overline{\theta}}{\partial m_G} = \frac{h(\overline{w})}{1+h(\overline{w})}\frac{\partial s_{inv}^*}{\partial m_G} \qquad (3.E.1)$$

$$\frac{\partial\overline{w}}{\partial m_G} = -\frac{1}{1+h(\overline{w})}\frac{\partial s_{inv}^*}{\partial m_G} \qquad (3.E.2)$$

Now, we differentiate Eq.(3.8):

$$\frac{\partial\underline{\theta}}{\partial m_G} = \frac{\partial H\left(s_{inv}^* - \underline{\theta}\right)}{\partial m_G} - \frac{\partial(\overline{m} - m_G)}{\partial m_G} \Leftrightarrow \frac{\partial\underline{\theta}}{\partial m_G} = -\frac{\partial H\left(\underline{w}\right)}{\partial\underline{w}}\frac{\partial\left(\underline{\theta} - s_{inv}^*\right)}{\partial m_G} + 1 \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial\underline{\theta}}{\partial m_G} = h\left(\underline{w}\right)\left[\frac{\partial s_{inv}^*}{\partial m_G} - \frac{\partial\underline{\theta}}{\partial m_G}\right] + 1 \Leftrightarrow \frac{\partial\underline{\theta}}{\partial m_G} = \frac{1 + h\left(\underline{w}\right)\frac{\partial s_{inv}^*}{\partial m_G}}{1 + h\left(\underline{w}\right)} \qquad (3.E.3)$$

$$\frac{\partial\underline{w}}{\partial m_G} = \frac{1}{1+h\left(\underline{w}\right)}\left(1 - \frac{\partial s_{inv}^*}{\partial m_G}\right) \qquad (3.E.4)$$

From Eq.(3.9), we have:

$$(m^* + m_P)K\left(\underline{\theta} - s_{bank}^*\right) - m_P K\left(\overline{\theta} - s_{bank}^*\right) = \frac{rm^*}{1+r}$$

Differentiating Eq.(3.9), we get:

$$\frac{\partial s_{bank}^*}{\partial m_G} = Z_1 + Z_2\frac{\partial\overline{\theta}}{\partial m_G} + Z_3\frac{\partial\underline{\theta}}{\partial m_G} \qquad (3.E.5)$$

where

$$Z_1 = \frac{\frac{r}{1+r} - K(\underline{\theta} - s_{bank}^*)}{(m^* + m_P)k\left(\underline{\theta} - s_{bank}^*\right) - m_P k\left(\overline{\theta} - s_{bank}^*\right)} < 0, \qquad (3.E.6)$$

$$Z_2 = \frac{1}{1 - \frac{m^* + m_P}{m_P} \frac{k(\underline{\theta} - s_{bank}^*)}{k(\overline{\theta} - s_{bank}^*)}} < 0, \qquad (3.E.7)$$

$$Z_3 = \frac{1}{1 - \frac{m_P}{m^* + m_P} \frac{k(\overline{\theta} - s_{bank}^*)}{k(\underline{\theta} - s_{bank}^*)}} > 0, \qquad (3.E.8)$$

Differentiating Eq.(3.10), we get:

$$H\left(\underline{\theta} - s_{inv}^*\right) + \int_{\underline{\theta}}^{\overline{\theta}} h(\theta - s_{inv}^*)\, K(\theta - s_{bank}^*) d\theta = c \Leftrightarrow$$

$$\Leftrightarrow H\left(\underline{w}\right) + \int_{\underline{w}}^{\overline{w}} h(w) K(w + s_{inv}^* - s_{bank}^*) dw = c \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial H\left(\underline{w}\right)}{\partial m_G} + \frac{\partial}{\partial m_G}\left[\int_{\underline{w}}^{\overline{w}} h(w) K(w + s_{inv}^* - s_{bank}^*) dw\right] = 0 \Leftrightarrow$$

$$\Leftrightarrow \varphi_1 \frac{\partial \overline{w}}{\partial m_G} + \varphi_2 \frac{\partial \underline{w}}{\partial m_G} + \varphi_3 = 0 \qquad (3.E.9)$$

Where,

$$\varphi_1 = h(\overline{w}) K(\overline{w} + s_{inv}^* - s_{bank}^*) - Z_2 z > 0, \qquad (3.E.10)$$

$$\varphi_2 = h\left(\underline{w}\right)\left(1 - K\left(\underline{w} + s_{inv}^* - s_{bank}^*\right)\right) - Z_3 z > 0, \qquad (3.E.11)$$

$$\varphi_3 = Z_1 z < 0, \qquad (3.E.12)$$

$$z = \int_{\underline{w}}^{\overline{w}} h(w) k(w + s_{inv}^* - s_{bank}^*)\, dw. \qquad (3.E.13)$$

Combining equations (3.E.2), (3.E.4), and (3.E.9), this yields:

$$-\varphi_1 \frac{1}{1 + h(\overline{w})} \frac{\partial s_{inv}^*}{\partial m_G} + \varphi_2 \frac{1}{1 + h\left(\underline{w}\right)}\left(1 - \frac{\partial s_{inv}^*}{\partial m_G}\right) + \varphi_3 = 0 \Leftrightarrow$$

$$\Leftrightarrow \frac{\partial s_{inv}^*}{\partial m_G} = \frac{\frac{\varphi_2}{1 + h\left(\underline{w}\right)} + \varphi_3}{\frac{\varphi_1}{1 + h(\overline{w})} + \frac{\varphi_2}{1 + h\left(\underline{w}\right)}} > 0 \qquad (3.E.14)$$

From eq. (3.E.1), we get

$$\frac{\partial\overline{\theta}}{\partial m_G}=\frac{h(\overline{w})}{1+h(\overline{w})}\frac{\partial s_{inv}^{*}}{\partial m_G}>0 \qquad (3.E.15)$$

From Eq.(3.E.3), we have

$$\frac{\partial\underline{\theta}}{\partial m_G}=\frac{1+h\left(\underline{w}\right)\frac{\partial s_{inv}^{*}}{\partial m_G}}{1+h\left(\underline{w}\right)}>0 \qquad (3.E.16)$$

Using Eq.(3.E.5), we get

$$\frac{\partial s_{bank}^{*}}{\partial m_P}=Z_1+Z_2\frac{\partial\overline{\theta}}{\partial m_P}+Z_3\frac{\partial\underline{\theta}}{\partial m_P}>0 \qquad (3.E.17)$$

Which completes the proof.

Appendix 3.F

Estimations of Model in Equations 3.11-3.13[a,b]

Variables	Coefficients	(z-statistic)
Equation 3.11		
R_{GR}	0.2190***	(10.05)
$R_{GR} * D1_{crisis}$	0.1356	(1.59)
$R_{GR} * D2_{crisis}$	0.2565***	(5.04)
Constant	0.0001	(0.19)
Equation 3.13 (EGARCH)		
$\frac{e_{PT}}{\sqrt{\mathrm{h}_{PT}}}$ (-1)	-0.0719**	(-2.39)
$\frac{\lvert e_{PT}\rvert}{\sqrt{\mathrm{h}_{PT}}}$ (-1)	0.4091***	(8.74)
log(h_{PT}) (-1)	0.8173***	(8.05)
t	0.0004***	(6.14)
Constant	-1.6888**	(-2.05)
Statistics		
Log-Likelihood	2448.92	
Chi-Square	227.29	
Sample Size	970	

[a]Robust z-statistics in brackets.

[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively. Robust z-statistics are shown in parentheses. R_{GR} (First differences of Greek Sovereign yields), $D1_{crisis}$ (dummy variable which takes the value 1 from 18 October 2009 to 22 April 2010 and 0 elsewhere), $D2_{crisis}$ (dummy variable which takes the value 1 from 23 April 2010 to 6 April 2011 and 0 elsewhere), and t (linear trend variable).

Chapter 4

A Unified Early Warning System for Banking and Currency Crises: Channels of Crises interaction as Leading Indicators

Abstract: We examine the role of the channels of interaction that run from banking to currency crises (and vice-versa) in signalling these two types of crises. We propose a unified Early Warning System (EWS) for banking and currency crises, jointly estimating the likelihood of both types of crisis using a system of two dynamic probit equations. For each equation, we add multiplicative terms between the leading indicators and the interaction effects from the other type of crisis to assess the channels of crises interaction empirically. We find several of these channels to be leading indicators. We also find that including channels of crises interaction improves the predictability power of the EWS substantially.

KEYWORDS: Channels of Crises interaction, Early Warning Systems, Banking Crises, Currency Crises, Emerging Markets

JEL CODES: F31, F47, G01, G21

4.1. Introduction

Following the deregulation of financial markets across many parts of the world in the 1980s, banking and currency crises have become closely intertwined. To explain such tight ties, various authors have theoretically suggested the existence of interaction effects that run from one type of crisis to the other, i.e. the occurrence of a crisis affecting the likelihood of the other type of crisis. In particular, these crises interaction effects can occur via several channels. For instance, Velasco (1987) suggests that countries may become vulnerable to currency attacks when policymakers use their international reserves to deal with banking problems, thus linking banking to currency crises. The Asian Financial Crisis of 1997 is an unequivocal episode on how these channels of crises interaction can link banking and currency crises together. In fact, this crisis inspired the development of theoretical models, the so-called "third-generation" models, which contributed toward understanding the role of banking problems in causing currency crises (e.g. Jeanne and Wyplosz, 2003). Given the importance that theory ascribes to the interactions between banking and currency crises, incorporating channels of crises interaction should help predict both types of crises when using Early Warning Systems (EWS). Hence, what role do the channels of crises interaction play in predicting banking and currency crises?

So far, in the EWS literature on banking and currency crises, several models include leading indicators that typically help to predict the other type of crisis (e.g. Kaminsky and Reinhart, 1999). In this sense, these models allow capturing vulnerabilities from the other sector to predict a type of crisis. However, while the inclusion of variables that are indicators of vulnerabilities of the other type of crisis may be of value for this purpose, these EWS studies have made limited analyses of accounting for the channels of crises interaction. Hence, the goal of this study is to examine the role of channels of crises interaction in predicting banking and currency crises systematically and explicitly. To do so, we depart from the EWS literature in four ways.

First, we introduce a unified EWS for banking and currency crises, i.e. we jointly estimate the likelihood of both types of crises using a system of two equations. Since there are several theoretical reasons to expect links between the two types of crisis, there may be feedback effects between them. Thus, the resulting framework allows us to study bidirectional crises interaction effects, controlling for common causes between the two types of crises.

Second, we introduce a dummy variable that identifies the occurrence of banking (currency) crises in the currency (banking) crisis equation, instead of using a limited number of leading indicators that predicts banking (currency) crises. Including these dummy variables allows us to test directly if the presence of a banking (currency) crisis signals future currency (banking) crises, i.e. this dummy variable accounts for the episodes of crises interaction effects.

Third, we offer a new approach to gauge empirically the channels of crises interaction that is consistent with the theoretical literature. According to the theoretical literature, the channels of crises interaction exist because a banking (currency) crisis interacts with the vulnerabilities leading to currency (banking) crises (e.g. Velasco, 1987). As we move from theory to prediction, we replace these vulnerabilities by leading indicators. Accordingly, to each equation, we add multiplicative terms between the leading indicators and the interaction effects from the other type of crisis (measured by the dummy variable). In this paper, we refer to these new measures (i.e. the multiplicative terms) as the channels of crises interaction. For example, in the currency crisis equation, we introduce multiplicative terms between the leading indicators of currency crises and the interaction effects from banking crises. Including these terms allow us to assess if the contribution of leading indicators to the likelihood of currency crises depends on the presence of a banking crisis – some of these vulnerabilities may gain relevance to signal currency crises if and only if a banking crisis occurs.

Finally, we highlight the implications of crises interaction effects (and the channels of crises interaction) to the performance evaluation of the EWS. Since the nature of banking and currency crises may depend on the presence of crises interaction effects, we compare the predictive power of each EWS when the crises interaction effects are present with when they do not occur. Ultimately, this exercise allows examining if introducing the channels of crises interaction into an EWS enhances the predictive power when crises interaction effects are present.

Our main findings are as follows. First, for all EWS, our results unambiguously suggest that the equations of banking and currency crises should be jointly estimated. These results motivate the need for a unified EWS for banking and currency crises.

Second, we find that several channels of interaction from currency crises (measured by the multiplicative terms) signal future banking crises. In particular, we find that, in the presence of a currency crisis, a stock market collapse, real devaluations, and the ratio of short-term external debt to reserves have significant impacts on the likelihood of future banking crises.

Third, we also find that several channels of interaction from banking crises signal future currency crises. In particular, we find that interest rates, the inflation rate, stock market collapses, exchange rate overvaluation, and a reduction in reserves exacerbate the likelihood of currency crises, following the onset of a banking crisis.

Fourth, we find that including channels of crises interaction improves substantially the in-sample predictability power of the EWS. This improvement occurs for all subsamples, suggesting that including channels of crises interaction effects allows the EWS to better signal crises with crises interaction effects as well as single crises.

Finally, we find that the predictive power for currency crises is substantially higher for the observations when crises interaction effects are present than when crises interaction effects are absent, regardless of the EWS. This set of results suggests that the nature of currency crises may depend on the presence of interaction effects from banking crises, thus reinforcing our motivation for the use of a unified EWS for banking and currency crises.

The results presented in this study have important policy implications. First, the policymaker should be vigilant of both types of crises to predict more successfully banking and currency crises. Second, some policies may actually have the opposite result if the policymaker does not consider the channels of crises interaction.

The paper is organized as follows. Section 4.2 discusses the related literature. Section 4.3 presents the methodology. Section 4.4 describes the data. Section 4.5 presents the results for various EWS (with and without channels of crises interaction). Section 4.6 concludes.

4.2. Literature Review

This study relates to two strands of literature. The first strand proposes theoretical channels linking banking and currency crises; the second strand empirically studies banking and currency crises. In this review, we present the two strands, and we show how we can contribute to the EWS literature by accounting for crises interaction effects in an EWS.

The first strand, reviewed, for example, in Kaminsky and Reinhart (1999) and Glick and Hutchinson (2001), has focused on explaining how banking and currency crises interact with each other. These theoretical studies propose an abundance of channels of interaction between these types of crises, i.e. chains of causality that run from banking to currency crises and vice-versa.

From banking crises to balance-of-payments problems, numerous studies stress that, when dealing with banking sector problems, the central bank may act inconsistently with a stable exchange rate regime, leaving the external sector vulnerable to speculative attacks (see, for example, Velasco, 1987; Obstfeld, 1988; Calvo and Mendonza, 1996). For instance, after a bank collapse, the government may use international reserves to redeem domestic deposits. Both Velasco (1987) and Calvo and Mendonza (1996) argue that the decline in foreign exchange reserves can limit the government's ability to defend the exchange rate. The reduced ability may be sufficient to leave the external sector vulnerable to speculative attacks, which will be perceived by speculators who attack the currency. In fact, Calvo and Mendonza (1996) stress that the higher the mismatch between M2 and foreign exchange reserves, the more likely redeeming deposits provokes a loss of reserves sufficient enough to expose the external sector to speculative attacks. On a different direction, Obstfeld (1988) argues that policymakers may choose to increase inflation to avoid bankruptcies. However, increasing inflation may be inconsistent with the stability of the exchange rate, leaving the external sector vulnerable to speculative attacks.

Regarding the inverse interaction – i.e. the chain of causation that runs from currency to banking crises – various studies have focused on the real effects that a depreciation/devaluation may have on the financial sector and the domestic economy, which may culminate in banking problems (see, for example, Mishkin, 1996; Stoker, 1996; Chang and Velasco, 2000). Mishkin (1996) stresses that the higher the amount of liabilities denominated in foreign currency, the more likely a currency crisis deteriorates the balance sheets of firms and banks. This deterioration increases asymmetric information problems, which may lead to banking problems. Chang and Velasco (2000) show that a real depreciation may lead to a loss of value in the non-tradable goods sector, inducing bankruptcies among these firms and increasing the likelihood of banking crises. On a different direction, Stoker (1996) indicates that a speculative attack tends to increase abnormally interest rates. This unusually high level in interest rates may lead to a credit crunch, which increases the probability of bankruptcies and banking crises.

Finally, the "third-generation" models proposed several explanations on how banking and currency crises can endogenously reinforce one another (e.g. Jeanne and

Wyplosz, 2003; Burnside, Eichenbaum, and Rebelo, 2004). For instance, Jeanne and Wyplosz (2003) present a model in which they link together both feedbacks into a vicious spiral. More specifically, they model the events in the following order: *(1)* a currency depreciation triggers bank runs due to the currency mismatch in the balance sheets of the banking sector; (2) banking problems lead to a credit crunch; (3) this credit crunch incentivises the policymaker to depreciate the currency in order to avoid a severe recession. Burnside *et al.* (2004) instead focus on the presence of government guarantees and show how these guarantees may lead to self-fulfilling twin crises. This study shows that, because of these guarantees, banks expose themselves to exchange rate risk and, thus, declare bankruptcy after a devaluation.

The second strand of the literature encompasses numerous empirical works that study banking and currency crises. We may divide this second strand into two large bodies of work. On the one hand, there have been studies that focus on the crises determinants and test if crises interaction effects explain/cause banking and/or currency crises (see, for example, Kaminsky and Reinhart, 1999; Glick and Hutchinson, 2001; Babecký, Havránek, Matějů, Rusnák, Šmídková, and Vašíček, 2014). These studies, however, do not study the signalling ability of these crises interaction effects and have made limited analysis regarding early warning indicators. On the other hand, early warning studies, i.e. works that focus on the identification of early warning indicators, have been limited in the consideration of crises from the other type (e.g. Kaminsky *et al.*, 1998; Berg and Pattillo, 1999; Demirgüc-Kunt and Detragiache, 2000). While there have been some studies that consider leading indicators from the other type of crisis, to the best of our knowledge, there has not been a single study that has introduced the occurrence of the other type of crisis, let alone the analysis of crises interaction channels. We now review these two large bodies of work.

Starting by the works focusing on crises determinants, based on the conclusions stressed in the first strand, these studies examine if the onset of a type of crisis increases the probability of occurrence of another type of crisis. We can broadly group this literature into three categories depending on the approaches used to test the crises interaction effects as crises determinants.

First, the seminal paper of Kaminsky and Reinhart (1999) is one of the first studies to analyse empirically the link between banking and balance-of-payments crises. Using a univariate approach, these authors compare the unconditional probabilities of banking and currency crises to the probabilities conditional on the occurrence of another type of crisis. Kaminsky and Reinhart (1999) conclude that after the 1980s the probability of a currency crisis conditioned on the beginning of banking sector problems is well above the unconditional probability of a currency crisis, suggesting that banking crises tend to precede balance-of-payments problems. These authors do not find evidence to support the inverse causation.

Second, using multivariate approaches, a few studies test for unidirectional causation between crises (see Eichengreen and Rose, 1998; Rossi, 1999; and Kaminsky, 2006). While Eichengreen and Rose (1998) introduce a dummy variable of currency crashes to explain banking crises, Kaminsky (2006) consider a dummy variable of banking crises to classify classes of currency crises. Both studies do not find evidence in favour of crises interaction effects to cause crises. Rossi (1999) analyses the determinants of both types of crises but estimate two separate probit equations, one for each type of crisis. For each equation, Rossi (1999) includes a dummy variable representing the other type of crisis to test for crises interactions effects. Like Eichengreen and Rose (1998), Rossi (1999) does not find that currency crises significantly contribute to the likelihood of banking crises. Still, Rossi (1999) finds that banking crises may cause currency crises.

Third, numerous studies consider bidirectional crises interaction effects and jointly estimate the probability of both types of crises (see Glick and Hutchinson, 2001; Falcetti and Tudela, 2008; Candelon, Dumitrescu, Hurlin, and Palm, 2013; Babecký *et al.*, 2014). The major difference between these studies and the ones presented above is that they jointly estimate the probability of both types of crises. By doing this, these studies can account for bidirectional effects between each type of crisis, simultaneously controlling for common causes of these types of crises. The seminal paper of Glick and Hutchison (2001) is the first study to use a system approach to determine simultaneously the probability of banking and currency crises and test for causal effects between both types of crises. Glick and Hutchinson (2001) find evidence of contemporaneous common causes in emerging market economies, suggesting that these crises are closely intertwined. Falcetti and Tudela (2008) develop a dynamic bivariate probit to model banking and currency crises. Besides considering contemporaneous effects, these authors propose lagged crises interaction effects. In line with Glick and Hutchinson (2001), Falcetti and Tudela (2008) find that banking and currency crises are driven by contemporaneous common fundamentals, i.e. the error terms are contemporaneously correlated. Nevertheless, these authors do not find evidence of a significant causal link between banking and currency crises. More recently, Candelon *et al.* (2013) propose a non-linear VAR to examine the interactions between currency and banking crises.[13] Contrary to Falcetti and Tudela (2008), Candelon *et al.* (2013) find strong causal links between currency and banking crises. Finally, Babecký *et al.* (2014) use a panel VAR model to analyse the interactions of banking, currency, and debt crises in developed economies. These authors also find that currency crises are preceded by banking crises, but not vice-versa.

Turning to the EWS studies on banking and currency crises, in contrast to the works above, these studies examine the ability of indicators to predict/signal future crises.

Except for the EWS models in Kaminsky and Reinhart (1999), the EWS studies often cited in the literature have focused on a specific type of crisis, dividing the EWS literature into two large bodies of work: EWS of banking crises and EWS of currency crises (e.g., Kaminsky *et al.*, 1998; Berg and Pattillo, 1999; Demirgüç-Kunt and Detragiache, 2000). While the EWS literature of banking crises identifies leading indicators of banking crises (e.g., Demirgüç-Kunt and Detragiache, 2000; Davis and Karim, 2008), the EWS literature of currency crises identifies leading indicators of currency crises (e.g., Kaminsky *et al*., 1998; Berg and Pattillo, 1999).

Despite focusing on different types of crises, since there are theoretical reasons to expect connections between banking and currency crises, several models in both bodies of literature included some leading indicators that may capture the influence of vulnerabilities potentially leading to the other type of crisis (e.g. Kaminsky *et al*., 1998; Demirgüç-Kunt and Detragiache, 2000).

On the one hand, several EWS on banking crises have included indicators of currency fragilities, such as movements in terms of trade, the current account, the ratio of M2 to foreign exchange reserves, and changes in the exchange rate, among others (see, for example, Kaminsky and Reinhart, 1999; Demirgüç-Kunt and Detragiache, 2000; Davis and Karim, 2008). Kaminsky and Reinhart (1999) and Demirgüç-Kunt and Detragiache (2000) are two of the first studies to develop EWS for banking crises. Despite the differences in methodologies, among other results, both studies find that the ratio of M2 to reserves is the only indicator of external sector problems to be a significant leading indicator of banking crises. Davis and Karim (2008) develop and compare several EWS for banking crises. For several specifications, these authors suggest that change in terms of trade and the ratio of M2 to foreign exchange reserves are significant leading indicators of banking crises.

[13] The authors also extended the model to include interaction effects from sovereign debt crises in a smaller sample.

On the other hand, numerous EWS studies on currency crises have included indicators of banking vulnerabilities, such as the M2 multiplier, the private credit growth rate, the ratio M2 to international reserves, the spread between lending and deposit interest rates, among others (e.g., Kaminsky *et al.*, 1998; Berg and Pattillo, 1999; Bussiere and Fratzscher, 2006). Kaminsky *et al.* (1998) suggest that, among these leading indicators, only the ratio of M2 to international reserves is among the top five leading indicators with the best performance. Moreover, they also suggest that bank deposits and the spread between lending and deposit interest rates should be removed from the EWS since they introduce excessive noise. Berg and Pattillo (1999) implement the Kaminsky *et al.* (1998) model and apply it to a multivariate probit regression. In line with Kaminsky *et al.* (1998), they find that the ratio of M2 to international reserves is a significant leading indicator of currency crises. Bussiere and Fratzscher (2006) include credit growth, the deposit/lending interest rate spreads, the ratios of M1 and M2 to GDP, and bank deposits. Only the credit growth is found to be a leading indicator of currency crises.

We argue that, while the inclusion of leading indicators of fragilities associated with the other type of crisis may help in increasing the predictability power of the EWS, it, however, does not allow for explicitly accounting and identifying the role of the channels of crises interaction in predicting banking and currency crises. Our study, therefore, contributes to the EWS literature on banking and currency crises by examining the role of channels of crises interaction in signalling banking and currency crises. To do so, we depart from the EWS literature in four ways.

First, we adapt the approach found in the empirical studies on the crises determinants, jointly estimating an EWS for both types of crises. Since we consider potential crises interaction effects, we allow for the existence of links between banking and currency crises, which implies that there may be feedback effects between the two types of crises. Thus, using a system of two equations to estimate an EWS, we allow for bidirectional feedback effects as well as controlling for common causes between the two types of crises. To the best of our knowledge, this is the first work to propose a unified EWS for banking and currency crises.

Second, we include a dummy variable that identifies the occurrence of the other type of crisis in each equation in the unified EWS, as a simple indicator of crises interaction effects. For instance, a dummy variable identifying the occurrence of banking crises is included to predict future currency crises and vice-versa. The choice to include these dummy variables rather than including a limited number of leading indicators has the advantage of not having to rely on the signalling ability of particular indicators to capture crises interaction effects. Moreover, the inclusion of crises interaction effects in an EWS allows for testing if these effects are leading indicators of these two types of crises.

Third, we develop an approach to include and account for channels of crises interaction in an EWS. Based on the theoretical literature, the channels of crises interaction exist because a banking (currency) crisis interacts with the vulnerabilities leading to currency (banking) crises. Moving from theory to prediction, we replace those vulnerabilities with leading indicators. Accordingly, an approach to gauge empirically these channels possibly requires introducing multiplicative terms between the leading indicators and the interaction effects from the other type of crisis (measured by the dummy variable).[14] These multiplicative terms allow us to assess if the contribution of leading indicators to the likelihood of currency (banking) crises depends on the presence of interaction effects from banking (currency) crises, i.e. allow us to test if some leading indicators may gain relevance to signal currency (banking) crises if and only if a banking (currency) crisis occurs. To the best of our knowledge, these multiplicative terms have not been used in EWS models nor in the empirical literature on crises determinants.

Finally, we assess if adding the crises interaction effects and the channels of crises interactions improves the predictive power of the EWS. We complement the performance evaluation of the EWS by comparing the predictive power of each EWS when the crises interaction effects are present with when they do not occur. Since the presence of crises interaction effects may determine the nature of banking and currency crises, this exercise allows for a more comprehensive evaluation of the EWS. To the best of our knowledge, the present study is the first to highlight the implications of the presence of crises interaction effects in evaluating the EWS.

4.3. Methodology

This section begins with a discussion of the various crisis-dating methodologies that have been used in the empirical literature on banking and currency crises. It then proceeds to present the leading indicators that we select and construct. Afterwards, this

[14] The use of multiplicative terms has been recently introduced in EWS to control for non-linear behaviour concerning contagion effects (e.g., Ahrend and Goujard, 2015; Lang and Schmidt, 2016). Specifically, these multiplicative terms account for vulnerabilities that may influence the contribution of a crisis in a country to the likelihood of a crisis in another country.

section describes the econometric methodology and concludes by addressing the model selection criteria.

4.3.1. Banking Crises Identification

The empirical research on signalling banking crises commonly uses two methodologies to date crises. First, numerous empirical studies of banking crises resort to established databases of banking crises that were constructed using the events method (see, for example, Demirgüç-Kunt and Detragiache, 1998; Beck, Demirgüç-Kunt, and Levine, 2006; Joyce, 2011). The events method dates banking crises based on the occurrence of exceptional events such as bank runs, bank failures, mergers, and government interventions (e.g., Reinhart and Rogoff, 2013; Babecký *et al*., 2014; Laeven and Valencia, 2018). For instance, Caprio and Klingebiel (1996) consider a banking crisis when a banking system displays a ratio of non-performing loans to the total loans of the banking system higher than 10% or when banking experts consider that the crisis is systemic.[15]

Despite these comprehensive and systematic databases of banking crises being commonly used in the literature, the majority of these datasets is only available at a yearly frequency. Exceptions to these yearly databases are Babecký *et al.* (2014) and Geršl and Jašová (2018). Babecký *et al.* (2014) constructed a quarterly dataset of occurrences of banking crises in EU and OECD countries. To do so, these authors have considered various published studies and have conducted a comprehensive survey among country experts (mostly from central banks) to crosscheck for the timing of crisis periods. Geršl and Jašová (2018) applied the same methodology as Babecký *et al.* (2014) and extended the database to eight emerging market economies.

The second methodology to identify banking crises uses market-oriented measures (see, for example, Von Hagen and Ho, 2007; Candelon *et al*., 2013; Hahm, Shin, and Shin, 2013). These measures account for tensions in the money market, particularly in short-term interest rates and/or in central bank reserves. The underlying hypothesis of these measures is that banking crises are characterized by a sharp increase in the banking system's demand for central bank reserves.[16] Facing this increase, the central

[15] According to these authors, the use of expert judgment was due to lacking data and because some official estimates may underestimate the problem.
[16] Von Hagen and Ho (2007) develop on the reasons behind this conjecture.

bank may react in two ways. If the central bank targets bank reserves, it keeps the supply of bank reserves constant and short-term interest rates rise. If, instead, the operating target is short-term interest rates, the central bank injects additional reserves into the banking system. Thus, by measuring the change in banks' reserves and/or in short-term interest rates, these indicators of money market tension are likely to increase sharply when banking crises occur. When compared with the established databases of banking crises, these measures have the main advantage of only requiring data on interest rates and on reserves from the central bank, which are traditionally available at a monthly frequency.

Given the above discussion, and since we use quarterly data and our sample includes only emerging market economies, we also choose to use a market-oriented definition of banking crises. More specifically, we adopt the Nominal Money Market Pressure Index (NMMPI) developed by Jing, de Haan, Jacobs, and Yang (2015). The NMMPI is based on the money market pressure index firstly proposed by Von Hagen and Ho (2007). Jing *et al.* (2015) adapted the construction of the money market pressure index so that the crises identified by their index are more in line with the crisis episodes identified by Laeven and Valencia (2013). The NMMPI is defined by the following expression:

$$NMMPI_{i,t} = \omega_1 \Delta\gamma_{i,t} + \omega_2 \Delta NIR_{i,t}, \tag{4.1}$$

$$\omega_1 = \frac{\frac{1}{\sigma(\Delta\gamma_{i,t})}}{\frac{1}{\sigma(\Delta\gamma_{i,t})} + \frac{1}{\sigma(\Delta NIR_{i,t})}}, \omega_2 = \frac{\frac{1}{\sigma(\Delta NIR_{i,t})}}{\frac{1}{\sigma(\Delta\gamma_{i,t})} + \frac{1}{\sigma(\Delta NIR_{i,t})}}$$

where $\gamma_{i,t}$ is the ratio of reserves to bank deposits in country i at time t, $NIR_{i,t}$ is the nominal short-term interest rate in country i at time t, Δ operator represents the difference operator, and $\sigma_{\Delta\gamma}$ and $\sigma_{\Delta i}$ are the standard deviations of the two components. Following Jing *et al.* (2015), we apply rolling eight-quarter periods to calculate the standard deviations.

According to Jing *et al.* (2015), a banking crisis is defined as an event in which the NMMPI meets two criteria: (1) it exceeds the 98.5$^{\text{th}}$ percentile of the sample distribution of the NMMPI (PERC) for the country under consideration; (2) the increase in the NMMPI from the previous period is greater than 5%, i.e.:

$$BC_{i,t} = \begin{cases} 1 \; if \; NMMPI_{i,t} > PERC(NMMPI_i, 98.5\%) \; and \; \Delta\%\left(NMMPI_{i,t}\right) > 5\% \\ 0 \; otherwise \end{cases} \tag{4.2}$$

By requiring an increase in the NMMPI greater than 5%, this criterion allows for the possibility of no banking crisis episodes in some countries during the sample period. Moreover, following Von Hagen and Ho (2007), we disregard all observations in a 4-quarter time window starting with the first period in which the index signals a crisis and then apply the index again to look for additional crisis episodes.

The next step is to define the signalling horizon of a banking crisis. Our EWS does not have the goal to predict the exact timing of banking crises, but to signal whether a banking crisis occurs within a specific time horizon. Thus, after identifying banking crisis episodes, we construct our dependent variable by transforming the contemporaneous variable $BC_{i,t}$ into a forward-looking variable $Y_{i,t}^{B}$, which is defined as:

$$Y_{i,t}^{B} = \begin{cases} 1 \; if \; \exists \; k = 1, \dots, 4 \;\; s.t. \;\; BC_{i,t+k} = 1 \\ 0 \; otherwise \end{cases} . \tag{4.3}$$

Notably, our model attempts to predict whether a crisis will occur during the next four quarters. We follow the common practice of the EWS literature on banking crises in choosing the length of the signalling period (e.g., Davis, Karim, and Liadze, 2011; Babecký *et al*., 2014; Christensen and Li, 2014).

4.3.2. Currency Crises Identification

Two general definitions of currency crises are widely used in the empirical literature on currency crises. First, numerous studies define currency crises based exclusively on devaluation episodes (see, for example, Frankel and Rose, 1996; Falcetti and Tudela, 2008; Hahm *et al*., 2013). For instance, Frankel and Rose (1996) define a currency crash as a depreciation of the nominal exchange rate of at least 25% that is also at least a 10% increase in the rate of nominal depreciation. While this method has the advantages of being simple to construct and not requiring much information, by exclusively focusing on devaluation episodes, according to Kaminsky *et al.* (1998), this method does not take into account failed speculative attacks, which were averted by central bank's interventions. In these cases, currency market turbulences may be reflected in sharp increases in domestic interest rates and/or substantial losses of foreign-exchange reserves.

Second, several empirical studies adopt broader definitions of currency crises, which can capture those different manifestations of speculative attacks (see, for example, Eichengreen, Rose, and Wyplosz, 1995; Kaminsky *et al*., 1998; Bussiere and Fratzscher, 2006). These definitions are based on pressure indices that account for other tensions in the foreign exchange market. Specifically, besides considering devaluation episodes, these indices account for large losses of international reserves and/or steep increases in domestic interest rates. The underlying rationale of these definitions of currency crises is that those different manifestations of speculative attacks also negatively affect the domestic economy and should be considered in an EWS.

Given the above discussion, we follow the common practice of the literature and apply an Exchange Market Pressure index (EMP) in the spirit of Kaminsky *et al*. (1998) to identify currency crisis episodes. The EMP is defined by the following equation:

$$EMP_{i,t} = \omega_e \left(\frac{e_{i,t} - e_{i,t-1}}{e_{i,t-1}}\right) - \omega_{RES} \left(\frac{RES_{i,t} - RES_{i,t-1}}{RES_{i,t-1}}\right) \quad (4.4)$$

where $e_{i,t}$ is the nominal exchange rate of country i at time t against the US dollar and $RES_{i,t}$ the foreign exchange reserves of country i at time t.[17] Following Glick and Hutchinson (2001) and Bussiere and Fratzscher (2006), we set the weights ω_e and ω_{res} to be the relative precision of each variable, where precision is defined as the inverse of the variance of each variable for all countries over the full sample period. After the construction of the EMP, the empirical literature defines a currency crisis ($CC_{i,t}$) as an event when the EMP is above its country mean by a number of standard deviations (SD). This number has been chosen between the values from 1.5 to 3 (see, for example, Kaminsky *et al*., 1998; Bussiere and Fratzscher, 2006; Frost and Saiki, 2014). We follow the common practice in the literature and set to two standard deviations as in, for example, Glick and Hutchinson (2001), Bussiere and Fratzscher (2006), and Comelli (2016). Thus, a currency crisis is defined as:

$$CC_{i,t} = \begin{cases} 1 \ if \ EMP_{i,t} > \overline{EMP_i} + 2SD(EMP_i) \\ 0 \ if \ otherwise \end{cases}. \quad (4.5)$$

[17] Note that this market pressure index of currency crises does not consider episodes of policy intervention involving sharp rises in interest rates. To see the reasons behind this choice see, for example, Sachs *et al.* (1996), Kaminsky and Reinhart (1999), and Glick and Hutchinson (2001).

The next step is to define the signalling horizon of a currency crisis. As we did in the construction of our dependent variable for banking crises, we transform the contemporaneous variable $CC_{i,t}$ into a forward-looking variable $Y_{i,t}^{c}$, which is defined as:

$$Y_{i,t}^{c} = \begin{cases} 1\ if\ \exists\ k = 1, \dots, 4\ \ s.t.\ \ CC_{i,t+k} = 1 \\ 0\ otherwise \end{cases} . \tag{4.6}$$

In other words, our model tries to predict whether a currency crisis will occur during the next four quarters. Although the common practice of the literature is to use longer time horizons (see, for example, Kaminsky *et al*., 1998; Berg and Pattillo, 1999; Mulder, Perrelli, and Rocha, 2012), a few empirical studies on currency crises also use a signalling horizon of four quarters, including Burkart and Coudert (2002) and Bussiere and Fratzscher (2006). Moreover, as stated in the Literature Review, we are the first study to develop a unified EWS for banking and currency crises. Since we jointly estimate both types of crisis, we choose the 4-quarter horizon for currency crises to apply the same time horizon as in the banking crisis dependent variable. In addition to this, the choice of a shorter horizon may be more adequate to study crisis dynamics, such as contagion and crises interactions effects, because these dynamics tend to be rapid and may affect more the likelihood of crises in the first four quarters. Increasing the signalling horizon may reduce the ability of these dynamics to signal crises.

4.3.3. Independent Variables

This section begins with a presentation of established leading indicators that were selected for each type of crisis. Since our key contribution is introducing crises interaction effects in EWS, the choice of leading indicators is intended to be as neutral as possible. Taking into account that we develop a unified EWS for banking and currency crises, the choice of leading indicators has these two types of crises into consideration. Thus, we select several of the most used indicators in these two large bodies of literature. We can broadly group these variables into four categories: real sector variables, financial sector variables, external sector variables, and fiscal variables. Kaminsky *et al.* (1998) and

Frankel and Saravelos (2012) use similar categorizations. Variables used in the EWS literature have been recently surveyed by Kauko (2014) for banking crises and by Frankel and Saravelos (2012) for currency crises.

This section ends with a discussion of the methods used to construct both contagion and crises interaction variables. For the former variable, this section describes in some detail the methodologies available in the EWS literature. For the latter variable (critical to the contribution of this study), this section reviews the different approaches that are only available in the empirical literature of crises determinants, and discusses whether these approaches can be adapted into an EWS framework.

4.3.3.1. Leading Indicators of Banking and Currency Crises

Starting with real sector indicators, we include the real GDP growth rate. Theoretically, in a robustly growing economy, default probability and banking problems are expected to decline as well as the probability of experiencing currency crises. In practical terms, however, unequivocal evidence supporting the real GDP growth's signalling ability does not exist for both types of crises. Regarding banking crises, while several empirical studies suggest that slow or negative real GDP growth seems to be a leading indicator (see, for example, Kaminsky and Reinhart, 1999; Beck *et al.*, 2006; Davis and Karim, 2008), a few studies fail to support its predictive power (see, for example, Joyce, 2011; Kauko, 2012; Sarlin and Peltonen, 2013). Regarding currency crises, while some studies suggest a negative impact of stronger real GDP growth rates on the likelihood of currency crises (see, for example, Kaminsky, 2006; Comelli, 2014; Zhao, de Haan, Scholtens, and Yang, 2014), others do not find a significant effect (see, for example, Eichengreen, Rose, and Wyplosz, 1996; Bussiere and Fratzscher, 2006; Frost and Saiki, 2014).

Turning to the financial sector, we select the following indicators: private credit (as a percentage of GDP and growth rate), the real interest rate, inflation, the ratio of M2 to foreign reserves, and the stock market growth rate. Private credit measures (as a percentage of GDP and growth rate) are intended to indicate bank fragility. While high levels of the ratio of private credit to GDP may signal excessive lending, rapid credit growth may imply a decline in lending standards. Thus, the more vulnerable the banking system, the more likely it is to occur a banking crisis. These measures are almost consensual in the banking crisis literature since various studies find that the higher these measures of private credit, the higher the likelihood of a crisis (see, for example, Demirgüç-Kunt and Detragiache, 2000; Beck *et al*., 2006; Jordà, Schularick, and Taylor, 2011). These credit measures are also used in signalling currency crises because, as it was stated in the Literature Review, it is quite standard to introduce measures reflecting banking sector problems in the EWS for currency crises. The rationale underlying this decision is that the more likely banking crises, the higher it is the probability of currency crises. Various studies, however, suggest that these credit indicators do not signal currency crises, as for example Burkart and Coudert (2002), Falcetti and Tudela (2008), and Frost and Saiki (2014). Yet, Kaminsky *et al.* (1998) and Bussiere and Fratzscher (2006) find a significant contribution of credit growth to the likelihood of currency crises.

With respect to the real interest rate, despite being selected in both types of literature, this rate may indicate different vulnerabilities for each type of crisis. For banking crises, a higher real interest rate may increase the possibility of bank failures because it translates into higher costs of funds for banks, thus negatively affecting debtors' solvency. For currency crises, a higher real interest rate may reflect a higher risk premium, which ultimately can contribute to a higher probability of currency crises. Regarding the signalling power of this indicator, several empirical studies find that high real interest rates tend to precede banking crises, as for example Demirgüç-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), and Beck *et al.* (2006). But, regarding currency crises, there is mixed evidence in the literature. While various studies suggest that real interest rates increase the likelihood of currency crises (see, for example, Kaminsky and Reinhart, 1999; Cumperayot and Kouwenberg, 2013; Zhao *et al*., 2014), some studies do not find that this indicator signals currency crises (see, for example, Kaminsky *et al*., 1998; Kaminsky, 2006; Bauer, Herz, and Karb, 2007).

The inflation rate is a common leading indicator for both types of crises. High inflation rates not only may lead to inflated bank assets (which can lead to banking problems), but they are also associated with expectations of a higher realignment of the currency (which may provoke a speculative attack on the currency). The predictive power of inflation is quite consensual for both types of crises, especially in non-developed countries (for banking crises, see, for example, Demirgüç-Kunt and Detragiache, 1998; Beck *et al*., 2006; Joyce, 2011; for currency crises, see, for example, Eichengreen *et al*., 1996; Kaminsky *et al*., 1998; Burkart and Coudert, 2002).

The ratio of M2 to foreign exchange reserves indicates to what extent the liabilities of the banking system are backed by international reserves. Since in Emerging Market

Economies much of the expansion of M2 may be attributed to large capital inflows (Calvo and Mendonza, 1996), higher values of M2 can signal a higher exposure to capital outflows. In the event of large capital outflows, the demand for foreign currency increases significantly, which can imply a large drain of foreign reserves if the mismatch between M2 and foreign exchange reserves is large enough. Thus, higher ratios may indicate the country's vulnerability to capital outflows and, it should contribute positively to the likelihood of banking crises as well as to the probability of currency crises. Regarding the predictability power of this leading indicator, the literature finds mixed evidence for both types of crises. While some studies suggest that high ratios of M2 to foreign exchange reserves significantly signal banking crises (see, for example, Kaminsky and Reinhart, 1999; Beck *et al.*, 2006; Evrensel, 2008), others do not find evidence in favour of this indicator (see, for example, Demirguc–Kunt and Detragiache, 2002; Joyce, 2011; Shen and Hsieh, 2011). Concerning currency crises, various studies find that high ratios of M2 to reserves tend to precede currency crises (see, for example, Kaminsky *et al.*, 1998; Berg and Pattillo, 1999; Comelli, 2014). But, Glick and Hutchinson (2001) and Bussiere and Fratzscher (2006) do not find a significant effect from this ratio to the likelihood of currency crises.

The stock market growth rate is a common leading indicator in EWS for banking and currency crises. On the one hand, since a stock market crash affects banks' collateral value and deteriorates their balance sheets, the evolution of the stock market influences the banking sector. As a market crash tends to be preceded by a boom, stock returns may positively or negatively affect the likelihood of banking crises, depending on the signalling horizon used. On the other hand, the burst of asset price bubbles tends to precede external sector problems. In the event of a large fall in stock prices, foreign investors may retrieve their money, which may lead to large capital outflows, and, consequently currency problems. Regarding the empirical evidence of this indicator on the likelihood of future banking crises, we find several studies that indicate that stock prices lack predictive power (see, for example, Kaminsky and Reinhart, 1999; Von Hagen and Ho, 2007; Duca and Peltonen, 2013). But, a few studies suggest that market booms tend to increase the likelihood of banking crises, as for example Drehmann, Borio, and Tsatsaronis (2011), Roy and Kemme (2011), and Sarlin and Peltonen (2013). Regarding currency crises, we find substantial evidence in the literature in favour of stock returns' predictive power (see, for example, Kaminsky *et al.*, 1998; Kaminsky and Reinhart, 1999;

Cumperayot and Kouwenberg, 2013). Bussiere and Fratzscher (2006) and Kaminsky (2006), however, fail to support the stock returns' ability to signal currency crises.

To capture the influence of the external sector, we include the growth rate of international reserves, the current account (as a percentage of the GDP), a measure of overvaluation, and the ratio of short-term external debt to foreign exchange reserves. The growth rate of foreign exchange reserves is the most frequent statistically significant warning indicator in the EWS literature of currency crises, according to Frankel and Saravelos (2012). But, since this leading indicator is not commonly selected in the EWS literature of banking crises, we include this variable only in the currency crisis equation. As stated in the Literature Review, a depletion of reserves may leave the country vulnerable to sudden speculative attacks. Thus, sharp decreases in foreign exchange reserves are expected to increase the likelihood of currency crises. There is substantial evidence in the literature to support reserves growth's predictive power (see, for example, Kaminsky *et al.*, 1998; Berg and Pattillo, 1999; Comelli, 2014).

Current account deficits may indicate a lack of national savings over investment, which may induce the banking system to access to foreign capital inflows. According to McKinnon and Pill (1997), these capital inflows may lead to overlending cycles, which can exacerbate current account deficits leading to loss of competitiveness and culminating in banking problems and/or currency crises. Numerous studies find a negative association between the current account and banking crises, as, for example, Rose and Spiegel (2012), Duca and Peltonen (2013), and Sarlin and Peltonen (2013). Yet, a few studies fail to support current account's predictive power in some specifications (e.g. Kauko, 2012; Hmili and Bouraoui, 2015). Concerning currency crises, we find various studies that suggest a negative impact of the current account on the likelihood of currency crises (see, for example, Kaminsky *et al.*, 1998; Kaminsky, 2006; Cumperayot and Kouwenberg, 2013).

Overvaluation is a common indicator of external sector fragility, since it negatively affects the competitiveness of domestic industries. Thus, overvaluation is expected to positively correlate with the likelihood of currency crises. Moreover, since overvaluation contributes to undermining the competitiveness of exporting firms, the higher the index, the more likely it is to firms go bankrupt and the more likely the occurrence of a banking crisis. We follow the common practice of the literature in constructing the overvaluation measure as the deviation of the real exchange rate from its trend, using a Hodrick-Prescott Filter (see, for example, Falcetti and Tudela, 2008; Duca and Peltonen, 2013; Comelli, 2014). There is substantial evidence in both EWS literature on banking and currency crises to support the predictive power of this indicator (see, for example, Berg and Pattillo, 1999; Kaminsky and Reinhart, 1999; Bussiere and Fratzscher, 2006; Von Hagen and Ho, 2007).

The ratio of short-term external debt to foreign exchange reserves may contribute positively to the likelihood of banking and currency crises, since it measures the ability of a country to pay back external debts within a short period, thus signalling risk of experiencing disruptive capital outflows. Several studies suggest that high values of this ratio tend to precede banking crises (see, for example, Falcetti and Tudela, 2008; Shen and Hsieh, 2011; Ahrend and Goujard, 2015). Regarding currency crises, various studies find that high ratios of short-term external debt to reserves precede currency crises (see, for example, Kaminsky *et al*., 1998; Bussiere and Fratzscher, 2006; Kaminsky, 2006).

Finally, regarding the fiscal sector, we include the ratio of fiscal surplus to GDP. While banking crises in non-developed countries are associated with large fiscal deficits, these deficits may also lead to a continuous loss of international reserves and ultimately can increase the likelihood of currency crises (as in Krugman, 1979). But, despite being traditionally chosen in the EWS literature, fiscal surpluses seem to have low predictive power for both types of crises (see, for example, Eichengreen *et al*., 1996; Kaminsky and Reinhart, 1999; Sarlin and Peltonen, 2013). Despite this common result, a few studies find that fiscal deficits positively affect the likelihood of banking crises (see, for example, von Hagen and Ho, 2007; Davis and Karim, 2008; Duca and Peltonen, 2013) as well as the likelihood of currency crises (see, for example, Kaminsky *et al*., 1998; Bussiere and Fratzscher, 2006; Kaminsky, 2006).

4.3.3.2. Contagion Variables

In the EWS literature, contagion refers to the effect that a crisis in a country may have on the likelihood of a crisis in another country. Despite the conformity on the definition of contagion, there are different techniques for modelling contagion. We can categorize these techniques into two broad groups. On one group, numerous studies consider contagion as a dummy variable, which takes the value of unity when another country has a crisis (see, for example, Joyce, 2011; Lang and Schmidt, 2016; Pedro, Ramalho, and da Silva, 2018). This technique has the advantages of being very simple to construct and not requiring much information. But, there are also significant drawbacks with this approach, because it cannot differentiate the severity of contagion effects nor take into account that there are countries more important than others to the domestic economy.

On the other group, another common practice in the EWS literature is to construct a continuous variable by weighting crises elsewhere in the world. The rationale behind these weighting schemes is that the likelihood that a crisis in a country spreads to another country depends on the intensity of the connections (through economic or financial channels) between these countries. These schemes vary across the literature and can be grouped into four categories, depending on the specific contagion channels the authors intend to capture.

The first group of papers uses geographical proximity to construct the contagion variable, as for example Burkart and Coudert (2002), Frost and Saiki (2014), and Dawood (2016). The goal of this indicator is to capture regional contagion since these studies argue that the most significant contagion effects are expected to occur inside the same region due to cultural and macroeconomic similarities and trade relations (see, for example, Pericoli and Sbracia, 2003). There are, however, various examples of crises spreading to non-neighbouring countries, including the Mexican peso crisis of 1994, the Russian crisis of 1998, and the Global Financial Crisis of 2008. The main drawback of this weighting scheme is it would miss those contagion episodes.

The following two weighting schemes take into account specific contagion channels: the trade and the common lender channels. The first scheme uses trade statistics between countries to weight foreign crises so that the contagion variable is higher when important trading partners of a country are in crisis (see, for example, Eichengreen *et al.*, 1996; Glick and Rose, 1999; Haile and Pozo, 2008). The idea behind this measure is that a foreign crisis is more likely to spread to the domestic country if the foreign country is an important trading partner. The second weighting scheme measures how strongly a country competes for bank funds with countries in crisis (see, for example, Fratzscher, 2003; Forbes and Warnock, 2012; Minoiu, Subrahmanian, and Berea, 2015). The underlying hypothesis of this measure is that a foreign crisis is more likely to spread to the domestic economy if they share the same common lender. To capture the common lender channel, this weighting scheme uses the BIS consolidated banking statistics, which report banking systems' financial claims on the rest of the world and provide a measure of the risk exposures of lenders' national banking systems. Despite constructing significant measures of contagion, these two weighting schemes only take into account specific contagion channels, which may not be sufficient to capture the majority of contagion episodes. For instance, several Emerging Market Economies depend on capital inflows through financial markets, which make these economies vulnerable to contagion effects through financial markets. These contagion effects, however, are not considered in the previous weighting schemes.

Finally, another weighting scheme captures financial market contagion. The rationale of this measure is that the higher the degree of financial market integration between two countries, the more likely a crisis in a country spreads to the other country. This weighting scheme commonly uses correlations between stock returns (see, for example, Patro, Qi, and Sun, 2013; Christensen and Li, 2014; Constantin, Peltonen, and Sarlin, 2018). These correlations can be applied to a general stock market index or a specific sector index – for example, Patro *et al*. (2013) and Constantin *et al.* (2018) use the returns for banking sector stock indices. The main advantage of this weighting scheme is that, according to the literature that empirically tests contagion, cross-market correlations can be driven by changes on several fundamentals (see, for example, Forbes and Rigobon, 2002). This means that market co-movements may reflect several contagion channels, such as trade linkages, the common lender, and change in the beliefs of investors, among others. Thus, by encompassing several contagion sources, this weighting scheme ultimately may capture the majority of contagion episodes in our sample.

Given the above discussion, we choose the last weighting scheme to construct the contagion variables. Since we study banking and currency crises, we construct a financial contagion variable for each type of crisis. For the banking crisis contagion, we define contagion as:

$$CONT_{i,t}^{B} = \sum_{j \neq i} BC_{j,t} * correl(r_i, r_j)_t \qquad (4.7)$$

where $BC_{j,t}$ is the occurrence of a banking crisis in country j at quarter t, r_i and r_j are the daily stock returns for country i and j, and $correl(r_i, r_j)_t$ is the correlation between those daily returns during quarter t.[18] This methodology is also adopted by, for example,

[18] j is varying in a set of countries that include all the countries in the sample and also Developed Countries. The latter set of countries was included because it may have important implications for Emerging Market Economies. For example, we would miss the contagion effects from the Global Financial Crisis of 2008 without broadening the set of countries. The use of other regions (beyond the sample of countries) in the

Fratzscher (2003) and Christensen and Li (2014). Analogously, we define currency crisis contagion as:

$$CONT^{C}_{i,t} = \sum_{j \neq i} CC_{j,t} * correl(r_i, r_j)_t \tag{4.8}$$

where $CC_{j,t}$ is the occurrence of a currency crisis in country j at quarter t, and the rest of the terms in Equation (4.8) are defined in a similar way to those of Equation (4.7).

4.3.3.3. Crises interaction Variables

By crises interaction effects, we refer to the effects that a banking (currency) crisis may have on the likelihood of a currency (banking) crisis in the same country. According to numerous theoretical studies presented in the Literature Review, banking and currency crises interact with each other through different channels. In this section, we describe how crises interaction effects can be introduced in an EWS.

As stated in the Literature Review section, crises interaction effects have been considered only in the empirical literature of crises determinants. But, while the literature of crises determinants uses a contemporaneous dependent variable, the EWS literature commonly adopts a forward-looking dependent variable. Given the difference in the dependent variable, it may be the case that some approaches to construct the crises interaction variable cannot be adapted into an EWS framework. In this section, we review these different approaches and discuss whether they can be adapted into an EWS framework.

The common practice in the empirical literature is to consider these effects as a dummy variable, which takes the value of unity when they are present (see, for example, Kaminsky and Reinhart, 1999; Glick and Hutchinson, 2001; Candelon *et al.*, 2013). Despite the convergence in the definition of crises interaction effects, however, the empirical literature has different perspectives to establish the *timing* and the *duration* of crises interaction effects. We can categorize these perspectives into three broad groups.

contagion variable is a common practice in the literature (see, e.g. Joyce, 2011). The Developed Countries used to calculate the contagion variable are reported in Appendix 4.C.

In the first group of studies, Eichengreen and Rose (1998) and Glick and Hutchinson (2001) consider that crises interaction effects can contemporaneously influence the likelihood of another type of crisis. For instance, if a banking crisis occurs, it influences the likelihood of occurring a currency crisis in the same period. Thus, in this group of studies, crises interaction effects are assumed to be simultaneous and to endure only one period.

In the context of EWS, however, the dependent variables are forward-looking, which means that considering simultaneous crises interaction effects would require both types of crises to interact in the future. But, explicitly introducing that type of information is not possible in an EWS framework because that type of information is not known at the present moment. Thus, it is only feasible to consider lagged crises interaction effects, i.e. a present crisis affecting the probability of the other type of crisis in the future. This approach is analogous to the one used in contagion effects. As we stated in the subsection above, contagion effects only account for the effects that a present crisis in a country affects the probability of a future crisis in another country.

Although contemporaneous effects are not allowed, the introduction of lagged effects does not undermine the potential consequences that crises interaction effects may have in an EWS. In fact, the theoretical literature supports for lagged causal crises interaction effects, as we already referred to in the Literature Review. Moreover, the empirical literature on crises determinants has also considered lagged effects.

The following two groups of studies (the second and third groups) assume lagged crises interaction effects but diverge in the duration of crises interaction effects. In the second group of studies, Rossi (1999) and Falcetti and Tudela (2008) consider crises interaction effects to have a simple one-period lagged effect from one type of crisis to the other. For instance, Falcetti and Tudela (2008) consider simple one-quarter lagged effects, i.e. a banking (currency) crisis period affects the likelihood of a currency (banking) crisis in the following quarter. The main drawback of assuming a simple one-period lagged effect, however, is that it only accounts for crises interaction effects in the following period. But, it might be the case that, depending on the vulnerabilities in the economy, crises take different amounts of time to interact with the other type of crisis. For instance, crises interaction effects may affect the likelihood of the other type of crisis only two, three or four quarters after. Thus, this assumption could lead to misidentifying the actual impact of crises interaction effects.

The third group of studies considers lag-window crises interaction effects in order to take into account the diversity of durations of crises interaction effects, as for example Kaminsky and Reinhart (1999), Glick and Hutchinson (2001), and Candelon *et al.* (2013). The length of the lag window can be from only two quarters to one or two years. For instance, Candelon *et al.* (2013) consider that crises interaction effects start when a crisis occurs and can endure for four quarters more. By considering lag-window effects, these studies overcome the problems with simple one-period lagged effects, thus providing a more flexible and comprehensive timing for accounting crises interaction effects.

Given the above discussion, we consider the last perspective to construct the crises interaction variables. We follow Candelon *et al.* (2013) and consider a lag window of four quarters. This means that crises interaction effects start when a crisis occurs and endures for four quarters more. But, the dependent variable is forward-looking in our case, which means that crises interaction effects from four quarters in the past can affect a crisis that may happen four quarters ahead. Thus, from a fundamental point of view, the length of this lag window encompasses until eight quarters of interaction between banking and currency crises (four quarters in the past plus four quarters in the future), which is in line with several definitions of twin crises, as for example, Glick and Hutchinson (2001) and Laeven and Valencia (2018).

We construct a crises interaction variable for each type of crisis. We define the variable of crises interactions from banking to currency crises ($CI_{i,t}^{B\to C}$) as:

$$CI_{i,t}^{B\to C} = \begin{cases} 1, & if \sum_{j=0}^{4} BC_{i,t-j} > 0 \\ 0, & \text{otherwise.} \end{cases} \tag{4.9}$$

where $BC_{i,t}$ is the occurrence of a banking crisis in country i at quarter t. Analogously, we define the variable of crises interactions from currency to banking crises ($CI_{i,t}^{C\to B}$) as:

$$CI_{i,t}^{C\to B} = \begin{cases} 1, & if \sum_{j=0}^{4} CC_{i,t-j} > 0 \\ 0, & otherwise. \end{cases} \tag{4.10}$$

where $CC_{i,t}$ is the occurrence of a currency crisis in country i at quarter t.

4.3.4. Econometric Methodology

The object of this section is to present the models that will be estimated in Section 4.5. As stated in the Literature Review, we consider that banking and currency crises interact with each other and we jointly estimate the probabilities of both types of crisis using a system approach. More particularly, we estimate a system of two dynamic probit equations, with each equation predicting the likelihood of a type of crisis. The system approach has been used in the crises determinants literature (see, for example, Glick and Hutchinson, 2001; Falcetti and Tudela, 2008; Babecký *et al*., 2014), but, to the best of our knowledge, it has not been used to estimate EWS.

We first detail the notation that will be used in this section. The sample contains N countries $i = \{1, \dots, N\}$, observed during T_i periods (quarters) $t = \{1, \dots, T_i\}$. We consider $Y_{i,t}^{B}$ and $Y_{i,t}^{C}$ to be vectors of limited dependent variables. As reported in Subsections 4.3.1 and 4.3.2, the dependent variable $Y_{i,t}^{B}$ ($Y_{i,t}^{C}$) takes the value of one if a banking (currency) crisis occurs in the next four quarters for country i in period t and zero otherwise.

As it is standard in probit regressions, the dependent variable – for example, $Y_{i,t}^{B*}$ – is a latent continuous variable associated with $Y_{i,t}^{B}$, according to a many-to-one mapping $Y_{i,t}^{B} = \tau(Y_{i,t}^{B*})$, with $\tau(.)$ being the normal cdf.

The first model we estimate – the Baseline model – is intended to be a representation of the literature and includes the macroeconomic and financial leading indicators that were presented and discussed in Subsection 4.3.3.1.[19] We also include a contagion variable to each type of crisis, since it is widely used in the more recent empirical studies (see, for example, Forbes and Warnock, 2012; Christensen and Li, 2014; Minoiu *et al.*, 2015). The contagion variables were constructed following the methodology presented in Subsection 4.3.3.2. We estimate the Baseline model as displayed below:

$$\begin{cases} Y_{i,t}^{B*} = X_{i,t}^{B} * \beta^{B} + CONT_{i,t}^{B} * \gamma^{B} + \sum_{k=0}^{p^{B}} BC_{i,t-k} * \varphi_{t-k}^{B} + \varepsilon_{i,t}^{B} \\ Y_{i,t}^{C*} = X_{i,t}^{C} * \beta^{C} + CONT_{i,t}^{C} * \gamma^{C} + \sum_{k=0}^{p^{C}} CC_{i,t-k} * \varphi_{t-k}^{C} + \varepsilon_{i,t}^{C} \end{cases}, \qquad \rho_{\varepsilon_{i,t}^{B}, \varepsilon_{i,t}^{C}} \neq 0 \tag{4.11}$$

[19] This is a broad representation, as the existing EWS literature does not jointly estimate both types of crisis.

where X_{it}^{B} ($X_{i,t}^{C}$) is an array of macroeconomic and financial leading indicators of banking (currency) crises and a constant term, $CONT_{i,t}^{B}$ ($CONT_{i,t}^{C}$) is a vector representing contagion effects from banking (currency) crises from other countries, $BC_{i,t}$ ($CC_{i,t}$) is a vector of occurrence of banking (currency) crises, respectively, β^{B}, β^{C}, γ^{B}, γ^{C}, φ^{B}, and φ^{C} are vectors of parameters to be estimated, p^{B} and p^{C} are the maximum lags to be determined, and $\varepsilon_{i,t}^{B}$ $\varepsilon_{i,t}^{C}$ are the disturbance vectors.

In Equation (4.11), the introduction of contemporaneous and lagged values of $BC_{i,t}$ and $CC_{i,t}$ allows us to test for state dependence, i.e. whether present and past instances of banking (currency) crises affect the likelihood of future banking (currency) crises.[20] We introduce state dependence to take into account the evidence that shows that the longer a country is in a crisis, the higher the probability of exiting the crisis will be, regardless the political intervention (see, for example, Tudela, 2004). Moreover, according to Bussiere (2013), Candelon, Dumitrescu, and Hurlin (2014), and Antunes, Bonfim, Monteiro, and Rodrigues (2018), dynamic models that include state dependence tend to outperform other specifications.

Finally, we allow for a contemporaneous correlation between the terms $\varepsilon_{i,t}^{b}$ and $\varepsilon_{i,t}^{c}$ ($\rho_{\varepsilon_{i,t}^{B},\varepsilon_{i,t}^{C}}$). This term is pivotal for the system approach because it connects both equations. Since the dependent variables are forward-looking, this term allows capturing unforeseeable shocks that happen in the future that are common to both types of crisis. Thus, this term may allow capturing part of the contemporaneous common causes between these types of crisis.

We then propose three augmented models. In the first augmented model – the Baseline 2 model – we include contagion multipliers. These multipliers are multiplicative terms between leading indicators and the contagion variable (see Ahrend and Goujard, 2015; Lang and Schmidt, 2016). These multiplicative terms account for variables that capture vulnerabilities that may influence the contribution of contagion effects to the likelihood of crises. For instance, Ahrend and Goujard (2015) argue that contagion shocks are more likely to influence the probability of financial crises when a country's banking system is more internationally integrated. Thus, to capture such effect, they propose a multiplicative term between the country's bank debt and the contagion variable. Despite

[20] Since the dependent variable is forward-looking, the introduction of contemporaneous crisis indicators does not generate endogeneity. Moreover, lags are chosen by optimizing the information criteria.

not being the focus of this study, we opt to add contagion multipliers mainly because they have been recently introduced in some EWS studies with significant results (e.g. Ahrend and Goujard, 2015; Lang and Schmidt, 2016). We estimate the Baseline 2 model as displayed below:

$$\begin{cases} Y_{i,t}^{B*} = X_{i,t}^{B} * \beta^{B} + CONT_{i,t}^{B} * \gamma^{B} + X_{i,t}^{B} * CONT_{i,t}^{B} * \delta^{B} + \\ \qquad + \sum_{k=0}^{p^B} BC_{i,t-k} * \varphi_{t-k}^{B} + \varepsilon_{i,t}^{B} \\ Y_{i,t}^{C*} = X_{i,t}^{C} * \beta^{C} + CONT_{i,t}^{C} * \gamma^{C} + X_{i,t}^{C} * CONT_{i,t}^{C} * \delta^{C} + \\ \qquad + \sum_{k=0}^{p^C} CC_{i,t-k} * \varphi_{t-k}^{C} + \varepsilon_{i,t}^{C} \end{cases}, \quad \rho_{\varepsilon_{i,t}^{B},\varepsilon_{i,t}^{C}} \neq 0 \tag{4.12}$$

The terms in Equation (4.12) are defined in a similar way to those of Equation (4.11). $X_{i,t}^{B} * CONT_{i,t}^{B}$ ($X_{i,t}^{C} * CONT_{i,t}^{C}$) is an array of contagion multipliers that affect the likelihood of banking (currency) crises.

After presenting two models that broadly represent the literature of EWS on banking and currency crises, the following two models are the key contributions of our study because we add crises interaction effects. As stated in Literature Review, the introduction of crises interaction effects in an EWS has not been considered.

The second augmented model – the Crises interaction model – is constructed upon the Baseline 2 model. To this model, we add a crises interaction variable to each equation, i.e. we allow for causal effects between banking and currency crises. These crises interaction variables were constructed following the methodology presented in Subsection 4.3.3.3. We estimate the Crises interaction model (CI) as shown below:

$$\begin{cases} Y_{i,t}^{B*} = X_{i,t}^{B} * \beta^{B} + CONT_{i,t}^{B} * \gamma^{B} + X_{i,t}^{B} * CONT_{i,t}^{B} * \delta^{B} + CI_{i,t}^{C\to B} * \mu^{B} + \\ \qquad + \sum_{k=0}^{p^B} BC_{i,t-k} * \varphi_{t-k}^{B} + \varepsilon_{i,t}^{B} \\ Y_{i,t}^{C*} = X_{i,t}^{C} * \beta^{C} + CONT_{i,t}^{C} * \gamma^{C} + X_{i,t}^{C} * CONT_{i,t}^{C} * \delta^{C} + CI_{i,t}^{B\to C} * \mu^{C} + \\ \qquad + \sum_{k=0}^{p^C} CC_{i,t-k} * \varphi_{t-k}^{C} + \varepsilon_{i,t}^{C} \end{cases}, \quad \rho_{\varepsilon_{i,t}^{B},\varepsilon_{i,t}^{C}} \neq 0 \tag{4.13}$$

The terms in Equation (4.13) are defined in a similar way to those of Equation (4.12). $CI_{i,t}^{C\to B}$ ($CI_{i,t}^{B\to C}$) is a vector of crises interaction effects that accounts for causal effects from currency (banking) to banking (currency) crises.

Finally, the third augmented model – the Channels of Crises interaction model – is constructed upon the CI model. To this model, we add channels of crises interaction. These channels are multiplicative terms between leading indicators and the crises interaction variable. Analogous to contagion multipliers, the channels of crises interaction allow assessing if the contribution of leading indicators to the likelihood of crises depends on the presence of crises interaction effects. We estimate the Channels of Crises interaction model (CCI) as presented below:

$$\begin{cases} Y_{i,t}^{B*} = X_{i,t}^{B} * \beta^{B} + CONT_{i,t}^{B} * \gamma^{B} + X_{i,t}^{B} * CONT_{i,t}^{B} * \delta^{B} + CI_{i,t}^{C\to B} * \mu^{B} + \\ \qquad + X_{i,t}^{B} * CI_{i,t}^{C\to B} * \theta^{B} + \sum_{k=0}^{p^{B}} BC_{i,t-k} * \varphi_{t-k}^{B} + \varepsilon_{i,t}^{B} \\ Y_{i,t}^{C*} = X_{i,t}^{C} * \beta^{C} + CONT_{i,t}^{C} * \gamma^{C} + X_{i,t}^{C} * CONT_{i,t}^{C} * \delta^{C} + CI_{i,t}^{B\to C} * \mu^{C} + \\ \qquad + X_{i,t}^{C} * CI_{i,t}^{B\to C} * \theta^{C} + \sum_{k=0}^{p^{C}} CC_{i,t-k} * \varphi_{t-k}^{C} + \varepsilon_{i,t}^{C} \end{cases}, \quad \rho_{\varepsilon_{i,t}^{B},\varepsilon_{i,t}^{C}} \neq 0 \quad (4.14)$$

The terms in Equation (4.14) are defined in a similar way to those of Equation (4.13). $X_{i,t}^{B} * CI_{i,t}^{C\to B}$ ($X_{i,t}^{C} * CI_{i,t}^{B\to C}$) is an array of channels of crises interaction that affect the likelihood of banking (currency) crises.

4.3.5. Selection Criteria

We follow the common practice on the EWS literature to select the most parsimonious models (see, for example, Bussiere and Fratzscher, 2006; Mulder *et al*., 2012; Manasse, Savona, and Vezzoli, 2016). We first include all possible indicators at the same time and subsequently remove variables according to two criteria. First, we base the selection on the economic theoretical background – given the discussion above in Subsection 4.3.3, any variable that shows the wrong sign is discarded. Second, we remove all variables that are not statistically significant.[21] In the final model, we re-test all variables that were removed during the process.

4.4. Data

We use a panel data set that includes quarterly observations from 1970 to 2016 on the 21 Emerging Market Economies (EMEs) listed in Appendix 4.A. The empirical literature that studies currency or banking crises had been developed based on a sample that includes the period from 1970 to 2000 (see, for example, Glick and Hutchinson, 2001; Falcetti and Tudela, 2008; Mulder *et al*., 2012). This particular period includes the most significant episodes of twin crises and ends at 2000 since afterwards the frequency of crises dropped substantially (see, for example, Laeven and Valencia, 2018). But, the most recent studies tend to consider a wider period, which includes the aftermath of the Global Financial Crisis (see, for example, Candelon *et al*., 2013; Hahm *et al*., 2013). Since we develop a unified EWS on banking and currency crises, we choose to include the Global Financial Crisis period in our sample. To this end, our choice of selecting the period from 1970 to 2016 is in line with the most recent studies.[22]

The list of countries includes all EMEs defined by IMF (2016), excluding Bulgaria, Latvia, and Lithuania due to unavailability of data.[23] Our sample of EMEs is close to those in recent EWS studies for currency and banking crises, including Davis and Karim (2008), Klomp and de Haan (2009), and Minoiu *et al.* (2015). We follow the common practice of the literature and choose to include only EMEs in our EWS model for two reasons. First, several studies argue that the fundamental determinants of financial and external fragility in EMEs are different from those in developed and in developing economies (see, for example, Bussiere and Fratzscher, 2006; Falcetti and Tudela, 2008; Joyce, 2011). Second, Hutchinson and Noy (2005) point out that EMEs appear to be more vulnerable to twin crises. Since we are interested in assessing the impact of crises interaction

[21] Note that the last three models (Baseline 2, Crisis Interaction, and Channels of Crisis Interaction) include multiplicative terms between continuous variables. If a continuous variable is not significant but its multiplicative term is, we keep both variables in the regression.
[22] 2016 was the most recent year available when data was retrieved.
[23] This classification of Emerging Market Economies by the IMF has remained unchanged since 2011. This classification can be found, for example, in note 2 of Figure 1.1 (pp. 4) in IMF (2016).

effects, we opt to include only these economies, which appear to be more vulnerable to the effects of the interactions between banking and currency crises.

The set of variables is described in Appendix 4.B, which contains the full list of variables and sources. For the explanatory variables, we follow the common practice in the literature and transform all indicators for each country into percentiles of the distribution (see, for example, Berg and Pattillo, 1999; Kaminsky, 2006). The use of percentiles may be crucial when working with a diverse sample of countries because it enables the distinction between usual and unusual values for each indicator in each country. For instance, according to Kaminsky (2006), a monthly 20% fall in stock prices may be normal in some economies but may be a strong crash in other economies.

We applied the definitions of banking and currency crises presented in Subsections 4.3.1 and 4.3.2, respectively to our data. We identified 25 banking crises in 17 countries and 57 currency crises in 20 countries, out of the 21 EMEs included in our sample. Moreover, while 20% of the banking crisis episodes in our sample was preceded by a currency crisis within a year, more than 21% of the currency crisis episodes in our sample was preceded by a banking crisis within a year. As it has been stated by the literature, financial crises have become more intertwined and these numbers are a reflex of this reality (see, for example, Laeven and Valencia, 2018). These numbers also reinforce our decision to include crises interaction effects as leading indicators of banking and currency crises.

Our main data source for the macroeconomic variables is the International Financial Statistics (IFS) from the IMF. Debt variables are from the Joint External Debt Hub (JEDH) database, jointly developed by the BIS, IMF, OECD, and World Bank. Financial variables were retrieved from Datastream. Appendix 4.B contains further details concerning the dataset. The result is an unbalanced panel data set with a maximum of 2842 observations.

4.5. Results

This section has three subsections. In Subsection 4.5.1, we estimate the coefficients of the four EWS, and discuss the results of our estimations, focusing on the channels of crises interaction (our key contribution). In subsection 4.5.2, we analyse the in-sample predictability power for the models assuming two cut-off probabilities widely used in the literature. Subsection 4.5.3 provides with a more extensive in-sample accuracy analysis assuming several alternative strategies for the policymaker.

4.5.1. The Four EWS: Regression Results

Table 4.1 presents estimates for our four EWS, specified in equations (4.9) to (4.12) in Subsection 4.3.4. The table displays the coefficients both for the Banking Crisis Equation and for the Currency Crisis Equation, after applying our selection criteria described in Subsection 4.3.5 to the broad choice of variables listed in Subsection 4.3.3. All standard errors are estimated robustly.[24]

We start by presenting the results on the Error Term Structure. For all EWS, these results point to a statistically significant correlation between the error terms of both equations, unambiguously suggesting that the two equations should be jointly estimated. These results further motivate the need for a unified EWS for banking and currency crises.

We now turn to the analysis of the four EWS, whose estimates are presented in Columns (1) to (4). Columns (1) and (2) focus on the leading indicators and on the contagion effects (from a crisis in a country to the same type of crisis in another country) to the likelihood of crises. These columns do not include the interaction effects from one type of crisis to the other type, thus allowing us to compare the results from our dataset with the results in the literature.[25] Column (1) does not consider the contagion multipliers, whereas Column (2) includes multiplicative terms between the leading indicators and the contagion variable (to assess the role of the leading indicators in the presence of contagion effects).

Column (1) shows the selected variables for the Banking Crisis Equation and for the Currency Crisis Equation. Regarding the former equation, the selected variables include private credit (as a percentage of GDP), the real interest rate, the inflation rate, the ratio of M2 to reserves, the real effective overvaluation index, the ratio of short-term external debt to reserves, and the contagion variable. These variables are broadly in line with the variables considered in the EWS literature on banking crises, as for example in Kaminsky and Reinhart (1999) and Beck *et al.* (2006).

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[24] In each EWS, we perform specification tests to detect serial correlation and heteroscedasticity in the errors.
[25] This is not an exact comparison since the EWS literature does not jointly estimate both types of crisis, as discussed in Section 4.3.2.

Table 4.1 – Bivariate probit estimations of banking and currency crises' probabilities[a,b]

Variables	Baseline		Baseline 2		Crises interaction		Channels of Crisis Interaction	
	(1)		(2)		(3)		(4)	
Banking Crisis Equation								
CRED/GDP	0.2631***	(5.21)	0.2749***	(5.11)	0.2759***	(5.12)	0.2870***	(5.25)
RIR	0.1326*	(1.85)	0.4757***	(4.04)	0.4581***	(3.88)	0.5430***	(4.30)
INF	0.3604***	(4.75)	0.7798***	(6.76)	0.7542***	(6.56)	0.8154***	(6.68)
M2/RES	0.2690***	(3.72)	0.2713***	(3.50)	0.2697***	(3.49)	0.2777***	(3.36)
Δ%STM	-		-0.0728	(-0.93)	-0.0572	(-0.73)	0.0154	(0.19)
REERO	0.4904***	(7.07)	0.6343***	(7.39)	0.6335***	(7.36)	0.6666***	(7.76)
STED/RES	0.1823**	(2.35)	0.1829**	(2.21)	0.1789**	(2.16)	0.0992	(1.03)
$CONT^B$	0.1580***	(3.03)	0.2542***	(4.18)	0.2529***	(4.16)	0.2382***	(3.93)
Contagion Multipliers								
RIR * $CONT^B$			-0.2331***	(-3.55)	-0.2313***	(-3.53)	-0.2406***	(-3.59)
INF * $CONT^B$			-0.3806***	(-5.24)	-0.3839***	(-5.29)	-0.3966***	(-5.21)
Δ%STM * $CONT^B$			0.1077**	(2.50)	0.1075**	(2.51)	0.0750*	(1.76)
REERO * $CONT^B$			-0.1105**	(-2.13)	-0.1051*	(-2.02)	-	
Crises interaction and Channels								
$CI^{C\rightarrow B}$					-		-1.1955***	(-2.63)
Δ%STM * $CI^{C\rightarrow B}$							-0.3895*	(-1.86)
REERO * $CI^{C\rightarrow B}$							-0.9222***	(-3.51)
STED/RES * $CI^{C\rightarrow B}$							0.4514**	(2.51)
Constant	-2.8618***	(-14.53)	-3.0228***	(-13.90)	-3.0284***	(-13.88)	-3.1275***	(-13.31)
Currency Crisis Equation								
RIR	0.2271***	(3.21)	0.2460***	(3.30)	0.1551***	(2.21)	0.1278	(1.46)
INF	0.1472**	(2.22)	0.1440**	(2.03)	-		0.0563	(0.71)
Δ%STM	-0.1403***	(-2.62)	-0.1626***	(-2.82)	-0.1476**	(-2.54)	-0.0959	(-1.54)
REERO	0.6853***	(11.06)	0.7101***	(11.09)	0.7152***	(11.03)	0.7065***	(10.26)
CA/GDP	-0.1759***	(-3.37)	-0.1973***	(-3.57)	-0.2078***	(-3.68)	-0.2383***	(-4.13)
STED/RES	0.1130*	(1.94)	0.1367**	(2.07)	0.1417**	(2.14)	0.1271*	(1.85)
Δ%RES	-0.1916***	(-3.09)	-0.2292***	(-3.54)	-0.2088***	(-3.16)	-0.1714**	(-2.50)
$CONT^C$	-		0.0325	(0.57)	0.0551	(0.99)	-0.0130	(-0.20)

(Continued)

Table 4.1 – Bivariate probit estimations of banking and currency crises' probabilities[a,b] (Continued)

Variables	Baseline		Baseline 2		Crises interaction		Channels of Crisis Interaction	
	(1)		(2)		(3)		(4)	
Currency Crisis Equation								
Contagion Multipliers								
RIR * $CONT^C$			-		-		0.1425*	(1.77)
Δ%STM * $CONT^C$			0.0916*	(1.65)	0.1446***	(2.56)	0.1816***	(3.01)
STED/RES * $CONT^C$			-0.1121*	(-1.77)	-0.1458**	(-2.24)	-0.2007***	(-2.75)
Δ%RES * $CONT^C$			0.2053***	(3.16)	0.1974***	(3.00)	0.2269***	(3.34)
Crises interaction and Channels								
$CI^{B \to C}$					0.8582***	(4.71)	-	
RIR * $CI^{B \to C}$							0.4167*	(1.69)
INF * $CI^{B \to C}$							0.5469**	(2.47)
Δ%STM * $CI^{B \to C}$							-0.5420***	(-2.94)
REERO * $CI^{B \to C}$							0.4401**	(2.10)
Δ%RES * $CI^{B \to C}$							-0.5527**	(-2.39)
Constant	-2.0060***	(-16.07)	-2.0393***	(-15.51)	-2.0667***	(-15.50)	-2.0674***	(-15.26)
Error Term Structure								
$\rho_{\varepsilon^B_{i,t},\varepsilon^C_{i,t}}$	0.4398***	(22.30)	0.4744***	(23.48)	0.4871***	(25.27)	0.5272***	(26.88)
Statistics								
Log-Likelihood	-726.99		-693.94		-685.21		-660.61	
Akaike Criterion	1583.97		1535.87		1518.43		1487.23	
Schwartz Criterion	1951.76		1953.52		1936.08		1955.68	
McFadden R^2	0.46		0.49		0.49		0.51	
Crisis Periods (A)	245		245		245		245	
Tranquil Periods (B)	1873		1843		1843		1843	
Sample size (A+B)	2118		2088		2088		2088	

[a]Robust z-statistics in brackets.

[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively. - corresponds to variables that were not significant and were removed from the regression.

CRED/GDP (Private credit over GDP), RIR (Real interest rate), INF (Inflation rate), M2/RES (M2 over reserves), Δ%STM (Stock market growth rate), REERO (Real effective exchange rate overvaluation), CA/GDP (Current account over GDP), STED/RES (Short-term external debt over reserves), Δ%RES (reserves growth rate), $CONT^B$ (contagion, banking crises), $CONT^C$ (contagion, currency crises), $CI^{B \to C}$ (crises interaction effects from banking to currency crises), $CI^{C \to B}$ (crises interaction effects from currency to banking crises).

Regarding the Currency Crisis Equation, the selected variables are the real interest rate, the inflation rate, the stock market growth rate, the overvaluation index, the current account (as a percentage of GDP), the ratio of short-term external debt to reserves, and the growth rate of reserves. This selection of variables is broadly in line with the variables considered in the EWS literature on currency crises, as for example Kaminsky and Reinhart (1999) and Zhao *et al.* (2014); in the following sections, we use the results in Column (1) as a broad representation of the literature on EWS on banking and currency crises. This model presents a goodness-of-fit-measure of about 46%.

Column (2) of Table 4.1 adds the contagion multipliers, thus allowing the contribution of the leading indicators (to the likelihood of crises) to depend on the strength of contagion effects among countries. Regarding the Banking Crisis Equation, strong contagion effects partially offset the contributions of the real interest rate, the inflation rate, and the overvaluation index to the likelihood of banking crises. Domestic stock market growth becomes relevant to signal banking crises when coupled with strong contagion effects.

Regarding the Currency Crisis Equation, strong contagion effects partially offset the contributions of the stock market growth rate, the ratio of short-term external debt to reserves, and the reserves growth rate to the likelihood of currency crises. By adding contagion multipliers, the Baseline 2 Model performs better than the Baseline Model, with a lower value for the Akaike information criterion and a higher McFadden R-squared (about 49%).

Columns (3) and (4) of Table 4.1 present the key results of our study as they include crises interaction effects, whereby a banking crisis affects the likelihood of a future currency crisis or/and vice-versa. While Column (3) only adds crises interaction effects, Column (4) also introduces multiplicative terms between crises interaction effects and leading indicators, i.e. the *channels of crises interaction*. Analogous to the contagion multipliers, these channels allow the contribution of the leading indicators (to the likelihood of crises) to depend on the presence of crises interaction effects.

Column (3) presents the estimates for the Crises interaction Model (CI), suggesting that the interaction effects from banking to currency crises (coefficient on $CI^{B\rightarrow C}$) are a leading indicator of currency crises. The inverse (coefficient on $CI^{C\rightarrow B}$), however, does not significantly signal banking crises. These results are consonant with the literature on the determinants of financial crises, as Kaminsky and Reinhart (1999) and Rossi (1999) suggest that banking crises cause currency crises but not the reverse. Our results go a step further beyond causality, suggesting that banking crises *signal* future currency crises but not the reverse. The CI model has a similar goodness-of-fit to the Baseline 2 Model but a lower bias and variance (information criteria).

Column (4) of Table 4.1 presents the estimates of the Channels of Crises interaction Model (CCI), the key contribution of our paper. This column adds multiplicative terms between the crises interaction effects and the leading indicators, thus allowing the contribution of the leading indicators to the likelihood of a currency (banking) crisis to depend on the existence of a banking (currency) crisis.

The estimates of the crises interaction channels in the Banking Crisis Equation in Column (4) suggest that currency crises affect the impact of the stock market growth, the overvaluation index, and the ratio of short-term external debt to reserves on the likelihood of banking crises. We comment on the estimates of these three channels in turn. First, the coefficient on the stock market growth multiplicative term ($\Delta\%STM * CI^{C\rightarrow B}$) suggests that currency crises open a channel for a stock market collapse to have an impact on the likelihood of banking crises. The importance of the stock market in linking currency to banking crises is in line with Singh (2009): when a currency crisis causes a stock market crash, the collapse in asset prices weakens the banking system's net worth and may lead to a banking crisis.

Second, while the overvaluation index (REERO) *per se* positively contributes to the likelihood of banking crises, the multiplicative term $REERO * CI^{C\rightarrow B}$ decreases the probability of banking crises. This result suggests that real devaluations in the context of a currency crisis are prone to cause banking crises.

Third, the ratio of short-term external debt to reserves (STED/RES) has a significant impact on the likelihood of banking crises in the presence of a currency crisis (its impact is not significant without currency crises). This result is consistent with findings in the theoretical literature on the links from currency to banking crises, including Mishkin (1996), Krugman (1999), or Chang and Velasco (2000). For instance, Mishkin (1996) explains that currency crises deteriorate the balance sheets of firms with debt contracts denominated in foreign currency. The higher the ratio of short-term external debt to reserves, the more likely the deterioration increases asymmetric information problems and leads to bank problems.

Finally, we find a negative interaction effect from currency to banking crises ($CI^{C\rightarrow B}$). This result appears to go against the one we find in the CI (Column 3 of Table 4.1) and the general findings in the literature (including, Kaminsky and Reinhart, 1999;

Rossi, 1999; Falcetti and Tudela, 2008). This result may occur since the coefficient on $CI^{C \to B}$ captures the residual effects as we also account for the channels via stock market growth, the overvaluation index, and the ratio of short-term external debt to reserves.

Regarding the Currency Crisis Equation in Column (4), the estimates of the crises interaction channels suggest that banking crises influence the impact of the real interest rate, the inflation rate, the stock market growth, the overvaluation index, and the reserves growth rate on the likelihood of currency crises. We comment on the estimates of these five channels in turn. First, the real interest rate (RIR) has a significant impact on the likelihood of currency crises in the presence of a banking crisis (its impact is not significant without banking crises). This result suggests that increasing interest rates may exacerbate the possibility of currency crises, following the onset of a banking crisis. This result is in line with Shin (2005), who argues that increasing interest rates in a context of a fragile banking sector may deteriorate even further the banking sector, precipitating a rush for the exits by foreign lenders and, consequently, a currency crisis.

Second, the inflation rate (INF) has a significant effect on the probability of currency crises when there is a banking crisis (its impact is not significant without banking crises). This result indicates that the inflation rate aggravates external vulnerability in the presence of a banking crisis. This result is consistent with Obstfeld (1988), who argues that policymakers may precipitate a currency crisis if they choose to increase inflation in order to mitigate bank problems.

Third, the stock market growth rate (Δ%STM) has a significant effect on the likelihood of currency crises in the presence of a banking crisis (its impact is not significant without banking crisis). The negative sign on the coefficient of the multiplicative term $\Delta\%STM * CI^{B \to C}$ suggests that a stock market collapse increases the likelihood of currency crises, when coupled with a banking crisis. This result is also in line with Shin (2005), who points out that a collapse in the stock market puts increasing pressure into the banking system, when assets are marked-to-market. This deterioration in the net worth of a weak banking system alarms foreign lenders, who may precipitate massive capital outflows and lead to a currency crisis.

Fourth, the coefficient of the overvaluation index multiplicative term ($REERO * CI^{B \to C}$) suggests that banking crises exacerbate the impact of overvaluation on the likelihood of currency crises (the isolated impact of the REERO is also significantly positive).

Since currency overvaluation is a common indicator of external sector fragility, our results suggest it is more likely that a banking crisis causes currency crises when the external sector is more fragile.

Fifth, the coefficient of the reserves growth rate multiplicative term ($\Delta\%RES * CI^{B\rightarrow C}$) indicates that banking crises exacerbate the impact of a reduction in reserves on the likelihood of currency crises (the isolated impact of the reserves growth rate is also significantly negative). This result is in line with Velasco (1987), who states that if policymakers use their international reserves to deal with a banking crisis, their reserves may fall below the critical point where speculators will attack the currency.

We highlight that the interest rate, the inflation rate, and stock market growth do not per se (i.e., without banking crises) contribute to the likelihood of currency crises. However, the previous EWS (Columns 1 to 3) suggest that these variables were leading indicators of currency crises. These two results together suggest that the effects that the previous EWS find only occur in the presence of banking crises, which we can only find introducing the channels of crises interaction.

Finally, contrary to the CI model and the general findings in the literature, we find no evidence of positive causal effects from banking to currency crises ($CI^{B\rightarrow C}$), once taking into account the effects from the channels of crises interaction. This result suggests that the mere occurrence of a banking crisis is not critical for the likelihood of future currency crises, rather it is the circumstances/fragilities in the economy coupled with a banking crisis that influence the likelihood of future currency crises.

Adding the channels of crises interaction improves the quality of EWS since the CCI presents the highest goodness-of-fit (51%) and the lowest Akaike criterion among all tested models.

4.5.2. In-Sample Performance with Pre-determined Cut-offs

In order to assess the accuracy of the four EWS estimated in Table 4.1, we undertake an in-sample predictability power analysis. This analysis consists of using the EWS to estimate the probabilities of banking and currency crises, converting these probabilities into crisis signals, and confronting these signals with the actual occurrence of crises. A powerful in-sample predictability implies that the signals discern crises from tranquil periods.

Tables 4.2 and 4.3 present the in-sample predictability power analysis for the EWS for banking and currency crises, respectively. We use cut-off probabilities to convert the estimated probabilities from each EWS into crisis signals. In this subsection, we exogenously set these cut-off probabilities equal to the values commonly used in the EWS literature (either 50% or 25%, e.g. Berg and Pattillo, 1999; Mulder *et al*., 2012). Setting these cut-offs means that each EWS signals a crisis if and only if the estimated probability in the EWS exceeds the cut-off probabilities (either 50% or 25%). Columns (1) to (4) present the results for the 50% cut-off for each of the four EWS, and columns (5) to (8) present the results for the 25% cut-off.

We take the Baseline Model (in columns 1 and 5) as a broad representation of the literature, with the Baseline 2 Model (in columns 2 and 6) considering additionally the contagion multipliers, and the Crises interaction Model (in columns 2 and 6) adding the crises interaction effects. Since our main contribution to the literature is the inclusion of channels of crises interaction, we focus on the Channels of Crises interaction model, the results for which are presented in columns (4) and (8).

Besides evaluating the in-sample predictability power for all observations, we complement our analysis by dividing the total sample into two subsamples: one subsample with the observations without crises interaction effects (i.e. crises interaction variable = 0) and a subsample with the observations with crises interaction effects (i.e. crises interaction variable = 1). We consider these three different samples to better assess the performance of our EWS. For example, we compare the EWS's predictability power in the presence of crises interaction effects with their predictability power when there are no crises interaction effects – ideally, the EWS should have a high predictive power in both subsamples. The three sets of rows in Table 4.2 present the results for each of the three samples in the case of banking crises, with 11% of the observations featuring interaction effects from currency crises. Table 4.3 uses the same presentation approach for the case of currency crises, with 6% of the observations including interaction effects from banking crises.

Table 4.2 – In-sample accuracy of crisis probabilities for the next four quarters for various EWS specifications (Banking crises)

	Banking crises							
	Bas	**Bas 2**	**CI**	**CCI**	**Bas**	**Bas 2**	**CI**	**CCI**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Cut-off Probability of 50%				Cut-off Probability of 25%			
1. All Observations								
1.A Total Correctly Called Observations[a]	95%	96%	96%	96%	94%	94%	94%	94%
1.B Pre-crisis Periods Correctly Called[b]	13%	20%	21%	23%	32%	43%	41%	46%
1.C Tranquil Periods Correctly Called[c]	99%	99%	99%	99%	97%	97%	97%	97%
1.D False Alarms[d]	55%	42%	39%	33%	64%	63%	64%	61%
1.E Efficiency Measure = B-D	**-42%**	**-22%**	**-18%**	**-10%**	**-32%**	**-20%**	**-23%**	**-15%**
2. When Crises interaction variable = 0				**(89% of all observations)**				
2.A Total Correctly Called Observations[a]	95%	96%	96%	96%	94%	94%	94%	94%
2.B Pre-crisis Periods Correctly Called[b]	13%	20%	22%	24%	33%	45%	43%	45%
2.C Tranquil Periods Correctly Called[c]	99%	99%	99%	99%	97%	96%	96%	97%
2.D False Alarms[d]	57%	44%	41%	34%	65%	63%	63%	62%
2.E Efficiency Measure = B-D	**-44%**	**-24%**	**-19%**	**-10%**	**-32%**	**-18%**	**-20%**	**-17%**
3. When Crises interaction variable = 1				**(11% of all observations)**				
3.A Total Correctly Called Observations[a]	94%	97%	97%	97%	94%	96%	96%	97%
3.B Pre-crisis Periods Correctly Called[b]	13%	14%	14%	14%	31%	14%	14%	57%
3.C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%	97%	98%	98%	98%
3.D False Alarms[d]	33%	0%	0%	0%	55%	80%	80%	50%
3.E Efficiency Measure = B-D	**-20%**	**14%**	**14%**	**14%**	**-23%**	**-66%**	**-66%**	**7%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012).

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

Lines A to D in Tables 4.2 and 4.3 display several measures of predictability power widely used in the EWS literature on banking crises (e.g. Demirgüç-Kunt and Detragiache, 1998) and on currency crises (e.g. Kaminsky *et al.*, 1998; Berg and Pattillo, 1999). These measures use two related concepts: "correct calls" and "false alarms". Correct calls happen when either a signal is followed by a crisis four quarters ahead, or the

EWS does not emit any signal before a tranquil period. False alarms happen when a signal is not followed by a crisis four quarters ahead. Line A shows the percentage of total correct calls; Line B shows the percentage of pre-crisis periods correctly called (i.e. the percentage of correct calls when a crisis occurs four quarters ahead); Line C shows the percentage of tranquil periods correctly called (i.e. the percentage of correct calls when there is no crisis four quarters ahead); Line D shows the percentage of false alarms. Finally, as suggested by Mulder *et al.* (2012), Line E shows a simple efficiency measure given by the difference between the percentage of pre-crisis correctly called and the percentage of false alarms. Thus, the measure implies that the higher the pre-crisis correctly or the lower the number of false alarms, the larger that difference would be and the more efficient/better the model.

Table 4.2 presents the measures of predictability power for banking crises. The first set of rows (from 1.A to 1.E) shows the results for all observations. Row 1.A shows that CCI correctly calls 96% of the observations for the 50% cut-off. Rows 1.B and 1.C suggest that it is substantially more difficult to predict crises than tranquil periods – the measures of predictability are noticeably lower for the pre-crisis periods for both cut-offs. Moreover, the choice of cut-offs has clear implications for the measures of pre-crisis correctly called and false alarms. One the one hand, raising the cut-off from 25% to 50% reduces false alarms from 61% to 33% for CCI. On the other hand, raising the cut-off reduces crises correctly called from 46% to 23%. Row 1.E provides the measure of efficiency that accounts for the net impact on both measures, and shows a five percentage points efficiency gain from moving from the lowest to the highest cut-off.

Let us now compare the relative performance of the four EWS in each of the three samples. In the sample with all observations, CCI is the most efficient EWS at predicting banking crises (Row 1.E). For both cut-off probabilities, this higher efficiency arises both from a higher percentage of pre-crisis correctly called (Row 1.B) and from less false alarms (Row 1.D) than the other EWS. This suggests that the inclusion of channels of crises interaction improves the predictability power of EWS for banking crises.

Dividing the total sample into the subsample of the observations without crises interaction effects (Rows 2.A to 2.E) and the subsample with crises interaction effects (Rows 3.A to 3.E) permits a better evaluation of the performance of the EWS. The results for the subsample of observations without crises interaction effects are similar to the results with all observations. This may not be surprising because this subsample contains 89% of all observations. Remarkably, CCI outperforms the other EWS by most measures of predictability power even when there is *no* crises interaction effects (Rows 2.A to 2.E). This suggests that CCI is the best EWS at predicting single banking crises.

The results for the subsample with crises interaction effects show no substantial differences among the EWS in columns (2) to (4) for the 50% cut-off. For this cut-off, these three EWS are equally efficient (Row 3.E). Differences among the EWS are visible for the 25% cut-off, with CCI performing much better than the other EWS (Row 3.E). Overall results for all samples suggest that CCI is the most efficient at predicting banking crises, both at the 50% and at the 25% cut-offs.

Table 4.3 displays measures of predictability power for currency crises and, again, we focus on the CCI model (columns 4 and 8). When considering all observations, CCI is the best EWS for the highest cut-off by all measures in Rows 1.A to 1.E, but has a broadly similar performance to the other EWS for the lowest cut-off.

Restricting the sample to observations without crises interaction effects, CCI is the best at minimising false alarms for the 50% cut-off. As in banking crises, there are again performance gains from adding the channels of crises interaction to an EWS even when there are *no* crises interaction effects. The results are broadly similar among the four EWS for the 25% cut-off.

When we restrict the sample to observations with crises interaction effects, Row 3.E suggests that the relative performance of each EWS varies substantially with the cut-off probability. For the highest cut-off probability – columns (1) to (4) – CCI outperforms the other EWS based on the efficiency measure, with the highest percentage of pre-crisis correctly called (74%) at the expense of more false alarms (19%). These results suggest that incorporating channels of crises interaction from banking to currency crises helps to call currency crises that are accompanied by banking crises. For the lowest cut-off probability – columns (5) to (8) – the results are broadly similar among the four EWS.

The choice of the cut-off has more implications for the EWS comparison when analysing currency crises than when analysing banking crises across the three samples. For the case of banking crises, CCI tends to outperform others regardless of the cut-off. However, for the case of currency crises, the most efficient model depends on the cut-off. For the highest cut-off, CCI outperforms the others across the three samples. For the lowest cut-off, our results indicate that, while CCI is never the most efficient model, the most efficient model varies across samples and the CCI model's efficiency does not substantially differ from the highest efficiency level, for each sample.

Table 4.3 – In-sample accuracy of crisis probabilities for the next four quarters for various EWS specifications (Currency crises)

	Currency crises							
	Bas	**Bas 2**	**CI**	**CCI**	**Bas**	**Bas 2**	**CI**	**CCI**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	Cut-off Probability of 50%				Cut-off Probability of 25%			
1. All Observations								
1.A Total Correctly Called Observations[a]	92%	92%	92%	92%	90%	90%	90%	90%
1.B Pre-crisis Periods Correctly Called[b]	19%	18%	22%	24%	42%	45%	46%	45%
1.C Tranquil Periods Correctly Called[c]	99%	99%	99%	99%	95%	94%	94%	94%
1.D False Alarms[d]	33%	41%	33%	27%	57%	57%	56%	56%
1.E Efficiency Measure = B-D	**-14%**	**-23%**	**-11%**	**-3%**	**-14%**	**-12%**	**-10%**	**-11%**
2. When Crises interaction variable = 0	**(94% of all observations)**							
2.A Total Correctly Called Observations[a]	92%	92%	92%	92%	90%	90%	90%	90%
2.B Pre-crisis Periods Correctly Called[b]	13%	13%	13%	13%	36%	40%	38%	37%
2.C Tranquil Periods Correctly Called[c]	99%	99%	99%	99%	95%	94%	95%	95%
2.D False Alarms[d]	46%	52%	42%	35%	64%	63%	62%	63%
2.E Efficiency Measure = B-D	**-33%**	**-40%**	**-29%**	**-22%**	**-28%**	**-23%**	**-24%**	**-26%**
3. When Crises interaction variable = 1	**(6% of all observations)**							
3.A Total Correctly Called Observations[a]	85%	82%	85%	87%	87%	87%	81%	83%
3.B Pre-crisis Periods Correctly Called[b]	51%	43%	69%	74%	74%	74%	86%	86%
3.C Tranquil Periods Correctly Called[c]	99%	98%	92%	93%	93%	92%	79%	82%
3.D False Alarms[d]	5%	12%	23%	19%	19%	21%	38%	33%
3.E Efficiency Measure = B-D	**46%**	**31%**	**46%**	**55%**	**55%**	**53%**	**48%**	**53%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012).

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

We finish this subsection with three final remarks. First, the in-sample predictability power increases (with minor exceptions) as we move from the baseline models (with or without contagion multipliers, but without crises interaction effects) to the CCI model – that is when we compare columns (1) and (2) with column (4), and columns (5) and (6) with column (8). These improvements suggest that the inclusion of the crises interaction channels is key for forecasting crises (regardless of the presence of crises interaction effects). These improvements highlight the relevance of our contribution.

Second, comparing the CI model with the CCI model suggests that having a simplistic view of crises interaction effects (i.e., with no consideration of the channels of crises interaction) neglects important interaction mechanisms, since including the channels of crises interaction enhances substantially the predictive power of the EWS. This improvement can be seen when comparing columns (3) and (7) with columns (4) and (8): in most cases, the CCI has a higher percentage of pre-crisis periods correctly called, and a lower percentage of false alarms than the CI. Using the 50% cut-off, the efficiency measure increases for five cases (and remains stable for the other case) as we move from CI to CCI.

Third, as we split the total sample into the two subsamples, we identify a substantial difference in the predictive power between the two subsamples for the case of currency crises (Table 4.3). For this type of crisis, we verify that, at the 50% cut-off, the efficiency measures for the observations without crises interaction range from -40% to -22%, whereas the efficiency measures for the observations with crises interaction range from +31% to +55% (at the 25% threshold, these efficiency measures range from -28% to -23%, and from +48% to 55%, respectively). This set of results suggest that these EWS are substantially more suitable to predict currency crises when they are accompanied by banking crises than to predict single currency crises. Taking into account that these EWS jointly estimate both types of crises, this set of results further motivate the need for a unified EWS to predict currency crises that are accompanied by banking crises.

4.5.3. In-Sample Performance with Alternative Strategies

In the previous section, we exogenously set the cut-off probabilities to convert the estimated probabilities from each EWS into crisis signals. Although those two cut-off levels (25% and 50%) are commonly used in the literature, they are arbitrary and may cause limitations in the analysis because the relative performance of EWS may differ with respect to different cut-off levels. In order to overcome those limitations, we complement the in-sample performance analysis by considering alternative strategies to select the cut-off probabilities. Several strategies have been proposed in recent studies in the EWS literature (e.g. Mulder *et al*., 2012; Comelli, 2014), considering potential policymaker's objectives.

We choose the five strategies suggested by Mulder *et al.* (2016). The first two strategies restrict the percentage of false alarms. In the first strategy, the policymaker has zero tolerance for false alarms (i.e., for each EWS, we choose the lowest cut-off probability for which no false alarms arise). In the second strategy, the policymaker allows at most 30% of false alarms (i.e., we select the lowest cut-off in which 30% of false alarms are issued). The following two strategies (strategies 3 and 4) bound the percentage of pre-crisis periods not called. In the third strategy, the policymaker has zero tolerance for crisis not called (i.e., we pick the highest cut-off that guarantees 100% of pre-crisis correctly called). In the fourth strategy, the policymaker aims to have at least 70% of pre-crisis periods correctly called (i.e., we choose the highest cut-off such that a minimum of 70% of crisis is correctly called). In the final strategy, the policymaker selects the cut-off probability that offers the highest number of pre-crisis correctly called minus false alarms (i.e. we select the cut-off that maximizes the efficiency measure proposed by e.g. Mulder *et al.*, 2012).

Tables 4.4 to 4.9 present measures of predictability power analysis for our EWS considering the five strategies presented above. These measures of predictability power are the ones we have used in the previous subsection. To ease the interpretation of the results, the tables also present the average of the measures of predictability across the five strategies. For the sake of exposition, we focus on the efficiency measure, given by the difference between the percentage of pre-crisis periods correctly called and the percentage of false alarms. As we also have done in the previous section, we split the sample into two complementary subsamples depending on the presence of crises interaction effects.

We present the results in separate Tables. Tables 4.4 to 4.6 present measures of predictability power of each EWS for banking crises. While Table 4.4 displays the results for all observations, Table 4.5 (Table 4.6) present the results for observations without (with) crises interaction effects. As we did in the previous section, we focus on the CCI model.

When considering all observations, we find that (based on the efficiency measure) (1) CCI is superior or equally desirable to any of the other EWS across all strategies, i.e. no EWS is superior to CCI, and (2) the Bas model is inferior to any of the other EWS across all strategies (Table 4.4, Row E). Restricting the sample to observations without crises interaction effects, Table 4.5 suggests that, when using the efficiency measure (Row E), (1) CCI is only inferior to the other models for strategy 5, and (2) the Bas model is always inferior to any of the other EWS, underperforming substantially in strategies 1, 2, and 4. When we restrict the sample to observations with crises interaction effects, CCI is on average substantially better than the other EWS – the average efficiency measure of the CCI is 31%, which is noticeably higher than the averages of the other models, 6% or 7%. These findings reinforce the results of the previous section, suggesting that including the crises interaction channels tends to enhance the EWS predictability power for banking crises (regardless of the presence of crises interaction effects).

Tables 4.7 to 4.9 display measures of predictability power analysis of each EWS for currency crises. As done for banking crises, in Table 4.7 we present the results for all observations, while in Tables 4.8 and 4.9 we present the results depending on the presence of crises interaction effects.

When considering all observations, CCI is, on average, superior to the other models (Table 4.7, Row E). Restricting the sample to observations without crises interaction effects, Table 4.8 suggests that CCI, on average, outperforms the other EWS (Row E) when there is no crises interaction. In addition, when other models are more efficient than CCI model, they are more efficient by only one percentage point. When we restrict the sample to observations with crises interaction effects, CCI is superior or equally desirable to the other EWS for strategies 1 to 3 (Table 4.6, Row E). In addition, the CI model is the least efficient model (or one of the least efficient models) in the presence of interaction effects from banking crises. These results are in line with the previous section, since including channels of crises interaction improves the EWS's ability to predict currency crises (as well as banking crises); and merely considering crises interaction effects (i.e., with no consideration of the channels of crises interaction) may compromise the EWS's ability to predict currency crises accompanied by banking crises.

Table 4.4 – In-sample Performance for Banking Crises – Alternative Strategies for All Observations

All Observations	Bas	Bas 2	CI	CCI
Strategy 1: Zero tolerance of False Alarms	(97%)	(95%)	(94%)	(94%)
A Total Correctly Called Observations[a]	95%	96%	96%	96%
B Pre-crisis Periods Correctly Called[b]	2%	1%	2%	3%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	33%	0%	0%	0%
E Efficiency Measure = B-D	**-32%**	**1%**	**2%**	**3%**
Strategy 2: At most 30% of False Alarms	(97%)	(62%)	(60%)	(54%)
A Total Correctly Called Observations[a]	95%	96%	96%	96%
B Pre-crisis Periods Correctly Called[b]	2%	15%	16%	21%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	33%	26%	29%	29%
E Efficiency Measure = B-D	**-32%**	**-11%**	**-13%**	**-8%**
Strategy 3: Zero Tolerance of Crisis Not Called	(0.2%)	(0.3%)	(0.3%)	(0.3%)
A Total Correctly Called Observations[a]	32%	47%	46%	49%
B Pre-crisis Periods Correctly Called[b]	100%	100%	100%	100%
C Tranquil Periods Correctly Called[c]	29%	45%	43%	47%
D False Alarms[d]	94%	92%	92%	92%
E Efficiency Measure = B-D	**6%**	**8%**	**8%**	**8%**
Strategy 4: At least 70% of Crisis Called	(10%)	(12%)	(13%)	(14%)
A Total Correctly Called Observations[a]	87%	91%	92%	92%
B Pre-crisis Periods Correctly Called[b]	70%	71%	71%	71%
C Tranquil Periods Correctly Called[c]	88%	92%	93%	93%
D False Alarms[d]	78%	70%	69%	68%
E Efficiency Measure = B-D	**-8%**	**1%**	**2%**	**3%**
Strategy 5: Highest B-D	(0.2)	(1%)	(1%)	(1%)
A Total Correctly Called Observations[a]	32%	60%	58%	59%
B Pre-crisis Periods Correctly Called[b]	100%	99%	99%	99%
C Tranquil Periods Correctly Called[c]	29%	58%	56%	57%
D False Alarms[d]	94%	90%	91%	90%
E Efficiency Measure = B-D	**6%**	**9%**	**8%**	**9%**
Average of above strategies				
A Total Correctly Called Observations[a]	68%	78%	78%	78%
B Pre-crisis Periods Correctly Called[b]	55%	57%	58%	59%
C Tranquil Periods Correctly Called[c]	69%	79%	78%	79%
D False Alarms[d]	66%	56%	56%	56%
E Efficiency Measure = B-D	**-11%**	**1%**	**2%**	**3%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012). Numbers in brackets represent the thresholds used.

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

Table 4.5 – In-sample Performance for Banking Crises – Alternative Strategies when Crises interaction Effects are Absent (89% of All Observations)

When Crises interaction variable ($CI^{C \rightarrow B}$) = 0	Bas	Bas 2	CI	CCI
Strategy 1: Zero tolerance of False Alarms	(97%)	(95%)	(94%)	(77%)
A Total Correctly Called Observations[a]	95%	95%	96%	96%
B Pre-crisis Periods Correctly Called[b]	1%	1%	2%	3%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	50%	0%	0%	0%
E Efficiency Measure = B-D	**-49%**	**1%**	**2%**	**3%**
Strategy 2: At most 30% of False Alarms	(97%)	(62%)	(62%)	(54%)
A Total Correctly Called Observations[a]	95%	96%	96%	96%
B Pre-crisis Periods Correctly Called[b]	1%	15%	16%	22%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	50%	28%	26%	30%
E Efficiency Measure = B-D	**-49%**	**-13%**	**-10%**	**-8%**
Strategy 3: Zero Tolerance of Crisis Not Called	(0.2%)	(0.3%)	(0.3%)	(0.3%)
A Total Correctly Called Observations[a]	32%	48%	47%	48%
B Pre-crisis Periods Correctly Called[b]	100%	100%	100%	100%
C Tranquil Periods Correctly Called[c]	29%	46%	44%	46%
D False Alarms[d]	94%	92%	92%	92%
E Efficiency Measure = B-D	**6%**	**8%**	**8%**	**8%**
Strategy 4: At least 70% of Crisis Called	(11%)	(13%)	(14%)	(14%)
A Total Correctly Called Observations[a]	89%	92%	92%	92%
B Pre-crisis Periods Correctly Called[b]	70%	70%	70%	70%
C Tranquil Periods Correctly Called[c]	89%	93%	93%	93%
D False Alarms[d]	76%	69%	68%	68%
E Efficiency Measure = B-D	**-6%**	**1%**	**2%**	**2%**
Strategy 5: Highest B-D	(0.2%)	(8%)	(11%)	(10%)
A Total Correctly Called Observations[a]	32%	88%	91%	90%
B Pre-crisis Periods Correctly Called[b]	100%	86%	81%	82%
C Tranquil Periods Correctly Called[c]	29%	89%	92%	90%
D False Alarms[d]	94%	74%	69%	72%
E Efficiency Measure = B-D	**6%**	**13%**	**12%**	**10%**
Average of above strategies				
A Total Correctly Called Observations[a]	69%	84%	84%	84%
B Pre-crisis Periods Correctly Called[b]	54%	54%	54%	55%
C Tranquil Periods Correctly Called[c]	69%	86%	86%	86%
D False Alarms[d]	73%	53%	51%	52%
E Efficiency Measure = B-D	**-19%**	**1%**	**3%**	**3%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012). Numbers in brackets represent the thresholds used.

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

Table 4.6 – In-sample Performance for Banking Crises – Alternative Strategies when Crises interaction Effects are Present (11% of All Observations)

When Crises interaction variable ($CI^{C \to B}$) = 1	Bas	Bas 2	CI	CCI
Strategy 1: Zero tolerance of False Alarms	(93%)	(43%)	(49%)	(37%)
A Total Correctly Called Observations[a]	94%	97%	97%	99%
B Pre-crisis Periods Correctly Called[b]	6%	14%	14%	57%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	0%	0%	0%	0%
E Efficiency Measure = B-D	**6%**	**14%**	**14%**	**57%**
Strategy 2: At most 30% of False Alarms	(40%)	(43%)	(49%)	(31%)
A Total Correctly Called Observations[a]	95%	97%	97%	98%
B Pre-crisis Periods Correctly Called[b]	25%	14%	14%	57%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	20%	0%	0%	20%
E Efficiency Measure = B-D	**5%**	**14%**	**14%**	**37%**
Strategy 3: Zero Tolerance of Crisis Not Called	(1%)	(3%)	(3%)	(1%)
A Total Correctly Called Observations[a]	54%	73%	72%	77%
B Pre-crisis Periods Correctly Called[b]	100%	100%	100%	100%
C Tranquil Periods Correctly Called[c]	51%	72%	71%	77%
D False Alarms[d]	88%	90%	90%	88%
E Efficiency Measure = B-D	**12%**	**10%**	**10%**	**12%**
Strategy 4: At least 70% of Crisis Called	(5%)	(6%)	(6%)	(6%)
A Total Correctly Called Observations[a]	79%	81%	81%	91%
B Pre-crisis Periods Correctly Called[b]	75%	71%	71%	71%
C Tranquil Periods Correctly Called[c]	80%	81%	81%	92%
D False Alarms[d]	81%	89%	89%	78%
E Efficiency Measure = B-D	**-6%**	**-18%**	**-18%**	**-7%**
Strategy 5: Highest B-D	(1%)	(43%)	(49%)	(37%)
A Total Correctly Called Observations[a]	54%	97%	97%	99%
B Pre-crisis Periods Correctly Called[b]	100%	14%	14%	57%
C Tranquil Periods Correctly Called[c]	51%	100%	100%	100%
D False Alarms[d]	88%	0%	0%	0%
E Efficiency Measure = B-D	**12%**	**14%**	**14%**	**57%**
Average of above strategies				
A Total Correctly Called Observations[a]	75%	89%	89%	93%
B Pre-crisis Periods Correctly Called[b]	61%	43%	43%	68%
C Tranquil Periods Correctly Called[c]	76%	91%	90%	94%
D False Alarms[d]	55%	36%	36%	37%
E Efficiency Measure = B-D	**6%**	**7%**	**7%**	**31%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012). Numbers in brackets represent the thresholds used.

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

Table 4.7 – In-sample Performance for Currency Crises – Alternative Strategies for All Observations

All Observations	Bas	Bas 2	CI	CCI
Strategy 1: Zero tolerance of False Alarms	(75%)	(79%)	(78%)	(82%)
A Total Correctly Called Observations[a]	92%	91%	91%	92%
B Pre-crisis Periods Correctly Called[b]	4%	4%	7%	9%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	0%	0%	0%	0%
E Efficiency Measure = B-D	**4%**	**4%**	**7%**	**9%**
Strategy 2: At most 30% of False Alarms	(51%)	(54%)	(52%)	(48%)
A Total Correctly Called Observations[a]	92%	92%	92%	92%
B Pre-crisis Periods Correctly Called[b]	19%	17%	22%	24%
C Tranquil Periods Correctly Called[c]	99%	99%	99%	99%
D False Alarms[d]	30%	29%	30%	29%
E Efficiency Measure = B-D	**-11%**	**-12%**	**-8%**	**-5%**
Strategy 3: Zero Tolerance of Crisis Not Called	(0.2%)	(1%)	(1%)	(1%)
A Total Correctly Called Observations[a]	15%	31%	35%	29%
B Pre-crisis Periods Correctly Called[b]	100%	100%	100%	100%
C Tranquil Periods Correctly Called[c]	7%	24%	29%	22%
D False Alarms[d]	91%	89%	88%	89%
E Efficiency Measure = B-D	**9%**	**11%**	**12%**	**11%**
Strategy 4: At least 70% of Crisis Called	(11%)	(12%)	(13%)	(12%)
A Total Correctly Called Observations[a]	81%	82%	82%	82%
B Pre-crisis Periods Correctly Called[b]	70%	70%	70%	70%
C Tranquil Periods Correctly Called[c]	82%	83%	83%	84%
D False Alarms[d]	73%	71%	70%	70%
E Efficiency Measure = B-D	**-3%**	**-1%**	**0%**	**0%**
Strategy 5: Highest B-D	(4%)	(3%)	(3%)	(2%)
A Total Correctly Called Observations[a]	58%	56%	56%	47%
B Pre-crisis Periods Correctly Called[b]	97%	97%	97%	100%
C Tranquil Periods Correctly Called[c]	54%	51%	52%	42%
D False Alarms[d]	83%	84%	83%	85%
E Efficiency Measure = B-D	**14%**	**13%**	**14%**	**15%**
Average of above strategies				
A Total Correctly Called Observations[a]	68%	70%	71%	68%
B Pre-crisis Periods Correctly Called[b]	58%	58%	59%	61%
C Tranquil Periods Correctly Called[c]	68%	72%	73%	69%
D False Alarms[d]	56%	55%	54%	55%
E Efficiency Measure = B-D	**2%**	**3%**	**5%**	**6%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012). Numbers in brackets represent the thresholds used.

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

Table 4.8 – In-sample Performance for Currency Crises – Alternative Strategies when Crises interaction Effects are Absent (94% of All Observations)

When Crises interaction variable ($CI^{B\rightarrow C}$) = 0	Bas	Bas 2	CI	CCI
Strategy 1: Zero tolerance of False Alarms	(64%)	(79%)	(78%)	(76%)
A Total Correctly Called Observations[a]	92%	92%	92%	92%
B Pre-crisis Periods Correctly Called[b]	5%	2%	1%	2%
C Tranquil Periods Correctly Called[c]	99%	100%	100%	100%
D False Alarms[d]	33%	0%	0%	0%
E Efficiency Measure = B-D	**-28%**	**2%**	**1%**	**2%**
Strategy 2: At most 30% of False Alarms	(64%)	(66%)	(57%)	(50%)
A Total Correctly Called Observations[a]	92%	92%	92%	93%
B Pre-crisis Periods Correctly Called[b]	5%	7%	9%	13%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	33%	27%	29%	28%
E Efficiency Measure = B-D	**-29%**	**-20%**	**-20%**	**-15%**
Strategy 3: Zero Tolerance of Crisis Not Called	(0.2%)	(1%)	(1%)	(1%)
A Total Correctly Called Observations[a]	14%	29%	35%	28%
B Pre-crisis Periods Correctly Called[b]	100%	100%	100%	100%
C Tranquil Periods Correctly Called[c]	6%	23%	29%	21%
D False Alarms[d]	92%	90%	89%	90%
E Efficiency Measure = B-D	**8%**	**10%**	**11%**	**10%**
Strategy 4: At least 70% of Crisis Called	(10%)	(11%)	(10%)	(10%)
A Total Correctly Called Observations[a]	78%	79%	80%	81%
B Pre-crisis Periods Correctly Called[b]	70%	70%	70%	70%
C Tranquil Periods Correctly Called[c]	79%	80%	81%	82%
D False Alarms[d]	78%	76%	76%	75%
E Efficiency Measure = B-D	**-8%**	**-6%**	**-6%**	**-5%**
Strategy 5: Highest B-D	(4%)	(3%)	(3%)	(2%)
A Total Correctly Called Observations[a]	57%	56%	56%	46%
B Pre-crisis Periods Correctly Called[b]	98%	98%	96%	99%
C Tranquil Periods Correctly Called[c]	53%	52%	53%	42%
D False Alarms[d]	85%	85%	85%	87%
E Efficiency Measure = B-D	**13%**	**13%**	**11%**	**12%**
Average of above strategies				
A Total Correctly Called Observations[a]	67%	70%	71%	68%
B Pre-crisis Periods Correctly Called[b]	56%	55%	55%	57%
C Tranquil Periods Correctly Called[c]	68%	71%	73%	69%
D False Alarms[d]	64%	56%	56%	56%
E Efficiency Measure = B-D	**-8%**	**-1%**	**-1%**	**1%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012). Numbers in brackets represent the thresholds used.

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

Table 4.9 – In-sample Performance for Currency Crises – Alternative Strategies when Crises interaction Effects are Present (6% of All Observations)

When Crises interaction variable ($CI^{B\rightarrow C}$) = 1	Bas	Bas 2	CI	CCI
Strategy 1: Zero tolerance of False Alarms	(52%)	(54%)	(75%)	(82%)
A Total Correctly Called Observations[a]	85%	83%	82%	85%
B Pre-crisis Periods Correctly Called[b]	49%	43%	40%	49%
C Tranquil Periods Correctly Called[c]	100%	100%	100%	100%
D False Alarms[d]	0%	0%	0%	0%
E Efficiency Measure = B-D	**49%**	**43%**	**40%**	**49%**
Strategy 2: At most 30% of False Alarms	(21%)	(18%)	(41%)	(34%)
A Total Correctly Called Observations[a]	85%	85%	85%	86%
B Pre-crisis Periods Correctly Called[b]	80%	83%	80%	86%
C Tranquil Periods Correctly Called[c]	87%	86%	87%	86%
D False Alarms[d]	28%	29%	28%	29%
E Efficiency Measure = B-D	**52%**	**54%**	**52%**	**57%**
Strategy 3: Zero Tolerance of Crisis Not Called	(2%)	(1%)	(1%)	(3%)
A Total Correctly Called Observations[a]	51%	47%	39%	58%
B Pre-crisis Periods Correctly Called[b]	100%	100%	100%	100%
C Tranquil Periods Correctly Called[c]	31%	25%	14%	40%
D False Alarms[d]	62%	64%	67%	59%
E Efficiency Measure = B-D	**38%**	**36%**	**33%**	**41%**
Strategy 4: At least 70% of Crisis Called	(29%)	(27%)	(50%)	(54%)
A Total Correctly Called Observations[a]	88%	86%	86%	87%
B Pre-crisis Periods Correctly Called[b]	71%	71%	71%	71%
C Tranquil Periods Correctly Called[c]	95%	92%	92%	94%
D False Alarms[d]	14%	22%	22%	17%
E Efficiency Measure = B-D	**57%**	**50%**	**49%**	**54%**
Strategy 5: Highest B-D	(28%)	(22%)	(53%)	(34%)
A Total Correctly Called Observations[a]	89%	87%	87%	87%
B Pre-crisis Periods Correctly Called[b]	74%	77%	69%	86%
C Tranquil Periods Correctly Called[c]	95%	92%	95%	87%
D False Alarms[d]	13%	21%	14%	27%
E Efficiency Measure = B-D	**61%**	**56%**	**55%**	**57%**
Average of above strategies				
A Total Correctly Called Observations[a]	80%	78%	76%	81%
B Pre-crisis Periods Correctly Called[b]	75%	75%	72%	78%
C Tranquil Periods Correctly Called[c]	82%	79%	78%	81%
D False Alarms[d]	23%	27%	26%	26%
E Efficiency Measure = B-D	**52%**	**48%**	**46%**	**52%**

[a] As percentage of the total number of observations. A correctly called observation occurs when: (i) the crisis probability exceeds the threshold and a crisis occurs in the next four quarters, or (ii) the crisis probability does not exceed the threshold and no crisis occurs in the next four quarters.

[b] As percentage of the total number of crisis. A crisis is correctly called when situation (i) of note a occurs.

[c] As percentage of the total number of tranquil periods. A tranquil period is correctly called when situation (ii) of note a occurs.

[d] As percentage of the total number of alarms. A false alarm happens when the estimated crisis probability exceeds the threshold but no crisis occurs in the next four quarters.

The accuracy measures and respective definitions are as in Mulder *et al.* (2012). Numbers in brackets represent the thresholds used.

Bas (Baseline Model), Bas 2 (Baseline 2 Model), CI (Crises interaction Model), CCI (Channels of Crises interaction Model)

4.6. Conclusions

In this paper, we examine the role of the channels of interaction that run between banking and currency crises in signalling these two types of crises. Overall, we highlight four main contributions to the literature.

First, we develop a unified EWS for banking and currency crises, jointly estimating the likelihood of these two types of crises using a system of two equations. Second, we assess if crises interaction effects signal banking and currency crises. Third, we offer a new approach to gauge empirically the channels of crises interaction. Fourth, when analysing the in-sample predictive power of the EWS, we divide the total sample into two subsamples depending on the presence of crises interaction effects. We then compare the predictive power of each EWS across the two subsamples.

Our findings are as follows. For all EWS, our results show a statistically significant correlation between the error terms of the two crisis equations, unambiguously suggesting that these equations should be jointly estimated. These results motivate the need for a unified EWS for banking and currency crises.

We find that several channels of interaction from currency crises signal future banking crises and vice-versa. First, currency crises allow stock market collapses to have an impact on the likelihood of future banking crises, which is in line with Singh (2009). Second, real devaluations following currency crises may cause banking crises. Third, the ratio of short-term external debt to reserves signal banking crises in the presence of a currency crisis (in line with e.g. Mishkin, 1996). Fourth, increasing interest rates signal currency crises, following the onset of a banking crisis (in line with Shin, 2005). Fifth, the inflation rate increases the likelihood of currency crises in the presence of a banking crisis (in line with e.g. Obstfeld, 1988). Sixth, stock market collapses may provoke currency crises, when coupled with a banking crisis (in line with Shin, 2005). Seventh, banking crises aggravate the impact of the exchange rate overvaluation on the likelihood of currency crises. Finally, banking crises exacerbate the impact of a reduction in reserves on the likelihood of currency crises (in line with Velasco, 1987).

Additionally, when analysing the in-sample predictability power of the EWS, we find three broad results. First, CCI outperforms (with minor exceptions) the baseline models (with or without contagion multipliers, but without crises interaction effects). This predominance is visible across different subsamples (all observations, and observations with and without crises interaction effects). These results suggest that including channels of crises interaction effects allows the EWS to better signal crises with crises interaction effects as well as single crises.

Second, comparing the CI model with the CCI model suggests that having a simplistic view of crises interaction effects (i.e., with no consideration of the channels of crises interaction) neglects important interaction mechanisms, since including the channels of crises interaction enhances substantially the predictive power of the EWS. In most cases, CCI has a higher percentage of pre-crisis periods correctly called, and a lower percentage of false alarms than the CI model.

Third, as we split the total sample into two complementary subsamples, we identify a substantial difference in the predictive power between the two subsamples for the case of currency crises. For this type of crisis, we verify that the EWS's predictive power is substantially lower for the observations without crises interaction effects than for the observations with crises interaction effects. This set of results suggests that the unified EWS are more suitable to predict currency crises when they are accompanied with banking crises than to predict single currency crises, thus motivating the need for a unified EWS to predict currency crises that are accompanied by banking crises.

The results presented in this study have important policy implications. Our results motivate the need for a unified EWS for banking and currency crises, and thus being vigilant of both types of crisis can be crucial for policymakers. Additionally, our results show that incorporating channels of crises interaction enhances substantially the EWS's predictive power and thus introducing the channels between crises may be imperative to predict banking and currency crises. Finally, because our results indicate that some leading indicators can have different repercussions depending on the existence of crises interaction effects, some conventional policies may actually be counterproductive if policymakers do not consider the channels of crises interaction. For instance, increasing interest rates is a common policy to avoid currency crises but our results suggest that it may backlash and increase the likelihood of currency crises in the presence of banking problems.

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Appendix 4.A: Sample Composition

The 21 emerging market economies included in our sample are: Argentina, Brazil, Chile, China, Colombia, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Romania, Russia, South Africa, Thailand, Turkey, Ukraine, and Venezuela.

Appendix 4.B: Data Description

Variable	Data source	Frequency
Central Bank borrowed reserves	IMF: IFS line 26g	Quarterly
Central government surplus	IMF: IFS line ccsd	Quarterly where available, otherwise interpolated from the corresponding annual series applying a linear technique
CPI inflation	International Monetary Fund (IMF): International Financial Statistics (IFS) line 64	Quarterly
Current account of goods and services, net	IMF: IFS line 78afd	Quarterly
Nominal short-term (deposit) interest rate	IMF: IFS line 60b	Quarterly, we stretched back some of the series by applying the discount rate when deposit rates were not available
Foreign exchange reserves	IMF: IFS line 1d.d	Quarterly
M2	IMF: IFS lines 34 + 35	Quarterly
Nominal exchange rate	IMF: IFS line rf	Quarterly
Private credit	IMF: IFS line 32d	Quarterly
Real GDP	IMF: IFS line 99b	Quarterly where available, otherwise interpolated from the corresponding annual series applying a linear technique
Short-term external debt	Joint External Debt Hub	Annual; we interpolated applying a linear technique
Stock Market Indices	Datastream	Quarterly
Total deposits	IMF: IFS line 24 + 25 + 26c	Quarterly

Appendix 4.C: Developed countries considered in the contagion variable

The 27 developed economies included in the contagion variable are: Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, and United States.

Chapter 5

Final Remarks

This thesis contributes to the literature on financial crises, focusing explicitly on two distinct financial crises dynamics: contagion and crises interaction. While the former can be broadly defined as the transmissions of a crisis in one country to other countries, the latter can be defined as the effects of a crisis on vulnerabilities leading to different types of crisis in the same country. In the three essays presented in this thesis, we focus on these dynamics to improve our understanding of the causes of financial crises and how to prevent them.

In the first essay, we undertake a comprehensive analysis of financial contagion in the GFC by analysing relevant contagion dynamics beyond the effects directly stemming from the US. To do so, instead of just considering the contagion effects from the ground-zero market (US stock market), we hypothesise that any market may contaminate other markets in reaction to the initial shock stemming from the ground-zero.

Our main findings can be summarised as follows. First, we find the US directly transmitted very few contagion effects during the GFC, which is in sharp contrast with the majority of the findings in the literature. Second, we find that Latin American and Emerging Asian markets are the largest transmitters of endogenous contagion effects in the GFC. Third, cross-asset contagion was as frequent as within-asset contagion during the GFC. Fourth, there was an abnormally high number of contagion effects within the Euro Area sovereign bond market during the GFC, several months before the beginning of the Eurozone Sovereign Debt Crisis (ESDC). Fifth, Emerging Asian stock markets received very few contagion effects from advanced markets. Finally, our results indicate that EMEs transmitted on average more contagion effects than AEs.

We argue that our findings are critical to improving our understanding of how the GFC transmitted to the rest of the globe. By identifying the origins of contagion effects, our results indicate that even if the policymaker had isolated the connections to the United

States and its toxic assets, domestic markets might have been affected by other markets. This result thus allows the policymaker to design a more comprehensive contingency plan to ensure financial stability.

The second essay examines the role of a domestic banking system in the context of contagion within the sovereign bond market. We model a global game, in which the domestic banking system may assist its government, acting as a backstop against speculative attacks. Afterwards, we use the model's results to shed light on the contagion dynamics from Greece to Portugal during the beginning of the ESDC, focusing on the role played by the Portuguese banking system.

Our key results are as follows. First, the more the domestic banking system holds its sovereign debt, the less likely it is the speculative attack to succeed. Second, a strong negative shock to the capital of the national banking system may trigger a speculative attack, as international speculators perceive domestic banks to be weaker. Third, we find that while contagion effects from the Greek to the Portuguese sovereign bond market can only be traced after the Greek official request for assistance, international lenders started reducing their exposure to Portugal several months before. Fourth, our model reconciles these two apparently contradictory facts since Portuguese banks backed up their government until April 2010, offsetting the reduction in the exposure of international investors and contributing to limiting the pressure on Portuguese government bond yields.

The results presented in this essay have important policy implications. By showing that the stability of the sovereign bond market may be compromised after a negative shock to the capital of the national banking system, this essay recommends a more coordinated policy response between monetary and fiscal authorities.

In the final essay, we examine the role of the channels of interaction that run between banking and currency crises in signalling these two types of crises. To do so, we develop a unified EWS for banking and currency crises, offering a new approach to gauge empirically the channels of crises interaction.

Our findings can be summarised as follows. First, our results motivate the need for a unified EWS for banking and currency crises. Second, we find that several channels of interaction from currency crises signal future banking crises and vice-versa. Third, we find that the inclusion of channels of crises interaction allows the EWS to better signal crises with crises interaction effects as well as single crises. Fourth, having a simplistic view of crises interaction effects neglects important interaction mechanisms. Fifth, our results suggest that the unified EWS are more suitable to predict currency crises when they are accompanied by banking crises than to predict single currency crises.

We argue that our findings have important policy implications. Our results suggest that being vigilant of both types of crisis can be crucial for policymakers. Additionally, our results show that introducing crises interaction channels may be imperative to predict banking and currency crises. Finally, we suggest that some conventional policies may actually be counterproductive if policymakers do not consider the channels of crises interaction.

Concluding, the three essays presented in this thesis improved our understanding of the causes of financial crises. More specifically, we suggest that having a more in-depth view of the dynamics of financial crises allows us to produce valuable knowledge that can be used to help to prevent financial crises in the future.