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The Macroeconomic Sources of Credit Risk

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"Os artistas novos [...] Queren chegar a xenios profundando.
Pensan que o arte está nos miolos i estruchan a cachola"

Castelao

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Resumen

Esta tesis estudia las fuentes macroeconómicas del riesgo de crédito, proporcionando un análisis en tres dimensiones: corporativa, soberana, y política. El primer capítulo estudia las fuentes macroeconómicas de los excesos de rendimiento de los bonos corporativos. La evidencia empírica sugiere la existencia de un riesgo sistemático que está siendo valorado en las primas de crédito corporativas, así como la existencia de una transferencia de riesgo público-a-privado entre los mercados de crédito soberano y corporativo. El segundo capítulo explora la transferencia de riesgo soberano entre economías pertenecientes a una misma área monetaria. Encontramos que el mercado soberano de crédito permite un canal de trasferencia de riesgo desde los países con problemas de financiación hacia el resto de países a través del precio del riesgo de crédito. Finalmente, el tercer capítulo discute el papel de las autoridades monetarias en cuanto a la gestión del riesgo sistémico. Documentamos una respuesta asimétrica del riesgo sistémico a las actuaciones de las diferentes autoridades monetarias.

Abstract

This thesis studies the macroeconomic sources of credit risk, providing an analysis in three different dimensions: corporate, sovereign, and policy. The first chapter addresses the macroeconomic sources of corporate bond excess returns. The empirical evidence suggests the existence of a systematic risk being priced in the corporate spreads, and a public-to-private risk transfer between the sovereign and corporate credit markets. The second chapter explores the risk spillovers between financially distressed and non-distressed economies. I find that the sovereign credit market enables a risk transmission channel from riskier to healthier economies through the default risk premia. Finally, the third chapter discusses the role of monetary authorities on managing systemic risk. I document an asymmetric response of systemic risk to actions from different monetary authorities.

Chapter 1.

Introduction

The consequences of the financial crisis that started in August 2007 are still present in the current time. The illiquidity shock associated to the mortgage subprime crisis in the US led to large losses in bank balance sheets that resulted in the collapse of Lehman Brothers in September 2008. Along with the mortgage crisis, a sovereign crisis in Europe has disturbed the borrowing cost of the main European economies. This scenario of high credit constraints has deteriorated the ability of firms to raise external financing and made investors more risk-averse about the ability of firms to repay their debts.

In light of those events, some important questions arise both from an asset pricing and policy perspective. From an asset pricing view, the borrowing cost of firms within a financially distressed context is a question of enormous interest. For example, how are investors translating the default probabilities into prices? What are the main drivers of corporate default premia during those stressed periods? Also, the impact of sovereign economies is relevant. Do investors care about sovereign risk when pricing the corporate bonds? Should they be concerned with the sovereign risk of other economies?

From a policy point of view, the monetary authorities have started an evolutionary process towards more financial risk awareness and macro-prudential oversight by creating new financial institutions as, for example, the Financial Stability Oversight Council (FSOC) and the European Systemic Risk Board (ESRB). These new institutions are designed to monitor, assess, and mitigate systemic risk, which may lead to adverse consequences in the real economy. In this scenario, what is the role played by monetary authorities to manage the systemic risk? Have they controlled for the default risk of the firms?

This thesis studies the determinants of credit risk during financially distressed periods. In particular, I focus on the effect of financial and macroeconomic variables on the borrowing cost of corporate firms and sovereign economies. The objective of the thesis is to provide a thorough description of the credit risk prices at three levels of analysis using the information contained in the credit derivatives market. Firstly, at the corporate level, I focus on corporate expected excess returns and their macroeconomic sources. Secondly, at the sovereign level, I study the risk transfer from distressed towards healthier sovereign debt. Thirdly, at the policy level, I explore the potential effect of monetary policy on firms' default and systemic risks. Each of the chapters of the thesis is related to these three levels of analysis.

It is crucial for this analysis to quantify the credit risk. In this way, the instrument used for measuring credit risk comes from the credit derivative markets. Among those markets, the Credit Default Swaps (CDS, hereafter) are the most extensively used contracts for credit risk transferring. CDSs are financial instruments that allow debt holders to hedge against the default risk. For the purpose of this thesis, the CDS contracts are suitable for measuring the credit risk prices because they are more liquid than the corresponding bond market, they are designed without complex guarantees or embedded options, they provide a simple way to short credit risk, and the information disseminates faster in the CDS market than in the bond market (Pan and Singleton, 2008; Blanco et al., 2005; Forte and Peña, 2009).

After appearing in the US in the late 1990s, the CDS market exploded over the subsequent decade to over 45 trillion US dollars in mid-2007, as reported by the International Swaps and Derivatives Association (ISDA, 2007). Although the notional outstanding CDS decreased during the financial crisis, it reached approximately $26 trillion at mid-year 2010 (ISDA, 2010). Default swaps focused primarily on municipal bonds and corporate debt during the 1990s, but after 2000, the CDS market expanded internationally into sovereign bonds and structured finance products, such as asset-backed securities. The increasing trading volume of the CDS market could be attributed to several aspects such as the lack of regulation (CDS are traded on over-the-counter markets) or the potential for speculative investors and hedge fund managers to manage these insurance contracts without going long on the underlying asset.

As previously mentioned, this thesis is structured in three chapters. Chapter 2 studies the economic factors behind corporate default risk premia in Europe during the financial crisis. Instead of studying the determinants of credit spread changes (e.g. Elton et al., 2001; Collin-Dufresne et al., 2001). I employ information embedded in Credit Default Swap contracts to quantify expected excess returns from the underlying bonds during market-wide default circumstances. This chapter provides a general overview of the prices of default risk and their measurement. The empirical analysis disentangles (i) the compensation for the future changes in the creditworthiness of the bond issuer that might vary from expectations from (ii) the remuneration for the surprise jump in the bond price at the event of default. The former is called the distress risk premium and has been studied by Pan and Singleton (2008) and Longstaff et al. (2011) for emerging sovereign debt. The later is usually referred to as jump-at-default premium and has been previously studied by Jarrow et al. (2005), Driessen (2005) and Berndt et al. (2005).

The results show that the risk premia associated with systematic factors influencing default arrivals represent approximately 40% of the total CDS spread (on median). These premia also exhibit a strong source of commonality; a single principal component explains approximately 88% of their joint variability. This factor significantly covaries with aggregate illiquidity and sovereign risk variables. Empirical evidence suggests a public-to-private risk transfer between the sovereign credit spreads and the corporate risk premia. Finally, the compensation in the event of default is approximately 14 basis points of the total CDS spread. This finding is of interest for portfolio managers as a significant amount of jump-at-default risk may not be diversifiable.

The Chapter 3 studies the default risk transmission of sovereign debt in a context where sovereign default risk is not perceived as a rare event. The related literature studies the connections between the CDS market and the bond and/or stock markets – for example, Blanco et al., 2005; Forte and Peña, 2009; Norden and Weber, 2009; or Delatte et al., 2012. And Favero and Missale (2012) analyze the relationships between the sovereign yield spreads of the main European economies, finding empirical evidence for substantial transmission effects. Relatively little is known about the nature of default risk transmission in sovereign credit markets. Under a scenario where the government bonds have lost their previous role as a domestic safe asset (Dötz and Fisher, 2011) and the expected fiscal policy plays an important role in long term interest rates (Laubach, 2009), it becomes crucial to understand the linkages between changes and the volatility of sovereign credit spreads, in particular, among the Eurozone countries.

The methodological approach of this chapter consists of three parts. First, I estimate two bivariate BEKK-GARCH models to analyze the spillover effects between distressed and non-distressed debt. Second, I use the decomposition technique described by Pan and Singleton (2008) to break the CDS spread down into two drivers: (i) the distress risk premium and (ii) its default component. Lastly, I conduct a regression analysis of the components of sovereign CDS spreads for non-distressed economies against a risk factor that is representative of the behavior of the distressed countries.

The contribution of the chapter is threefold. First, I document a market fragmentation in the European sovereign credit markets between the non-distressed and the distressed countries in terms of their CDS levels and their conditional volatilities. Second, the analysis based on the use of the GARCH methodology suggests a unidirectional volatility transmission pattern from the distressed to the non-distressed economies inside the Eurozone. Third, the regression analysis supports the fact that the sovereign credit market enables a risk transmission channel from distressed to non-distressed debt mainly through the price of default. The countries suffering distress do not represent a major source of default risk for the healthier countries. The findings of the chapter are relevant for policy measures aimed at mitigating the market fragmentation between distressed and non-distressed sovereign debt markets that share the same currency.

Lastly, the Chapter 4 explores the role of monetary policy as a mechanism to treat disruptions in the credit derivatives markets. The monetary authorities face the new responsibility of preventing default events that can trigger disastrous economic conditions. In this chapter I stress the importance of foreign monetary policies in integrated economies.

There are two main strands of literature regarding the role of foreign monetary policies. The first strand of literature has focused on the reaction of the financial markets. In the cross-section, Ehrmann and Fratzscher (2004) find that firms with financial constraints are more affected by monetary policy. The stock markets more financially integrated with the foreign economic region and the stocks of firms with larger foreign sales have larger reactions to foreign monetary policy shocks (Wongswan, 2006, 2009; Hausman and Wongswan, 2011; Ammer et al., 2010). The second strand of literature has explained that monetary policy cooperation can be counterproductive (Rogoff, 1985), and that inward-looking monetary policy is not necessarily problematic (Obstfeld and Rogoff, 2002). Pappa (2004) argues that for the Federal Reserve and the ECB to cooperate, one has to assume a high degree of trade links of the US and the Eurozone.

This chapter investigates the effects of monetary policy on the firms' default probability and systemic risk measures. In a micro perspective, foreign monetary policy possibly affects the firm's specific default risk. I find that the firms' foreign monetary policy exposure depends on the firms' degree of internationalization. In a macro perspective, the monetary policy can affect the systemic default risk of all firms. The ubiquitous nature of systemic default risk and the different monetary policies across countries add up difficulties for monetary authorities to effectively tackle it. The findings indicate different responses of firm-specific default risk and systemic risk to the stance of US and Eurozone monetary policies. These results claim the need by the systemic risk supervisors to join efforts in the struggle against large default events.

This thesis, while providing a broad description of the European credit derivatives market during stressed scenarios, corroborates that there is a significant risk transfer from the public environment towards the private environment – or public-to-private risk transfer. Most notably, the results suggest that the sovereign risk raises the price demanded by corporate debt investors and that the monetary policy plays a significant role in the credit derivatives market. This leaves open the question of whether or not the international authorities should agree to coordinate policies to circumvent credit market disruptions.

Chapter 2.

What drives corporate default risk premia? Evidence from the CDS market

2.1. Introduction

What are the main drivers of corporate default risk premia? Do they change during periods of financial distress? Do investors care about factors such as sovereign risk or aggregate illiquidity when pricing the excess return of corporate bonds? These questions are of paramount importance in the scenario in which market-wide defaults and liquidity restrictions have significantly raised corporate and sovereign borrowing costs. Several answers have been provided from the sovereign side (Longstaff et al., 2011), but a comprehensive analysis of the corporate risk premium and the nature of its relationship with the public sector has not yet been performed.

This chapter analyzes the macroeconomic factors behind the corporate default risk premium. Our objective is to examine what are the sources of excess expected return, instead of studying the determinants of credit spread changes (e.g. Collin-Dufresne et al., 2001). As opposed to previous analyses on corporate credit spreads, we focus on the default risk premium embedded in such spreads. We employ information in credit default swap (CDS) prices in an innovative manner to learn how investors assess the risk of changes in corporate bond returns under widespread default circumstances. Consistent with Longstaff et al. (2011) in the case of sovereign default risk, our approach relies on the information content of corporate default swaps to obtain fairer estimates of credit spreads instead of bonds, which are usually traded in frictional markets. Our analysis disentangles the compensation for those future changes in the creditworthiness of the bond issuer that might vary from expectations (Pan and Singleton, 2008) – the *distress* risk premium – from the remuneration for the surprise jump in the bond price at the event of default – the *jump-at-default* premium.[1] In this way, we explore common factors across firms that might affect those premia and which portion of this co-movement is attributable to macro-financial variables. Additionally, we stress the link between corporate and sovereign default risks, quantifying the effect of shocks in sovereign risk on corporate risk premia. To this end, an analysis of the European debt crisis during the period 2006-2010 would provide a unique position to observe the possible risk channels between public and corporate sectors.[2] To our knowledge, this is the first article drawing a complete picture of the default risk premia in European firms while searching the main drivers of these premia.

Our empirical findings contribute to the existing literature in several ways. First, our results show that compensation for changes in the default environment accounts for approximately 40% of total CDS spreads (on median). Moreover, a strong source of commonality among European distress risk premia is revealed by a principal component (PC) analysis showing that one factor explains appoximately 88% of their joint variability. When examining the loading coefficients, this first PC represents an equally weighted contribution of firms and is interpreted as an aggregate level of distress risk premium. Notably, we find positive and significant beta coefficients when projecting this

[1] Jump-at-default risk premium (Pan and Singleton, 2006) is indistinctly named default event (Driessen, 2005), credit event (Collin-Dufresne et al., 2010) or jump-at-event (Longstaff et al., 2011) premium. For purposes of clarification, we reserve the term default risk premium to indicate the entire compensation for default embedded in credit spreads. As discussed in Section 2.2.1, our default risk premium is the sum of distress plus jump-at-default premia.

[2] Europe comprises a significant share of the global CDS market in terms of geographical focus of products – approximately 40% of CDS index products are based on European entities –, market share of dealers – 66% and 50% of the dealers contributing to calculation of the iTraxx Europe indices and the CDX indices are domiciled in Europe, respectively –, and currency denomination – approximately 39% of CDS are denominated in Euros (ECB, 2009).

PC onto aggregate illiquidity and sovereign risk variables. The adjusted-R^2 coefficients of the regressions are close to 70% for the entire period, rising to appoximately 75% after the Lehman's bankruptcy in September 2008. These results suggest that aggregate illiquidity and sovereign risk may act as pricing factors of European corporate CDS. Along these lines, recent articles focus on the importance of liquidity in credit markets (Bongaerts et al., 2011; Acharya et al., 2013), but there is not much evidence on the study of sovereign risk and its relevance in the credit derivative pricing and risk management.

Second, we study the dynamic relationship between the distress risk premium and macro-financial variables. We shed light on the documented public-to-private risk transference (see Dieckmann and Plank, 2012) quantifying how financial shocks affect the distress risk premium. We show that shocks in the sovereign CDS market lead to shocks in the aggregate level of distress risk premium demanded by corporate investors and that illiquidity also plays an important role as a driving factor of the distress risk premium.

Third, the compensation at the event of default is approximately 3.82 for the firms under study. This jump-at-default premium estimate is consistent with those previously reported in the literature for the US market (Driessen, 2005). Economically, the median jump-at-default premium is approximately 14 basis points (bps). Within the context of our theoretical framework, the empirical evidence suggests that a significant amount of jump-at-default risk may not be diversifiable.[3] Further results suggest that a systematic factor may be behind jump-at-default compensation; for example, a PC analysis reveals that one (two) factor(s) explain approximately 59% (78%) of the total co-movement in jump-at-default premia. These PC factors co-vary significantly with aggregate illiquidity and stock market variables.

Finally, our findings corroborate the relationship between CDS and liquidity found in Tang and Yan (2007) and Bongaerts et al. (2011), among others. Liquidity is a puzzling component of the CDS market; protection buyers become more risk-adverse

[3]Under the conditionally diversifiable hypothesis of Jarrow et al. (2005) for a large portfolio of bonds, the jump-at-default risk premium will only be diversified away if such premium is equal to one or, equivalently, if actual and risk-neutral default probabilities are equal. However, a small number of bonds in the portfolio and/or the possibility that some firms default simultaneously may make it impossible to diversify away the jump-at-default risk.

during financially distressed periods, having induced demand pressure beginning with the onset of the financial turmoil in August 2007. However, this hedging pressure pushes up expected returns, increasing the speculative demand of other investors (Bongaerts et al., 2011). Thus, either a high level of liquidity or lack of liquidity can widen CDS premia. Our results show that distress and jump-at-default risk premia widen during periods of vanishing market liquidity. We document a positive and significant relationship between aggregate default risk premia and the first principal component of 5-year CDS bid-ask spreads, particularly during distressed periods.

The drivers of CDS returns and CDS spreads have received increasing attention in the empirical literature, but such attention is still scant.[4] Literature analyzing the European case is even scarcer, but see, for example, Dieckmann and Plank (2012) and Berndt and Obreja (2010) for examinations of the default swaps written on European government debt and European firms. In this context, we take a step forward by exploring the risk premia embedded in CDS prices instead of using the plain CDS spreads. On the one hand, this chapter analyzes the degree of variation over time in the distress risk premia and their determinants during a deep financial and economic crisis. On the other hand, we also explore the reward for changes in the bond price in the event of default, following Jarrow et al. (2005), Driessen (2005) and Berndt et al. (2005). All studies previously referred to have focused primarily on U.S. firms and they covered periods before the financial crisis started in August 2007. The extension to European firms or more recent time span is nonexistent. As opposed to those studies, our sample involves CDS data for almost one hundred European firms over a broad period from 2006 to 2010, which covers the recent financial crisis. The dataset consists of biweekly spreads of the most liquid 1-, 3- and 5-year CDS contracts for senior unsecured debt of European investment-grade firms.[5] Our portfolio is composed of a well-diversified set of investment grade firms across ten industries and different countries.

This chapter adopts the intensity approach of Lando (1998) and Duffie and Singleton

[4]See, for instance, Tang and Yan (2007), Cremers et al. (2008), Das and Hanouna (2009), Ericsson et al. (2009), Zhang et al. (2009) or Bongaerts et al. (2011).

[5]In the market, 91% of single-name CDS contracts refer to non-sovereigns in terms of amount outstanding and 67% of these single-name CDS contracts are investment grade.

(1999) for studying the default risk premium.[6] Our estimation strategy follows a two-step procedure, such as that developed by Driessen (2005). First, we obtain the maximum likelihood (ML) estimates of the risk-neutral mean of default arrival rates $\left(\lambda^{\mathbb{Q}}\right)$ from a sample of corporate CDS spreads of 85 firms from 2006 to 2010. Assuming that the default event is diversifiable, a first estimate of the default premium – a fully distress risk premium – is obtained. In this case, our modeling proposal may underestimate expected excess corporate bond returns (Driessen, 2005). However, the absence of defaults in the sample and the high quality of the firms in our study seem to suggest the suitability of this approach; moreover, the robustness in the estimation of more parsimonious models is also appraised. We then employ this first-stage risk premium estimate to analyze its relationship with a set of macro-financial variables. This procedure was previously implemented by Pan and Singleton (2008) and Longstaff et al. (2011) to extract the compensation for unexpected default arrivals from a sample of sovereign CDS spreads.

Second, we exploit information at our disposal on the actual probabilities of default as those provided by Moody's KMV expected default frequencies (EDFs). From this database, we calculate the ML actual default intensity $\left(\lambda^{\mathbb{P}}\right)$ estimates to analyze the compensation for the surprise jump in the bond price at the event of default. This jump-at-default risk premium is computed by the ratio $\lambda^{\mathbb{Q}}/\lambda^{\mathbb{P}}$, as shown by Yu (2002), Driessen (2005) or Pan and Singleton (2006).

Thus, this chapter fully characterizes the corporate default risk premium embedded in European CDS, analyzing its relationship with financial variables and emphasizing the sovereign and liquidity variables. The remainder of this chapter is organized as follows. Section 2.2 presents the theoretical framework of the default risk premium. Section 2.3 shows the main features of European CDS data. Section 2.4 estimates the distress risk premium, and its relationship with macroeconomic variables is explored in

[6] As suggested by one referee, an alternative would be a structural modeling approach. Intensity and structural models are theoretically connected by an imperfect information argument. Duffie and Lando (2001) show that a structural model with asymmetric information of a firm's asset value results in the existence of a default intensity for outsiders to the firm. Additional references on intensity pricing models for bonds and CDS are Duffie and Singleton (1999), Duffee (1999) or Longstaff et al. (2005), among many others.

Section 2.5. Section 2.6 analyzes the jump-at-default premium. Finally, Section 2.7 draws conclusions.

2.2. The model

This section presents the theoretical approach to the default risk premium. The discussion and notations here are primarily taken from Jarrow et al. (2005) and Singleton (2006).

2.2.1. Understanding the sources of risk premia

To illustrate the different sources of risk premia embedded in a defaultable security, consider the price $P(t, X_t)$ of a credit-sensitive instrument that depends on a set of state variables X_t. These variables follow a diffusion process,

$$dX_t = \mu_X^{\mathbb{P}}(X_t, t)dt + \sigma_X(X_t, t)dB_t^{\mathbb{P}}, \tag{2.1}$$

where $\mu_X^{\mathbb{P}}$ and σ_X are the drift and instantaneous volatility, respectively, under the actual measure $\mathbb{P}$. Girsanov's theorem permits a representation of equation (2.1) under the risk-neutral measure $\mathbb{Q}$,

$$B_t^{\mathbb{Q}} = B_t^{\mathbb{P}} + \int_0^t \Lambda_t ds, \tag{2.2}$$

so that the risk-neutral process for the state variables results,

$$dX_t = \left(\mu_X^{\mathbb{P}}(X_t, t) - \sigma_X(X_t, t)\Lambda_t\right) dt + \sigma_X(X_t, t)dB_t^{\mathbb{Q}}, \tag{2.3}$$

where Λ_t is the price of risk and the drift $\mu_X^{\mathbb{Q}}$ under the risk-neutral measure is

$$\mu_X^{\mathbb{Q}} = \mu_X^{\mathbb{P}}(X_t, t) - \sigma_X(X_t, t)\Lambda_t \ . \tag{2.4}$$

We are interested in the excess return of the defaultable security. Because the price $P(t, X_t)$ is a function of the state variables X_t, we apply Ito's lemma under $\mathbb{Q}$ and $\mathbb{P}$ measures, respectively,

$$\begin{aligned} dP(X_t,t) &= \frac{\partial P(X_t,t)}{\partial t}dt + \frac{\partial P(X_t,t)}{\partial X_t}r_t dt + \frac{\partial P(X_t,t)}{\partial X_t}\sigma_X(X_t,t)dB_t^{\mathbb{Q}} \\ &+ \frac{1}{2}\frac{\partial^2 P(X_t,t)}{\partial X_t^2}\sigma_X^2(X_t,t)dt + (w_t - P(X_t,t))\,\lambda_t^{\mathbb{Q}}dt, \end{aligned} \tag{2.5}$$

$$\begin{aligned} dP(X_t,t) &= \frac{\partial P(X_t,t)}{\partial t}dt + \frac{\partial P(X_t,t)}{\partial X_t}\left(r_t + \sigma_X(X_t,t)\Lambda_t\right)dt + \frac{\partial P(X_t,t)}{\partial X_t}\sigma_X(X_t,t)dB_t^{\mathbb{P}} \\ &+ \frac{1}{2}\frac{\partial^2 P(X_t,t)}{\partial X_t^2}\sigma_X^2(X_t,t)dt + (w_t - P(X_t,t))\left(\lambda_t^{\mathbb{Q}} + \Gamma_t\lambda_t^{\mathbb{P}}\right)dt, \end{aligned} \tag{2.6}$$

where the risk-neutral drift in expression (2.5) is the risk-free rate r_t and w_t is the recovery value. Former terms come from Ito's lemma for jumps and Girsanov's theorem,

$$M_t^{\mathbb{Q}} = N_t - \int_0^t \Gamma_t \lambda_s^{\mathbb{P}} ds \ . \tag{2.7}$$

Finally, the expected excess return e_t is defined as the difference of expectations under $\mathbb{Q}$ and $\mathbb{P}$ measures,

$$\begin{aligned} e_t &\equiv E^{\mathbb{P}}\left[\frac{dP(X_t,t)}{P(X_t,t)}\right] - E^{\mathbb{Q}}\left[\frac{dP(X_t,t)}{P(X_t,t)}\right] \\ &= \frac{1}{P_t}\frac{\partial P_t}{\partial X_t}\sigma_X(X_t,t)\Lambda_t + \frac{w_t - P(X_t,t)}{P(X_t,t)}\lambda_t^{\mathbb{P}}\Gamma_t \ . \end{aligned} \tag{2.8}$$

Expression (2.8) contains an economically important result. According to this equation, investors are rewarded two ways. The first reward is compensation for the volatility of state variables X_t. Not surprisingly, Λ_t represents the price of risk (risk premium per unit of volatility), and it multiplies the volatility $\sigma_X(X_t, t)$ of risk factors. Economically, this term accounts for changes in the risk environment and is named the distress risk premium. Pan and Singleton (2008) and Longstaff et al. (2011) have previously analyzed the distress risk premium in the context of sovereign default swaps.

Jarrow et al. (2005) note that investors compensate both for changes in the credit environment and against the event of default itself. The second reward referred to above comes from the term $(w_t - P(X_t,t))/P(X_t,t)\lambda^{\mathbb{P}}\Gamma_t$, and it represents the expected payoff associated with a (downward) jump in the price of the bond if the reference entity does restructure (Pan and Singleton, 2006). We refer to this as the jump-at-default premium. The market price of risk at the event of default is Γ_t, which we will analyze in Section 2.6. The jump-at-default premium has been previously studied by Yu (2002), Driessen (2005) and Berndt et al. (2005).

Finally, the excess return equation (2.8) is zero if there is no compensation for distress or jump-at-default risks ($\Lambda_t = \Gamma_t = 0$).

2.2.2. Pricing the default swap

A Credit Default Swap (CDS) is a contract between two parties to receive insurance against the default of a certain bond (the reference entity). In a CDS, the insured (the protection buyer) is willing to pay a certain percentage (spread) over the total amount of the bond (notional) to the insurer (the protection seller). This annual spread is usually paid quarterly up to the maturity of the contract, if there is no default. In the event of a default, the protection seller receives the defaulted bond, and restores its amount to the protection buyer. Longstaff et al. (2005) and Pan and Singleton (2008) provide the following formula for the price of a CDS contract $CDS_t(M)$ with maturity M in an intensity based setting,

$$\frac{1}{4}CDS_t(M)\sum_{i=1}^{4M} E_t^{\mathbb{Q}}\left[e^{-\int_t^{t+.25i}(r_s+\lambda_s^{\mathbb{Q}})ds}\right] = L^{\mathbb{Q}}\int_t^{t+M} E_t^{\mathbb{Q}}\left[\lambda_u^{\mathbb{Q}}e^{-\int_t^{u}(r_s+\lambda_s^{\mathbb{Q}})ds}\right]du, \qquad (2.9)$$

where r_t, $\lambda_t^{\mathbb{Q}}$ and $L_t^{\mathbb{Q}}$ are the risk-free interest rate, default intensity and loss given default (under the recovery of face value assumption) of the referenced bond under the $\mathbb{Q}$ measure at t, respectively. The risk-neutral loss given default is 60%, a standard assumption in the literature.[7] The left-hand side of expression (3.10) indicates the (quarterly) premium on the sum of expected discounted cash flows received by the protection seller. The right-hand side is the expected discounted payoff received by the protection buyer if the bond defaults. Single-name CDS contracts are written without upfront payments, which equals both sides of equation (3.10).

2.2.3. Distress risk premium

Expression (2.8) permits us to formalize our estimation strategy. In the first step, we assume no compensation for the event of default itself ($\Gamma_t = 0$). This assumption is the conditionally diversifiable hypothesis of Jarrow et al. (2005), stating that jump-at-default risk is purely idiosyncratic when risk-neutral and actual default probabilities are equal, conditional to the existence of an infinite number of bonds in the economy and independence between default processes. As a first approach to our problem, these conditions seem to be reasonably satisfied because, in practice, (i) the probability of a simultaneous default in our sample is negligible as a result of the high quality of firms involved and, (ii) the number of bonds employed here may be considered high enough.

Previous arguments had led to the conclusion that investors are rewarded for unexpected risk-neutral default arrivals because of changes in the credit environment. To further hone our definition of the distress risk premium, we introduce additional assumptions about the default intensity process into expression (3.10). We impose an Ornstein-Uhlenbeck process for the logarithms of the default intensity $\lambda_t^{\mathbb{Q}}$ under the risk-neutral measure $\mathbb{Q}$,

$$d \ln \lambda_t^{\mathbb{Q}} \quad = \quad \kappa^{\mathbb{Q}} \left(\theta^{\mathbb{Q}} - \ln \lambda_t^{\mathbb{Q}} \right) dt + \sigma dB_t^{\mathbb{Q}}, \tag{2.10}$$

[7] One referee raised the issue of whether the fixed recovery rate assumption could be a source of model risk. We note that papers, as Houweling and Vorst (2005), show that CDS spreads are relatively insensitive to the assumed recovery rate. Longstaff et al. (2005) mention that their estimation results are virtually identical when other recovery values are employed. Recent literature assumes a fixed recovery rate when pricing default swaps as Pan and Singleton (2008) or Longstaff et al. (2011), which is consistent with industry standard assumptions.

where parameters $\kappa^{\mathbb{Q}}$, $\theta^{\mathbb{Q}}$ and σ capture the mean-reversion rate, the long-run mean, and the volatility of the process, respectively. By adopting this framework, the intensity is ensured to be positive. Unfortunately, expectations in (3.10) have no solution in a closed-form, so we implement a Crank-Nicholson scheme on the associated Feynmann-Kac equation.

Assuming a market price of risk Λ_t from $\mathbb{P}$ to $\mathbb{Q}$ of the form,

$$\Lambda_t = \delta_0 + \delta_1 \ln \lambda_t^{\mathbb{Q}}, \tag{2.11}$$

the risk-neutral intensity $\lambda^{\mathbb{Q}}$ under the actual measure $\mathbb{P}$ results in

$$d \ln \lambda_t^{\mathbb{Q}} \quad = \quad \kappa^{\mathbb{P}} \left(\theta^{\mathbb{P}} - \ln \lambda_t^{\mathbb{Q}}\right) dt + \sigma dB_t^{\mathbb{P}}, \tag{2.12}$$

with $\kappa^{\mathbb{P}} = \kappa^{\mathbb{Q}} - \delta_1 \sigma$ and $\kappa^{\mathbb{P}} \theta^{\mathbb{P}} = \kappa^{\mathbb{Q}} \theta^{\mathbb{Q}} + \delta_0 \sigma$. Within this framework, the drift adjustment from the diffusive part must compensate the risk factors (such as changes in economic fundamentals, etc.) that influence the intensity process.

To measure the size of the distress risk premium, we employ the strategy in Longstaff et al. (2011). Because expressions (2.12) and (2.10) are equal when there is no risk premium ($\Lambda_t = 0$) in CDS contracts, any departure of CDS spreads using risk-neutral CDS_t equation (3.10) and actual $CDS_t^{\mathbb{P}}$,

$$\sum_{i=1}^{4M} E_t^{\mathbb{P}} \left[e^{-\int_t^{t+.25i} (r_s + \lambda_s^{\mathbb{Q}})\, ds} \right] CDS_t^{\mathbb{P}}(M) = 4\, L^{\mathbb{Q}} \int_t^{t+M} E_t^{\mathbb{P}} \left[\lambda_u^{\mathbb{Q}} e^{-\int_t^u (r_s + \lambda_s^{\mathbb{Q}})\, ds} \right] du, \tag{2.13}$$

quantifies the distress risk premium in CDS spreads.

2.3. The characteristics of the European CDS data

2.3.1. Some features of the CDS market

In addition to serious concerns about transparency and counterparty risk from the financial crisis, credit derivatives have increased in popularity and liquidity during the last decade. Credit derivatives in general, and CDS in particular, have become a market standard for assessing the creditworthiness of a large number of corporations. These instruments have made credit risk trading swift and easily accessible. The credit derivative market has grown much faster than other derivative markets, with the size of the credit derivatives market increasing from US$900 billion in June 2000 to US$32 trillion in June 2011 (although it had reached US$62 trillion in December 2007).[8] The size of the CDS market has shrunk significantly since the second half of 2008. Several major participants have left the market, such as Lehman Brothers, Merrill Lynch, and Bears Stearns. Banks participate in "termination cycles", leading to the compression of redundant positions through multilateral terminations. Additionally, the activity in the market for structured credit has also dropped.[9] A more detailed analysis about the structure of the European CDS market can be found in ECB (2009) and in Berndt and Obreja (2010).

Default swap spreads approximate the spreads of referenced bonds. This fact comes from the replicating portfolio of a CDS, whose payments can be reproduced by a long position in a defaultable bond and a short position in a riskless bond (Berndt and Obreja, 2010). Then, the CDS spread is close to the difference between the yields of a risky and a risk-free bond. Recent empirical literature suggests that CDS spreads are better measures of default risk than bond spreads. Several reasons support this argument: first, the corporate CDS market is more liquid than the corresponding bond market,

[8] Notional amounts outstanding in all surveyed contracts, according to ISDA Market Survey 2010 (BIS, 2011).

[9] After the failure of Lehman Brothers, legislators in the U.S. and the European Union began developing regulatory reform. The debate focuses on protocols to standardize CDS documentation and on introducing central counterparties and making central clearing mandatory for CDS. The proposed legislation aims to enhance the stability and efficiency of the market and to reduce systematic risk.

maybe because CDS contracts provide a simple way to short credit risk (Blanco et al., 2005). Second, the primary corporate debt market began to dry up since the early stages of the financial crisis. At the same time, the CDS corporate market has been maintained as a reasonably liquid market.[10] Third, there are difficulties to construct bond spreads in practice. Bond spreads can be computed as the difference between the yield-to-maturity of the corporate and the sovereign bonds. The benchmark sovereign bond should have similar cash-flows (at least same term-to-maturity) to obtain the yield spread. Fourth, the European core countries were affected by flight-to-liquidity and flight-to-quality effects; on the contrary, European peripheral countries were under pressure. Finally, the CDS market has a leading role in the price discovery process. This is consistent with the hypothesis that market-wide new information disseminates faster in the CDS than in the bond markets (Blanco et al. (2005), Forte and Peña, 2009).

2.3.2. Descriptive Statistics

Our data are taken from Markit Group Ltd., a comprehensive database that is becoming increasingly and extensively employed in academic articles as a result of its high quality standards to create a composite CDS spread. This spread is computed as the midpoint between the bid and the ask quotes provided by different contributors after removing stale data, outliers, and other quotes that fail the data quality tests. The sample is composed of the single-name CDS spreads contained in the Markit iTraxx Europe index. This index comprises the 125 most liquid European corporate CDS names. We have taken the default swaps belonging to Senior Unsecured Debt, denominated in Euros and with a modified-modified (MM) restructuring clause,[11] which is standard in European

[10] An increasing amount of literature (e.g., Tang and Yan, 2007; Das and Hanouna, 2009; Bedendo et al., 2009; Bongaerts et al., 2011) has been analyzing the relevant role that liquidity is playing in the CDS market. Nevertheless, the expected liquidity premium is small for investment grade firms as those under study (Bongaerts et al., 2011).

[11] The three most commonly used credit events are failure to pay, bankruptcy and restructuring. Because restructuring can occur in several ways, the restructuring clause standardizes what is qualified as a credit event and its settlement conditions. Under a MM clause, restructuring agreements are considered credit events, and deliverable bonds must have a maturity less than 60 months for restructured obligations and 30 months for other obligations.

contracts (see Berndt and Obreja, 2010). To ensure the quality of our sample, we have fixed high standards to the data following the criteria of Schneider et al. (2010). As an additional criterion, we discard those firms without available bid-ask quotes from CMA database. Then, our sample results in 85 European firms from 14/Jun/2006 to 31/Mar/2010 with 1-, 3- and 5-year spreads at biweekly frequency.

As shown in Table 2.1, our sample covers a wide number of high quality rated companies across different sectors and countries. Firms are distributed along ten different industries, including Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrials, Oil & Gas, Technological, Telecommunications and Utilities. Financials and Consumer Services represent approximately the 35% of the total number of firms. There are firms from 13 different countries. The United Kingdom, Germany and France are the countries with the larger population of firms. As for credit quality, 45% of the sample is AA- or A-rated companies, and the rest are rated BBB.[12] Thus, our conclusions mainly concern investment-grade companies.

To provide a clearer picture of the data, Table 2.2 includes a summary of the main statistics for 5-year CDS spreads (other maturities are available upon request). An average firm in the sample has a mean spread of 84 basis points (bps). The market perceives utility firms as firms with better credit quality than financial firms, even though the latter firms have higher ratings in general. By contrast, an average firm from the Basic Materials sector has the highest mean and volatility in CDS spreads. With respect to the time series behavior of spreads, autocorrelation coefficients for the spread changes are not generally persistent. Consumer Goods and Industrials exhibit autocorrelations higher than 0.14 on average, indicating that past changes in the spreads of these sectors may be an important source of information when determining current spreads. In non reported statistics we observe that firms domiciled in peripheral countries do not show higher spread volatilities than those from the remaining European countries. In summary, our sample consists primarily of high credit quality companies that mainly belong

[12]Markit provides a composite rating measure named "average rating". Because companies are rated by different agencies, Markit transforms the alphabetic scale to numerical using a table of equivalences when more than one rating is available. Then, scores are added and the sum divided by the number of ratings. A noninteger result is rounded to the nearest integer.

Table 2.1.: Distribution of firms across sectors, ratings and countries

	BM	CG	CS	Fin	HC	Ind	OG	Tech	TC	Util	Total
					Panel A.- Rating AA						
France	0	0	0	3	0	0	1	0	0	0	4
Germany	0	0	0	1	0	0	0	0	0	0	1
Italy	0	0	0	1	0	0	0	0	0	0	1
Spain	0	0	0	1	0	0	0	0	0	0	1
Total	0	0	0	6	0	0	1	0	0	0	7
					Panel B.- Rating A						
Finland	0	0	0	0	0	0	0	0	0	1	1
France	0	0	1	1	0	0	0	0	1	1	4
Germany	1	2	0	2	1	1	0	0	0	3	10
Italy	0	0	0	1	0	0	0	0	0	1	2
Netherlands	1	1	0	1	0	1	0	0	0	0	4
Norway	0	0	0	0	0	0	0	0	1	0	1
Portugal	0	0	0	1	0	0	0	0	0	1	2
Spain	0	0	0	0	0	0	0	0	0	1	1
Sweden	0	0	0	0	0	0	0	0	1	0	1
United Kingdom	0	1	1	2	0	1	0	0	0	1	6
Total	2	4	2	8	1	3	0	0	3	9	32
					Panel C.- Rating BBB						
Austria	0	0	0	0	0	0	0	0	1	0	1
France	0	1	3	0	0	3	1	0	1	0	9
Germany	1	0	1	0	0	1	0	0	1	0	4
Greece	0	0	0	0	0	0	0	0	1	0	1
Italy	0	0	0	0	0	1	0	0	1	1	3
Netherlands	1	0	2	0	0	1	0	1	1	0	6
Spain	0	0	0	0	0	0	1	0	1	1	3
Sweden	0	2	0	0	0	1	0	0	0	0	3
Switzerland	0	0	0	1	0	2	0	0	0	0	3
United Kingdom	2	1	7	0	0	1	0	0	2	0	13
Total	4	4	13	1	0	10	2	1	9	2	46
					Panel D.- All Ratings						
Total	6	8	15	15	1	13	3	1	12	11	85

The distribution of firms across different sectors, ratings and countries. Ratings vary from AA to BBB. Sectors correspond to Basic Materials (BM), Consumer Goods (CG), Consumer Services (CS), Financial (Fin), Health Care (HC), Industrials (Ind), Oil & Gas (OG), Technological (Tech), Telecommunications (TC) and Utilities (Util).

to the Consumer Services, Financial and Industrial sectors.

Table 2.2.: Average summary statistics for 5-year CDS spreads

	Mean (bps)	Median (bps)	Std (bps)	Skew	Kurt	Min (bps)	Max (bps)	$\overline{\Delta s}$ (bps)	Acorr(Δs) (1st lag)
Basic Materials	112.33	79.66	109.76	1.49	5.03	22.66	532.83	0.4275	0.0135
Consumer Goods	73.28	65.60	53.80	0.94	3.36	16.23	235.07	0.4183	0.1455
Consumer Services	99.43	84.07	68.99	1.18	4.40	26.27	316.64	0.4021	0.1184
Financials	72.25	74.67	56.69	0.45	2.56	7.07	227.59	0.8568	-0.0279
Industrials	96.52	79.43	81.49	1.37	5.14	18.87	381.39	0.5944	0.1547
Telecommunications	80.41	73.40	45.58	0.79	2.92	25.40	213.44	0.3853	-0.0420
Utilities	65.71	56.63	52.00	0.85	3.40	10.91	234.53	0.5714	0.0231
Others	69.99	55.80	57.88	1.51	5.05	15.97	268.85	0.3747	0.1010
Overall	83.86	72.93	64.02	1.00	3.84	17.83	290.40	0.5330	0.0573

Average of the main statistics for the 5-year CDS spreads: the mean, median, standard deviation, skewness, kurtosis, minimum, maximum, mean of the differenced spreads, and 1st lag autocorrelation coefficient for the differenced spreads. "Others" group contains Health Care, Oil and Gas, and Technology sectors. The sample consists of biweekly CDS spreads for 85 European firms included in the Markit database, covering from 14/Jun/2006 to 31/Mar/2010.

2.4. Risk-neutral default intensity estimates

This section estimates the distress risk premium. We introduce the econometric methodology for the risk-neutral intensity $\lambda^{\mathbb{Q}}$ parameter estimates and results about the distress risk premium.

2.4.1. Econometric framework and data

We employ the CDS sample of 85 European firms across different sectors previously described, and our estimation procedure is taken from Pan and Singleton (2008). Roughly speaking, we maximize the likelihood of the joint density of the $\lambda_t^{\mathbb{Q}}$ process and a vector of mispricing errors conditional to a given set of parameters. We briefly review its main steps. First, we assume that three-year CDS contracts are perfectly priced.[13] We

[13]Our sample is not significatively affected by differential liquidity across the CDS curve. The liquidity across maturities does not seem to be a major concern for our sample of investment grade companies,

conjecture a time series for $\lambda_t^{\mathbb{Q}}$ conditional to a parameter set $\left(\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma\right)$ by inversion of expression (3.10). Second, mispricing errors of one (ϵ_{1y}) and five-year (ϵ_{5y}) CDS contracts are normally distributed with zero mean and standard deviations σ_{1y} and σ_{5y}, respectively. Third, we also employ the 1-, 3-, 6-, 9- and 12- months of Euribor rate and 2-, 3-, 4- and 5-year maturities of the Euro-swap rate to construct the risk-free curve, consistent with and similar to US studies, such as Berndt et al. (2005).[14] Intermediate periods have been bootstrapped from the previous curve. Euribor rates and interest rate swap quotes are obtained from IHS Global Insight. Fourth, expectation (3.10) is computed using a Crank-Nicholson discretization scheme for the corresponding partial differential equation. Finally, we maximize the density function,

$$\begin{aligned} f^{\mathbb{P}}(\Theta, \lambda_t^{\mathbb{Q}}) &= f^{\mathbb{P}}(\epsilon_{1y}|\sigma(1)) \times f^{\mathbb{P}}(\epsilon_{5y}|\sigma(5)) \times f^{\mathbb{P}}(\ln \lambda_t^{\mathbb{Q}}|\kappa^{\mathbb{P}}, \kappa^{\mathbb{P}}\theta^{\mathbb{P}}, \sigma) \\ &\times \left|\partial CDS^{Q}(\lambda_t^{\mathbb{Q}}|\kappa^{\mathbb{Q}}, \kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}, \sigma)/\partial \lambda_t^{\mathbb{Q}}\right|^{-1}, \end{aligned} \tag{2.14}$$

with parameter vector $\Theta = (\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}\kappa^{\mathbb{Q}}, \sigma, \kappa^{\mathbb{P}}, \theta^{\mathbb{P}}\kappa^{\mathbb{P}}, \sigma_{1y}, \sigma_{5y})$, $f^{\mathbb{P}}(\cdot)$ as the density function of the Normal distribution and Δt equal to 1/26. This estimation method has been also employed in a similar context by Berndt et al. (2005) and Longstaff et al. (2011).

2.4.2. Distress risk premia across sectors and ratings

Table 2.3 provides the summary statistics of ML estimates.[15] On average, mean-reversion rates are higher under actual than under risk-neutral measures ($\kappa^{\mathbb{P}} > \kappa^{\mathbb{Q}}$). Additionally,

because bid-ask spreads are typically higher for lower-rated firms (Bongaerts et al., 2011). Moreover, Longstaff et al. (2011) point out that the liquidity and bid-ask spreads of the 1-, 3-, and 5-year contracts are reasonably similar although the 5-year contracts have typically higher trading volume. In our case, an inspection of the bid-ask spreads reveals that the differences across maturities are small (1 to 3 bps on median).

[14] One referee raised the issue of using Euro-swap rates as proxies for the risk-free rate, in light of the financial crisis events during 2007-2009. Despite its limitations, literature does not seem to provide a clear substitute superior to our measure. For example, Houweling and Vorst (2005) find that mean absolute pricing errors of a hazard-rate pricing model that uses the treasury curve as discount rate performs very badly for investment grade issuers. Within a similar modeling choice as ours, Longstaff et al. (2011) notice that the estimates are not sensitive to the choice of the discounting curve because this curve is applied symmetrically to the cash flows from both legs of the CDS contract.

[15] For the sake of brevity, the estimates of individual intensity processes are included in the Appendix.

long-run parameters are higher under $\mathbb{Q}$ than $\mathbb{P}$ measures ($\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}} > \kappa^{\mathbb{P}}\theta^{\mathbb{P}}$). These parameter values indicate that the arrival of credit events is more intense in the risk-neutral (higher long-run means) than in the actual environment. Moreover, the differences between risk-neutral and actual processes tend to increase as time goes by, as a result of the higher value of $\kappa^{\mathbb{P}}$ with respect to $\kappa^{\mathbb{Q}}$. The negative sign of coefficients δ_0 and δ_1 confirms that the default environment worsens under risk-neutral more than the actual measure. This evidence seems to account for and address a systematic risk premium related to the arrival of unexpected credit events that is being priced in the market (Pan and Singleton, 2008).

Table 2.3.: Summary statistics for maximum likelihood estimates

				Percentile			
Parameter	Mean	Std.	Min	10	50	90	Max
$\kappa^{\mathbb{Q}}$	-0.15	0.65	-1.50	-1.41	0.20	0.41	0.50
$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	-0.43	1.98	-3.20	-1.87	-1.64	3.14	4.08
σ	1.85	0.64	0.85	1.21	1.69	2.94	3.29
$\kappa^{\mathbb{P}}$	2.53	2.79	0.24	0.40	1.07	8.05	8.83
$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	-14.68	16.33	-50.00	-47.94	-6.00	-2.59	-1.61
σ_{1y}(bps)	14.42	8.43	6.05	8.50	10.94	21.92	50.00
σ_{5y}(bps)	29.70	15.41	6.05	10.94	30.47	50.00	50.00
δ_0	-6.08	6.40	-21.08	-17.05	-2.43	-0.25	0.35
δ_1	-1.14	1.23	-4.00	-3.12	-0.49	0.01	0.24

Summary statistics for maximum likelihood estimates of risk-neutral $\lambda_t^{\mathbb{Q}}$ process. $\kappa^{\mathbb{Q}}$ and $\kappa^{\mathbb{P}}$ denote the mean-reversion rates of $\lambda_t^{\mathbb{Q}}$ under the risk-neutral and actual measures, respectively. $\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$ and $\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$ are the long-run mean of $\lambda_t^{\mathbb{Q}}$ under the risk-neutral and actual measures, respectively. σ is the instantaneous volatility. Finally, σ_{1y} and σ_{5y} represent the volatility of the misspricing for 1- and 5-year maturities. δ_0 and δ_1 are the market price of risk parameters.

To obtain guidance in the performance of our estimations, Table 2.3 displays the (averaged) volatilities of mispricing errors for 1-year (σ_{1y}) and 5-year (σ_{5y}) contracts, respectively. As shown, mispricing fluctuates approximately 14 bps and 30 bps for 1- and 5-year contracts, respectively. Because CDS spreads reach hundreds of basis points, these values address the reasonably good performance of our model. To further motivate the goodness-of-fit of the model, Table 3.9 compares the sample versus the fitted spreads by means of a panel data regression with robust standard errors to unobserved firm and time effects. Table 3.9 shows a reasonable performance of the model. The R-squared coefficients are above 90% with non significant intercepts and beta coefficients that are not significantly different from one.

Table 2.4.: Projections of sample values onto fitted values for the logOU model

	$\Delta CDS_{it}^{sample} = \beta_0 + \beta_1 \Delta CDS_{it}^{theo} + \epsilon_{it}$				
Maturity	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	RMSE (bps)	N
1 Year	8.07e-07	0.95	0.91	8	8415
	(306e-07)	(0.03)			
5 Year	24.3e-07	1.04	0.96	4	8415
	(221e-07)	(0.04)			

This table shows the projections of the sample CDS spread increments onto their fitted counterparts. The standard error of the coefficients are in parentheses and have been calculated as in Petersen (2009) to allow for correlation across time and across firms.

A first look at the results is provided in Figure 2.1. This figure depicts the evolution of the distress risk premium of 5-year CDS contract through time for different quartiles (upper graph), ratings (medium graph) and certain sectors (lower graph). Vertical bars denote the subsample periods. From Figure 2.1, we can draw several conclusions: First, it is clear that the risk premium increased substantially in August 2007 with respect to early dates and suffers from the events of the financial crisis (such as the BNP Paribas freezing and the Lehman Brothers' failure). This result seems to be robust across ratings and sectors, highlighting the systematic nature of the chosen events. Second, the upper graph in Figure 2.1 shows that risk premium behavior varies across time. On median, the distress risk premium is approximately zero during the pre-crisis period and increases to 50 bps after August 2007. Lehman's collapse seems to trigger the risk premium, which reaches approximately 100 bps during the ensuing weeks. Moreover, those risk premia exhibit a high degree of co-movement. This evidence is important and economically relevant because it might be addressing that common aggregate factors are being priced systematically by investors. Finally, a higher risk premium is demanded to lower rating firms (medium graph). The lower graph shows how risk premia differ across sectors.

Surprisingly enough, investors seem to demand systematically lower risk premia from Financial than Basic or Consumer Sectors, at least in Europe.

Table 2.5 quantifies the size of the distress risk premium estimates for ratings (Panel A), sectors (Panel B) and overall (Panel C) in absolute and relative terms, and these results corroborate the previous findings. With respect to ratings, the risk premium increases as the rating deteriorates. Risk premia accounts for (in median) approximately 25% of AA rated companies, rising to almost 50% (in median) in the case of BBB firms. With regard to the sectors, all sectors show a median risk premia of 40%, with the exceptions being, again, the Financial (33%) and Utilities (37%) sectors.

Table 2.5.: Descriptive statistics for distress risk premium

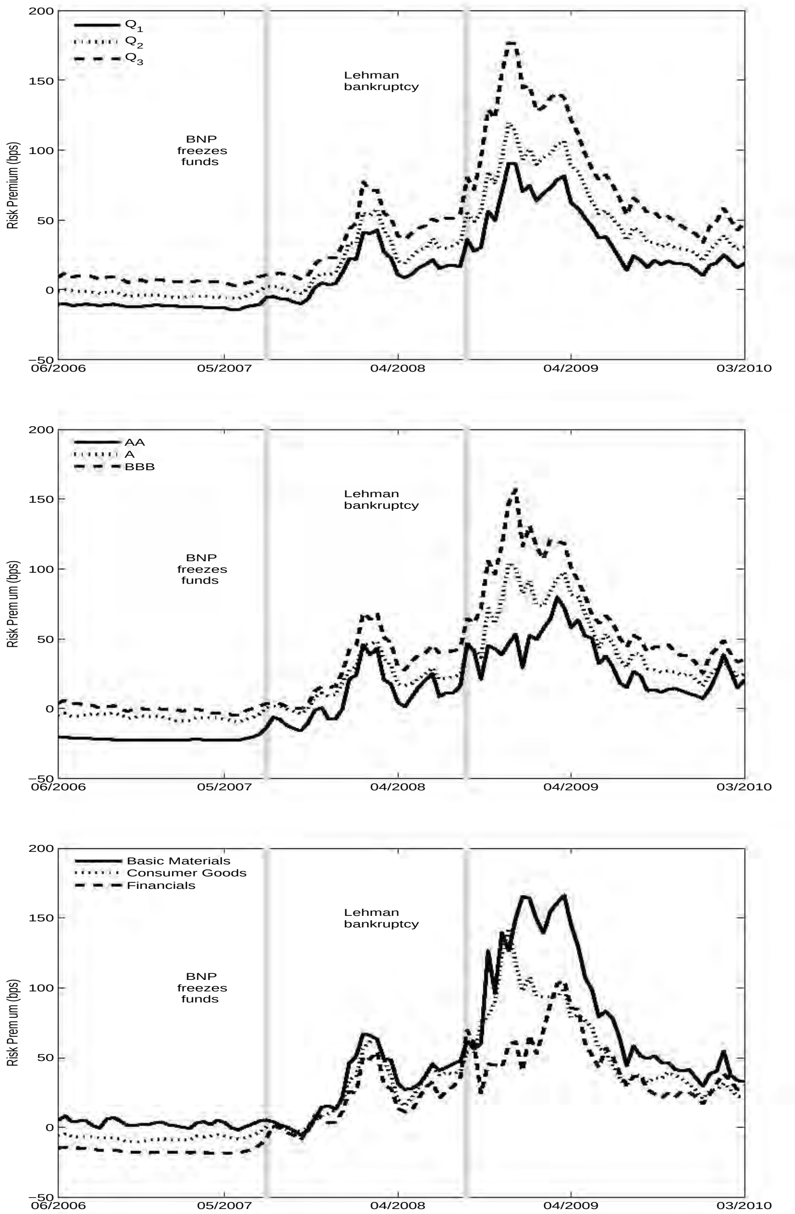
	Risk premium (bps)			Risk premium Fraction			
	Mean	Median	Std.	Mean	Median	Std.	N
Panel A.- Ratings							
AA	10.94	12.43	30.57	-134.26	25.44	258.19	7
A	26.71	21.55	32.54	5.05	37.11	64.53	32
BBB	47.01	37.70	47.47	33.33	46.16	32.40	46
Panel B.- Sectors							
Basic Materials	54.87	43.99	53.27	35.37	49.04	40.59	6
Consumer Goods	34.66	29.33	36.89	22.61	44.69	49.71	8
Consumer Services	46.52	35.28	51.69	21.94	42.10	46.53	15
Financials	21.38	20.71	32.04	-55.16	33.42	146.25	15
Health Care	17.57	13.59	27.35	14.57	40.90	59.05	1
Industrials	44.01	38.09	42.22	33.30	45.18	30.43	13
Oil&Gas	39.71	29.15	41.16	-12.08	40.44	88.30	3
Technological	36.22	24.64	41.93	42.52	47.15	15.42	1
Telecommunications	36.36	28.31	38.44	32.23	42.06	28.93	12
Utilities	26.13	19.26	33.19	1.76	36.64	67.97	11
Panel C.- Overall							
Total	36.40	29.54	40.45	8.88	41.05	63.09	85

Summary of main statistics for absolute and relative distress risk premia for 5-year default swaps by ratings (Panel A), sectors (Panel B) and overall (Panel C). Absolute risk premium is defined as $(CDS^{\mathbb{Q}} - CDS^{\mathbb{P}})$. Relative risk premium is $(CDS^{\mathbb{Q}} - CDS^{\mathbb{P}})/CDS^{\mathbb{Q}}$. The sample comprises data from 14/June/2006 until 31/March/2010.

2.4.3. Principal components analysis

The joint behavior of the risk premia suggests different sources of commonality in the data. We explore this possibility by carrying out a principal component (PC) analysis in the risk premium series. Figure 2.2 exhibits the scores of the first three principal components (PC1, PC2 and PC3, respectively) of (standardized) distress risk premium values. The explained variance is in parenthesis. Figure 2.2 shows that an important source of

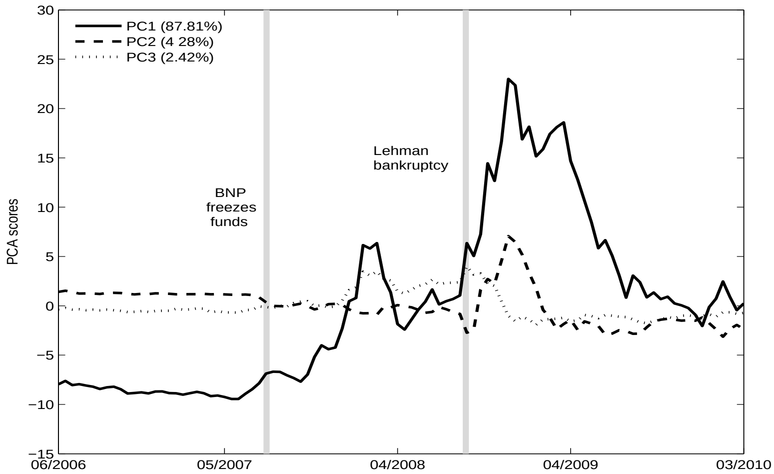
Figure 2.1.: Distribution of distress risk premium along time



The evolution through time of risk premia by quartiles (upper graph), ratings (medium graph) and sectors (bottom graph). The graphs depict the risk premium embedded in the five-year CDS contract. Rating and sector figures display the median statistic for each day. The sample period covers from 01/Jun/2006 to 31/Mar/2010. Vertical bars indicate subsample periods.

commonality lies behind risk premia. For example, one factor explains approximately 88% of the joint variability in the risk premium levels. Although not reported here, the loading coefficients (available upon request) show that first PC coefficients are always positive and have values ranging from 0.09 to 0.11, approximately. In economic terms, this may be interpreted as an equally weighted contribution of firms to the distress risk premium, or as an aggregate level of distress risk compensation. Not surprisingly, the correlation coefficient between PC1 scores and the time series of the cross-sectional median of 5-year CDS spreads is 0.89, indicating clearly that PC1 is related to the general level of credit risk in the economy.

Figure 2.2.: Principal components of distress risk premium



The evolution through time of the first three principal components (PC1, PC2 and PC3, respectively) of risk premium over time. Variance explained (in percentage) are in parentheses. The sample period covers from 01/Jun/2006 to 31/Mar/2010. Vertical bars indicate subsample periods.

With regard to the second principal component, the explained variance increases a 4.28% with the inclusion of the PC2 variable. The loading coefficients are positive in approximately 54% of the total number of firms. This result indicates a possible fragmentation of market information into firms that contribute positively and negatively to PC2. The loading coefficients (available upon request) indicate that all financial sector firms have negative coefficients. In this sense, PC2 is possibly capturing the differences between the Financial sector and other sectors in the economy. We calculate the (cross-sectional) mean time series of the financial CDS spreads to explore this point. Similarly, we repeat this exercise for the remainder of the non-financial companies. The correlation coefficient between PC2 scores and the difference financial and nonfinancial firm spreads is 0.53. Therefore, there is a strong relationship between PC2 and the spread between financial and non-financial default swaps.

In summary, the distress risk premium substantially increased beginning in August 2007, peaking after the Lehman collapse. This premium varies over time, exhibiting strong co-movement. The first and second principal components are related to the aggregate level of distress risk premium and the spread between the financial and the remaining sectors, respectively. On median, the distress risk premium accounts for approximately 40% of the total CDS spread.

2.5. Macroeconomic sources of risk premium

This section explores the macroeconomic drivers of the default risk premium, analyzing the financial variables affecting the aggregate risk premium. Following this, we study the dynamics of the aggregate risk premium.

2.5.1. Variable descriptions

The observed commonality in risk premia seems to suggest the existence of a pricing factor in corporate CDS spreads. To analyze the possible sources of such co-movement, we project the first (PC1) and second (PC2) principal components of distress risk premium onto a set of financial and macro variables by means of OLS regressions. Our set of financial variables accounts for variables related to liquidity, monetary policy, and equity and debt markets, among others. Because we are particularly concerned about the public-to-private risk transfer, we also control for sovereign risk in the economy.

The importance of the CDS market illiquidity on risk premia is studied. We employ the bid-ask spread as a proxy for the illiquidity of the 5-year default swap contracts, following

Tang and Yan (2007) and Bongaerts et al. (2011), among others. CDS bid-ask spreads are taken from CMA. Diving into further detail, we study the influence of aggregate market illiquidity by taking the first principal component of 5-year CDS bid-ask spreads (ILLIQ) of the firms under study. The loading coefficients of the ILLIQ variable are approximately equal, which can be understood as an average of bid-ask spreads. This first factor accounts for 81.06% of the variance of the total bid-ask spreads in the sample. Although a puzzling liquidity influence has been considered, we expect a positive beta for this variable (higher illiquidity leads to higher CDS spreads).

As for variables representing the stock market, we choose the Eurostoxx 50 Index (ESTOXX50) and the CBOE implied volatility index (VIX) for the next 30 days. These variables capture the stock market sentiment and risk appetite (Pan and Singleton, 2008; Longstaff et al., 2011). We control for currency risk by using the dollar-euro exchange rate (USD/EUR) because the CDS contracts are denominated in Euros and most of the dealers are either North American or Eurozone corporations. Additionally, the Euro overnight index average (EONIA) is included as a general stance of monetary authority decisions (Maddaloni and Peydró, 2011). To account for counterparty risk underlying the Euribor-swap curve, the spread between the 3-month Euribor and the overnight interest swap (EURIBOR-OIS) is included. We also incorporate information about the slope (SLOPE) of the term structure of interest rates as an indication of overall economic health (Collin-Dufresne et al., 2001; Ericsson et al., 2009). The slope is computed as the difference between the 10-year and the 2-year yield of German bonds. These two maturities represent the most liquid segment of the German sovereign bond market.

Finally, sovereign crisis appears to raise corporate default rates (Moody's, 2009). However, Dieckmann and Plank (2012) show evidence that a sovereign CDS market incorporates possible financial industry bailouts, maybe through a private-to-public risk transfer. They also note the possibility of negative feedback loops. No matter the causal relationship among public and private sectors, it seems reasonable that investors require higher spreads for corporate debt when sovereigns begin showing difficulties. In this context, we study whether the distress risk premium required by corporate market participants is affected by the sovereign default risk. The sovereign default risk is proxied through the first (SOVPC1) and second (SOVPC2) principal components of 5-year sovereign CDS spreads. We employ senior external contracts on 15 Western European countries whose firms are included in the Markit database. Our available sample includes contracts denominated in US dollars under the Old Restructuring clause. Table 2.6 provides fundamental statistics and loadings for the first two principal components. Notice that SOVPC1 is a weighted average of CDS spreads, accounting for 93.4% of the total variation. This first component is usually associated with the level of sovereign risk in the economy (Groba et al., 2013). The second component SOVPC2 accounts for 4.5% of the variation, and it assigns the lowest negative loadings to Greece, Portugal, and Spain. This second component could be interpreted as measuring distance between financially distressed and non-distressed countries.

Table 2.6.: Country statistics

	Government statistics		5-year sovereign CDS	
Country	Debt/GDP (%)	Deficit/GDP (%)	SOVPC1 Loading	SOVPC2 Loading
Austria	69.6	-4.1	0.26	0.18
Belgium	96.2	-5.9	0.26	0.05
Denmark	41.8	-2.7	0.25	0.27
Finland	43,8	-2.6	0.26	0.16
France	78.3	-7.5	0.26	-0.07
Germany	73.5	-3.0	0.26	0.06
Greece	127.1	-15.4	0.23	-0.56
Ireland	65.6	-14.3	0.26	0.06
Italy	116.1	-5.4	0.26	-0.07
Netherlands	60.8	-5.5	0.26	0.22
Norway	43.1	10.5	0.26	0.25
Portugal	83.0	-10.1	0.24	-0.50
Spain	53.3	-11.1	0.26	-0.33
Sweden	42.8	-0.7	0.26	0.22
United Kingdom	69.6	-11.4	0.27	-0.04

All Western European countries with firms included in the Markit's database with available sovereign CDS spreads for all the sample period. The GDP, Gross Debt and Deficit are those reported by Eurostat for the year 2009. The sovereign CDS contracts are denominated in USD dollars under the Old Restructuring clause. The first component SOVPC1 explains 93.43% of the variability, and the second component SOVPC2 explains 4.49%. The sample period for the sovereign CDS spread covers from 14/Jun/2006 to 31/Mar/2010.

2.5.2. OLS estimates

We explore the risk factor changes that might be related to the variation of the main principal components of distress risk premia. To this end, we run the following ordinary least squares (OLS) autocorrelation-robust standard error regressions,

$$\begin{aligned}\Delta DRP_{pt} &= \beta_{p0} + \beta_{ILLIQ}\Delta ILLIQ_t + \beta_{ESTOXX50}\Delta ESTOXX50_t + \beta_{VIX}\Delta VIX_t \\ &+ \beta_{UDS/EUR}\Delta UDS/EUR_t + \beta_{EONIA}\Delta EONIA_t \\ &+ \beta_{EURIBOR-OIS}\Delta EURIBOR - OIS_t + \beta_{SLOPE}\Delta SLOPE_t \\ &+ \beta_{SOVPC1}\Delta SOVPC1_t + \beta_{SOVPC2}\Delta SOVPC2_t + \varepsilon_{pt}\,, \qquad (2.15)\end{aligned}$$

where ΔDRP_{pt} is the change of the principal component p of distress risk premium variables, with the other variables previously having been defined. Additionally, we examine three different stages of the crisis; in particular, we account for those subperiods when BNP freezes three funds (09/Aug/2007), and Lehman Brothers fails (15/Sep/2008). These two events represent potential dates for structural changes in the corporate credit spreads.

Table 2.7 displays the OLS estimates for first and second principal components of distress risk premium. Models I and V include the entire period, while Models II to IV and VI to VIII refer to the different subsamples under study. With regard to the first component, there is a positive and significant relationship to changes in the aggregate illiquidity, as measured by 5-year bid-ask spreads. When analyzing by subsamples, the illiquidity variable is positive and statistically significant during crisis periods (Models III and IV). Coefficients are estimated with precision, and the adjusted-R^2 coefficients are higher than 70% when illiquidity is significant (Models I, III and IV), indicating the high explanatory power of this variable on the regressions. These results are economically relevant because they document a positive contribution of aggregate illiquidity to risk premium, particularly during times of distress. Thus, default swap investors appear to price the aggregate illiquidity into the CDS market.

Sovereign risk also displays a positive beta on distress risk premia and it has a sta-

Table 2.7.: Regression for principal components of distress risk premia

Dependent variable	ΔDRP_{1t}				ΔDRP_{2t}			
Model	(I) All period	(II) <09/Aug/2007	(III) $\geq$ 09/Aug/2007 <15/Sep/2008	(IV) $\geq$15/Sep/2008	(V) All period	(VI) <09/Aug/2007	(VII) $\geq$ 09/Aug/2007 <15/Sep/2008	(VIII) $\geq$15/Sep/2008
Cons.	0.0623	0.0884	0.0113	0.0754	0.0289	0.0240	0.0000	0.0150
$\Delta ILLIQ_t$	0.4766***	0.0453	0.3350**	0.5027***	0.1012**	0.0690**	0.0132	0.1474***
ΔESTOXX50$_t$	0.0011	0.0012**	0.0003	0.0009	0.0022***	0.0003**	0.0008	0.0046***
ΔVIX$_t$	0.0348	0.0204	0.0835	0.0299	0.0460	0.0122	0.0253	0.0734
ΔUSD/EUR$_t$	4.9876	0.8497	0.0572	11.3396	1.6109	1.5175*	1.0266	5.3595
ΔEONIA$_t$	0.4136	0.0666	0.2812	0.4486	0.6742	0.0662	0.4277*	1.1281
ΔEURIBOR OIS$_t$	1.0704	7.0873**	0.6105	0.6847	1.1974	1.1434	0.3328	2.8799
ΔSLOPE$_t$	1.2827	0.1034	0.1870	2.4537	0.3983	0.6703**	0.8050	0.9615
ΔSOVPC1$_t$	0.7308***	5.4239*	1.7270	0.6193**	0.0353	3.0250***	0.4766	0.0185
ΔSOVPC2$_t$	0.0643	13.7572**	11.0095***	0.2128	0.2645	0.1628	2.2198**	0.1515
Obs.	99	30	28	41	99	30	28	41
R^2 Adj	0.7003	0.5360	0.7488	0.7080	0.1625	0.6871	0.3276	0.2329

OLS regressions of first DRP_{1t} and second DRP_{2t} principal components of distress risk premium against different macro-financial variables. The table reports the estimated OLS coefficients and their significance, according to White (1980) heteroskedasticity-consistent t-statistics. The date 09/Aug/2007 refers to the day that BNP Paribas froze three investment funds, and 15/Sep/2008 refers to the date that Lehman Brothers filed for bankruptcy. The sample period covers from 14/Jun/2006 to 31/Mar/2010. *, **, and *** denote the significance at 10%, 5% and 1%, respectively.

tistically significant effect, although different patterns are observed in each subsample. Aggregate sovereign risk contributes to the distress risk premium after the Lehman collapse (Model IV), and peripheral risk seems to influence the early periods of the sample (Models II-III). Regarding the latter, the negative sign observed at first becomes positive and non-significant in the last part of the sample, perhaps indicating a change in the perception of sovereign risk. At the beginning, sovereign risk shows a partial, diversifiable risk (Model II-III), while it indicates a market-wide problem at the end (Model IV). This is an important result, suggesting that the financial reliability of sovereign economies raises concerns about the creditworthiness of their domiciled firms, at least from the market perspective. This effect is stressed after the Lehman default (Model IV). Because PC1 of sovereign CDS spreads captures the level of sovereign risk, this could be evidence that investors are pricing this risk in the economy.

With regard to the second principal component, Table 2.7 outlines a significant and positive contribution of the stock market to PC2. Because PC2 is interpreted as the differences in risk compensation between financial and nonfinancial firms, positive returns in the stock market are associated with greater differences between these premia.

This result is stressed after the Lehman failure (Model VIII), when investors are more concerned about problems in the financial sector. This empirical finding, together with positive and significant beta coefficients for illiquidity in this period, suggests flight-to-liquidity and flight-to-quality effects. Finally, the explanatory power of the regressions before the crisis (Model VI) indicates that PC2 was influenced by other markets, such as the exchange or sovereign market.

Notably, VIX is not statistically significant. Our proxy for counterparty risk, the spread EURIBOR-OIS, is significant during the first subsample (Model II). According to our results, the increments in the EURIBOR-OIS spread, exchange rates or the slope of the term structure do not have an effect on the aggregate corporate distress risk premium.

In conclusion, investors seem to price the deterioration of market-wide liquidity and aggregate sovereign risk conditions, particularly during periods of financial stress. Finally, the distance between financial and non-financial premia widens during the post-Lehman bankruptcy scenario.

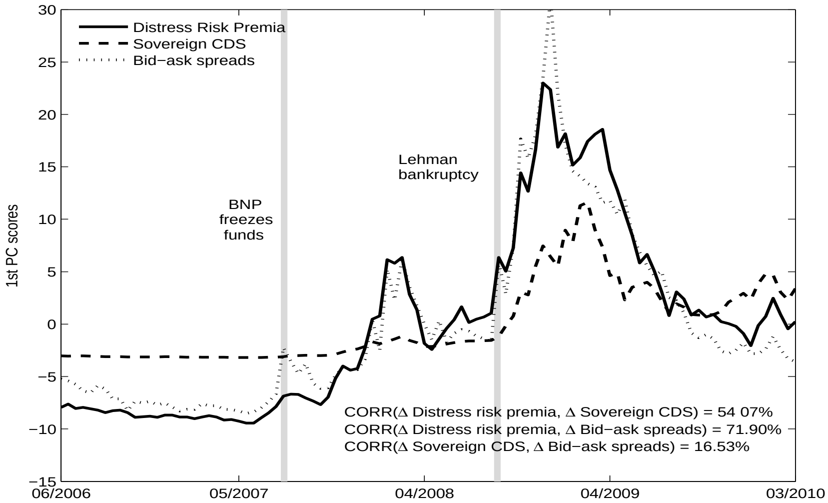
2.5.3. Public-to-private risk transference

We turn next to the existence of a public-to-private risk transference in the default risk premium. Dieckmann and Plank (2012) show evidence that the sovereign CDS market incorporates possible financial industry bailouts through a private-to-public risk transfer. Alter and Schüler (2012) also analyze the dynamic behavior between the sovereign and financial industries in European default swaps, finding that bank spreads affect the sovereign ones, prior to state interventions. However, the direction of this relationship reverses after the bailout programs. To assess whether our findings are affected by the financial firms contained in the sample, we perform a panel data analysis using a dummy variable to control for financial firms.[16] Our results remain qualitatively similar with liquidity and sovereign risks as main factors behind the risk premia.

[16] The panel data regressions are available in the Appendix

Our previous analysis in Section 2.5.2 above showed that there is a strong relationship between the aggregate distress risk premium and the sovereign and illiquidity variables. Figure 2.3 plots the evolution over time of first principal components of the distress premium, sovereign spreads and illiquidity, respectively. At first glance, a strong degree of co-movement among those variables is clear. For example, the correlation coefficient between the distress risk premia and sovereign spreads is 0.54, rising to 0.71 when accounting for the pairwise correlation between distress risk premia and illiquidity.

Figure 2.3.: Principal components for distress risk premium, bid-ask spreads and sovereign risk



The first principal components for distress risk premium, bid-ask spreads and sovereign risk over time. The sample period covers from 01/Jun/2006 to 31/Mar/2010. Vertical bars indicate subsample periods.

In exploring the possibility of a dynamic relationship between the distress risk premia and the sovereign and illiquidity variables, we propose a vector autoregressive (VAR) analysis to measure the effect of those variables on the corporate distress risk premium. Our conjecture is that distress risk premia – not only the default rates – increase when sovereign market conditions erode. We argue that investors anticipate the uncertainty about future economic situations when sovereign CDS spreads rise because sovereign spreads are generally viewed as a lower bound for corporate debt borrowing costs.

Table 2.8 presents the results of Granger causality Wald tests for the first equation of the VAR model. Under the likelihood ratio test, our VAR model includes up to six lags of the differenced variables under study. The Wald test allows us to analyze whether the lags of the sovereign or illiquidity variables are significant when preceding the distress risk premium. The results show that the first principal component of distress risk premium is driven by the aggregate level of sovereign risk in the European debt market and the aggregate illiquidity in the corporate CDS market. This finding supports the idea that sovereign conditions affect the prices of corporate credit risk, in addition to the corporate default rates.

Table 2.8.: Granger causality Wald tests for VAR(p=6)

Equation	R^2	Excluded	χ^2	df	Prob > χ^2
ΔDRP_{1t}		$\Delta ILLIQ$	19.497	6	0.003
ΔDRP_{1t}	0.3719	ΔSOVPC1	16.971	6	0.009
ΔDRP_{1t}		ALL	36.896	12	0.000

Results for a VAR model with 6 lags according to the likelihood-ratio test. The sample is composed of 93 biweekly observations. The sample period covers from 14/Jun/2006 to 31/Mar/2010.

2.6. Jump-at-default risk premium

We complete our analysis by looking at compensation for the default itself. This section addresses the results about the jump-at-default risk premium in European firms.

2.6.1. Definition

Investors compensate for changes in the credit environment, in addition to compensating against the event of default (Jarrow et al., 2005). Economically, the jump-at-default premium captures the risk associated with a jump in price of the bond if the reference entity does restructure (Pan and Singleton, 2006). The conditional diversifiable assumptions in Section 2.2.3 are relaxed here, for example, by considering that there are a finite number of bonds in the economy. Thus, the jump-at-default price of the risk term in expression (2.8) might not be negligible ($\Gamma_t \neq 0$).

The price of jump-at-default risk is assumed as $\Gamma_t = 1 - \mu_t$, with μ_t defined as,

$$\lambda_t^{\mathbb{Q}} = \mu_t \lambda_t^{\mathbb{P}}, \tag{2.16}$$

where $\lambda_t^{\mathbb{Q}}$ and $\lambda_t^{\mathbb{P}}$ are the risk-neutral and actual default intensities, respectively, at time t. Parameter μ_t is usually referred to as the jump-at-default premium, and it has been previously studied in Driessen (2005) and Berndt et al. (2005). When μ_t equals one, risk-neutral and actual default intensities are similar and there is no compensation for the event of default. Although the ratio μ_t has usually been assumed constant for simplicity (cf. Driessen (2005); Jarrow et al., 2005), our focus here is to explain its temporal variation.

It follows from equation (2.16) that the concurrence of $\lambda_t^{\mathbb{Q}}$ and $\lambda_t^{\mathbb{P}}$ intensities is necessary for computing the jump-at-default risk premium. We closely follow Driessen (2005) and Berndt et al. (2005) in calculating the ratio $\lambda_t^{\mathbb{Q}}/\lambda_t^{\mathbb{P}}$.[17] On the one hand, $\lambda^{\mathbb{Q}}$ estimates are taken from CDS data, and they were previously obtained in Section 2.4. On the other hand, we use the Expected Default Frequencies (EDFs) of Moody's KMV as a proxy for actual default probabilities, which is based on the Merton (1974) model for pricing corporate debt. Moody's uses its extensive data set on historic default frequencies to build an empirical distribution that maps the distance-to-default of Merton (1974) into a real default probability called the EDF. Thus, the EDFs are forward-looking default probabilities that are available to public and private companies. For a detailed description of the KMV estimates of EDF, see Bharath and Shumway (2008).

The literature generally employs the EDFs as proxies for actual default probabilities. In general, the EDFs have a higher predictive power than credit ratings.[18] In this sense,

[17]Driessen (2005) estimates the relationship between $\lambda_t^{\mathbb{P}}$ and $\lambda_t^{\mathbb{Q}}$ using U.S. corporate bond price data, assuming that conditional default probabilities are equal to average historical default frequencies by credit rating. Berndt et al. (2005) follow a two-step procedure, first estimating the $\lambda_t^{\mathbb{P}}$ model parameters with monthly Moody's KMV EDF measures of default probability, and then estimating the $\lambda_t^{\mathbb{Q}}$ parameters with weekly U.S. CDS rates and EDFs.

[18]Rating agencies are harshly criticized for their failure to predict the crises at firms such as Penn Central Transportation Company in 1970, Orange County in 1994, Enron in 2001, WorldCom in 2002 or Lehman Brothers in 2008. For example, the European Parliament (2009) commented that credit rating agencies failed to reflect early enough in their credit ratings the worsening market conditions, on the one hand, and to adjust their credit ratings in time following the deepening market crisis, on

EDFs depend on stock prices and are time-variant. Empirical studies corroborate the accuracy of EDFs for predicting default. For instance, Kealhofer (2003) shows that EDFs correctly identify 72% of defaults, while credit ratings identify only 61%. Bharath and Shumway (2008) conclude that 65% of defaulting firms had probabilities in the higher decile during the quarter they default; moreover, hazard models that include Merton's default probabilities have better out-of-sample performance. And Korablev and Dwyer (2007) validate the default predictive power of EDFs by computing accuracy ratios. Additionally, using EDFs to determine the default premium has been also referred to in Berndt et al. (2005) for US corporate CDS spreads, in Vassalou and Xing (2004) for stock prices and in Pan and Singleton (2006) for the CDS spreads of Japanese banks.

The actual intensity process $\lambda_t^{\mathbb{P}}$ comes from the definition of the EDF,

$$EDF(T) = 1 - E_t^{\mathbb{P}}\left[e^{-\int_t^T \lambda_s^{\mathbb{P}} ds} | \mathcal{F}_t\right], \qquad (2.17)$$

and we assume an Ornstein-Uhlenbeck process for the logarithms of the default intensity,

$$d\ln\lambda_t^{\mathbb{P}} \quad = \quad \alpha^{\mathbb{P}}(\beta^{\mathbb{P}} - \ln\lambda_t^{\mathbb{P}})dt + \sigma dB^{\mathbb{P}}, \qquad (2.18)$$

where parameters $\alpha^{\mathbb{P}}$, $\beta^{\mathbb{P}}$ and σ capture the long-run mean, mean-reversion rate and volatility of the process, respectively.

2.6.2. Estimation procedure and results

We combine our CDS sample with the data provided by Moody's KMV. Our new dataset is composed of biweekly 1-, 3- and 5-year EDF and CDS for 75 firms from 01/Jun/2006 to 31/Mar/2010. To estimate the $\lambda_t^{\mathbb{P}}$ parameters, we maximize the likelihood of the joint density of process (2.18) and the mispricing errors conditional to a set of parameters.[19]

the other. A number of papers are focused on providing theories that explain why ratings change relatively seldom, such as the rating stability hypothesis related to the through-the-cycle approach (e.g., Howe, 1995) and the policy of rating bounce avoidance (e.g., Cantor, 2001)

[19]This procedure is similar to that described in Subsection 2.4.1. We detail certain steps: First, we assume that the one-year EDFs are observed without error. As the shortest maturity available, we assume that the 1-year EDF is the best proxy available for instantaneous actual default probability,

For the sake of brevity, a summary of the main statistics of the EDF measure and the ML estimated parameters are provided in the Appendix.

Table 2.9 details the sample statistics for the parameter of the jump-to-default premium μ_t in equation (2.16) across ratings (Panel A), sectors (Panel B), and overall (Panel C). The (averaged) median risk premium is 3.82. This value is within the range of those estimates previously reported in the literature for the US in earlier sample periods. For example, Driessen (2005) reports risk premium values of 1.83, 2.61 and 2.37 for a weekly sample of AA, A and BBB US corporate bonds from 1991 to 2000. Berndt et al. (2005) obtain a distribution of risk premium estimates with the 1st and 3rd quartiles equal to 1.12 and 3.55, respectively, for a CDS and EDF sample from 2000 to 2004. Finally, Pan and Singleton (2006) observe risk premia between 1.00 and 3.00 – and even less than one – for a short sample of Japanese banks. No other estimates of jump-at-default risk premia for European firms, or for US firms during more recent periods, are available to us.

To provide additional insights about the size of the jump-at-default premium, Table 2.9 translates those μ_t estimates to basis points. To illustrate this point, we employ the definition of jump-at-default premium in expression (2.8). For example, a jump-at-default risk premium of 3.00 is equivalent to $-60\% \times 0.0020 \times (1 - 3.00) = 24.00$ bps, assuming a recovery of 40% and an annual default probability of 20 bps (a reasonable value for the historical default rate of BBB bonds). As shown in Table 2.9, our (averaged) median jump-at-default estimate is 13.26 bps. These results indicate that an important economic contribution for excess returns comes via compensation in case of a default event. For example, the mean risk premium almost doubles when passing from the A to the BBB rating – similar results apply for volatilities. Focusing on sectors with more than 10 firms in the sample, Table 2.9 shows that Consumer Services (Industrials) exhibit the higher (lower) median jump-at-default premia. Conversely, Industrials (Utilities)

consistent with Berndt et al. (2005). A possible path for $\lambda_t^{\mathbb{P}}$ is obtained by the inversion of expression (2.17). Second, mispricing errors of three- (ϵ_{3y}) and five-year (ϵ_{5y}) EDFs are normally distributed errors with zero mean and standard deviations $\sigma(3)$ and $\sigma(5)$, respectively. Finally, we employ the finite-difference method of Crank-Nicholson to compute the expectation (2.17) for the intensity process (2.18).

Table 2.9.: Descriptive statistics for jump-at-default premium

	Risk premium ($\lambda^{\mathbb{Q}}/\lambda^{\mathbb{P}}$)			Risk premium (bps)			
	Mean	Median	Std.	Mean	Median	Std.	N
Panel A.- Ratings							
AA	6.57	5.74	3.90	19.72	18.19	15.48	7
A	5.64	3.66	5.41	21.18	10.62	47.05	29
BBB	6.05	3.61	6.31	38.40	14.33	77.21	39
Panel B.- Sectors							
Basic Materials	6.72	4.53	6.63	58.28	13.88	104.81	6
Consumer Goods	7.44	3.91	9.10	43.06	14.77	68.46	3
Consumer Services	6.48	4.75	5.49	43.47	19.49	60.00	13
Financial	5.70	3.70	5.48	20.53	14.33	50.62	15
Health Care	5.84	5.32	4.16	13.06	12.71	10.98	1
Industrials	4.50	2.48	4.91	17.77	5.35	89.91	12
Oil and Gas	6.81	5.13	5.73	20.19	8.45	63.32	3
Technological	2.84	1.44	2.73	26.68	2.34	57.02	1
Telecommunications	7.61	4.60	7.32	31.40	16.77	37.50	11
Utilities	4.63	2.81	4.62	23.92	10.94	36.11	10
Panel C.- Overall							
Total	5.94	3.82	5.74	30.00	13.26	59.79	75

Summary statistics for jump-at-default risk premia by ratings (Panel A), sectors (Panel B) and overall (Panel C). Jump-at-default risk premium is defined as the ratio $\lambda^{\mathbb{Q}}/\lambda^{\mathbb{P}}$. The sample comprises data from the period from 14/June/2006 until 31/March/2010.

displays the higher (lower) volatilities. Finally, the financial sector is on the average and median of the remaining sectors.

Figure 2.4 depicts the evolution of the jump-at-default risk premium for different quartiles (upper graph), ratings (medium graph) and certain sectors (lower graph). For ease of explanation, we kept the conversion to basis points of our results. Vertical bars denote subsample periods. Figure 2.4 allows us to draw several conclusions. First, it is clear that the jump-at-default premium has increased substantially in August 2007 with respect to early dates, and it suffered from the events during the financial crisis (such as the BNP Paribas freezing and the Lehman Brothers' failure). Second, this premium shows time-varying behavior, as Berndt et al. (2005) reported. Third, investors seem to demand, on median, higher levels of jump-at-default premia (medium graph) from lower rated companies, particularly during periods of stress. Finally, the Financial sector exhibits lower fluctuations in the jump-at-default premium compared to other sectors, such as Basic Materials or Consumer Goods, even though the Financial sector was viewed suspiciously during the international crisis beginning in August 2007. This last result could be a result of the "too-big-to-fail" hypothesis, because national bank rescue packages and other ECB measures might translate into lower compensation in the event of default.

We perform a factor analysis to explore sources of commonality in the data that documents a first (second) factor that accounts for 58.94% (18.60%) of the common variance. These values are lower than those reported for the distress risk premium, perhaps indicating more idiosyncratic behavior for jump-at-default than distress premium. Interested in their relationship with financial variables, Table 2.10 displays the OLS regressions between the first (JAD_{1t}) and second (JAD_{2t}) jump-at-default risk premium principal components and the financial variables in Section 2.5.1. Again, aggregate illiquidity is revealed as an important factor when considering jump-at-default premia, particularly after the Lehman default. The stock market variable ESTOXX50 is also significant and estimated with high precision.

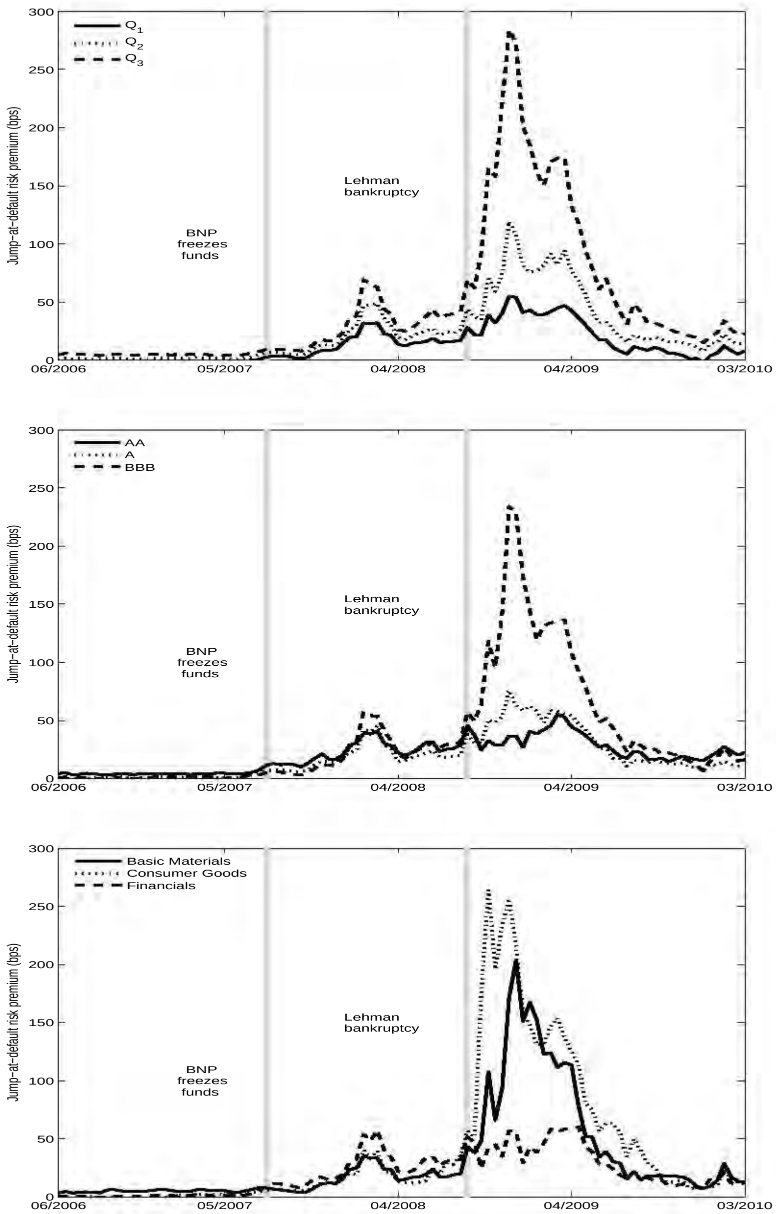
Table 2.10.: Regression for principal components of jump-at-default risk premia

Dependent variable	ΔJAD_{1t}				ΔJAD_{2t}			
Model	(I) All period	(II) <09/Aug/2007	(III) $\geq$ 09/Aug/2007 <15/Sep/2008	(IV) $\geq$15/Sep/2008	(V) All period	(VI) <09/Aug/2007	(VII) $\geq$ 09/Aug/2007 <15/Sep/2008	(VIII) $\geq$15/Sep/2008
Cons.	0.0347	0.1276	0.0788	0.0106	0.0253	0.0198	0.1007	0.0486
$\Delta ILLIQ_t$	0.5318***	0.1128	0.5754	0.4716***	0.1275***	0.0741	0.0130	0.2029***
ΔESTOXX50$_t$	0.0037**	0.0000	0.0074	0.0069**	0.0012	0.0009	0.0028*	0.0039***
ΔVIX$_t$	0.0783	0.0180	0.1955	0.1038	0.0260	0.0225	0.1135**	0.0650
ΔUSD/EUR$_t$	2.3459	1.3521	0.5064	10.0183	2.6549	2.2623	0.1628	1.1201
ΔEONIA$_t$	0.2922	0.5136	1.0795	0.0072	0.5980	0.4095	0.8406	0.9375
ΔEURIBOR OIS$_t$	4.4043*	5.8592	2.2248	2.9215	0.8479	2.7214	0.3660	1.3491
ΔSLOPE$_t$	0.4509	0.9376	3.5187	2.7928*	0.5385	1.3190*	0.9848	0.4429
ΔSOVPC1$_t$	0.2394	10.6792**	2.4876	0.1546	0.1637	7.1030**	1.0574	0.2554*
ΔSOVPC2$_t$	0.3265	14.4402	24.6994***	0.0776	0.3620	3.4860	4.5438**	0.1835
Obs.	99	30	28	41	99	30	28	41
R^2 Adj	0.3485	0.4539	0.5184	0.5462	0.2385	0.4958	0.2309	0.4952

OLS regressions of first JAD_{1t} and second JAD_{2t} principal components of jump-at-default risk premia against different macro-financial variables. The table reports the estimated OLS coefficients and their significance according to White (1980) heteroskedasticity-consistent t-statistics. The date 09/Aug/2007 refers to the day that BNP Paribas froze three investment funds, and 15/Sep/2008 refers to the date that Lehman Brothers filed for bankruptcy. The sample period covers from 14/Jun/2006 to 31/Mar/2010. *, **, and *** denote the significance at 10%, 5% and 1%, respectively.

In summary, we report a jump-at-default risk premium of 3.82 for European firms, which is somewhat higher than those previously reported in the literature for the US market and for periods before August 2007. In terms of basis points, the jump-at-default

Figure 2.4.: Distribution of jump-at-default risk premium along time



The evolution of jump-at-default risk premia over time by quartiles (upper graph), ratings (medium graph) and sectors (bottom graph), respectively. Rating and sector figures display the median statistic for each day. The sample period covers from 01/Jun/2006 to 31/Mar/2010. Vertical bars indicate the subsample periods.

risk premium accounts for approximately 14 bps. The jump-at-default premium also shows two main sources of commonality, showing a statistically significant relationship between aggregate illiquidity and stock market variables.

2.7. Conclusions

The financial crisis that started in August 2007 resulted in a substantial increase in the cost of borrowing for firms. Higher spreads during recessions reflect the rising number of defaults (quantity of risk) and the higher degree of risk aversion (the risk premium) during difficult times. Lenders become more uncertain about their own skills in assessing the creditworthiness of their borrowers and other lenders. In other words, investors become more aware of the risk and the price of risk increases, giving rise to a systematic risk even if the creditworthiness of the average borrower does not deteriorate (Flannery, 1996).

This chapter has focused on the corporate default risk compensation under general default circumstances. We employ the information contained in European corporate default swaps to extract accurate estimates of expected excess returns during years 2006-2010, a period that includes the credit crisis. The methodology employed here allowed us to disentangle the entire compensation for default risk into two parts, the compensation for systematic risk factors, or the distress risk premium, and the premium for bearing the risk of bond price decline at the event of default, or the jump-at-default premium.

Our findings suggest that approximately 40% of total CDS spread is compensation for distress risk premium. We also report a dominant source of commonality on distress risk premium series, in which a first (second) factor accounts for the 87.8% (4.3%) of the total variability. Moreover, empirical evidence reveals a strong relationship between the first principal component of distress risk premia and aggregate illiquidity, particularly during financially stressed periods. Illiquidity betas are positive and statistically significant, and the explanatory power of regressions after August 2007 exceed 70%. Additionally, we report a public-to-private risk transfer between distress risk premium and sovereign spreads. These results indicate that illiquidity and sovereign risk could be acting as pricing factors for European corporate spreads during financially stressed periods.

Using an extensive database of Moody's EDF default probabilities, we also examined compensation for jump-at-default risk. We document a jump-at-default risk premium of 3.82 for European firms, somewhat higher than those previously reported in the literature for the US market and for periods before August 2007. Jump-at-default premia also exhibit a high commonality and temporal variation, and it co-varies significantly with aggregate illiquidity and the stock market.

In conclusion, this chapter has studied empirically the corporate default risk premium for a sample of European firms, disentangling those compensations based on risk factors and credit event risks, while characterizing their size and behavior. Our results seem to confirm the existence of one common factor that drives the 88% (59%) movement of the distress (jump-at-default) risk premia for the sample we studied. This may indicate that an important fraction of systematic risk is being priced into the market via those premia. The empirical evidence suggests that aggregate illiquidity and sovereign risk could be acting as pricing factors in corporate credit spreads. We also document a leading role of sovereign risk for distress risk premia. These results might have important implications for risk management and policy measures oriented toward a framework of stability.

Chapter 3.

The impact of distressed economies on the EU sovereign market

3.1. Introduction

Credit default swaps (CDS, hereafter) are financial instruments that allow debt holders to hedge against default risk. After appearing in the US in the late 1990s, the CDS market exploded over the subsequent decade to over 45 trillion US dollars in mid-2007, as reported by the International Swaps and Derivatives Association (ISDA, 2007). Although the notional outstanding CDS decreased during the financial crisis, it reached approximately 26 trillion at mid-year 2010 (ISDA, 2010). Default swaps focused primarily on municipal bonds and corporate debt during the 1990s, but after 2000, the CDS market expanded internationally into sovereign bonds and structured finance products, such as asset-backed securities. The increasing trading volume of the CDS market could be attributed to several aspects such as the lack of regulation (CDS are traded on over-the-counter markets) or the potential for speculative investors and hedge fund managers to manage these insurance contracts without going long on the underlying asset. According to Chen et al. (2011), the majority of CDS trades were interdealer transactions; however, these authors provide evidence of broad participation in the CDS market as aggregate trading activity did not appear to be concentrated among a small number of dealers.

Compared to the extensive literature on the connections between the CDS market and the bond and/or stock markets (see, for example, Blanco et al., 2005; Forte and Peña, 2009; Norden and Weber, 2009; or Delatte et al., 2012; among others), relatively little is known about the nature of default risk transmission in sovereign credit markets. Recent articles show the increasing interest in the sovereign default risk channels. Dötz and Fisher (2011) document how the market perceptions of European sovereign risk changed after the rescue of Bear Stearns in March 2008: default events within the Eurozone are currently perceived as having non-negligible probabilities, reflecting how some countries are seen as a domestic safe haven at the expense of others. Similarly, Favero and Missale (2012) analyze the intertemporal relationships between the sovereign yield spreads of the main European economies, finding empirical evidence for substantial contagion effects. Under this type of a scenario, where some government bonds have lost their previous role as a domestic safe asset, it becomes crucial to understand the linkages between changes and the volatility of sovereign credit spreads, in particular, among the Eurozone countries.

This chapter explores the nature of default risk transmission both inside and outside of the Eurozone using the information content in the sovereign CDS spreads. As noted by Longstaff et al. (2011), the use of CDS contracts leads to more accurate estimates of the credit spreads and returns than those based on sovereign bond data.[1] Instead of focusing on the potential destabilizing effects of default swaps on the security markets, we stress the crossing effects of the time-varying fluctuations of CDS spreads. Our major concern is to provide additional insights into the nature of default risk transmission in the Eurozone. In particular, we try to assess whether the interactions between the

[1] The CDS spreads generally approximate the spreads of the referenced bonds. However, time-varying differences or basis risk between the CDS and the sovereign bond spreads could appear for several reasons. First, the empirical literature on the role of the CDS markets in the discovery process is consistent with the hypothesis that new market-wide information disseminates faster in the CDS than in the bond markets (Forte and Peña (2009), Delis and Mylonidis (2011)). Second, cash-flow differences between default swap contracts and bonds can also cause differences in spreads (Longstaff et al., 2005). Finally, the sovereign CDS market is more liquid than the corresponding sovereign bond market. CDS contracts provide a simple way to short credit risk, a costly strategy when implemented in the secondary cash market (Blanco et al., 2005).

peripheral (Greece, Ireland, Italy, Portugal and Spain) and the core countries is affected by the sharing of the euro as the common currency. Additionally, we estimate which portion of the sovereign CDS increment is attributable either to changes in default probabilities or to investor compensation by means of risk premia. Finally, we also address the time-evolution of the impact of peripheral countries on the components of the CDS spreads.

Our methodological approach consists of three parts. First, we estimate two bivariate BEKK-GARCH models to analyze the spillover effects between peripheral, core and non-EMU countries. Second, we use the decomposition technique described by Pan and Singleton (2008) to break the CDS spread down into two drivers: (i) the risk premium and (ii) its default component. The risk premium represents the compensation to investors due to changes in the default environment, commonly referred as the *distress* risk premium[2] (see Pan and Singleton, 2008; Longstaff et al., 2011). Lastly, we conduct a regression analysis of the components of sovereigns CDS spreads for non-distressed economies against a risk factor that is representative of the behavior of the peripheral countries.

The contribution of the chapter is threefold. First, we document a market segmentation between the central and the peripheral countries. A factorial analysis reveals two orthogonal components that distinguish the information content of the peripheral and the non-peripheral CDS spreads. These results extend to the CDS levels and their conditional volatilities, and, in accordance with Laubach (2009), they provide additional evidence supporting fragmentation in the credit markets. A preliminary analysis based on the use of the GARCH methodology for the CDS factors that drive distressed and non-distressed economies suggests a unidirectional volatility transmission pattern from the distressed to the non-distressed economies inside the European Economic and Monetary Union (EMU). A similar analysis for distressed and non-EMU economies does not reveal significant volatility spillover effects from inside to outside the euro, suggesting

[2] The distress risk premium differs from the *default event* premium, i.e., the compensation required for the bond price changes at the event of default. The default event premium has been the subject of analysis in previous studies such as Driessen (2005) or Berndt et al. (2005). A theoretical discussion about the default event premium can be found in Jarrow et al. (2005) or Yu (2002).

that retaining the local currency acts as a firewall.

Second, we estimate the compensation to investors for bearing the risk of default in non-distressed economies. According to Pan and Singleton (2008), our estimates are consistent with a systematic risk related to the future default uncertainty. The results also report an (averaged) median risk premium of 56% over the total CDS spreads. Although similar levels of risk premium are found on the median, this component is less volatile outside the EMU. Finally, our regression analysis supports the fact that the default contagion channels are represented not only by the risk premium but also by the default probabilities. Empirical evidence also indicates that the former channel is relatively more important than the latter. Our empirical findings are robust after controlling for both local and global macroeconomic and financial variables.

To summarize, this chapter analyzes the default risk channels between peripheral and central EU members using the information content of sovereign CDS spreads. The remainder of the chapter is as follows. Section 3.2 introduces the data and its main features. Section 3.3 directly analyzes the volatility transmission in the CDS spreads. Section 3.4 explores the determinants of sovereign CDS spreads and Section 3.5 presents the decomposition of CDS spreads into default and risk premium constituents. Finally, Section 3.6 provides some conclusions.

3.2. Data analysis

This section first presents our dataset. We next analyze the heteroskedastic behavior of default swaps. Finally, we explore the existence of commonalities in our data.

3.2.1. The dataset

Our sample comprises weekly CDS spreads with 1-, 3- and 5-year maturities of Senior Unsecured Sovereign debt denominated in USD under the Old Restructuring clause.[3]

[3] ISDA identifies six credit events: bankruptcy, failure to pay, debt restructuring, obligation default, obligation acceleration, and repudiation/moratorium. The Old Restructuring clause qualifies any restructuring event as a credit event, and any bond of maturity up to 30 years is deliverable.

Data are collected from CMA, which has been provided by Datastream.[4] Our dataset spans from January 2008 to July 2012, a period characterized by a significant increase in CDS levels, high volatility and uncertainty in the Eurosystem. We select the member countries of the EU since 1995 with available CDS spreads. More precisely, we collect the most important economies in terms of GDP that belong to the EMU – Austria, Belgium, Germany, Finland, France, Greece, Ireland, Italy, the Netherlands, Portugal and Spain – as well as some control countries – Denmark, Sweden and the United Kingdom (UK) – outside of the EMU area.

3.2.2. Univariate volatility analysis

A common feature in financial series is heteroskedasticity. This subsection analyzes the behavior of the univariate conditional variances for 5-year CDS spread increments, a matter of interest in a subsequent analysis. From the different families of GARCH models at our disposition, we select the Exponential GARCH, or EGARCH, introduced by Nelson (1991),

$$\Delta CDS_t = c + \varphi \Delta CDS_{t-1} + \epsilon_t \qquad (3.1)$$

$$\ln(h_t) = \alpha_0 + \sum_{j=1}^{q} g_j(z_{t-j}) + \sum_{i=1}^{p} \beta_i \ln(h_{t-i}) \qquad (3.2)$$

$$g_j(z_{t-j}) = \alpha_j z_{t-j} + \psi_j(|z_{t-j}| - E|z_{t-j}|) \qquad j = 1, \dots, q \qquad (3.3)$$

$$z_t \sim iid\, N(0,1)$$

where the mean equation follows an AR(1) process, and p and q denote the lags for the variance and the innovations, respectively. There are several reasons behind our modeling choice. First, the EGARCH allows for an asymmetric response to shocks; in this way, the model captures whether upward movements in the CDS spread market are followed by higher volatilities than the downward movements of the same magnitude.

[4] Mayordomo et al. (2010) provide empirical evidence that the quotes of the CMA database lead the price discovery process with respect to those provided by other databases such as Markit, JP Morgan or GFI, among others.

Second, our model does not require parameter restrictions to assure the positiveness of the conditional variance.

Table 3.1 reports the point estimates for the sample under study and Table 3.2 summarizes the structure of the final model considered with the corresponding diagnostic Lagrange Multiplier tests for the null hypothesis of no ARCH effects from the standardized residuals. Some interesting conclusions arise from these tables. First, we systematically observe the high persistence of volatility. This fact is reflected by the sum of the estimated GARCH parameters, which is close to one. Second, the parameters ψ_j that capture the asymmetries of shocks to the conditional variance are systematically positive (with the exception of Ireland). Within the context of our model, this pattern implies that the positive CDS increments tend to be associated with higher fluctuations. In contrast with the extant literature on asset markets, where the leverage effect means that a negative shock (bad news) increases the variance more than a positive shock, the nature of leverage for CDS is just the opposite. Therefore, parameter ψ_j is expected to be positive. In general, the parsimonious EGARCH(1,1) specification leads to standardized and squared standardized residuals that are free of autocorrelation for the core countries. However, additional heteroskedasticity structure is required for peripheral countries (see Table 3.2).

Table 3.1.: QML estimates of the EGARCH model for the CDS increments

This table reports the univariate QML estimates of the AR(1)-EGARCH(p,q) model of Nelson (1991),

$$
\begin{aligned}
\Delta CDS_t &= c + \varphi \Delta CDS_{t-1} + \epsilon_t \\
\ln(h_t) &= \alpha_0 + \sum_{j=1}^{q} g_j(z_{t-j}) + \sum_{i=1}^{p} \beta_i \ln(h_{t-i}) \\
g_j(z_{t-j}) &= \alpha_j z_{t-j} + \psi_j(|z_{t-j}| - E|z_{t-j}|) \qquad j = 1, \ldots, q \\
z_t &\sim iid\, N(0,1)
\end{aligned}
$$

The data comprise the 5-year CDS spread increments for each country. The p-values are in parentheses. The sample period spans from January 2008 to July 2012.

	Mean: AR(1)		Volatility: EGARCH(p,q)										
				β_{t-i}		α_{t-j}				ψ_{t-j}			
	c ($\times 10^{-2}$)	φ	α_0	β_{t-1}	β_{t-2}	α_{t-1}	α_{t-2}	α_{t-3}	α_{t-4}	ψ_{t-1}	ψ_{t-2}	ψ_{t-3}	ψ_{t-4}
Austria	-0.0033	-0.0008	-1.4437	0.0182	0.8764	0.2698	-0.0218			0.3955	0.6073		
	(0.272)	(0.992)	(0.046)	(0.668)	(0.000)	(0.012)	(0.846)			(0.000)	(0.001)		
Belgium	0.0132	0.0708	-0.2474	0.9813		0.2509				0.0843			
	(0.013)	(0.257)	(0.039)	(0.000)		(0.000)				(0.133)			
Germany	0.0016	0.1426	-1.0840	0.1395	0.7913	0.1251	0.1216	0.4071		0.5820	0.1882	-0.1735	
	(0.297)	(0.083)	(0.214)	(0.006)	(0.000)	(0.542)	(0.369)	(0.014)		(0.001)	(0.639)	(0.504)	
Denmark	0.0001	0.0672	-0.6937	0.6796	0.2698	0.2267				0.8312			
	(0.937)	(0.557)	(0.147)	(0.000)	(0.048)	(0.056)				(0.000)			
Finland	0.0014	0.1333	-1.0922	0.1180	0.8112	0.2824				0.5348			
	(0.479)	(0.436)	(0.237)	(0.320)	(0.000)	(0.035)				(0.000)			
France	0.0060	-0.3275	-0.8442	0.9395		0.1177				0.4996			
	(0.193)	(0.041)	(0.084)	(0.000)		(0.201)				(0.024)			
Greece	0.0119	-0.0092	0.1184	0.9700		0.1204	0.0533	0.2532	-0.0831	1.1461	-0.4078	0.3284	0.0149
	(0.023)	(0.910)	(0.062)	(0.000)		(0.157)	(0.561)	(0.067)	(0.460)	(0.000)	(0.006)	(0.027)	(0.903)
Ireland	0.0276	0.0596	-0.8261	0.9260		0.2075	0.0900			0.3053	0.0578		
	(0.000)	(0.000)	(0.012)	(0.000)		(0.124)	(0.633)			(0.339)	(0.765)		
Italy	0.0093	0.1340	-1.1851	0.3348	0.5682	0.2425	0.0518			0.4262	0.4546		
	(0.355)	(0.676)	(0.123)	(0.251)	(0.037)	(0.086)	(0.661)			(0.032)	(0.078)		
Netherlands	0.0012	0.2753	-1.0802	0.5174	0.4100	0.2644	-0.2836	0.2662		0.3379	0.1728	-0.0455	
	(0.700)	(0.000)	(0.197)	(0.100)	(0.167)	(0.036)	(0.043)	(0.104)		(0.024)	(0.423)	(0.810)	
Portugal	0.0185	0.0174	-0.5141	0.4239	0.5316	0.0359	0.2311	0.5418	-0.2671	0.4271	0.2871	-0.3990	0.5062
	(0.003)	(0.692)	(0.137)	(0.000)	(0.000)	(0.715)	(0.168)	(0.035)	(0.040)	(0.003)	(0.105)	(0.120)	(0.060)
Spain	0.0128	0.1758	-0.7331	0.1156	0.8267	0.1108	0.1513	0.2318	0.0622	0.4362	0.5314	-0.0939	-0.2030
	(0.308)	(0.448)	(0.496)	(0.490)	(0.000)	(0.394)	(0.500)	(0.035)	(0.652)	(0.075)	(0.066)	(0.546)	(0.399)
Sweden	0.0046	-0.2472	-0.5277	0.9635		0.2958				0.3914			
	(0.047)	(0.004)	(0.105)	(0.000)		(0.000)				(0.000)			
UK	0.0049	0.0631	-0.9500	0.9352		0.1852				0.4582			
	(0.074)	(0.636)	(0.105)	(0.000)		(0.002)				(0.027)			

Table 3.2.: LM tests of heteroskedasticity

	EGARCH(p,q)		Lags of LM test				
Country	p	q	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Austria	2	2	0.851	0.550	0.714	0.834	0.767
Belgium	1	1	0.803	0.872	0.898	0.922	0.948
Germany	2	3	0.657	0.575	0.748	0.618	0.751
Denmark	2	1	0.993	0.893	0.816	0.872	0.910
Finland	2	1	0.639	0.297	0.466	0.640	0.696
France	1	1	0.577	0.842	0.943	0.761	0.764
Greece	1	4	0.218	0.446	0.351	0.273	0.289
Ireland	1	2	0.568	0.513	0.542	0.702	0.646
Italy	2	2	0.947	0.988	0.999	0.999	0.995
Netherlands	2	3	0.995	0.990	0.989	0.969	0.983
Portugal	2	4	0.636	0.785	0.918	0.812	0.894
Spain	2	4	0.546	0.703	0.861	0.925	0.909
Sweden	1	1	0.914	0.855	0.385	0.556	0.537
UK	1	1	0.807	0.090	0.163	0.254	0.320

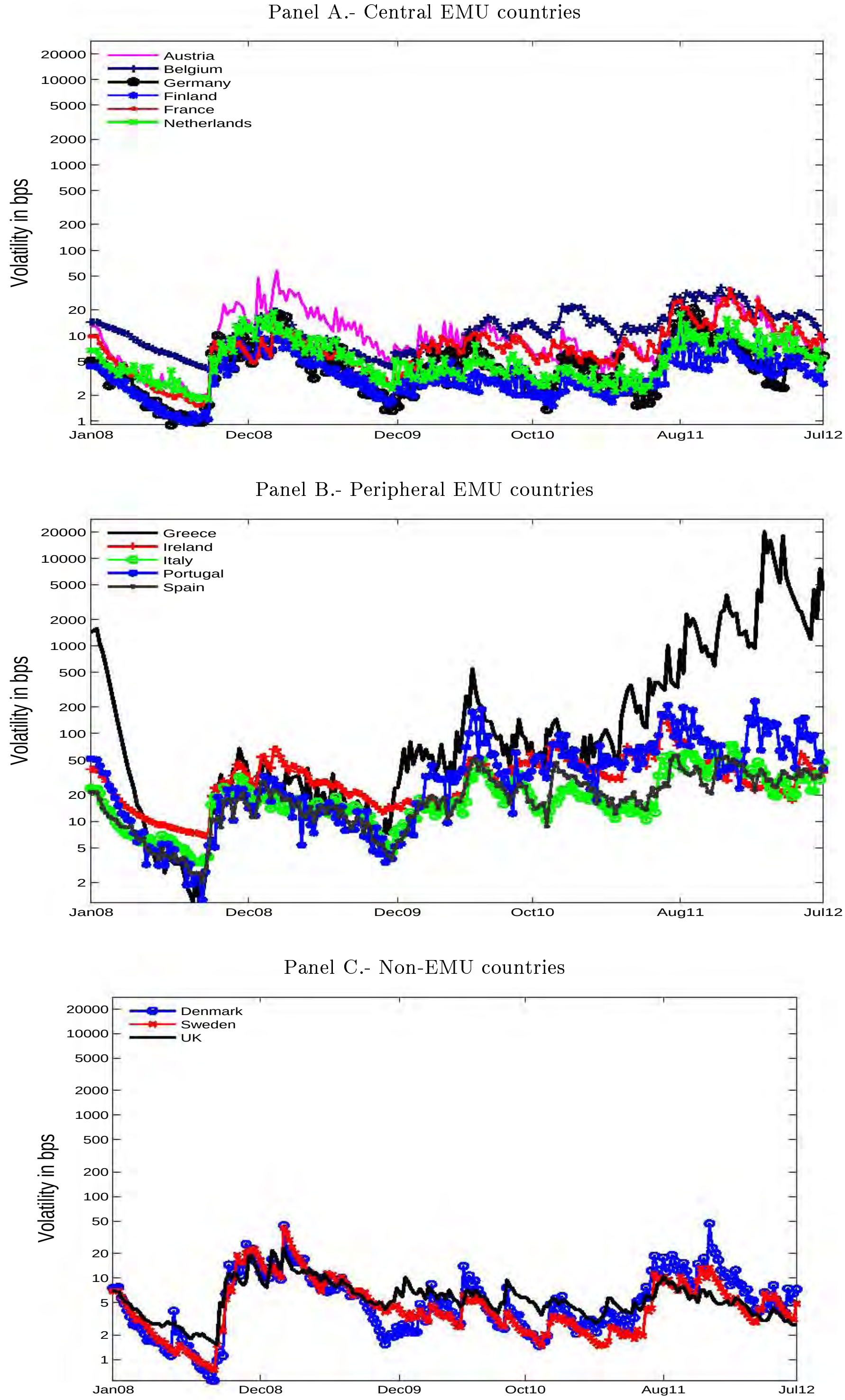
This table reports the p-values of the Lagrange Multiplier test at different lag lengths under the null hypothesis of no ARCH effects. This test of heteroskedasticity has been performed on the standardized residuals obtained from an AR(1)-EGARCH(p,q) univariate model applied to every country's 5-year CDS spread increments. The sample period spans from January 2008 to July 2012.

Figure 3.1 depicts the estimated conditional volatility for the central EMU (upper graph), peripheral EMU (medium graph) and non-EMU (lower graph) countries. To better appreciate the differences in the time-varying pattern, we use a logarithmic scale. From an inspection of Figure 3.1, we observe higher volatility for the peripheral economies. A high degree of comovement between the different groups of countries is also observed. Lastly, a shift in the volatility patterns appears to occur in the fall of 2008. This shift is consistent with the reassessment of the sovereign risk perceptions after the collapse of Lehman Brothers as noticed by Dieckmann and Plank (2012).

3.2.3. Factor analysis of CDS spreads

The existence of comovements between CDS spreads is addressed in several studies such as Longstaff et al. (2011) or Berndt and Obreja (2010), among others. However, not much is known about the presence of commonalities in the *volatilities* of CDS spreads. Table

Figure 3.1.: Volatility of 5-year CDS spread changes



This graph plots on a logarithmic scale (base 10) the conditional volatility (in basis points) from the estimated AR(1)-EGARCH(p,q) model for 5-year sovereign CDS spread increments. The central EMU countries are Austria, Belgium, Germany, Finland, France and the Netherlands. The peripheral EMU countries are Portugal, Ireland, Italy, Greece and Spain. The non-EMU countries are Denmark, Sweden and the UK. The sample frequency is weekly, and it spans from January 2008 to July 2012.

3.3 reports the factor analysis results for both CDS levels and volatilities. The Factors are denoted by F1-F3. The uniqueness columns refer to the idiosyncratic variance, that is, the variance that is exclusively attributable to the country and not shared with others. The greater the uniqueness, the lower the relevance of the country in the factor model. For ease of interpretation the factors are rotated using the varimax rotation technique.

Table 3.3.: Factor analysis for levels and variance of 5-year CDS increments.

	Mean				Variance			
Country	F1	F2	F3	Uniqueness	F1	F2	F3	Uniqueness
Panel A.- Loading factors								
Austria	0.8715	0.3591	0.2293	0.0135	0.6519	-0.4195	-0.0911	0.3317
Belgium	0.9756	-0.2197	0.0032	0.0000	0.7324	0.4569	-0.1533	0.1970
Germany	0.9746	0.0711	0.0689	0.0142	0.7254	-0.0090	0.1727	0.3147
Denmark	0.8886	0.4586	-0.0127	0.0000	0.7310	-0.2376	-0.2154	0.2166
Finland	0.9222	0.3364	0.0612	0.0154	0.8568	-0.2328	0.1345	0.1310
France	0.9741	-0.1162	-0.1034	0.0031	0.7536	0.4454	-0.3035	0.1267
Greece	0.6567	-0.0103	-0.3970	0.1830	0.0720	0.1386	-0.0506	0.8071
Ireland	0.8420	-0.3504	0.0723	0.0052	0.3145	0.2553	0.5046	0.5303
Italy	0.9622	-0.0721	-0.1295	0.0183	0.7015	0.5638	-0.0581	0.1581
Netherlands	0.9210	0.3052	0.0900	0.0149	0.7878	-0.2906	-0.0131	0.2047
Portugal	0.8916	-0.2587	-0.2412	0.0137	0.2843	0.4656	0.4389	0.4743
Spain	0.9043	-0.2580	-0.0940	0.0122	0.5899	0.5796	-0.0371	0.2721
Sweden	0.4770	0.7536	0.4455	0.0000	0.6183	-0.6504	0.0588	0.1374
UK	0.5749	0.4538	0.6209	0.0000	0.5374	-0.6440	0.1378	0.2452
Panel B.- Explained variance (%)								
Total	75.40	12.02	6.64	–	61.46	28.01	7.58	–

Factor analysis (rotated) for the mean (columns two to four) and variance (columns six to eight) of 5-year CDS spread increments. The time series of variance have been computed using the Nelson (1991) model. Panel A displays the loading factors for each country for the first three components and their uniqueness. Panel B exhibits the explained variance for each factor. The sample period spans from January 2008 to July 2012.

Some interesting results arise from Table 3.3. F1 and F2 in levels (volatilities) account for approximately 87% (89%) of the total explained variance. A close inspection of the factor loadings allows us to identify the countries that are related to each factor. With regard to the analysis in levels, F1 has large and positive coefficients for all countries. In contrast, F2 emphasizes the distinctive feature of the peripheral countries. Finally, Greece appears to be the least important country in the factor structure both in levels and volatilities. In conclusion, two sources of commonality attending to debt sustainability are identified from the European sovereign CDS market.

3.3. Volatility transmission between the peripheral and the non-peripheral areas

Motivated by the existence of orthogonal sources of commonality among the EU regions, this section analyzes the volatility transmission between these geographical areas. To avoid spurious causal relationships, we gather our sample around three different blocks of countries – peripheral EMU, non-peripheral EMU and selected EU countries (Denmark, Sweden and the UK) whose local currency is not the euro. This clustering is supported by the empirical findings from the factor analysis in Section 3.2.3, where a fragmentation of the sovereign default swap market into different groups is observed. Finally, we reduce the dimensionality of the problem by performing a factor analysis on each set of countries, keeping their first factor. In the three cases, just one principal component is observed following the rule of eigenvalues greater than one.

A multivariate heteroskedastic model is employed to capture any possible volatility spillovers between the common trends in the CDS. In particular, we estimate a bivariate GARCH from the pairs of first-differenced factors. We employ the popular BEKK model specification of Engle and Kroner (1995). Many other multivariate GARCH specifications are special cases of the BEKK specification, such as the factor model of Engle et al. (1990), the orthogonal GARCH model of Alexander (2001) or the GO-GARCH model of Weide (2002), among others. Our posited alternative (i) reduces the number of parameters to be estimated compared to other multivariate GARCH specifications such as, for example, the VECH model, and (ii) interestingly enough, the conditional covariance matrix is guaranteed to be positive definite by construction.

We propose the following BEKK specification:

$$\begin{pmatrix} \Delta PC_{r,t} \\ \Delta PC_{s,t} \end{pmatrix} = \begin{pmatrix} \alpha_{11} & 0 \\ 0 & \alpha_{22} \end{pmatrix} \begin{pmatrix} \Delta PC_{r,t-1} \\ \Delta PC_{s,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{r,t} \\ \epsilon_{s,t} \end{pmatrix}, \quad \epsilon_t \sim N(0, H_t) \tag{3.4}$$

$$H_t = CC' + \sum_{k=1}^{p} A_k^{'} \epsilon_{t-k} \epsilon_{t-k}^{'} A_k + \sum_{k=1}^{q} B_k^{'} H_{t-k} B_k \tag{3.5}$$

where H_t denotes the variance-covariance matrix; A_k, B_k and C are 2×2 parameter matrices; and C is lower triangular. The conditional variances depend on the lagged squared conditional variances and the lagged squared errors, whereas the covariances depend on the cross-products of the lagged conditional variances and errors, respectively. The diagonal elements in matrices A_k capture the own ARCH effects, while the diagonal elements in matrices B_k measure the own GARCH effects. The off-diagonal elements capture the potential cross-effects between the first differences of factors. The structure $p = q = 1$ appears to be a valid specification to capture the volatility dynamics.

For ease of interpretation, the elements of the covariance matrix in the case of $p = q = 1$ are expressed below:

$$\begin{aligned} \sigma^2_{r,t} &= c^2_{11} + a^2_{11}\epsilon^2_{r,t-1} + 2a_{11}a_{21}\epsilon_{r,t-1}\epsilon_{s,t-1} + a^2_{21}\epsilon^2_{s,t-1} + b^2_{11}\sigma^2_{r,t-1} \\ &+ 2b_{11}b_{21}\sigma_{rs,t-1} + b^2_{21}\sigma^2_{s,t-1} \end{aligned} \tag{3.6}$$

$$\begin{aligned} \sigma_{rs,t} &= c_{11}c_{21} + a_{11}a_{12}\epsilon^2_{r,t-1} + a_{11}a_{22}\epsilon_{r,t-1}\epsilon_{s,t-1} + a_{12}a_{21}\epsilon_{r,t-1}\epsilon_{s,t-1} + a_{22}a_{21}\epsilon^2_{s,t-1} \\ &+ b_{11}b_{12}\sigma^2_{r,t-1} + b_{12}b_{21}\sigma_{rs,t-1} + b_{11}b_{22}\sigma_{rs,t-1} + b_{22}b_{21}\sigma^2_{s,t-1} \end{aligned} \tag{3.7}$$

$$\begin{aligned} \sigma^2_{s,t} &= c^2_{21} + c^2_{22} + a^2_{12}\epsilon^2_{r,t-1} + 2a_{22}a_{12}\epsilon_{r,t-1}\epsilon_{s,t-1} + a^2_{22}\epsilon^2_{s,t-1} + b^2_{12}\sigma^2_{r,t-1} \\ &+ 2b_{22}b_{12}\sigma_{rs,t-1} + b^2_{22}\sigma^2_{s,t-1} \end{aligned} \tag{3.8}$$

where a_{ij} and b_{ij} denote the i-th row and j-th element of matrix A_1 and B_1, respectively.

The BEKK-GARCH specification presents some inference difficulties, because spillover effects are obtained via the multiplication/addition of various parameter estimates. Therefore, it is not possible to identify the source of volatility spillovers by directly checking the significance of the parameters involved in matrices A and B. We test the directional source of volatility transmission by regarding the significance of b^2_{21} and b^2_{12} in equations (3.6) and (3.8), respectively. We use the delta method to estimate the standard errors of the squared parameters.

Table 3.4 shows the Quasi-Maximum Likelihood (QML) estimation of the bivariate BEKK-GARCH models for each pair of factors (non-peripheral / peripheral and non-EMU / peripheral) considered, while Table 3.5 reports the model diagnostics based on the standardized residuals. From Table 3.5, our bivariate GARCH specification is a statistically valid representation of the cross-interactions for each pair of heteroskedastic factors under analysis.

Back to Table 3.4, we explore the directional causality between peer factors. Inside the EMU, we detect a unidirectional causal relationship from the peripheral to the non-peripheral countries for volatilities. The squared parameter involved is significantly different from zero at conventional significance levels. However, empirical evidence suggests that there is no transmission channel from the EMU-peripheral area to the non-EMU economies. Past volatility in peripheral countries does not anticipate an increase of volatility in non-EMU countries.

Figure 3.2 displays the estimated conditional correlations for each bivariate GARCH model. The correlation coefficients between peripheral and non-peripheral countries suggest a strong comovement inside the Eurozone. Moreover, the magnitude of the coefficients tends to be higher than that corresponding to the peripheral and non-EMU countries, especially until the beginning of January 2010.

3.4. The determinants of credit spreads

Because peripheral countries spill over into non-peripheral economies inside the EMU, this section analyzes the impact of the peripheral risk factor into the remainder sovereign CDS spreads.

3.4.1. Control variables

We run OLS regressions of CDS increments for non-EU and central EMU countries on the peripheral risk factor, but controlling for a set of local and global variables following

Table 3.4.: BEKK estimations

This table reports the BEKK estimations under the model,

$$\begin{aligned}\begin{pmatrix}\Delta PC_{r,t}\\ \Delta PC_{s,t}\end{pmatrix} &= \begin{pmatrix}\alpha_{11} & 0\\ 0 & \alpha_{22}\end{pmatrix}\begin{pmatrix}\Delta PC_{r,t-1}\\ \Delta PC_{s,t-1}\end{pmatrix} + \begin{pmatrix}\epsilon_{r,t}\\ \epsilon_{s,t}\end{pmatrix}, \quad \epsilon_t \sim N(0, H_t)\\ H_t &= CC^{'} + \sum_{k=1}^{p} A_k^{'}\epsilon_{t-k}\epsilon_{t-k}^{'}A_k + \sum_{k=1}^{q} B_k^{'}H_{t-k}B_k\end{aligned}$$

where c_{ij}, $a_{ij,k}$ and $b_{ij,k}$ denote the i-th row, j-th column element of the matrices C, A_k and B_k, respectively. The sample period spans from January 2008 to July 2012.

Non-Peripheral (r) *vs* Peripheral (s)			Non-EMU (r) *vs* Peripheral (s)		
	Coeff	p-value		Coeff	p-value
α_{11}	0.2028	0.0003	α_{11}	0.1907	0.0012
α_{22}	0.1701	0.0162	α_{22}	-0.0145	0.7997
c_{11}	0.1008	0.0443	c_{11}	0.0048	0.5288
c_{21}	0.0404	0.0000	c_{21}	-0.0149	0.0327
c_{22}	0.0185	0.0030	c_{22}	0.0001	0.9196
$a_{11,1}$	0.4696	0.0000	$a_{11,1}$	-0.7009	0.0000
$a_{12,1}$	-0.3005	0.0098	$a_{12,1}$	0.3425	0.0013
$a_{21,1}$	0.0441	0.5362	$a_{21,1}$	-0.3180	0.0000
$a_{22,1}$	0.5719	0.0000	$a_{22,1}$	0.8563	0.0000
$b_{11,1}$	0.8509	0.0000	$b_{11,1}$	-0.8603	0.0000
$b_{12,1}$	0.0011	0.9611	$b_{12,1}$	-0.0217	0.1623
$b_{21,1}$	0.1419	0.0158	$b_{21,1}$	0.0408	0.4029
$b_{22,1}$	0.8598	0.000	$b_{22,1}$	-0.8045	0.0000
Log-Likelihood	372.8807		Log-Likelihood	412.4141	

Figure 3.2.: Time-varying conditional correlation between factors

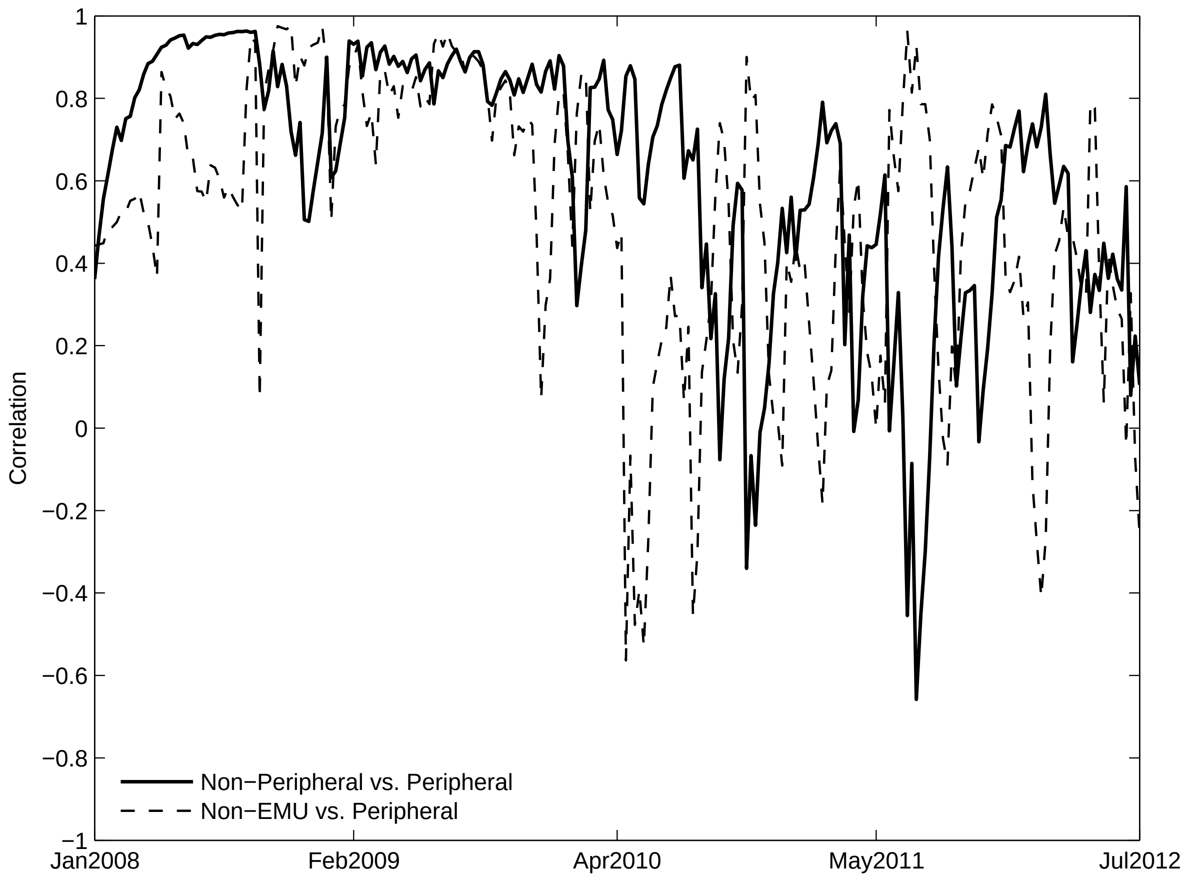


Table 3.5.: Ljung-Box Tests on the BEKK residuals

	Non-Peripheral *vs.* Peripheral		Non-EMU *vs.* Peripheral	
	Non-Peripheral	Peripheral	Non-EMU	Peripheral
Standardized residuals	13.0796	20.4741	24.4026	23.9629
	(0.8739)	(0.4286)	(0.2252)	(0.2440)
Squared-standardized residuals	16.2258	15.7444	30.0271	13.9007
	(0.7025)	(0.7323)	(0.0694)	(0.8355)

This table reports the Ljung-Box Portmanteau tests for the null of the absence of autocorrelation using 20 lags. The P-values are reported in parentheses. The residuals come from the BEKK model. The sample period spans from January 2008 to July 2012.

the research design in Longstaff et al. (2011). Table 3.6 provides a detailed description of the control variables as well as some recent papers that support the choice of these variables.

The local variables include a CDS liquidity proxy, the local stock market return and its realized volatility, the relevant exchange rate and its 1-month option implied volatility and the corresponding interest rate for each monetary region. Additionally, the global variables incorporate a worldwide CDS liquidity score, the EuroStoxx50 index returns, the volatility risk premium, the Chicago Board of Trade S&P 500 Implied Correlation Index, the constant maturity 5-year US Treasury yield and the spread between AA-rated and BBB-rated European corporates.

Concerning the local variables, some early articles have considered the CDS market to be a liquidity frictionless market (Blanco et al., 2005; Longstaff et al., 2005). However, Tang and Yan (2007) found that the liquidity measures are important determinants of default swap spreads. For that reason, we use Fitch's liquidity scores for the individual sovereign CDS. The higher the Fitch score is, the lower the CDS liquidity is. This measure takes into account the information content in the bid-ask spread, the staleness of quotes and the dispersion of mid-quotes across brokers. This variable has the advantage of summarizing several liquidity proxies into a single one, allowing for a direct comparison through time and across countries.

Table 3.6.: Variable definitions

Name	Definition	Main references
	Panel A.- Local variables	
LiqCDS	Fitch s Liquidity scores for each 5-year sovereign CDS. The higher the score is, the more illiquid is the CDS	Blanco et al. (2005), Longstaff et al. (2005), Tang and Yan (2007), Bongaerts et al. (2011)
StM Local	Primary stock market index for each country. The indices used are the following: ATX (Austria), BEL 20 (Belgium), DAX (Germany), OMXC 20 (Denmark), OMXH (Finland), CAC 40 (France), AEX (the Netherlands), OMXS 30 (Sweden), and FTSE 100 (the UK)	Longstaff et al. (2011), Dieckmann and Plank (2012)
StM Vol	20-day average realized volatility of the domestic stock market indices using the open-high-low-close volatility estimator of Garman and Klass (1980) in %	Zhang et al. (2009)
Forex	Exchange rate of the domestic currency (Euro, Danish Krone, Swedish Krona or British Pound) relative to USD	
Forex Vol	1-month option implied volatility in % for the exchange rate of the domestic currency (Euro, Danish Krone, Swedish Krona or British Pound)	Carr and Wu (2007), Hui and Chung (2011)
MP Rate	Monetary policy interest rate. Day-to-day money market interest rates on unsecured loans for each monetary region in %. The indices used are the Euro OverNight Index Average (EONIA), the Danish Kroner Tomorrow/Next interest rate (DKTONXT), the Stockholm Interbank Offered Rate (STIBOR), and the Sterling OverNight Index Average (SONIA)	
	Panel B.- Global variables	
LiqCDS Sov	Fitch s Liquidity Score for all 5-year sovereign CDS worldwide. The higher the score is, the more illiquid is the overall sovereign CDS market	
EuroStoxx50	EuroStoxx50 index	
Vol Premium	Difference between the VSTOXX and the 20-day average realized volatility in the EuroStoxx50 index. The VSTOXX is the EuroStoxx50 s 1-month option implied volatility in %. The realized volatility measure is calculated using the open-high-low-close volatility estimator of Garman and Klass (1980)	Collin-Dufresne et al. (2001), Pan and Singleton (2008), Carr and Wu (2006) , Carr and Wu (2009), Bollerslev et al. (2009), Bollerslev et al. (2011)
Imp Corr	On-the-run CBOE S&P 500 Implied Correlation Index in %	Driessen et al. (2009)
5y Yield	Constant maturity 5-year US Treasury s yield in %	
IG AA-BBB	Price spread between AA-rated and BBB-rated European investment grade corporates. Calculated using the IBOXX Euro Corporate Price Indexes for 3-5 year maturity bonds.	
CDS Peripheral	The first factor of the 5-year maturity sovereign CDS spreads for all peripheral countries	

The global variables are the same for each country. The local variables are specific to each country except the variables Forex, Forex Vol and MP Rate, which are specific to each monetary region (Eurozone, Denmark, Sweden and the UK). The sources for the variables are Datastream, Thomson Reuters and Yahoo Finance. The displayed references are those that can provide a better description of the variable or those that use a similar measure in their empirical research.

Stock markets also contain important information about the state of the local economy (Longstaff et al., 2011; Dieckmann and Plank, 2012). Moreover, Zhang et al. (2009) have also shown that the volatility of the stock market can predict a large variation in the corporate CDS spreads. We proxy local volatility using the open-high-low-close volatility estimator of Garman and Klass (1980).

The exchange rate could also provide additional information on the country's creditworthiness. Carr and Wu (2007) propose a joint modeling of the exchange rate volatility and the sovereign default risk to capture the co-movements between the volatility of the currency options and the sovereign CDS market. For this reason, we also include the option-implied volatility of the local currency. Finally, day-to-day money market interest rates on unsecured loans for each monetary region are a proxy for funding risk. These data complete the local information set.

With regard to the global variables, the Fitch's Liquidity Score for 5-year sovereign CDS worldwide is the global version of the individual Fitch measure previously mentioned. We also employ the premium for bearing the volatility risk of an option position. This volatility risk premium accounts for the difference between the implied and the realized volatility, and it represents the price of a variance swap contract (Carr and Wu, 2006, 2009; Bollerslev et al., 2009). We define this type of volatility risk premium as the difference between the 1-month VSTOXX option-implied volatility index and the realized volatility estimator of Garman and Klass (1980).

An increase in the stock market correlations can damage the investment opportunities and worsen the diversification benefits (Driessen et al., 2009). Thus, we incorporate the Chicago Board of Trade S&P 500 Implied Correlation Index. Moreover, we consider some standard market variables that capture the state of the economy such as (i) the 5-year US Treasury yield, which can be seen as a safe haven debt security in comparison to the European debt securities and (ii) the spread between AA-rated and BBB-rated European investment grade corporates, which summarizes the European corporate bond market situation.

Finally, the ΔCDS Peripheral variable comprises the first factor scores in the factor analysis structure involving the five peripheral countries. This variable captures the commonality among the financially distressed economies, and it is the main object of our analysis.

3.4.2. OLS estimates

Table 3.7 shows the resulting OLS estimates from projecting the individual default swap increments onto the local and global variable set. We also report the p-values based on the White (1980) heteroskedasticity-consistent estimate of the covariance matrix and the adjusted R^2. To emphasize the contribution of the peripheral component to the non-peripheral spreads, we repeat our regressions, omitting the related variable (ΔCDS Peripheral). In this way, the term R^2-Adj Before represents the adjusted coefficient of determination excluding the mentioned variable. Additionally, we also explore differences between EMU and non-EMU membership.

Several results arise from Table 3.7. For the local variables (panel A), the exchange rate fluctuations appear to be a key variable in explaining the CDS spread increments. Given that the CDS contracts are nominated in USD, a significant and positive coefficient for the exchange rates reveals that USD appreciation against the local currency results in increments of default swaps. However, stock market changes are not significant to explain spread changes, in contrast to the empirical findings reported in Longstaff et al. (2011) for 12 emerging economies. With regard to the global variables, no control variable is successful in explaining the CDS spread changes with the exception of the peripheral factor. However, the explanatory ability of these local and global variables is not as high as reported in Longstaff et al. (2011) for emerging countries as well as for some developed countries such as Japan.

The factor representing financially distressed economies significantly affects the increments of the CDS spreads. The associated coefficient is systematically positive. This pattern is noticeable for both EMU and non-EMU countries. Interestingly, the explanatory ability of the OLS clearly improves after the inclusion of the peripheral component as an additional regressor. While the adjusted R^2s excluding the peripheral CDS com-

Table 3.7.: Regression for 5-year CDS increments

	EMU						Non-EMU		
	Austria	Belgium	Germany	Finland	France	Netherlands	Denmark	Sweden	UK
Cons.	-0.000005	-0.000001	0.000016	-0.000009	0.000026	-0.000008	0.000011	-0.000017	-0.000012
					Panel A.- Local variables				
ΔLiqCDS	0.000214	0.000052	-0.000077	-0.000124	0.000037	-0.000358	0.000197	-0.000386	-0.000653
ΔStM Local	-0.000003**	0.000001	-0.000001**	-0.000000*	-0.000007***	-0.000021*	-0.000006	-0.000003	-0.000000
ΔStM Vol	-0.000038*	-0.000021	-0.000017	-0.000002	-0.000027	-0.000016	-0.000027	0.000013	0.000004
ΔForex	0.016470***	0.019866***	0.006035***	0.005780**	0.010869***	0.008698***	0.001256**	0.001218***	0.015759***
ΔForex Vol	-0.000019	0.000063	0.000031	-0.000016	0.000101***	0.000012	0.000025	-0.000001	0.000056
ΔMP rate	-0.000077	-0.000480	0.000090	0.000006	-0.000302	-0.000241	0.000182	-0.000707	0.000236
					Panel B.- Global variables				
ΔLiqCDS Sov	-0.000372	0.000376	-0.000224	-0.000119	-0.000088	0.000180	-0.000355	0.000171	0.000404
ΔEuroStoxx50	-0.000002	-0.000005*	0.000000	-0.000001	0.000005*	-0.000001	-0.000002***	-0.000001	-0.000002*
ΔVol Premium	-0.000005	-0.000007	-0.000004	-0.000005	-0.000003	-0.000010	-0.000009	-0.000008	-0.000009
ΔImp Corr	0.000019	0.000008	0.000005	0.000009	0.000031	0.000019	0.000014	-0.000002	0.000018
Δ5y Yield	0.000921	0.000273	0.000319	0.000052	0.000683**	0.000388	0.000134	0.000065	0.000172
ΔIG AA-BBB	0.000479**	0.000327	0.000153*	0.000100	0.000215	0.000113	0.000229	-0.000030	-0.000084
ΔCDS Peripheral	0.002234**	0.003637***	0.000850**	0.000865***	0.001880***	0.001101**	0.001024*	0.001464***	0.001465***
Obs.	236	236	236	234	236	224	231	217	207
R^2-Adj Before	0.2761	0.2636	0.3470	0.2482	0.3324	0.3045	0.2638	0.2454	0.3234
R^2-Adj	0.3249	0.3742	0.3930	0.3128	0.3943	0.3494	0.2946	0.3202	0.4043

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

The significance of the variables is tested using White (1980) t-statistics. The "R^2-Adj Before" row refers to the R-squared for the same regression but without including the variable "ΔCDS Peripheral". The "R^2-Adj" row is the adjusted R-squared for the displayed regression that includes the variable "ΔCDS Peripheral". The sample period spans from January 2008 to July 2012.

ponent range from 25% to 35%, the explanatory power of the regressions increases after the inclusion of this variable.

In conclusion, the behavior of the peripheral economies and the exchange rates are the main variables that account for CDS variability. However, we cannot appreciate a clear pattern for the effect of global variables.

3.5. Decomposing the CDS spreads

Previous empirical evidence suggests that there is a risk channel transmission from the peripheral to the non-peripheral countries. How this transference passes through each country poses an intriguing question. This section explores the nature of risk transmission at an individual level. We decompose the default swap spreads into two components: default risk and risk premium. This distinction allows us to disentangle the impact of distressed economies in EU countries due to changes in the default risk or the investors' risk appetite. We outline the methodology of Pan and Singleton (2008) for the CDS decomposition, providing an econometric framework for its estimation.

3.5.1. The model

We adopt the intensity approach of Pan and Singleton (2008) and Longstaff et al. (2011) to decompose the CDS spreads into default risk and risk premium components. Within this framework, the credit event is triggered by the first jump of a Poisson process with stochastic intensity,

$$d\ln\lambda_t^Q \;=\; \kappa^Q\left(\theta^Q - \ln\lambda_t^Q\right)dt + \sigma dW_t^Q, \tag{3.9}$$

where κ^Q, θ^Q and σ stands for the mean-reversion speed, the long-run mean and the volatility of the process, respectively. The log-intensities in (3.9) follow an Ornstein-Uhlenbeck process, which ensures the positiveness of the default intensity.

Under this formulation, Longstaff et al. (2005) or Pan and Singleton (2008) provide an expression for computing the CDS spreads,

$$CDS_t^Q(M) = \frac{4\,L^Q \int_t^{t+M} E_t^Q \left[\lambda_u^Q e^{-\int_t^u (r_s+\lambda_s^Q)\,ds}\right] du}{\sum_{i=1}^{4M} E_t^Q \left[e^{-\int_t^{t+.25i}(r_s+\lambda_s^Q)\,ds}\right]} \quad , \tag{3.10}$$

where M is the maturity of the CDS, r_t is the risk-free rate and L^Q is the risk-neutral expected losses. We consider a loss given default of 60%, which is a standard assumption in the literature.

The risk-neutral intensity process (3.9) admits an equivalent formulation in terms of the actual measure P,

$$d\ln\lambda_t^Q \;=\; \kappa^P(\theta^P - \ln\lambda_t^Q)dt + \sigma dW_t^P, \tag{3.11}$$

where $\kappa^P = \kappa^Q - \delta_1\sigma$ and $\kappa^P\theta^P = \kappa^Q\theta^Q + \delta_0\sigma$. Parameters δ_0 and δ_1 determine the market price of risk,

$$dW^Q \;=\; (\delta_0 + \delta_1 \ln\lambda^Q)dt + dW^P \tag{3.12}$$

From the previous expressions for the risk-neutral intensity, notice that equation (3.11) collapses to (3.9) when parameters δ_0 and δ_1 equal zero (no compensation for changes in the default environment). Then, if there is no risk premium embedded in the CDS spreads, expressions (3.9) and (3.11) are equal, and the difference between the CDS spreads (CDS^Q) computed under risk-neutral Q and actual P measures,

$$CDS_t^P(M) = \frac{4\,L^Q \int_t^{t+M} E_t^P \left[\lambda_u^Q e^{-\int_t^u (r_s+\lambda_s^Q)\,ds}\right] du}{\sum_{i=1}^{4M} E_t^P \left[e^{-\int_t^{t+.25i}(r_s+\lambda_s^Q)\,ds}\right]} \quad , \tag{3.13}$$

is zero. Otherwise, the divergences between CDS^Q and CDS^P capture the risk premium embedded in the CDS spreads for compensating changes in the default environment.

It is worth mentioning that our risk premium represents compensation due to changes in the default conditions (changes in economic fundamentals, etc.) rather than a reward for the default itself. The former is called *distress* premium, and it was previously analyzed by Pan and Singleton (2008) or Longstaff et al. (2011), among others. The latter is called default-event premium; it has been studied by Yu (2002), Pan and Singleton (2006), Driessen (2005) and Berndt et al. (2005), and it is out of the scope of our study. Jarrow et al. (2005) present a unifying framework of both premia within the intensity model.

3.5.2. Estimation procedure

We estimate the parameters of our model using maximum likelihood (ML). We summarize here the main steps involved. For simplicity, we denote λ^Q as λ. First, we assume that 3-year CDS contracts are perfectly priced; given a set of κ^Q, θ^Q and σ parameters, we recover a time series for λ by means of a non-linear optimization technique. Second, the differences between the sample and the theoretical 1- and 5-year CDS contracts are priced with normally distributed errors ϵ_{1y} and ϵ_{5y} with zero means and standard deviations $\sigma(1)$ and $\sigma(5)$, respectively. Third, we use the bootstrapped USD Libor-Swap curve as the risk-free rate to discount future payoffs. Specifically, we employ the 3-, 6-, 9- and 12-month USD Libor published by the British Bankers' Association. We also use the 2-, 3-, 4- and 5-year USD interest rate swaps from the Federal Reserve Statistical Release H.15. Fourth, the expectations in equations (3.10) and (3.13) when λ^Q follows a log-OU process are not in closed form, so they are computed using a Crank-Nicholson discretization scheme for the corresponding partial differential equation. Finally, the joint density function is

$$\begin{aligned} f^P(\Theta,\lambda) &= f^P(\epsilon_{1y}|\sigma(1)) \times f^P(\epsilon_{5y}|\sigma(5)) \times f^P(\ln\lambda|\kappa^P,\kappa^P\theta^P,\sigma) \\ &\times \left|\partial CDS^Q(\lambda|\kappa^Q,\kappa^Q\theta^Q,\sigma)/\partial\lambda\right|^{-1} \end{aligned} \tag{3.14}$$

with parameter vector $\Theta = (\kappa^Q, \theta^Q\kappa^Q, \sigma^Q, \kappa^P, \theta^P\kappa^P, \sigma(1), \sigma(5))$ and $f^P(\cdot)$ representing the density function of the Normal distribution, and Δt equal to 1/52.

3.5.3. Maximum likelihood estimates

Table 3.8 displays the ML estimates for the sample under study. We observe that the convergence of different default intensity processes to a particular long-run mean are faster in the actual world than in risk-neutral environments ($\kappa^P > \kappa^Q$), indicating that the default arrival rates as seen by risk-neutral investors tend to explode as time goes by. Moreover, the average default intensity level is much lower in the actual than in the risk-neutral measure $\kappa^Q\theta^Q > \kappa^P\theta^P$. Our results are quite similar to those reported in Pan and Singleton (2008) and Longstaff et al. (2011) in the context of emerging economies.

Table 3.8.: ML estimates for logOU model

Country	κ^Q	$\kappa^Q\theta^Q$	σ^Q	κ^P	$\kappa^P\theta^P$	$\sigma(1)$	$\sigma(5)$	LogLk
Austria	0.0423	-0.2625	0.9613	0.3391	-1.9816	0.0011	0.0010	3916.46
	(0.0091)	(0.0326)	(0.0078)	(0.3753)	(2.0386)	(0.0000)	(0.0001)	
Belgium	-0.0951	0.1094	1.1900	1.2505	-6.2719	0.0014	0.0008	3825.37
	(0.0086)	(0.0305)	(0.0101)	(0.7391)	(3.9398)	(0.0000)	(0.0000)	
Germany	0.0383	-0.2247	1.0111	0.5837	-3.7873	0.0004	0.0010	4319.61
	(0.0116)	(0.0516)	(0.0060)	(0.5287)	(3.4166)	(0.0000)	(0.0000)	
Denmark	0.0727	-0.4915	1.1102	0.3024	-1.9884	0.0006	0.0005	4294.69
	(0.0085)	(0.0334)	(0.0061)	(0.5102)	(3.0841)	(0.0000)	(0.0000)	
Finland	0.1520	-0.8825	1.0608	0.9904	-6.5735	0.0004	0.0006	4468.76
	(0.0096)	(0.0414)	(0.0049)	(0.4817)	(3.0949)	(0.0000)	(0.0000)	
France	-0.0337	0.1267	0.8960	0.4889	-2.7258	0.0008	0.0010	4045.66
	(0.0112)	(0.0399)	(0.0061)	(0.4866)	(2.7953)	(0.0000)	(0.0000)	
Netherlands	0.1155	-0.6886	1.0298	0.3143	-1.9318	0.0003	0.0010	4314.34
	(0.0098)	(0.0426)	(0.0061)	(0.4015)	(2.4851)	(0.0000)	(0.0000)	
Sweden	0.2117	-1.1923	1.2001	0.4758	-3.2467	0.0005	0.0004	4450.32
	(0.0076)	(0.0333)	(0.0057)	(0.4808)	(3.0685)	(0.0000)	(0.0000)	
UK	0.1683	-0.8854	1.1151	0.3626	-2.3770	0.0004	0.0011	4209.76
	(0.0106)	(0.0446)	(0.0061)	(0.5278)	(3.2166)	(0.0000)	(0.0001)	

This table provides the maximum likelihood estimates for the Pan and Singleton (2008) model. The standard errors are in parentheses. κ^Q, θ^Q and σ^Q denote the mean reversion, the long run mean and the instantaneous volatility of the default intensity process λ^Q under the Q probability measure, respectively. Analogously, κ^P and θ^P are the mean reversion rate and the long run mean under the objective measure P, respectively. $\sigma(M)$ is the deviation of the CDS spread mispricing for maturities 1- and 5-years. Weekly data are used from January 2008 to July 2012.

We also address the performance of the model under two different criteria. First, Figure 3.3 displays the cross-sectional, averaged pricing errors for our sample of countries. As shown, the pricing errors are (on average) close to zero. Second, Table 3.9 shows the projections of the sample CDS spread increments onto their theoretical counterparts. An intercept and slope coefficients close to zero and one, respectively, indicate a reasonable fit for the model. From Table 3.9, we systematically observe that the intercepts are zero and the slopes close to one, no matter the maturity considered. Additionally, the overall R-squared coefficient is 85% and the standard deviation of residuals is lower than four basis points.

Table 3.9.: Projections of sample values onto fitted values for the logOU model

	$\Delta CDS_t^{sample} = \beta_0 + \beta_1 \Delta CDS_t^{theo} + \epsilon_t$				
Maturity	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	std. res. (bps)	N
1 Year	-0.00	0.98	0.80	3.43	2115
	(0.00)	(0.01)			
5 Year	0.00	0.96	0.90	2.87	2115
	(0.00)	(0.01)			
Overall	0.00	0.97	0.85	3.16	4230
	(0.00)	(0.01)			

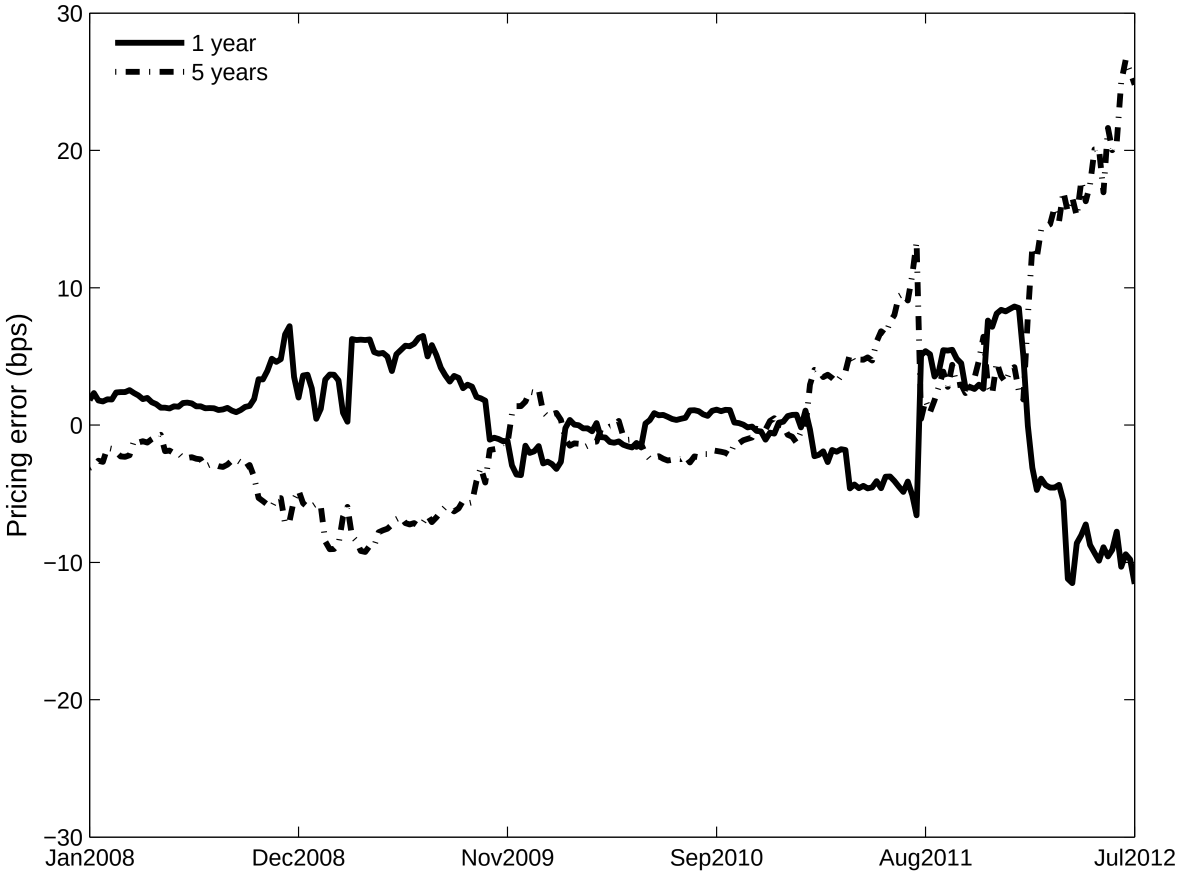
This table shows the projections of the CDS data increments onto their model counterparts. The standard deviations of the coefficients are in parentheses. The standard deviations of the residuals (std. res.) are shown in basis points.

Table 3.10 reports some descriptive statistics for the risk premium and risk premium fractions of the 5-year CDS spreads, respectively. The risk premium is computed as the difference between CDS^Q and CDS^P using expressions (3.10) and (3.13). In addition, we look at the contribution of the risk premium (in percentage) over the total spread of the CDS,

$$RPF \equiv (CDS^Q(M) - CDS^P(M))/CDS^Q(M) \tag{3.15}$$

or risk premium fraction (RPF), similarly to Longstaff et al. (2011). Some interesting conclusions arise from Table 3.10. For example, we observe that investors pay approximately 30.68 (47.00) basis points to German (French) default swaps in terms of risk compensation, approximately 57% (34%) of its total value. To the contrary, the protection sellers of countries outside of the EMU demand 31.60, 30.42 and 40.12 basis points for Denmark, Sweden and the UK, respectively. Outside of the EMU, this component

Figure 3.3.: Averaged pricing errors over time



Averaged pricing errors for 1- and 5-year CDS spreads. The theoretical spreads are computed using the ML estimates of the Pan and Singleton (2008) model in Table ??. The sample frequency is weekly, and it comprises January 2008 to July 2012.

represents (on average) approximately 56% of their total spreads. It should also be highlighted that the non-EMU countries exhibit lower variability in the risk premium fractions than the EMU countries. Again, the last result suggests that membership in a common currency arrangement could act as a contagion enhancer.

Table 3.10.: Decomposition of CDS for the non-peripheral countries

	Risk premium (bps)			Risk premium fraction		
Country	Mean	Median	Std.	Mean	Median	Std.
Austria	51.09	43.62	39.02	0.42	0.52	0.28
Belgium	70.21	60.00	82.05	0.18	0.52	0.74
Germany	30.68	29.44	21.21	0.57	0.66	0.23
Denmark	31.60	20.35	27.25	0.46	0.48	0.15
Finland	26.25	21.10	18.48	0.62	0.66	0.16
France	47.00	35.80	49.19	0.34	0.51	0.43
Netherlands	22.73	18.99	17.33	0.36	0.40	0.15
Sweden	30.42	28.00	21.64	0.63	0.66	0.07
UK	40.12	40.86	20.82	0.60	0.62	0.05

Descriptive statistics of the risk premium for 5-year CDS spreads. The risk premium is computed as the difference between CDS^Q and CDS^P. The risk premium fraction is the ratio between the risk premium and CDS^Q. The risk premiums are in basis points.

3.5.4. Disentangling the impact on risk premia and default components

This subsection revisits the analysis conducted in Section 3.4 to exploit the information content in the risk premium and default risk components of the sovereign CDS spreads. In this way, we project the constituents of the 5-year sovereign default swaps onto the risk peripheral factor, controlling for both the local and the global financial variables previously described in Section 3.4. Tables 3.11 and 3.12 summarize the OLS estimates. Again, we report the adjusted R^2 for the regressions including and not including the peripheral risk factor.

Is the market translating peripheral risk into higher central sovereign CDS risk premia? The results from Table 3.11 suggest an affirmative answer to this question. First, the slope coefficients that are associated with the peripheral factor are significantly different from zero at the conventional significance levels. The estimated effect on the

Table 3.11.: Regression for the distress risk premium

	EMU						Non-EMU		
	Austria	Belgium	Germany	Finland	France	Netherlands	Denmark	Sweden	UK
Cons.	-0.000009	-0.000021	0.000001	-0.000020	0.000008	-0.000013	0.000002	-0.000016	-0.000016
					Panel A.- Local variables				
ΔLiqCDS	0.000236	-0.000079	-0.000108	-0.000155	-0.000045	-0.000301	0.000174	-0.000204	-0.000499**
ΔStM Local	-0.000002**	0.000001	-0.000001*	-0.000000	-0.000004*	-0.000007	-0.000006	-0.000003	0.000000
ΔStM Vol	-0.000027*	-0.000005	-0.000013	-0.000002	0.000003	-0.000003	-0.000018	0.000011	0.000009
ΔForex	0.011120**	0.017610***	0.005867***	0.006277***	0.009897***	0.004615**	0.000785*	0.000827***	0.011305***
ΔForex Vol	-0.000036	0.000044	0.000016	-0.000007	0.000067*	0.000004	0.000013	-0.000004	0.000038
ΔMP rate	-0.000047	-0.000606	0.000006	-0.000007	-0.000316	-0.000168	0.000188	-0.000392	0.000173
					Panel B.- Global variables				
ΔLiqCDS Sov	-0.000191	0.000282	-0.000013	-0.000135	0.000217	0.000146	-0.000196	0.000037	0.000283
ΔEuroStoxx50	-0.000001	-0.000005**	0.000000	-0.000001	0.000003	-0.000001	-0.000002***	-0.000001	-0.000002**
ΔVol Premium	-0.000004	-0.000009	-0.000003	-0.000005	-0.000005	-0.000006	-0.000006	-0.000007*	-0.000007
ΔImp Corr	0.000015	0.000022	0.000006	0.000011	0.000035*	0.000010	0.000009	0.000002	0.000003
Δ5y Yield	0.000580	0.000226	0.000264	-0.000002	0.000440*	0.000210	0.000160	0.000053	0.000155
ΔIG AA-BBB	0.000354**	0.000214	0.000138*	0.000092	0.000095	0.000032	0.000182*	0.000007	-0.000072
ΔCDS Peripheral	0.001390*	0.003317***	0.000802**	0.000830***	0.001709***	0.000671**	0.000765*	0.001030***	0.000919***
Obs.	235	235	235	233	235	224	231	217	207
R^2-Adj Before	0.2604	0.2577	0.2719	0.2475	0.2569	0.2133	0.2782	0.2678	0.2798
R^2-Adj	0.2976	0.3748	0.3181	0.3100	0.3315	0.2605	0.3103	0.3390	0.3492

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

The significance of the variables is tested using White (1980) t-statistics. The "R^2-Adj Before" row refers to the R-squared for the same regression but without including the variable "ΔCDS Peripheral". The "R^2-Adj" row is the adjusted R-squared for the displayed regression that includes the variable "ΔCDS Peripheral". The sample period spans from January 2008 to July 2012.

Table 3.12.: Regression for the default risk component

	EMU						Non-EMU		
	Austria	Belgium	Germany	Finland	France	Netherlands	Denmark	Sweden	UK
Cons.	-0.000000	-0.000001	0.000000	-0.000002	0.000003	-0.000007	0.000003	-0.000004	-0.000006
Panel A.- Local variables									
ΔLiqCDS	0.000074	-0.000023	-0.000022	-0.000019	-0.000028	-0.000215*	0.000054	-0.000074	-0.000213**
ΔStM Local	-0.000001***	-0.000000	-0.000000*	-0.000000*	-0.000001*	-0.000007*	-0.000003	-0.000001	0.000000
ΔStM Vol	-0.000009	0.000000	-0.000002	-0.000000	0.000002	-0.000000	-0.000006	0.000004	0.000004
ΔForex	0.004167**	0.001817***	0.000902**	0.000796***	0.002220***	0.003368***	0.000383**	0.000267***	0.004852***
ΔForex Vol	-0.000011	0.000006	0.000003	-0.000000	0.000018**	0.000006	0.000003	-0.000001	0.000017
ΔMP rate	-0.000019	-0.000049	0.000004	0.000000	-0.000053	-0.000090	0.000104	-0.000112	0.000070
Panel B.- Global variables									
ΔLiqCDS Sov	-0.000026	0.000033	0.000005	-0.000015	0.000044	0.000097	-0.000069	0.000015	0.000125
ΔEuroStoxx50	-0.000000	-0.000000*	-0.000000	-0.000000	0.000001	-0.000000	-0.000001***	-0.000000	-0.000001**
ΔVol Premium	-0.000002	-0.000001	-0.000001	-0.000001	-0.000001	-0.000004	-0.000003	-0.000002	-0.000003
ΔImp Corr	0.000006	0.000002	0.000001	0.000001	0.000007*	0.000006	0.000004	0.000001	0.000001
Δ5y Yield	0.000259	0.000012	0.000029	-0.000004	0.000114**	0.000155	0.000091	0.000034	0.000084
ΔIG AA-BBB	0.000145**	0.000005	0.000016	0.000010	0.000009	0.000019	0.000078	0.000001	-0.000035
ΔCDS Peripheral	0.000524*	0.000299***	0.000123**	0.000098***	0.000360***	0.000457***	0.000385**	0.000348***	0.000399***
Obs.	235	235	235	233	235	224	231	217	207
R^2-Adj Before	0.2974	0.2920	0.2879	0.2561	0.2991	0.2373	0.2866	0.2724	0.2783
R^2-Adj	0.3328	0.4092	0.3328	0.3194	0.3806	0.2868	0.3237	0.3486	0.3482

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

The significance of the variables is tested using White (1980) t-statistics. The "R^2-Adj Before" row refers to the R-squared for the same regression but without including the variable "ΔCDS Peripheral". The "R^2-Adj" row is the adjusted R-squared for the displayed regression that includes the variable "ΔCDS Peripheral". The sample period spans from January 2008 to July 2012.

risk premium is systematically positive. Second, the relative increase in the adjusted R^2 after including the peripheral risk factor is, on average, approximately 24%. Third, exchange rates alone appear to exhibit a wide effect on the CDS risk premiums similar to that of the peripheral factor. The exchange rates are positive and significant at the conventional significance levels. Moreover, the stock market returns also retain some explanatory ability. The remaining local and global variables play a negligible role in explaining the CDS risk premia.

What about the effect of peripheral countries on the default risk for the central EU economies? In light of the results in Table 3.12, it is observed that the peripheral factor is again significant in explaining the CDS risk default risk across all of the countries. Again, the estimated parameter is systematically positive, revealing that the financially distressed economies tend to deteriorate the sovereign creditworthiness of the central EU economies. With regard to the local and global variables, the results remain qualitatively similar to those reported for the risk premium component.

In short, our empirical findings show that the risk factor of peripheral economies is a relevant variable that accounts for much of the variability of the European CDS components. We also detect that the exchange rate is a relevant variable to explain the time evolution of European CDS. However, global variables do not play a key role in driving the Euro sovereign credit spreads.

3.5.5. Is the impact stable over time?

As a robustness check, we examine whether the previous slope coefficients for the peripheral risk factor could be safely interpreted as the representative impact, on average, of the overall sample. To address this issue, we compute rolling-window regressions using a 1-year window. For the sake of brevity, Figure 3.4 only depicts the OLS slope coefficients (left column) and the relative adjusted R-squared ratios (right column) for the three largest economies (Germany, France and the UK).[5]

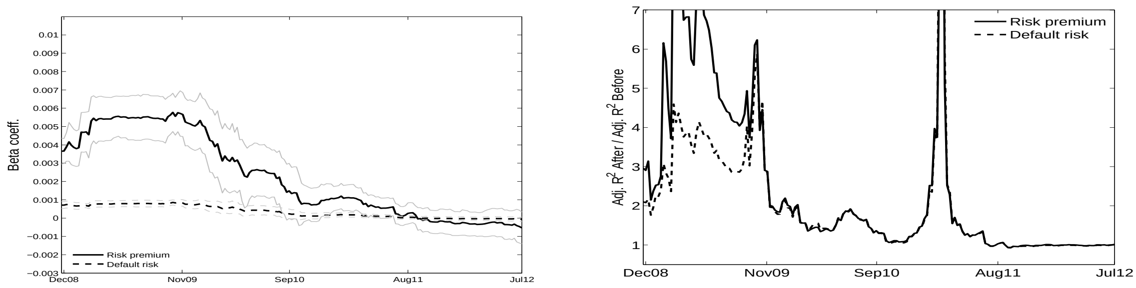
Several interesting aspects emerge from Figure 3.4. First, the impact of distressed

[5]Empirical findings for the remaining countries are available from the authors upon request.

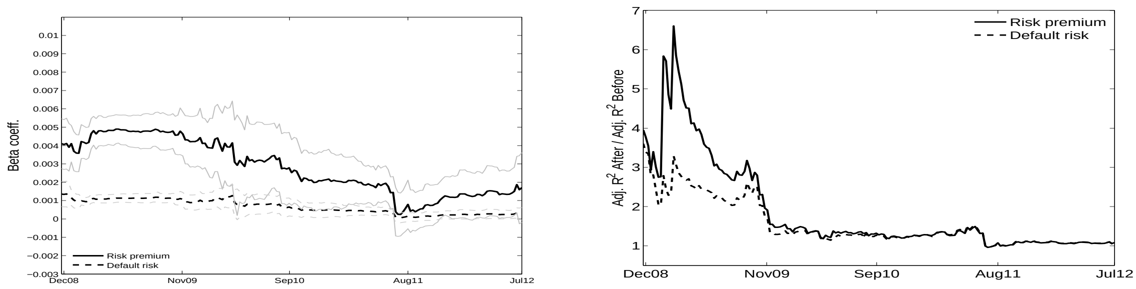
Figure 3.4.: Rolling window regressions

Time varying beta	Added explanatory power

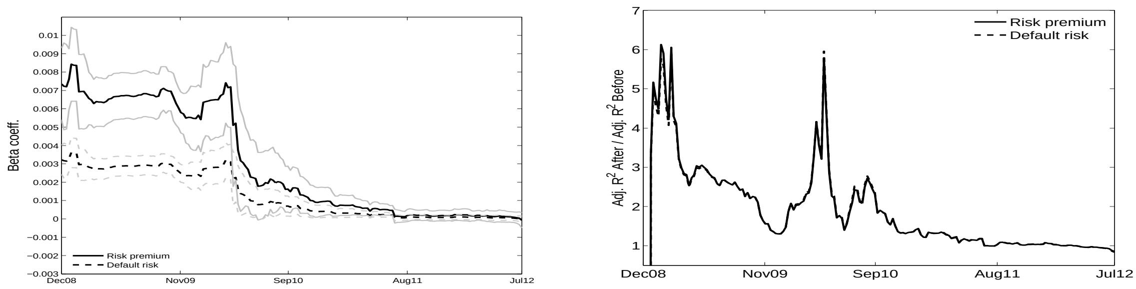
Panel A.- Germany



Panel B.- France



Panel C.- UK



The graphs come from regressions with a rolling window of 1 year. The regressions are estimated using OLS. The graphs in the first column are the beta sensitivities to the first factor of the peripheral countries. The grey lines represent the 95% confidence interval using White (1980) standard errors. The second column is the ratio of the adjusted R^2 from the regression that includes the first factor of peripheral CDS, and the Adj. R^2 from the same regression without including the first factor of the peripheral CDS.

economies on both the default and the risk premium is positive and relatively steady until the beginning of 2010. Second, during this time period, the effect on the default component remains lower than the corresponding effect on the risk premium. Third, the coefficients dramatically decrease after January 2010, becoming close to zero during the last part of the sample. This fact is consistent with the time evolution of the estimated conditional correlation coefficients between factors in Section 3.3. Assuming that contagion between two assets is defined as a significant increase in the degree of comovement between them (see Caporale et al., 2005; Rigobon, 2003), contagion in the sovereign market has gradually diminished. These negligible estimated slope coefficients may reflect a safe haven effect in the core countries since the beginning of the crisis. The scarcity of safe assets worldwide implies that the investors who are willing to allocate their funds have rushed to government assets in Germany and other core EMU countries. Once the credit portfolios have been reallocated, the peripheral risk becomes diversifiable.[6] Fourth, the peripheral risk factor remains a relevant regressor until January 2010. Hereafter, this additional explained ability substantially decreases over time, reinforcing the idea that peripheral risk does not represent a source of systematic risk during the last part of the sample.

3.6. Conclusions

The volatility of the credit default swaps inside the European Economic and Monetary Union significantly increased after 2008. The Keynesian treatment of the crisis in the hopes of encouraging economic growth led to fiscal imbalances that resulted in the significant updating of default risk expectations. Under a new scenario in which a sovereign credit event is not perceived as a *rare* event, it is a major concern to understand the credit risk interactions among EU countries. This chapter provides additional insights on the risk transmission channels inside and outside of the Eurozone from the perspective of the credit derivatives market during the period covering January 2008 to July

[6]We wish to thank the referee for suggesting this comment.

2012.

We analyze the spillover effects from the peripheral to the central EU economies as a reaction to some common global shocks. A preliminary overview reveals a strong commonality among the EU sovereign default swaps. We also find a CDS market fragmentation inside the Eurozone between the peripheral economies and the core countries. A significant risk transmission from the peripheral to the non-peripheral countries is empirically observed during the period analyzed.

To better understand the impact of distressed economies, we decompose the sovereign CDS spreads into their risk-premium and default risk components in accordance with the affine sovereign credit valuation proposed by Pan and Singleton (2008). In the case of EMU economies, the risk premium accounts for, on average, 42% of the total CDS spread. This percentage rises to 56% for the non-EMU countries. However, a sharp difference for the risk premium fluctuations between the EMU and the non-EMU countries is found. We find that both the risk premium and the default components of CDS spreads are partially explained by global and local macroeconomic factors. Peripheral risk plays a key role in explaining the CDS risk premium for the remaining EU members before 2010. After this point, the impact of peripheral risk gradually vanishes over time, most likely reflecting a safe haven effect in core countries since the beginning of the crisis.

In conclusion, the overall CDS spread not only reflects the default risk but also reflects a significant and relatively more important component due to compensation for changes in the economic outlook. Peripheral risk is significant in explaining the increase in the risk premium component until the beginning of 2010. The fact that the CDS market enables a risk transmission channel not only for default risk but also for the risk premium is undoubtedly of interest to the macro prudential authorities and policymakers. Our analysis reveals a financial fragmentation in two primary areas facing asymmetric borrowing costs. Maintaining the euro requires that monetary policy preserves price stability and controls credit conditions. Policy measures aimed at mitigating credit market fragmentation should require the active role of the European Central Bank in the secondary sovereign bond market. Additionally, our results document a reduction in the intensity of spillover effects after 2010. Whether this attenuation is due either to investors' asset substitutions or to recently adopted policy measures is a subject of further research.

Chapter 4.

Foreign monetary policy and firms' default risk

"Finally, we should consider whether the creation of an authority specifically charged with monitoring and addressing systemic risks would help protect the system from financial crises like the one we are currently experiencing [...] Any firm whose failure would pose a systemic risk must receive especially close supervisory oversight of its risk-taking, risk management, and financial condition, and be held to high capital and liquidity standards"

Ben S. Bernanke, Chairman of the Federal Reserve. Speech at the Council on Foreign Relations, Washington, D.C. "Financial Reform to Address Systemic Risk". March 10, 2009.

"The establishment of the ESRB [European Systemic Risk Board] will be a landmark event in how Europe deals preventively with systemic risk. It forms part of wider developments across the globe, including in the US with the newly created Financial Stability Oversight Council (FSOC). Very much like the ESRB, this council is a collaborative body bringing together the relevant US authorities with the aim of identifying systemic risk and responding to threats. We will aim for close cooperation with the FSOC and other authorities for macro-prudential oversight"

Jean-Claude Trichet, President of the ECB. Speech at the European Banking Congress, Frankfurt am Main. November 19, 2010

Does foreign monetary policy (MP) have any effect on domestic economies? What is the effect of external MP on domestic firms' default risk? How do different MPs interact? Is there an endogenous relationship between monetary policy and systemic default risk? Opposed to the comprehensive literature analyzing the impact of domestic MP on the risk-taking of domestic banks, the existence of crossover effects from different rate policies has not yet been addressed. As a natural extension, we wonder about the role of external MP in the stability of the domestic firms. The stability of the domestic economy and credit markets not only depends on the domestic monetary policy, because it also relies on the policies undertaken by foreign monetary authorities.

This chapter empirically addresses the importance of foreign monetary authorities on the default risk of domestic firms. Our main contribution is twofold. First, we document that foreign monetary authorities influence the default risk of domestic firms. This influence relies on the characteristics of the firm as those companies with higher foreign operations seem to be more exposed to foreign monetary policy. This evidence is robust to controls for business cycle, exchange rates or idiosyncratic firm characteristics. Second, we suggest the existence of an endogenous relationship between systemic default risk and monetary policy. The empirical findings reveal that (i) monetary authorities lower their interest rates under a systemic risk shock and that (ii) there might be a heterogeneous effect of different monetary policies on systemic risk. Particularly, a monetary tightening in the US leads to a decrease of systemic risk, but a monetary tightening in the Eurozone leads to an increase in systemic risk in the long term. These results can be interpreted as a warning call for the different monetary authorities to join efforts in the fight against systemic risk. To our knowledge, no similar study to date has examined the influence of foreign monetary policy on the default risk of domestic firms, and how this exposure to some extent depends on the degree of internationalization of the firms.

Our analysis is conducted in two perspectives. From a micro-perspective, we analyze the way that the default risk of individual firms is related to an external monetary policy. Along these lines, we study the role of foreign monetary policies on amplifying the default risk of domestic firms. At the individual level, the monetary policies have the ability to affect the bank loan supply, the risk taking attitudes of banks, the valuation of assets and liabilities, and the ability of firms to raise external financing. Although similar analyses have already been performed, we innovate on employing ex-ante default probability measures. Instead of historical accounting-based measures or past default history, we use the default probability implied from market prices of credit derivatives markets. We employ an extensive database on Credit Default Swaps (CDS), a derivative instrument whose liquidity has increased during recent years because it provides a simple way to short credit.

From a macro-perspective, we wonder about the possible endogenous role of MP with the systemic default risk. The financial crisis started in August 2007 revealed the significant role of MP in the stability of the financial system in particular, and the economy in general. In addition to the historical major goals of monetary policy – stable prices, growth, and unemployment (Friedman, 1968) –, the interaction between MP and systemic default risk has found room in the current banking research agenda. Not surprisingly, two new institutions, the Financial Stability Oversight Council (FSOC) and the European Systemic Risk Board (ESRB), were recently created to deal with the systemic risk.[1] Regardless of whether these new organisms should be dependent or independent of the central banks, we are interested in analyzing if monetary policy rates are a valid mechanism to lessen the systemic risk. Furthermore, we argue that due to the ubiquitous nature of systemic risk, the different regions' economic conditions (inflation, growth, or unemployment), and the different monetary authorities' targets, the monetary authorities might exert different effects on the systemic risk.

Our results stress the importance of domestic and foreign central banks for the credit

[1] In the US, the Dodd-Frank Wall Street Reform and Consumer Protection Act of July 21, 2010 establishes the Financial Stability Oversight Council (FSOC) to identify risks to the financial stability, to promote market discipline and to respond to threats to the stability of the United States financial system. This regulation is available at http://www.gpo.gov/fdsys/pkg/PLAW-111publ203/pdf/PLAW-111publ203.pdf . Similarly, in Europe the Regulation (EU) No 1092/2010 of the European Parliament and of the Council of November 24, 2010 establishes a European Systemic Risk Board (ESRB) to monitor, assess and mitigate the exposure to systemic risk. This regulation is available at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri OJ:L:2010:331:0001:0011:EN:PDF .

stability of the corporate sector during distressed episodes. From a policy perspective, our empirical evidence suggests that a coordinated monetary policy might be a more appropriate mechanism to deal with large systemic events.[2] Domestic monetary policy rates are not designed for dealing with systemic risks without borders. Our study is based on the US and the Eurozone, two of the major economies in the world. According to the IMF, between 2000 and 2009 the US and the Eurozone accounted for the 27% and 21% of the world GDP, respectively. They are also large trading partners. For example, the US exports to EMU countries represent a 19% of total exports, and the US imports from EMU countries reach a 17%.[3] This economic integration is mutual, and multinational firms in one region are likely to make investments in the other region. And as the domestic parent companies depend on foreign trades (exports and imports) and on their foreign affiliates, they are likely to depend on the foreign monetary policy as well.

Thus, this chapter analyzes the impact of foreign monetary authorities on the default risk of domestic firms, examining also their endogenous relationship with the default risk. The chapter is structured as follows. Section 4.1 discusses the related literature. Section 4.2 presents the data used to measure firm specific and systemic default risks. Sections 4.3 and 4.4 deal with the monetary policy effect on firms' default probabilities. Section 4.5 studies the empirical endogenous relationship between the monetary policy and systemic default risk. Section 4.6 summarizes and concludes.

[2] The thought of joining efforts in monetary policy is gaining importance in recent dates. There exist already examples of coordinated actions by central banks to solve specific issues. For instance, on October 8th, 2008 the Bank of Canada, the Bank of England, the ECB, the Federal Reserve, Sveriges Riksbank and the Swiss National Bank simultaneously announced reductions in policy interest rates. Announcement available at http://www.federalreserve.gov/newsevents/press/monetary/20081008a.htm . Also, in September 2011 the ECB, the Federal Reserve, the Bank of England, the Bank of Japan and the Swiss National Bank announced three-month dollar loans to banks due to the difficulties of European banks in obtaining dollar funding. Announcement available at http://www.ecb.int/press/pr/date/2011/html/pr110915.en.html

[3] The Bureau of Economic Analysis of the United States Department of Commerce provides detailed information for each country on exports, imports and foreign direct investment (FDI) made by multinational corporations. More information available at http://www.bea.gov/international/index.htm

4.1. Contribution to the existing literature

This article relies on the cross-sectional effects of different MPs, and their role in the default risk of the firms. To position our chapter in the current literature, we organize the existing articles around three major fields: the interaction among different MPs, the impact of MP in the default risk of the firms and the role of MPs in managing the systemic risk.

The cooperation between a domestic and foreign monetary authorities in a two-country world has already been suggested in the theoretical research. For example, Rogoff (1985) argues that under certain circumstances the monetary policy cooperation can be counterproductive, leading to higher inflation scenarios. Obstfeld and Rogoff (2002) conclude that even in a world tightly linked with world productivity shocks, it is not necessarily problematic that countries unilaterally design their monetary policy in an inward-looking decision-making process. In opposition to those arguments, Pappa (2004) recently allude at the cooperation between monetary authorities – the Fed and ECB – because of the high degree of trade links between the US and the Eurozone.

Concerning the literature analyzing the effects of MP in the default risk of firms, we outline two major groups.[4] On the one hand, some studies deal with the effect of default risk on lending supply. For example, Altunbas et al. (2010) find that banks with low (high) default risk supply more (less) loans during periods of rising 3-month Euribor rates. Gambacorta and Marques-Ibanez (2011) also find that banks with higher default probabilities have supplied less loans under a MP tightening during the recent crisis period. On the other hand, some papers explore the role of interest rates on default probabilities. For example, Altunbas et al. (2011) find that the effect of changes in MP rates on the default probability changes of banks is positive. Jiménez et al. (2011) assume

[4]These trends can also be organized within the two main effects of the MP described by the banking literature: the bank lending and the bank risk-taking behavior. The first strand studies the influence of monetary policy on the bank lending supply (Bernanke and Gertler, 1995). This lending channel of monetary transmission has been empirically tested using aggregate (Bernanke and Blinder, 1992; Kashyap et al., 1993) or specific (Kashyap and Stein, 2000; Jiménez et al., 2012) measures of lending. With regard to the risk-taking behavior, the related literature has analyzed the impact of MP on the willingness to take on risk in a search for yield (Rajan, 2006) or the softening of lending standards (Maddaloni and Peydró, 2011; Jiménez et al., 2007)

that banks can foresee the default probability of a loan, and use a dummy variable for firms with doubtful loans ratio as a measure that resembles an ex ante measure of credit risk. In this way, this chapter is closer to Jiménez et al. (2011), where we take ex-ante measures of credit risk as seen by the credit derivatives markets. As a corollary of this issue, Altunbas et al. (2010) argue that traditional accounting measures such as bank size, liquidity or market capitalization are no longer informative about the bank lending supply nor their financial stability, especially during distressed periods. These authors suggest that this is due to the financial innovation, the securitization, the off-balance sheet accounts and the mark-to-market accounting.

Previous evidences mainly stress the MP effect over the supply and/or default risk of loans. In other words, they focus on the asset side of the banks' balance sheet. More recently, there is an increasing attention to the effects of MP on the liability side of the firms and on the financial markets. Bernanke and Kuttner (2005) find that unexpected changes in the Federal funds target rate are negatively related to the returns of stock indexes. Therefore, a tight monetary policy increases the riskiness of a firm either through higher interest costs and weaker balance sheets, or reducing the willingness of investors to bear risk. This article directly addresses the effect of monetary policy on the creditworthiness of individual firms, stressing their liability side and ability to reimburse their debts.

Finally, systemic risk has become a new challenge for monetary authorities. Although MP rules are not designed to mitigate systemic risk, recent evidence suggests that monetary authority actions and the systemic risk might be endogenous. For example, MPs have acted as lenders of last resort or lowered interest rates as reaction to the sharp increments of systemic risk levels. With regard to the former, the central banks have provided liquidity in emergency situations to solvent but illiquid banks. In this way, pre-crises literature has paid attention to the possible creation of an international lender of last resort (Fischer, 1999; Goodhart, 1999; Repullo, 2000). The consequences of policies on the risk taking behavior has been partially addressed. For example, Acharya (2009) and Acharya et al. (2010) point out that Basel agreements, designed to constrain the individual risk of banks, are not a suitable tool to manage systemic risk. Then, the monetary policy that only supervises the systemic risk of its own firms might be short-sighted.

4.2. The data set

Our empirical analysis involves the matching of several data sources to address the monetary policy influence on the creditworthiness of individual and aggregate firms. Finally, we also present the set of control variables employed. This section describes them in detail.

4.2.1. Monetary policy variables

The primary monetary policy tool used by Monetary Authorities is the short-term interest rate market. This is a conventional mechanism to affect the cost of external financing for all the agents in the economy. The policy rates represent the general stance of monetary policy. Our study pays attention to foreign monetary policies, but for practical purposes, we restrict our sample to two representative developed monetary regions. These are the US and the Economic and Monetary Union of the European Union (EMU), which issue the dollar and the euro currencies.

The general functioning of the short-term interest rate is the following. First, the Monetary Authority sets the nominal or target interest rate, then the effective interest rates at which participant banks borrow will be closed to the target rate. The ECB considers as key rates, the interest rates on the Main Refinancing Operations (ECBMRO), deposit facilities and marginal lending facilities. Marginal lending facilities and deposit facilities determine the range where the effective overnight reference rate for the euro (EONIA) moves. And the ECBMRO interest rate is the target rate for the EONIA.[5] In the US case, the Federal Reserve publishes a target rate (FEDTRG) for the Effective OverNight

[5]For more information, go to http://www.ecb.int/stats/monetary/rates/html/index.en.html and http://www.euribor.org

Federal Funds rate (FEDON).[6] The ECBMRO and the FEDTRG represent the general stance of monetary policy in Europe and the US. For a more detailed description of these two markets, refer to Benito et al. (2007) and Piazzesi (2005).

4.2.2. Default probability variables

Traditionally, the banking literature has measured firm's specific default risk by means of accounting information. An important caveat of those measures is that they reflect ex-post default risk (e.g. Delis and Kouretas, 2011; Jiménez et al., 2013). We innovate on introducing information from the credit market that reflects ex-ante probabilities of default. These market based variables have the advantage that they specifically price the default risk of a firm. Moreover, their premium not only includes a compensation for default risk, but also a reward for the expected future changes in the creditworthiness of the issuer (Jarrow et al., 2005; Berndt et al., 2005; Díaz et al., 2013). In this way, Gilchrist et al. (2009) and Gilchrist and Zakrajšek (2012) find that credit spreads are a robust predictor of future economic activity. Surprisingly enough, the predictive ability of credit spreads mainly comes from the price of default risk rather than the default risk itself.

We employ the information from the credit derivatives market to extract (risk-neutral) default probabilities.[7] In particular, we use the credit default swap (CDS) contract, a credit derivative that provides insurance against the default of a reference entity. The CDS spread is the amount paid (in basis points) in a quarterly basis by the protection buyer to the protection seller. CDSs are traded in a lower friction market than the bond

[6] For more information, go to http://www.newyorkfed.org/markets/omo/dmm/fedfundsdata.cfm

[7] Alternatively, we also employ actual default probabilities from the Expected Default Frequency (EDF) estimates of Moody's KMV. The EDF data are forward-looking default probability measurements built with a version of the Merton (1974) model that combines accounting and stock market information. The EDFs default probabilities are comparable to credit ratings. Literature suggests that EDFs provide a higher predictive power than credit ratings (Kealhofer, 2003; Vassalou and Xing, 2004; Korablev and Dwyer, 2007; Bharath and Shumway, 2008; Campbell et al., 2008). EDFs have already been used in the related literature in Altunbas et al. (2011). More recently, some papers (Bharath and Shumway, 2008; Campbell et al., 2008) argue that the default prediction can be improved by using a reduced-form econometric approach, although they still stress the high default predictive power of measures based on the Merton (1974) model.

market, and there exists a consensus among the financial literature on using CDS spreads as measures of default risk (Longstaff et al., 2005). To build a simple estimator of the default probabilities from CDS spreads we follow Berndt and Obreja (2010), where the conditional default probability of default ($\lambda_t^{\mathbb{Q}}$) in a small time interval Δt results in

$$\lambda_t^{\mathbb{Q}}(T) = 4log\left(1 + \frac{CDS_t(T)}{4LGD_t}\right) \tag{4.1}$$

with $CDS_t(T)$ as the CDS spread with maturity T and LGD_t as the loss given default, both obtained from Markit. To translate these conditional default probabilities into cumulative (risk-neutral) default probability we just replace the default intensity estimates in the following formula

$$Q_t(T) = 1 - e^{-\lambda_t(T)\times T} \tag{4.2}$$

where the default probability depends on the constant default intensity of an homogeneous Poisson process.

Our sample consists on corporate default swap contracts that belong to the US and the EMU monetary regions. In particular, we select the constituents of CDX and iTraxx investment grade indexes, two standardized portfolios that comprise the most liquid corporate CDS contracts from the US (CDX) and Europe (iTraxx). This selection presents two main advantages. First, firms belonging to those indexes are the most liquid in the CDS market, so our conclusions are less likely to be biased by liquidity frictions. Second, the index constituents correspond to larger and internationalized firms, which usually present a large debt outstanding in the market. This circumstance makes those firms potentially exposed to foreign monetary authorities.

The dataset comprises a full spectrum of CDS spreads with maturities ranging from 6 month until 30 years. Our analysis mainly focuses on the probabilities extracted from the 5-year CDS spreads – the most liquid maturity –, but we also extend our estimations to other maturities for robustness. The period under study comprises from Jan/2000 to Dec/2009. The first CDS spread observation is available in Jan-2001, as the credit derivatives market has been recently developed. We use only the end-of-month observations of CDS spreads. For US firms, we use CDS contracts denominated in US dollars with the Modified Restructuring clause, and for European firms, we use CDS contracts denominated in Euros with the Modified-Modified Restructuring clause.[8] As a result, we have data for 210 firms from the US and Europe, where 169 of them are investment grade. Table 4.1 shows that our sample is distributed along a wide class of countries, industries, and ratings. The data is taken from the Markit database.

In addition to the information about firm's specific default risk provided by default swaps, our database also provides information about aggregate corporate credit risk. More in detail, we use the CDX and iTraxx indexes and tranche quotes from Markit. The payoff structure of those indexes equals to that of a collateral debt obligation (CDO), where the payments are allocated following a priority rule. According to their risk, equity (senior) investors agree to suffer the first (last) losses within the portfolio.[9] For example, the senior CDO tranches resemble the behavior of bonds that default under severe economic conditions (Coval et al., 2009). They are frequently used as a measure of systemic risk because they contain prices on the default of a large number of firms. The data sample spans from Jul/2005 to Dec/2009. Other periods have been dropped because of liquidity concerns.

4.2.3. Control variables

Finally, we control for observable firm characteristics that can affect the firms' sensitivity to monetary policies. In particular, we use three main firm characteristics: assets

[8] The restructuring clause defines the credit events that trigger settlement. The main difference is the maximum maturity of the deliverable obligation in case of a restructuring: 30 months in the Modified Restructuring clause, and 60 days in the Modified-Modified Restructuring clause.

[9] As the market requires upfront payments, we follow O'Kane and Sen (2003), Amato and Gyntelberg (2005) and Houdain and Guegan (2006) to transform the upfront payment to a running spread. Thus, a tranche with an upfront payment of 37.5%, a running spread of 500 basis points and risky duration of 3.75 is equivalent to a contract with a running spread of (37.5*100/3.75) + 500 basis points 1,500 basis points. We assume a risky duration of 3.75 to translate upfront payments into running spreads. Additionally, to compute a systemic default risk measure we also need the default-free term structure. We use the LIBOR-swap curve for US and the EURIBOR-swap curve for Europe by the bootstrapping method, which is usual in credit derivatives pricing.

Table 4.1.: Distribution of firms across sectors, average ratings and countries

	BM	CG	CS	Fin	HC	Ind	OG	Tech	TC	Util	Total
						Panel A.- By rating					
AAA	0	0	0	0	0	0	0	0	0	0	0
AA	0	0	1	9	1	1	1	0	0	2	15
A	3	7	6	12	5	7	2	5	3	9	59
BBB	8	14	26	2	4	17	6	2	9	7	95
BB	0	4	9	0	1	3	2	0	2	0	21
B	2	2	4	2	1	3	0	1	0	2	17
CCC	0	0	1	1	0	0	0	0	0	0	2
NR	0	1	0	0	0	0	0	0	0	0	1
						Panel B.- By country					
Austria	0	0	0	0	0	0	0	0	1	0	1
Finland	0	0	0	0	0	0	0	0	0	1	1
France	0	2	6	4	0	3	2	0	2	3	22
Germany	3	5	1	4	1	2	0	0	1	3	20
Greece	0	0	0	0	0	0	0	0	1	0	1
Italy	0	0	0	4	0	1	0	0	1	2	8
Luxembourg	1	0	0	0	0	0	0	0	0	0	1
Netherlands	2	2	2	1	0	2	0	1	1	0	11
Portugal	0	0	0	1	0	0	0	0	0	1	2
Spain	0	0	0	1	0	0	1	0	1	2	5
United States	7	19	38	11	11	23	8	7	6	8	138
						Panel C.- Overall					
TOTAL	13	28	47	26	12	31	11	8	14	20	210

This table shows the distribution of firms across different sectors, average ratings and countries. Ratings vary from AAA to CCC, and NR in case of a non rated firm. Sectors correspond to Basic Materials (BM), Consumer Goods (CG), Consumer Services (CS), Financial (Fin), Health Care (HC), Industrials (Ind), Oil & Gas (OG), Technological (Tech), Telecommunications (TC) and Utilities (Util). The sample period goes from Jan-2000 to Dec-2009.

liquidity (LIQ) measured as Cash and Receivables over Total Assets, capital ratio (CAP) measured as Shareholders' Equity over Total Assets, and assets size (SIZE) as the natural logarithm of the Total Assets.

We also include some control variables that potentially might affect the default risk of firms. For example, the dollar-euro exchange rate (USD-per-EUR) is a standard control for possible currency exposure of firms. Within the context of our analysis, we consider the exchange rate as an exogenous variable. Although this issue could result controversial in the case of currency crises, Kaminsky and Reinhart (1999) do not find a clear causal link between currency crises and banking crises. Both causal directions are possible between the two types of crises. They find that in general the banking crises begin before the currency collapse, and that the consequences are more severe when currency crisis and banking crisis happen together, than when they are isolated.

Another usual macroeconomic control is the term spread, measured as the difference between the 10- and 2-year government bond yields. More precisely, we employ the US and German government bonds (TERM-US and TERM-EMU, respectively). The reason is that in times of low short-term interest rates, when new stimuli are needed, central banks proceed with unconventional policies to facilitate government borrowing. In November 3rd 2010, the Fed announced a purchase of $600 billion of Treasury securities to avoid deflation risk.[10] Krishnamurthy and Vissing-Jorgensen (2011) use intra-day data in an event study approach to analyze the channels through which the Federal Reserve's announcements of long-term bonds' purchases – known as Quantitative Easing – lower long-term interest rates. In September 21st 2011, the Fed announced the purchase of $400bn of long-dated Treasuries financed with the sale of short-term securities. It was nicknamed as 'Operation Twist' because it sought to change the shape of the yield curve.[11] Similar policies were conducted by the ECB in order to calm the bond markets of the weakest countries. Central banks are able to affect the shape of the term structure through unconventional purchases of long-dated securities.

[10]See announcement on: http://www.newyorkfed.org/markets/opolicy/operating_policy_101103.html
[11]See announcement on: http://www.newyorkfed.org/markets/opolicy/operating_policy_110921.html

4.3. Crossover effects of monetary polices: a firm level approach

This section analyzes the existence of a crossover effect where the decisions of foreign monetary authorities impact on the firm's specific default risk. We stress the role of the internationalization of the firms as a transmission channel for foreign monetary policies.

4.3.1. Measuring the exposure to foreign monetary policies

We suggest that firms with more foreign operations are more affected by foreign monetary policies. In this way, our main assumption is that the degree of internationalization enables a risk transmission channel from outside monetary policies to national firms: the larger the foreign business, the higher the impact of foreign policy. Although this assumption is not new in the literature, we introduce an innovation when extending this idea to the corporate sector and when studying the effect on the default risk. For example, banks and firms hold an important amount of their assets and liabilities in foreign currencies (Grammatikos et al., 1986; Kedia and Mozumdar, 2003; Lane and Milesi-Ferretti, 2007; Tille, 2008). Foreign holdings are exposed to exchange rate risk and interest rate risk and even if the currency exposure is hedged, foreign interest rate risk arises whenever a firm mismatches the maturities of its foreign currency assets and liabilities (Grammatikos et al., 1986).

To empirically analyze the exposure to foreign monetary policies, we first identify the degree of internationalization of the firms. The most common measure of internationalization is the Foreign Sales as Percentage of Total Sales (TFSALEP). This variable measures the exposure to foreign sources of income, and it is available in Compustat for US firms.[12] The external sources of costs might offset and reduce the foreign exposure of the firm, because the TFSALEP variable only includes foreign sales. To control for

[12] Since 1997, firms are required to disclosure this information by the Statement of Financial Accounting Standards (SFAS, 131). The regulation is available at: http://www.fasb.org/pdf/fas131.pdf . However, the Compustat database only keeps track of the last 7 years, and we can only obtain the size of foreign sales since 2005.

this issue, we define the variable FORINC

$$FORINC = \frac{|\text{Foreign Pretax Income}|}{|\text{Domestic Pretax Income}| + |\text{Foreign Pretax Income}|} \tag{4.3}$$

as the ratio of foreign income or loss over the total amount of domestic plus foreign income or loss. To construct the variable FORINC, we use the domestic and foreign pre-tax income.[13] We employ absolute values because firms could have negative domestic and/or foreign income, which complicates the construction of a simple measure of foreign exposure for firms.

Similar variables to measure foreign exposure have been previously employed by the literature. For example, Sullivan (1994) created an aggregated measure of the degree of internationalization of a firm based on five different ratios.[14] Bodnar and Weintrop (1997) demonstrate the importance of foreign earnings for multinational firms, because the domestic and foreign earnings changes have significant positive associations with excess stock returns. Other literature links the foreign operations with currency exposure. Jorion (1990) and Pantzalis et al. (2001) find that the firms' stock returns currency exposure is related to the fraction of total sales made overseas by U.S. multinationals. For this reason, other research like Geczy et al. (1997) and Allayannis and Weston (2001) use foreign operations (measured by foreign sales or foreign pre-tax income) as proxies for foreign exchange-rate risk. More in detail, they find that firms using currency derivatives have greater foreign operations; the use of foreign currency derivatives is positively associated with firm market value in firms with foreign operations, and it is not associated with firm market value for firms without foreign operations. Moreover, firms with larger foreign operations are more likely to issue foreign currency debt to hedge their exposure (Kedia and Mozumdar, 2003).

[13] It is also mandatory for firms to report the foreign and domestic components of pre-tax income, according to the SEC Regulation ğ210.4-08(h). This regulation is available at: http://www.gpo.gov/fdsys/pkg/CFR-2011-title17-vol2/pdf/CFR-2011-title17-vol2-sec210-4-08.pdf .

[14] Unfortunately, this procedure is not advisable for us: firstly, the information to construct the measure of Sullivan (1994) is not available for our entire sample. Secondly, the effect of foreign monetary policy on the firm's default risk depends on the nature of international exposure: a long or a short position.

4.3.2. Sample descriptive statistics

Table 4.2 provides detailed information on the country of origin for the firms that appear in the most popular rankings on largest foreign investments: the Forbes and UNCTAD rankings. Forbes magazine has a raking of the top 100 largest foreign investments in the US.[15] By 2002, out of these 100 firms, 43 belong to the Eurozone, and 22 of them are in our sample. With respect to the UNCTAD ranking, our sample includes 51 out of the 100 top non-financial corporations by absolute total foreign assets from 2000 to 2008.[16] When considering the top 50 financial corporations by foreign-to-total affiliates and number of foreign affiliates for the period 2003 to 2009, 14 out of 50 firms are in our sample. Not surprisingly, our sample is composed of large firms as the total asset value of the US firms in sample was estimated in $6.439 trillion during 2007, representing the 46% of GDP of the United States. In the European case, our sample was worth €14.726 trillion during 2007, resulting in approximately the 163% of the GDP of the Eurozone.

Table 4.2.: Number of largest foreign firms by ranking

	US	US sample	Europe	EMU	EMU sample
Largest foreign investments in US			65	43	22
World's top 100 non-financials (2000-2008)	39	17	85	61	34
World's top 50 financials (2003-2009)	16	2	47	32	12

Each row is related to a ranking made by Forbes or UNCTAD. The first row is the 2002 Forbes' ranking titled "The Largest Foreign Investments In The US". It is a ranking of the 100 largest investments in the US by foreign firmsăby the revenue they make in the US. The second row is the 2000-to-2008 UNCTAD's annual rankings of "The world's top 100 non-financial Transnational Corporations", by the size of the foreign assets. And the third row refers to the 2003, 2004, 2006, 2008, and 2009 UNCTAD's annual rankings of "The Top 50 financial Transnational Corporations" ranked by the foreign-to-total affiliates ratio and the number of host countries. The columns represent the number of firms that belong to the regions where the firm is headquartered (US, Europe, or EMU), and the number of firms that belong to our US or EMU sample.

[15] According to Forbes, the foreign firms are ranked with the absolute amount of revenue they get from US investments. This information is available at http://www.forbes.com/free_forbes/2002/0722/foreign.html

[16] The UNCTAD classification ranks the world's top transnational corporations (TNC). A description of UNCTAD is available at http://archive.unctad.org/Templates/Page.asp?intItemID 2443&lang 1

Table 4.3 summarizes all firm-level accounting information that we could collect from Compustat Global Vantage, Compustat North America, and UNCTAD's rankings. Unfortunately, the variables TFSALEP and FORINC are not available for banks, and they are only observable in the 62% of the original sample of US firms. For EMU firms, we only have at our disposal the information in the UNCTAD rankings about the foreign-to-total Sales (TFSALEP), foreign-to-total Assets (FORASS), and foreign-to-total Employment (FOREMP). And this information is only available for the 47% of the EMU firms in our sample. When we consider also the information in UNCTAD on FORASS and FOREMP for US firms, we only have information on 17 US companies. In our sample, an average firm has a foreign-to-total Sales ratio of 32% in US and 62% in EMU countries. This means that it is likely that our EMU sample is more biased towards more international firms than the US sample.

Table 4.3.: Accounting numbers

	US (millions of US dollars						EMU (millions of Euros					
Variable	# Firms	Obs. (firm-year	Mean	Std. Dev.	Min	Max	# Firms	Obs. (firm-year	Mean	Std. Dev.	Min	Max
Panel A.- Annual Reports												
otal Assets (AT	138	1360	37786.61	83227.01	1061.6	1060505	72	716	155581.2	298330.6	4049	2202423
Cash & S Investments (CHE	136	1349	1872.195	4972.014	0	74585	72	716	16452.88	45648.77	23.677	410541
Accounts Receivable ($RECT$	123	1216	2591.056	4062.256	0	30726	57	566	8492.469	14129.11	333.7	123366
Equity (SEQ	136	1342	9705.416	14755.51	-3532	152027	72	716	13953.92	13111.59	-9951	69501
Net Sales ($SALE$	138	1359	21421.56	32785.95	19.317	402298						
Domestic Pretax Income ($PIDOM$	86	623	1051.218	5668.84	-105179	16239						
Foreign Pretax Income ($PIFO$	86	623	1098.83	2179.012	-3582	14957						
Panel B.- Ratios												
LIQ ($[CHE + RECT]/AT$	136	1342	.1624036	.1309679	.0007407	.6744421	72	716	.2131364	.1367624	.0029687	.9040849
CAP (SEQ/AT	136	1342	.321075	.1517489	-.1440755	.8097345	72	716	.2279833	.1448286	-.0933604	.6865051
Foreign-to-total Sales ($TFSALEP$	87	388	.324949	.2222151	0	1	34	123	.6304407	.1864184	.1775217	.9651292
FORINC ($\|PIFO\|/[\|PIDOM\| + \|PIFO\|]$	86	623	.3403981	.2741099	0	.999						
FORASS	17	204	.5357274	.1952422	.0594807	.9975873	34	122	.56041	.195678	.0840584	.9526457
FOREMP	17	204	.4979036	.1897753	.0399986	.9655092	34	121	.5732295	.1742303	.0512187	1

This table summarizes annual corporate information for the firms in our sample during the period 2000-2009. The data is mainly obtained from Compustat Global Vantage. The Compustat Mnemonics are between brackets. For US firms, the variables SALE, TFSALEP, PIDOM and PIFO are obtained from Compustat North America. For EMU firms, the variables TFSALEP, FORASS and FOREMP are obtained from the 2000-to-2008 UNCTAD's annual rankings of "The world's top 100 non-financial Transnational Corporations". The accounting numbers are reported in millions of US dollars for US firms and in millions of Euros for EMU firms. The variables LIQ, CAP, TFSALEP, FORINC, FORASS, and FOREMP are ratios between 0 and 1.

The high degree of correlation observed in Table 4.4 between the aggregate measures of foreign exposure is in agreement with previous findings of Sullivan (1994) and Kedia and Mozumdar (2003). In the empirical research these variables are sometimes dropped due to multicollinearity, because they do not provide additional information by themselves regarding the level of firm's default risk. Despite the high degree of correlation, the proxies can provide significant information about the impact of foreign monetary policy in the firm's default risk. And the sign of foreign monetary policy influence on default risk can differ depending if the firm has long or short foreign net position. For this reason, we keep the measures of internationalization separate instead of using one single measure as in Sullivan (1994).

Table 4.4.: Pairwise correlations

	US							EMU						
	LIQ	CAP	SIZE	TFSALEP	FORINC	FORASS	FOREMP	LIQ	CAP	SIZE	TFSALEP	FORINC	FORASS	FOREMP
LIQ	1.0000							1.0000						
CAP	0.1194	1.0000						0.1492	1.0000					
SIZE	-0.1383	-0.1253	1.0000					-0.2898	-0.5783	1.0000				
TFSALEP	0.3183	-0.0471	0.1402	1.0000				0.1732	0.2639	-0.5263	1.0000			
FORINC	0.3501	-0.0405	0.1328	0.6978	1.0000									
FORASS	0.2110	0.3911	-0.5511	0.6531	0.7168	1.0000		-0.1550	0.3444	-0.6466	0.7078		1.0000	
FOREMP	0.3363	0.2561	-0.4832	0.7023	0.7243	0.7780	1.0000	-0.0707	0.3220	-0.6524	0.7164		0.7585	1.0000

This table reports pairwise correlations in the period 2000-2009. The data is obtained from Compustat Global Vantage and Compustat North America. For each firm, the variables LIQ, CAP and SIZE are linearly interpolated from year to monthly frequency using the Compustat Global Vantage dataset from 1999 to 2010. For the variables TFSALEP, FORINC, FORASS and FOREMP, we only use the sample average between 2000 and 2009, because the large number of missing values does not allow for interpolation.

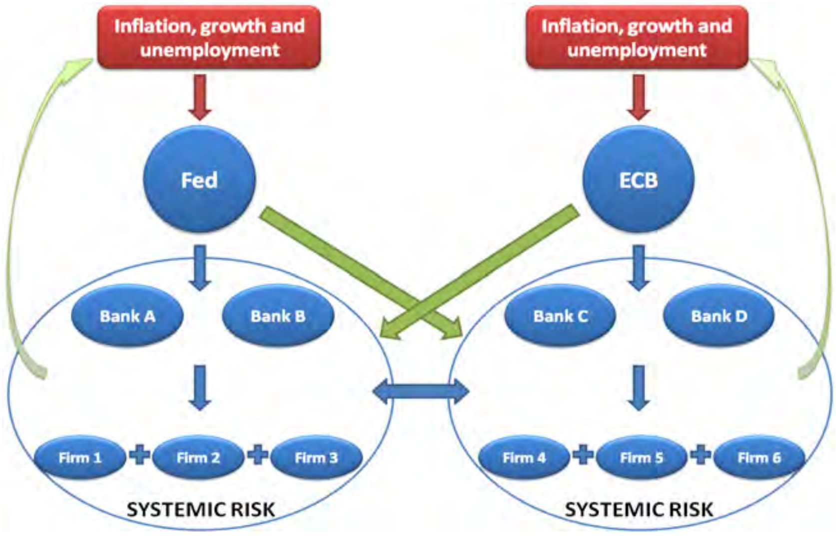
The accounting information obtained from Compustat and UNCTAD's rankings is scarce, it is not available for all firms, and certainly not available for every year. For each firm, the variables LIQ, CAP and SIZE are transformed from annual to monthly frequency by linear interpolation from the years 1999-to-2010.[17] Regarding the proxies for foreign exposure, the variables TFSALEP, FORINC, FORASS and FOREMP are unobserved for many years and interpolation is not possible. For that reason, we only use the sample average from 2000-to-2009 as a measure of the degree of internationalization.

[17]The results of our empirical findings remain regardless of the type of interpolation and even if we only use the sample average. This is because the accounting characteristics are important sources of firm information in the cross-section, but not in the time dimension.

4.3.3. Research design

The Figure (4.1) represents our two-monetary-authority world with regional targets (unemployment, inflation and growth). Nevertheless, the MP rates can affect domestic firms or foreign firms with foreign exposure. In this fashion, foreign monetary authorities can contribute to the domestic banks' loan supply and to the financial (in)stability of domestic firms. At an aggregated level, a large systemic event can give rise to periods of low economic activity, high inflation and high unemployment. In this section, we study empirically what types of firms are more likely to be affected by a foreign monetary policy – the crossover effect.

Figure 4.1.: Risk transfer flowchart



We want to analyze empirically the influence of short-term monetary policy on the firms' default risk as seen by the credit markets. And we are especially interested on identifying whether firms with more foreign operations are more affected by foreign monetary policy. Our empirical strategy is based on running for each monetary region panel regressions with the following general specification

$$
\begin{aligned}
logit\,(PD_{it}(M)) \;=\;& \beta_1 \text{STrate}_{t-1} + \beta_1' \text{Firm}_{it-1} \times \text{STrate}_{t-1} + \beta_1'' \text{DOI}_i \times \text{STrate}_{t-1} \\
+\;& \beta_2 \text{Foreign STrate}_{t-1} + \beta_2' \text{Firm}_{it-1} \times \text{Foreign STrate}_{t-1} + \beta_2'' \text{DOI}_i \times \text{Foreign STrate}_{t-1} \\
+\;& \text{CONTROLS}_{t-1}(\text{USD/EUR, GDP growth, Inflation, LTrate, Term Spread}) \\
+\;& \beta_0 + \beta_0' \text{Firm}_{it-1}(\text{Firm Dummy, Financials Dummy, LIQ, CAP, SIZE}) \\
+\;& \beta_0'' \text{DOI}_i(\text{TFSALEP, FORINC, FORASS, FOREMP}) + \varepsilon_{it}
\end{aligned} \tag{4.4}
$$

where $logit\,(PD_{it}(M))$ is the logistic transformation $ln\,(PD_{it}/(1 - PD_{it}))$ of the probability of default measure $PD_{it}(M)$ of firm i at month t for the horizon M. This logistic transformation assures that the probability of default is defined in the zero-one interval. It is important to notice that this is not a logistic regression where the dependent variable is an historical variable that takes value 1 when a default happens and 0 otherwise. We observe directly the forward looking default probabilities. The logit transformation guarantees that the probability of default $PD_{it}(M)$ of a firm i at time t over the next M years is bounded between zero and one. The error term ε_{it} captures all other factors not captured by the macroeconomic variables used that affect the firms' default probability. We cluster the standard errors by firm and month in case the residuals are correlated across firms or along time as suggested by Petersen (2009). In the robustness analysis we also use GLS estimation and the dynamic model of Arellano and Bond (1991).

The variables $STrate_{t-1}$ and $Foreign\ STrate_{t-1}$ are the domestic and foreign short-term interest rate at time $t-1$. We use the target interest rate as a measure of short-term monetary policy, but in robustness analysis we also employ the effective short-term interest rate and the Taylor rule residuals.

To identify the type of firms that are more exposed to the monetary policy, we interact the short-term interest rates with three types of firm characteristics. First, we use a dummy variable for financial firms (FIN). The reason is that the financial sector is the first sector that suffers more directly the monetary policy changes. Moreover, the number of financial firms in our sample is too small to derive further and general statements. Second, we use the capital ratio, the liquidity ratio and the firms' size as in Jiménez et al. (2012) as basic and aggregate firm-risk characteristics. And third, we use measures about the degree of internationalization or the degree of foreign operations (DOI) for every firm.[18] The use of DOI variables reduces the sample substantially. For instance, the foreign-to-total sales ratio is only available for half of the original sample. Notice that the capital, liquidity and size have been interpolated to monthly frequency, and for the DOI variables we only use the sample average due to the lack of data. It is important to highlight that the results do not change due to the interpolation or the interpolation methodology, because the firm characteristics mainly give cross-sectional information and not time-series information.

In order to isolate the effect of short-term interest rates on bank loans' lending standards from other macroeconomic variables Maddaloni and Peydró (2011) use the 10-year long-term government bond interest rate (LTrate), the GDP growth, and the inflation rate. In our study, the business cycle is a relevant control since the rate of default tends to increase during bad economic conditions. To obtain a monthly measure of the business cycle, we use the annual growth on quarterly nominal GDP and interpolate it to monthly frequency as Jiménez et al. (2012) does. Results are unaffected if we do not interpolate. In the baseline model, we only consider the domestic macroeconomic controls. In robustness, we also include the foreign macroeconomic controls, and the main findings remain.

The empirical strategy consists on performing initially the panel regression with the domestic and foreign monetary policy, and adding stepwise the macroeconomic, firm and DOI controls.

4.3.4. Empirical results

The main results that we find in our empirical study are summarized in Table 4.5. This table displays different specifications for the 5-year risk-neutral default probability. We proceed by adding stepwise the macroeconomic, firm and DOI controls.

[18]The DOI measures are not available for banks

Table 4.5.: Panel regression for 5-year implied default probabilities on target interest rates

Dependent variable	*logit* $(Q_{it}(5Y))$																		
Monetary region	US										EMU								
Model	I)	II)	III)	IV)	V)	VI)	VII)	VIIb)	VIII)	IX)	I)	II)	III)	IV)	V)	VI)	VII)	VIII)	IX)
Cons	-2 84	-3 37	-1 03	-1 06	-1 92	-2 02	0 90	-3 63	0 05	-0 11	-3 12	-3 29	-0 46	-2 20	-14 47	-10 83	-8 26	-8 03	-6 82
	0 00)	0 00)	0 01)	0 00)	0 12)	0 10)	0 44)	0 06)	0 99)	0 93)	0 00)	0 00)	0 69)	0 00)	0 00)	0 00)	0 00)	0 00)	0 00)
Panel A. US Monetary policy																			
$FEDTRG_{t-1}$	-29 26	-30 16		-13 59		24 58	28 56	37 91	-28 88	32 87	-32 63	-32 40	-45 53	-16 85	-14 72	23 93	57 05	25 44	37 21
	0 00)	0 00)		0 00)		0 02)	0 02)	0 00)	0 29)	0 01)	0 00)	0 00)	0 00)	0 00)	0 25)	0 07)	0 06)	0 36)	0 17)
$FIN_i \times FEDTRG_{t-1}$	-22 69	-21 04		-21 25		-17 96	-17 24	-20 36		-17 30	-14 42	-14 14	-8 45	-13 97	-4 48	-8 08			
	0 00)	0 00)		0 00)		0 01)	0 05)	0 03)		0 06)	0 00)	0 00)	0 00)	0 00)	0 22)	0 04)			
$LIQ_{i,t-1} \times FEDTRG_{t-1}$						0 58	-9 23	-14 76	-17 04	-8 66					-1 23	0 12	11 72	11 16	9 97
						0 94)	0 29)	0 14)	0 35)	0 33)					0 90)	0 99)	0 34)	0 17)	0 23)
$C\ P_{i,t-1} \times FEDTRG_{t-1}$						-6 44	-2 07	-6 17	-14 04	-2 34					3 02	-6 55	7 65	0 92	1 89
						0 39)	0 84)	0 57)	0 63)	0 82)					0 75)	0 46)	0 59)	0 93)	0 86)
$SIZE_{i,t-1} \times FEDTRG_{t-1}$						-3 59	-4 45	-4 97	0 32	-4 38					-2 53	-3 69	-6 37	-3 71	-3 37
						0 00)	0 00)	0 00)	0 87)	0 00)					0 00)	0 00)	0 01)	0 09)	0 11)
$TFS\ LEP_i \times FEDTRG_{t-1}$							10 00		5 39	9 64							-16 37	-26 06	-25 73
							0 10)		0 65)	0 11)							0 13)	0 01)	0 00)
$FORINC_i \times FEDTRG_{t-1}$								7 72											
								0 19)											
$FOR\ SS_i \times FEDTRG_{t-1}$									50 99									-23 79	-21 01
									0 03)									0 10)	0 14)
$FOREMP_i \times FEDTRG_{t-1}$									-26 91									45 00	43 24
									0 33)									0 00)	0 00)
Panel B. EMU Monetary policy																			
$ECBMRO_{t-1}$	32 62	35 56	18 07	24 12	55 30	24 92	9 75	6 19	-7 73	21 68	31 67	30 71		79 32		27 98	2 55	1 66	-29 72
	0 00)	0 00)	0 00)	0 00)	0 00)	0 05)	0 43)	0 65)	0 84)	0 13)	0 00)	0 00)		0 00)		0 16)	0 94)	0 96)	0 39)
$FIN_i \times ECBMRO_{t-1}$	17 30	9 91	-10 78	9 82	2 30	19 93	18 09	22 61		18 49	18 80	18 26		18 59		13 37			
	0 05)	0 19)	0 20)	0 22)	0 78)	0 03)	0 01)	0 00)		0 01)	0 00)	0 00)		0 00)		0 04)			
$LIQ_{i,t-1} \times ECBMRO_{t-1}$					7 08	5 66	31 03	35 67	73 49	31 36						-5 62	7 05	12 15	11 06
					0 32)	0 58)	0 01)	0 01)	0 00)	0 01)						0 52)	0 68)	0 44)	0 49)
$C\ P_{i,t-1} \times ECBMRO_{t-1}$					14 64	23 29	18 07	29 67	35 07	19 55						27 74	47 15	49 35	50 06
					0 11)	0 06)	0 18)	0 06)	0 34)	0 14)						0 11)	0 04)	0 01)	0 01)
$SIZE_{i,t-1} \times ECBMRO_{t-1}$					-4 61	-1 18	0 93	0 54	2 14	0 94						3 40	6 17	5 70	6 00
					0 00)	0 36)	0 49)	0 73)	0 55)	0 48)						0 01)	0 04)	0 02)	0 01)
$TFS\ LEP_i \times ECBMRO_{t-1}$							-29 84		-33 07	-29 77							-15 92	-18 59	-18 15
							0 00)		0 02)	0 00)							0 36)	0 47)	0 44)
$FORINC_i \times ECBMRO_{t-1}$								-22 12											
								0 00)											
$FOR\ SS_i \times ECBMRO_{t-1}$									-67 59									41 34	36 05
									0 15)									0 08)	0 08)
$FOREMP_i \times ECBMRO_{t-1}$									47 76									-35 74	-31 38
									0 10)									0 01)	0 02)
Panel C. Macro controls																			
USD/EUR_{t-1}			-0 99	-0 88	-0 90	-0 81	-0 84	-0 80	-0 88	-0 57			-0 46	-0 73	-0 95	-1 01	-1 19	-1 21	-1 09
			0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 01)			0 37)	0 01)	0 03)	0 00)	0 00)	0 00)	0 00)
$GDPG\text{-}US_{t-1}$			-16 28	-15 29	-14 64	-13 66	-14 28	-13 05	-13 93	-12 59									-9 01
			0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 00)									0 00)
$GDPG\text{-}EMU_{t-1}$										-6 45			-7 37	-22 03	-4 07	-18 02	-18 64	-18 33	-12 02
										0 09)			0 13)	0 00)	0 30)	0 00)	0 00)	0 00)	0 01)
$Inflation\text{-}US_{t-1}$			14 75	12 34	13 93	11 61	11 75	10 88	13 35	0 87									-5 40
			0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 85)									0 36)
$Inflation\text{-}EMU_{t-1}$										23 68			3 44	9 03	7 91	10 89	10 46	10 70	39 57
										0 03)			0 71)	0 16)	0 29)	0 07)	0 05)	0 05)	0 00)
$10\text{-}year\ rate\text{-}US_{t-1}$			-32 19	-23 38	-30 33	-22 13	-21 91	-20 35	-28 90	-14 22									-14 76
			0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 00)	0 13)									0 11)
$10\text{-}year\ rate\text{-}EMU_{t-1}$										-8 26			-7 49	-48 59	-1 87	-39 33	-41 65	-41 30	-15 29
										0 47)			0 50)	0 00)	0 84)	0 00)	0 00)	0 00)	0 20)
$TERM\text{-}US_{t-1}$			16 65	-3 90	14 79	-4 14	-8 35	-7 10	-13 72	-16 36									-1 73
			0 00)	0 59)	0 00)	0 57)	0 28)	0 35)	0 17)	0 11)									0 87)
$TERM\text{-}EMU_{t-1}$										30 99			-90 40	30 36	-63 48	34 43	36 81	37 05	53 85
										0 04)			0 00)	0 07)	0 00)	0 04)	0 03)	0 03)	0 00)
Panel D. Firm controls																			
$LIQ_{i,t-1}$					-1 71	-1 68	-2 44	-2 36	-4 84	-2 49					-0 58	-0 33	-1 07	-1 41	-1 13
					0 00)	0 00)	0 00)	0 00)	0 00)	0 00)					0 38)	0 44)	0 01)	0 00)	0 01)
$C\ P_{i,t-1}$					-3 38	-3 48	-3 35	-3 79	-0 58	-3 38					-0 52	-1 67	-2 30	-2 20	-2 65
					0 00)	0 00)	0 00)	0 00)	0 75)	0 00)					0 40)	0 03)	0 01)	0 01)	0 00)
$SIZE_{i,t-1}$					0 22	0 23	0 24	0 27	0 03	0 23					1 41	0 94	0 74	0 73	0 56
					0 05)	0 05)	0 13)	0 08)	0 94)	0 14)					0 00)	0 00)	0 00)	0 00)	0 01)
$TFS\ LEP_i$							-6 20			-6 16									
							0 00)			0 00)									
$FORINC_i$								1 98											
								0 00)											
$FOR\ SS_i$																			
$FOREMP_i$																			
Firm dummy	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIN dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs Firm-month)	12480	12480	12480	12480	12346	12346	8064	8106	1389	8064	5367	5367	5367	5367	5367	5367	2557	2557	2557
R^2- dj	0 1550	0 7234	0 7778	0 7859	0 8012	0 8123	0 7942	0 7904	0 7800	0 7961	0 4447	0 6717	0 6526	0 7598	0 7251	0 8035	0 8234	0 8300	0 8432

Panel regressions for the cumulative risk neutral default probabilities. Here, i stands for firm, and t stands for time. The p-values reported come from clustered standard errors by firm and by time, as suggested by Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The sample consists of monthly observations for 138 US and 72 EMU firms constituents of the CDX and iTraxx indexes. The sample period goes from Jan-2000 to Dec-2009.

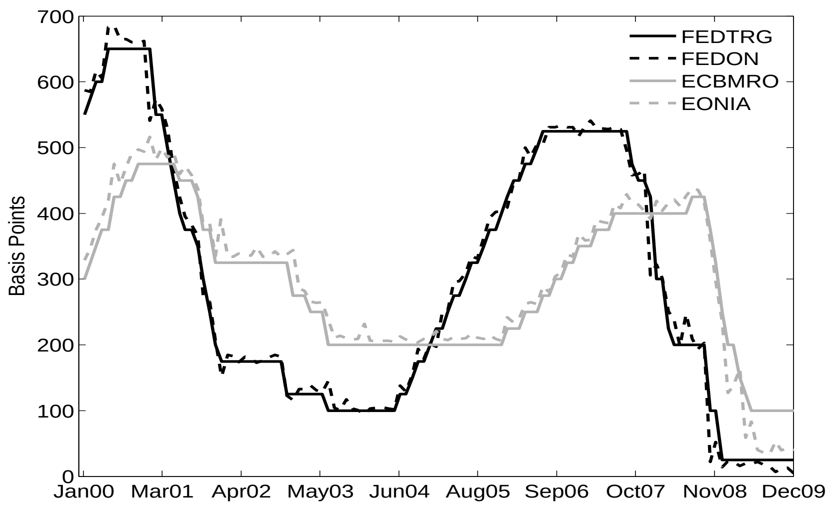
The models I-II show the most naive specification with only domestic and foreign target monetary policy interest in our two monetary regions US and EMU. In case of model II, we include firm dummies that proxy for unobservable time-invariant firm specific characteristics such as the risk management ability. The estimations show that an increase in the Fed rates decreases the default probabilities, but an increase of the ECB rates increases the default probabilities. The effect is more pronounced for financial firms. This very general empirical finding is robust to the specification of the regression, the data that we use (CDS or EDF), and even the maturities (unreported).

In order to control for other missing variables, we include the macroeconomic controls in models III-IV. Lower USD/EUR exchange rate, lower domestic GDP growth, and higher domestic inflation rate, and lower domestic long-term interest rates lead in general to higher default probabilities in the US. Although in Europe their statistical significance depends on the specification.

There exists the possibility that domestic monetary policy is endogenously affected by firms' default probabilities. We believe that domestic monetary policy has been fairly exogenous to firms' default risk for two reasons. Firstly, because monetary authorities haven't decisively showed their intentions for macro-prudential regulation until 2010 with the creation of the Financial Stability Oversight Council and the European Systemic Risk Board. And secondly, for a given firm, the monetary policy is quite exogenous to its unconditional default probability. Monetary authorities are more likely to endogenously respond to aggregate measures of systemic default events that lead to a large number of firms defaulting together. We will analyze this in the next section. Nevertheless, we exclude the domestic monetary policy in model IV and the sign of foreign monetary policy remains.

Why the US and EMU short-term interest rates affect negatively and positively – respectively – the firms' default risk? The interpretation is not so clear. We can think of two straightforward and complementary explanations for this behavior. Firstly, the FEDTRG and the ECBMRO are not in sync as we can see in Figure (4.2), because both monetary authorities pursue different economic targets. And the default probabilities might have a common movement between US and EMU firms as it seems in the examples of Figure (4.3). The different MP rates, and the similar timing of default probability levels would explain the different signs of the coefficients. Secondly, and most interestingly, the signs of the monetary policy rates would make sense if the firms in our sample held long positions (assets) in euros, and short-positions (liabilities) in dollars. This is partially corroborated by the negative sign of the exchange rate control for US and EMU firms. An US firm with assets denominated in euros facing an increase in the exchange rate, would have a higher dollar value of its assets and lower default probability. And an European firm with dollar denominated liabilities facing an increase in the exchange rate, would have a lower euro value of its liabilities and therefore lower default probability. This possibility might be too simplistic. In practice, it is not possible to know the exposure of a firm to foreign interest rates, if we do not know the composition of domestic and foreign assets and liabilities, and their maturity structure (Grammatikos et al., 1986) nor their derivative contracts.

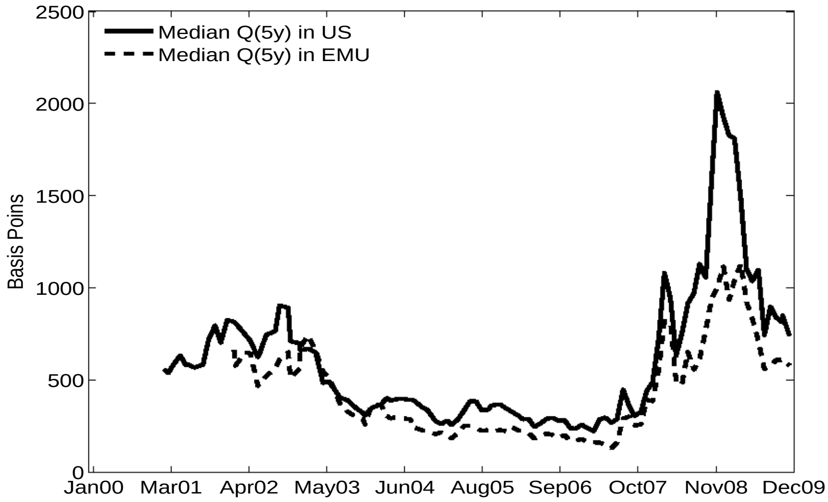
Figure 4.2.: Monetary Policy Rates



End of month observations. The period goes from Jan/2000 to Dec/2009.

The theory that directly relates the effects of monetary policy on firms' default risk is scarce. Bhamra et al. (2011) explains that fixed-income corporate obligations with a fixed nominal coupon increases the incentives of firms to default due to the monetary

Figure 4.3.: Median default probabilities implied from CDS spreads



End of month observations. The period goes from Jan/2000 to Dec/2009.

policy influence on expected inflation. In the dynamic model of González-Aguado and Suarez (2012), the effect of monetary policy on aggregate default rates depends on the horizon, and on the type of firm. A positive shift in the risk-free rate makes non-mature firms (defined as firms that never reached their target leverage ratio) to default in the short-run. Whereas mature firms tend to default more in the short-run under an interest rate cut because they have to adjust to their new, higher target leverage. Instead, higher interest rate reduces firms' target leverage and produces lower default rates in the long run. We will describe evidence that for our set of large and international firms, their degree of international operations influences their exposure to foreign monetary policy.

What type of firm in our sample is more exposed by monetary policy? The models V-VI include the capital, liquidity and size controls and its interactions with the short-term rates to identify the firms. The firm controls show, as expected, that the market assigns higher risk for firms with lower liquidity and capital. Although for EMU firms, the controls are not significative unless we add further controls. With the interactions of firm controls with short-term interest rates, we can identify the type of firms more exposed to monetary policy. When we exclude domestic monetary policy in specification V, a tightening of foreign monetary policy decreases the probability of default for larger firms. In model VI, a domestic monetary tightening affects more larger firms, but the sign is different for US firms than for EMU firms. So far, we haven't been able to identify a firm characteristic that interacted with the monetary policy is systematically significant, keeps a consistent sign across all specifications, and is able to explain the monetary exposure identified in models I-IV.

Does the degree of foreign operations explain the foreign monetary policy exposure? The models VII-IX feature the same regression than model VI but including the variables that measure the firms' degree of internationalization and their interaction with short-term interest rates. The disadvantage is that by including DOI variables, our sample decreases approximately by half, and does not include banks.

In the case of US firms, the model VII yields an interesting result: a loosening of foreign monetary policy increases the default probability of firms with higher foreign-to-total sales. In the model VIIb we repeat the estimation but instead of the foreign-to-total sales ratio we use our measure of foreign income or loss (FORINC). The variable FORINC measures the degree of internationalization of a firm taking into account netted foreign expenses that can decrease long foreign exposure and without considering the sign of the foreign exposure (positive or negative foreign income). Similarly, the effect of foreign monetary policy is stronger for firms with higher FORINC. In general, US firms with higher degree of foreign sales or income increase – respect to firms with no FORINC – their default probability when the foreign monetary authority loosens the interest rates. The model VIII includes the interaction with the variables FORASS and FOREMP that we were able to collect for a few firms from UNCTAD rankings, but they are not significant and the negative sign of the interaction with TFSALEP remains. The dotted coefficients reported come from dropped variables due to multicollinearity. The interaction with the dummy variable FIN is dropped because there are no financial firms with available FORASS and FOREMP. The variables TFSALEP, FORASS, and FOREMP are dropped due to their high level of correlation reported in Table 4.4 and in the studies of Sullivan (1994) and Kedia and Mozumdar (2003). Finally, the model IX repeats the model VII including the foreign macroeconomic controls. The interaction of TFSALEP with the foreign monetary policy keeps as a significant source of foreign monetary policy exposure.

In the case of EMU firms, the models VII-IX repeat the same specifications. Similarly to the US firms, the size seems to be an important characteristic for monetary policy exposure in some specifications, but it is not robust to all specifications. Again we can't obtain a general conclusion regarding liquidity, capital or size being the source of foreign monetary policy exposure. Contrary to the US scene, the variable FOREMP – which proxies the structural costs that a firm faces abroad – is also a source of exposure to the Federal Reserve short-term interest rates. And the sign of the interaction is the opposite of the interaction between TFSALEP and the foreign MP interest rates. Both variables TFSALEP and FOREMP are a measure of DOI, but their nature differs. The former proxies for foreign resources, and the latter proxies for foreign obligations. This different nature would explain the opposite signs of their interactions with foreign monetary policy.

In general, a loosening of the monetary policy in the US, or a tightening of the monetary policy in the Eurozone can lead to higher default probabilities for any firm in any country and for any maturity (unreported). In the cross-section, US firms with larger proportion of foreign sales have higher exposure to foreign monetary policy. And EMU firms with higher foreign-to-total employment ratio are more exposed to foreign monetary policy. The magnitude of the estimated coefficients implies a reasonably economically significant relationship between the default probability and the interaction of foreign monetary policy with the degree of foreign operations.

For example, based to the specification VII of Table 4.5, an average US non-financial firm with a cumulative 5-year market implied default probability of 10%, a liquidity ratio of 16%, a capital ratio of 32%, a log-size of 9.7, and a ratio of foreign-to-total sales of 32% during a period of average ECB interest rates of 3% would decrease its default probability up to 8.32% if the monetary policy decreased 1% (the sample standard deviation) up to 2%.[19]

[19]The calculation for an average US firm with average foreign sales is: $1/(1 + exp(-(ln(0.10/(1 - 0.10)) + (9.75 + 18.09 * 0 + 31.03 * 0.16 + 18.07 * 0.32 + 0.96 * 9.7 - 29.84 * 0.32) * (-0.01)))) = 8.32\%$

On the contrary, an identical firm without foreign sales, would decrease its default probability up to 7.62% if the monetary policy decreased 1% from 3% up to 2%.[20] In this case, a foreign monetary policy shock leads to a 23.8% decrease in the default probability of a firm without foreign sales, and only a decrease of 16.8% if the firm has average foreign-to-total sales ratio.

4.3.5. Robustness checks

In this section we conduct a series of robustness checks. In the first place, we check other definitions of monetary policy. In the second place, we reduce the frequency from monthly to quarterly. And in the third place, we test other estimation methodologies.

The target interest rate does not determine by itself the short-term interest rates. For instance, in the Eurozone, the effective interest rate not only depends on the rate of the main refinancing operations, but also on the marginal lending facility, the deposit facility, and the type of auction (Benito et al., 2007). For this reason, we display for EMU firms in Table 4.6 the same specification of the model VIII from Table 4.5, where instead of the target interest rate, we use the effective interest rate. Moreover, we repeat the regression for all horizons available of CDS implied default probabilities and EDF real default probabilities. Across all maturities and default measures, the firms with more foreign employment are more exposed to the monetary policy of the Federal Reserve. The coefficient is relatively constant for every maturity. This means, in general, that under an increase in foreign monetary policy, the change in the log odds ratio is the same for all maturities, and the change in the default probability is higher for higher horizons.

[20] The calculation for an average US firm without foreign sales is: $1/(1 + exp(-(ln(0.10/(1-0.10)) + (9.75 + 18.09 * 0 + 31.03 * 0.16 + 18.07 * 0.32 + 0.96 * 9.7 - 29.84 * 0) * (-0.01)))) = 7.62\%$

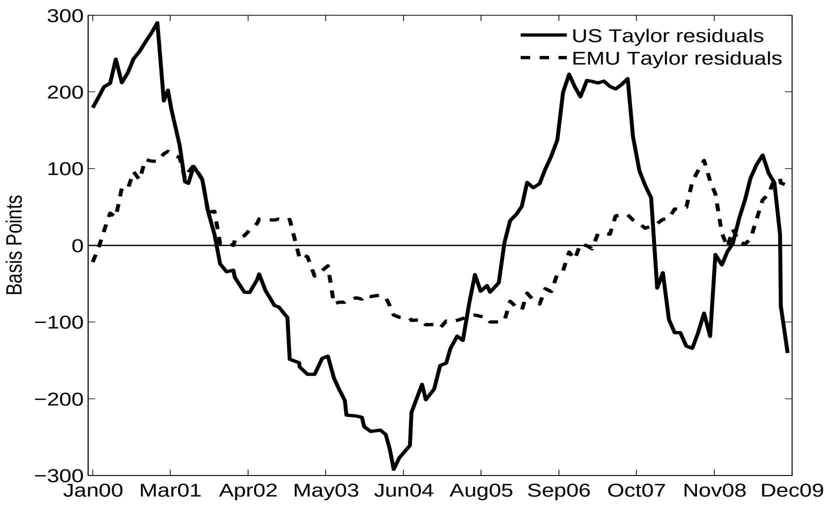
Table 4.6.: Panel regression for cumulative default probabilities on effective interest rates, EMU firms

Dependent variable	*logit* ($Q_{it}(T)$)											*logit* ($EDF_{it}(T)$)				
Model	(I) 6M	(II) 1Y	(III) 2Y	(IV) 3Y	(V) 4Y	(VI) 5Y	(VII) 7Y	(VIII) 10Y	(IX) 15Y	(X) 20Y	(XI) 30Y	(XII) 1Y	(XIII) 2Y	(XIV) 3Y	(XV) 4Y	(XVI) 5Y
Cons	15 57	13 31	11 99	11 23	11 23	9 67	10 35	9 25	8 85	8 28	9 42	0 79	0 84	1 01	1 39	1 62
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 89)	(0 88)	(0 85)	(0 79)	(0 74)
Panel A.- US Monetary policy																
FEDON_{t-1}	41 70	56 32	21 78	3 72	20 11	17 33	23 14	27 99	22 89	33 05	43 06	46 47	45 86	45 87	49 31	47 22
	(0 27)	(0 12)	(0 49)	(0 90)	(0 58)	(0 53)	(0 37)	(0 27)	(0 41)	(0 24)	(0 20)	(0 32)	(0 29)	(0 25)	(0 20)	(0 19)
$\text{FIN}_i \times \text{FEDON}_{t-1}$																
$\text{LIQ}_{i,t-1} \times \text{FEDON}_{t-1}$	14 29	18 83	13 82	13 67	14 11	11 79	10 68	11 08	12 76	14 26	17 84	11 68	11 72	10 12	8 11	6 96
	(0 09)	(0 03)	(0 10)	(0 11)	(0 28)	(0 16)	(0 22)	(0 19)	(0 16)	(0 12)	(0 12)	(0 66)	(0 64)	(0 67)	(0 72)	(0 74)
$\text{CAP}_{i,t-1} \times \text{FEDON}_{t-1}$	13 44	6 69	1 19	0 98	5 37	0 61	0 80	1 24	1 63	5 79	4 29	27 92	22 81	20 09	18 82	17 76
	(0 36)	(0 66)	(0 93)	(0 94)	(0 62)	(0 96)	(0 94)	(0 91)	(0 89)	(0 63)	(0 75)	(0 21)	(0 28)	(0 32)	(0 32)	(0 32)
$\text{SIZE}_{i,t-1} \times \text{FEDON}_{t-1}$	0 88	0 20	1 83	2 82	5 00	3 65	3 58	3 49	3 03	3 75	4 93	0 95	1 01	1 13	1 47	1 42
	(0 76)	(0 94)	(0 46)	(0 22)	(0 06)	(0 09)	(0 08)	(0 09)	(0 17)	(0 10)	(0 07)	(0 80)	(0 77)	(0 73)	(0 64)	(0 62)
$\text{TFSALEP}_i \times \text{FEDON}_{t-1}$	27 20	25 72	23 94	24 28	29 75	24 93	22 39	23 98	27 30	25 80	31 75	9 64	12 90	14 56	14 73	14 78
	(0 00)	(0 02)	(0 03)	(0 02)	(0 00)	(0 01)	(0 02)	(0 01)	(0 00)	(0 02)	(0 01)	(0 62)	(0 49)	(0 42)	(0 39)	(0 36)
$\text{FORASS}_i \times \text{FEDON}_{t-1}$	32 95	32 72	32 22	28 52	8 14	27 92	27 52	22 76	16 13	18 10	15 75	47 53	47 15	45 28	41 46	38 52
	(0 10)	(0 06)	(0 04)	(0 06)	(0 65)	(0 06)	(0 06)	(0 11)	(0 26)	(0 22)	(0 34)	(0 10)	(0 09)	(0 09)	(0 11)	(0 12)
$\text{FOREMP}_i \times \text{FEDON}_{t-1}$	42 63	51 92	50 14	47 79	40 92	47 19	46 01	43 45	41 17	38 81	41 47	55 02	52 14	48 37	45 35	40 92
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 02)	(0 02)	(0 03)	(0 03)	(0 03)
Panel B.- EMU Monetary policy																
EONIA_{t-1}	22 14	58 23	31 52	20 17	10 18	6 24	5 05	5 19	15 43	8 66	3 24	113 48	120 82	123 47	129 14	125 71
	(0 61)	(0 19)	(0 43)	(0 60)	(0 71)	(0 85)	(0 87)	(0 85)	(0 58)	(0 77)	(0 92)	(0 22)	(0 17)	(0 14)	(0 11)	(0 10)
$\text{FIN}_i \times \text{EONIA}_{t-1}$																
$\text{LIQ}_{i,t-1} \times \text{EONIA}_{t-1}$	5 05	0 92	6 59	6 57	0 69	7 35	6 88	4 73	2 60	2 54	1 45	2 51	4 12	2 96	3 47	3 27
	(0 74)	(0 95)	(0 67)	(0 68)	(0 95)	(0 63)	(0 65)	(0 75)	(0 87)	(0 86)	(0 93)	(0 93)	(0 89)	(0 92)	(0 90)	(0 90)
$\text{CAP}_{i,t-1} \times \text{EONIA}_{t-1}$	26 25	42 18	42 11	42 62	6 56	37 69	34 18	32 67	32 28	37 72	36 70	17 23	19 31	20 29	19 78	18 57
	(0 19)	(0 04)	(0 02)	(0 02)	(0 60)	(0 03)	(0 03)	(0 03)	(0 05)	(0 01)	(0 03)	(0 65)	(0 60)	(0 58)	(0 57)	(0 58)
$\text{SIZE}_{i,t-1} \times \text{EONIA}_{t-1}$	4 27	2 78	3 71	4 00	3 66	3 96	3 39	2 86	2 27	3 03	4 87	7 51	7 89	8 09	8 53	8 29
	(0 15)	(0 38)	(0 20)	(0 15)	(0 06)	(0 10)	(0 12)	(0 17)	(0 28)	(0 17)	(0 02)	(0 28)	(0 24)	(0 21)	(0 17)	(0 16)
$\text{TFSALEP}_i \times \text{EONIA}_{t-1}$	1 46	16 52	21 64	22 54	0 40	17 24	15 97	11 80	10 61	15 83	16 97	28 69	30 04	29 93	27 87	26 70
	(0 93)	(0 48)	(0 34)	(0 34)	(0 97)	(0 44)	(0 45)	(0 56)	(0 60)	(0 39)	(0 41)	(0 38)	(0 35)	(0 34)	(0 35)	(0 35)
$\text{FORASS}_i \times \text{EONIA}_{t-1}$	51 32	51 17	51 67	48 90	30 06	43 25	37 37	28 73	24 15	27 09	32 87	68 66	61 66	57 50	51 53	47 23
	(0 14)	(0 12)	(0 06)	(0 06)	(0 07)	(0 05)	(0 05)	(0 10)	(0 17)	(0 14)	(0 14)	(0 08)	(0 09)	(0 09)	(0 11)	(0 13)
$\text{FOREMP}_i \times \text{EONIA}_{t-1}$	47 14	47 20	41 05	38 53	31 18	34 86	30 00	25 26	24 11	21 96	25 08	76 04	73 07	71 72	70 29	66 33
	(0 01)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 01)	(0 01)	(0 02)	(0 02)	(0 03)	(0 04)	(0 04)	(0 04)	(0 04)
Panel C.- Macro controls																
USD/EUR_{t-1}	1 18	1 95	1 66	1 44	0 91	1 15	1 10	1 04	1 06	1 17	1 30	2 01	2 09	2 09	2 02	1 92
	(0 08)	(0 00)	(0 00)	(0 00)	(0 21)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
GDPG EMU_{t-1}	15 78	20 93	19 02	18 49	5 18	17 84	17 10	16 56	16 72	17 66	19 03	7 09	8 45	8 79	8 34	7 97
	(0 14)	(0 01)	(0 01)	(0 00)	(0 42)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 17)	(0 11)	(0 09)	(0 09)	(0 09)
$\text{Inflation EMU}_{t-1}$	1 73	4 51	1 36	0 96	6 42	5 58	7 99	9 53	8 30	7 62	6 80	1 08	2 96	3 70	3 83	3 84
	(0 86)	(0 61)	(0 86)	(0 89)	(0 27)	(0 33)	(0 11)	(0 03)	(0 07)	(0 11)	(0 21)	(0 85)	(0 62)	(0 54)	(0 52)	(0 51)
$\text{10 year rate EMU}_{t-1}$	75 03	60 95	52 69	46 27	3 65	36 79	33 77	28 98	26 87	26 65	33 69	2 25	1 92	1 88	1 63	1 26
	(0 00)	(0 00)	(0 00)	(0 00)	(0 79)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 77)	(0 81)	(0 81)	(0 83)	(0 86)
TERM EMU_{t-1}	15 12	12 43	10 51	8 73	49 55	8 94	8 90	9 76	8 26	7 66	9 33	44 17	45 30	45 27	44 03	41 85
	(0 63)	(0 68)	(0 68)	(0 70)	(0 01)	(0 63)	(0 58)	(0 48)	(0 57)	(0 61)	(0 59)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
Panel D.- Firm controls																
$\text{LIQ}_{i,t-1}$	1 67	1 80	1 78	1 67	1 05	1 48	1 37	1 20	1 13	1 16	1 07	2 49	2 32	2 22	2 07	1 93
	(0 00)	(0 00)	(0 00)	(0 00)	(0 12)	(0 00)	(0 00)	(0 00)	(0 01)	(0 01)	(0 07)	(0 17)	(0 18)	(0 17)	(0 17)	(0 17)
$\text{CAP}_{i,t-1}$	0 68	1 34	1 36	1 40	0 33	1 42	1 38	1 41	1 52	1 58	1 66	5 31	4 99	4 71	4 49	4 20
	(0 59)	(0 21)	(0 17)	(0 13)	(0 73)	(0 08)	(0 07)	(0 05)	(0 05)	(0 06)	(0 09)	(0 01)	(0 01)	(0 01)	(0 01)	(0 01)
$\text{SIZE}_{i,t-1}$	1 32	1 24	1 15	1 08	0 67	0 93	0 85	0 77	0 78	0 78	0 91	0 22	0 20	0 18	0 14	0 12
	(0 00)	(0 00)	(0 00)	(0 00)	(0 01)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 64)	(0 65)	(0 68)	(0 73)	(0 75)
TFSALEP_i																
FORASS_i																
FOREMP_i																
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIN dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs (Firm month)	2307	2552	2552	2550	1631	2557	2551	2545	2538	2506	2381	3807	3807	3807	3807	3807
R^2 Adj	0 8279	0 8367	0 8344	0 8269	0 8776	0 8132	0 7977	0 7813	0 7543	0 7481	0 7412	0 6727	0 6856	0 6936	0 6975	0 7001

Panel regressions for the cumulative risk neutral and objective default probabilities. Here, i stands for firm, and t stands for time. The p-values reported come from clustered standard errors by firm and by time, as suggested by Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The sample consists of monthly observations for 138 US and 72 EMU firms constituents of the CDX and iTraxx indexes. The sample period goes from Jan-2000 to Dec-2009.

Other concern is that the MP rates are partially determined by other macroeconomic variables. In the most simple monetary policy rule of thumb, as the Taylor rule, the monetary authority sets the target interest rates depending on the levels of GDP growth and inflation (Taylor, 1993, 2009). The Figure 4.4 plots the residuals of such Taylor rule. The residuals represent how tight or how loose the monetary policy is respect to the simplest Taylor rule. As example, the Table 4.7 displays for US firms the same specification of model VII from Table 4.5 where we use the Taylor rule residuals as a measure of tightness in the monetary policy. Results show across all maturities and default measures that a tightening of ECB monetary policy under the Taylor rule has a different effect on firms with higher proportion of foreign sales.

Figure 4.4.: Taylor rule residuals



The graph shows the Taylor rule residuals at monthly frequency. Taylor rule residuals are the residuals of the regressions of FEDTRG and ECBMRO rates on their respective GDP growth and inflation over the period Jan/2000 to Dec/2009. The annual GDP growth has been linearly interpolated from quarterly to monthly frequency.

Table 4.7.: Panel regression for cumulative default probabilities on Taylor residuals, US firms

Dependent variable	*logit* $(Q_{it}(T))$											*logit* $(EDF_{it}(T))$				
Model	(I) 6M	(II) 1Y	(III) 2Y	(IV) 3Y	(V) 4Y	(VI) 5Y	(VII) 7Y	(VIII) 10Y	(IX) 15Y	(X) 20Y	(XI) 30Y	(XII) 1Y	(XIII) 2Y	(XIV) 3Y	(XV) 4Y	(XVI) 5Y
Cons	1 09	1 07	1 79	2 00	3 96	2 29	2 85	3 53	4 45	5 36	8 22	4 03	3 78	3 53	3 31	2 95
	(0 49)	(0 42)	(0 17)	(0 09)	(0 01)	(0 04)	(0 01)	(0 00)	(0 00)	(0 00)	(0 00)	(0 01)	(0 02)	(0 02)	(0 03)	(0 04)
							Panel A.- US Monetary policy									
TAYLOR-US$_{t-1}$	21 97	18 09	27 96	35 11	44 02	35 91	30 37	25 33	15 71	11 15	6 85	25 18	27 68	29 37	29 25	28 80
	(0 20)	(0 26)	(0 05)	(0 01)	(0 00)	(0 00)	(0 01)	(0 03)	(0 22)	(0 44)	(0 71)	(0 20)	(0 15)	(0 12)	(0 11)	(0 10)
FIN$_i$×TAYLOR-US$_{t-1}$	4 93	-0 31	-1 03	-0 90	-8 56	-4 41	-6 43	-8 26	-8 64	-12 49	-17 88	-10 77	-11 49	-10 69	-11 01	-11 18
	(0 36)	(0 95)	(0 85)	(0 86)	(0 20)	(0 43)	(0 26)	(0 18)	(0 23)	(0 16)	(0 12)	(0 24)	(0 19)	(0 22)	(0 21)	(0 19)
LIQ$_{i,t-1}$×TAYLOR-US$_{t-1}$	1 71	-1 16	-5 01	-4 46	-1 60	-3 91	-1 78	-1 02	-0 48	2 87	7 42	-22 35	-19 64	-19 49	-20 64	-20 42
	(0 85)	(0 89)	(0 55)	(0 58)	(0 84)	(0 61)	(0 81)	(0 89)	(0 95)	(0 72)	(0 44)	(0 09)	(0 13)	(0 13)	(0 10)	(0 08)
CAP$_{i,t-1}$×TAYLOR-US$_{t-1}$	-3 61	-9 12	-10 22	-7 85	7 97	-5 22	-1 61	0 31	6 55	4 98	5 63	-20 39	-21 91	-21 62	-19 90	-18 60
	(0 71)	(0 36)	(0 29)	(0 39)	(0 42)	(0 58)	(0 86)	(0 97)	(0 52)	(0 67)	(0 71)	(0 18)	(0 15)	(0 15)	(0 18)	(0 18)
SIZE$_{i,t-1}$×TAYLOR-US$_{t-1}$	-3 57	-3 50	-4 13	-4 79	-4 90	-4 60	-3 97	-3 56	-2 91	-2 33	-1 81	-4 39	-4 78	-4 98	-4 96	-4 84
	(0 02)	(0 01)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 02)	(0 10)	(0 33)	(0 01)	(0 00)	(0 00)	(0 00)	(0 00)
TFSALEP$_i$×TAYLOR-US$_{t-1}$	9 23	5 98	4 24	3 28	14 09	-0 93	-2 07	-1 93	0 01	1 22	2 87	8 90	8 99	9 21	10 66	11 25
	(0 18)	(0 32)	(0 46)	(0 54)	(0 01)	(0 86)	(0 68)	(0 70)	(1 00)	(0 85)	(0 71)	(0 26)	(0 23)	(0 21)	(0 13)	(0 09)
							Panel B.- EMU Monetary policy									
TAYLOR-EMU$_{t-1}$	-36 42	-19 97	-31 30	-30 95	-66 93	-27 14	-10 49	9 38	28 83	39 21	63 26	63 77	59 31	56 92	56 82	52 35
	(0 45)	(0 57)	(0 37)	(0 32)	(0 12)	(0 36)	(0 72)	(0 77)	(0 48)	(0 39)	(0 33)	(0 09)	(0 11)	(0 12)	(0 11)	(0 12)
FIN$_i$×TAYLOR-EMU$_{t-1}$	105 94	69 72	67 53	63 35	86 04	63 62	66 15	69 93	73 90	72 09	98 17	51 63	51 00	46 33	43 24	40 60
	(0 02)	(0 02)	(0 02)	(0 03)	(0 04)	(0 02)	(0 02)	(0 02)	(0 04)	(0 04)	(0 06)	(0 09)	(0 09)	(0 11)	(0 13)	(0 15)
LIQ$_{i,t-1}$×TAYLOR-EMU$_{t-1}$	15 06	41 77	39 28	33 34	-0 39	31 08	25 10	18 99	9 11	-2 60	-27 98	32 10	20 62	18 92	22 72	25 05
	(0 68)	(0 13)	(0 14)	(0 20)	(0 99)	(0 20)	(0 30)	(0 46)	(0 75)	(0 93)	(0 49)	(0 29)	(0 49)	(0 52)	(0 43)	(0 36)
CAP$_{i,t-1}$×TAYLOR-EMU$_{t-1}$	46 66	36 70	36 26	29 48	23 26	20 28	7 40	1 47	-7 27	-15 67	-27 05	-4 73	2 79	5 77	7 09	10 22
	(0 23)	(0 24)	(0 25)	(0 34)	(0 55)	(0 50)	(0 81)	(0 96)	(0 86)	(0 72)	(0 65)	(0 87)	(0 93)	(0 84)	(0 80)	(0 69)
SIZE$_{i,t-1}$×TAYLOR-EMU$_{t-1}$	9 35	7 86	7 64	7 41	9 38	5 93	4 38	2 79	1 88	1 41	0 63	-1 66	-1 27	-1 14	-1 26	-1 14
	(0 07)	(0 05)	(0 06)	(0 05)	(0 04)	(0 09)	(0 21)	(0 46)	(0 68)	(0 78)	(0 93)	(0 68)	(0 75)	(0 77)	(0 74)	(0 75)
TFSALEP$_i$×TAYLOR-EMU$_{t-1}$	-81 47	-80 77	-69 63	-65 80	-39 34	-50 20	-47 37	-49 94	-50 36	-51 37	-62 11	-72 22	-69 06	-67 99	-68 68	-66 75
	(0 00)	(0 00)	(0 00)	(0 00)	(0 07)	(0 00)	(0 00)	(0 00)	(0 01)	(0 02)	(0 04)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
							Panel C.- Macro controls									
USD/EUR$_{t-1}$	-2 46	-2 07	-1 62	-1 39	-1 88	-0 99	-0 86	-0 82	-0 92	-1 06	-1 41	-2 18	-2 22	-2 20	-2 12	-2 00
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
GDPG-US$_{t-1}$	-14 17	-15 57	-14 96	-14 37	-3 02	-14 02	-12 28	-11 03	-11 50	-11 75	-12 70	-19 38	-19 10	-18 65	-17 94	-17 06
	(0 00)	(0 00)	(0 00)	(0 00)	(0 35)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
Inflation-US$_{t-1}$	18 41	13 92	13 66	13 06	14 86	11 80	10 05	8 18	9 09	11 07	15 65	-7 99	-8 03	-7 74	-7 42	-6 85
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 03)	(0 03)	(0 04)	(0 04)	(0 05)
10-year rate-US$_{t-1}$	-50 45	-38 82	-35 67	-32 54	-49 62	-26 18	-22 90	-20 05	-22 46	-27 11	-38 86	-2 70	-1 36	-0 69	-0 53	-0 66
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 80)	(0 90)	(0 95)	(0 96)	(0 94)
TERM-US$_{t-1}$	39 09	20 93	11 14	4 09	41 66	-7 07	-11 81	-17 26	-22 61	-20 47	-17 78	-18 12	-17 73	-16 89	-15 65	-14 32
	(0 00)	(0 09)	(0 32)	(0 70)	(0 00)	(0 46)	(0 17)	(0 04)	(0 02)	(0 03)	(0 14)	(0 09)	(0 09)	(0 10)	(0 12)	(0 13)
							Panel D.- Firm controls									
LIQ$_{i,t-1}$	-2 50	-2 50	-2 38	-2 21	-1 86	-1 95	-1 81	-1 75	-1 86	-1 98	-2 39	-3 57	-3 38	-3 27	-3 16	-3 02
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
CAP$_{i,t-1}$	-3 26	-3 13	-3 29	-3 05	-3 52	-2 93	-2 80	-2 84	-3 07	-3 25	-3 98	-4 00	-4 04	-3 94	-3 76	-3 57
	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)
SIZE$_{i,t-1}$	0 10	0 16	0 13	0 13	0 02	0 14	0 10	0 09	0 17	0 22	0 13	-0 40	-0 36	-0 34	-0 33	-0 31
	(0 60)	(0 36)	(0 45)	(0 41)	(0 93)	(0 36)	(0 52)	(0 55)	(0 35)	(0 26)	(0 59)	(0 01)	(0 02)	(0 02)	(0 02)	(0 02)
TFSALEP$_i$	-5 14	-6 10	-6 04	-6 18	-4 22	-6 44	-6 34	-6 76	-8 30	-9 85	-11 01	-0 83	-0 79	-0 65	-0 54	-0 44
	(0 00)	(0 00)	(0 00)	(0 00)	(0 01)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 00)	(0 21)	(0 23)	(0 32)	(0 39)	(0 48)
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FIN dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs (Firm-month)	6698	7958	7834	7999	4393	8064	7975	7819	7343	7269	6631	9937	9937	9937	9937	9937
R^2-Adj	0 8153	0 8143	0 8091	0 8060	0 8586	0 7899	0 7728	0 7522	0 7417	0 7489	0 7638	0 7705	0 7722	0 7728	0 7732	0 7731

Panel regressions for the cumulative risk neutral and objective default probabilities. Here, i stands for firm, and t stands for time. The p-values reported come from clustered standard errors by firm and by time, as suggested by Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The sample consists of monthly observations for 138 US and 72 EMU firms constituents of the CDX and iTraxx indexes. The sample period goes from Jan-2000 to Dec-2009.

There are two other concerns in the results showed so far. To begin with, if the errors are autocorrelated the estimated parameters might not be appropriate. We reduce the frequency from monthly to quarterly to alleviate the possibility of autocorrelated errors and also the importance of the interpolation applied on some variables that are not observed at high frequencies. Lastly, there might be unobservable or omitted time-variant macroeconomic variables, hence we will perform the regressions including a quarter dummy.

The Table 4.8 reports the results of three different models at quarterly frequency. The first model I is estimated by OLS assuming iid errors, and reports the p-values that come from clustered standard errors by firm and quarter. The model II reports GLS coefficients imposing heteroscedastic errors across firms and a firm-specific AR(1) structure. The GLS estimates are known to be more efficient, but it comes at the price of imposing an error structure.

The third model measures directly the persistence of the log odds ratio transformation of market implied default probabilities, and assumes contemporaneous shocks from exogenous variables. Jiménez et al. (2013) estimated a similar a dynamic model where their dependent variable ex-post measure of bank risk-taking is the log odds transformation of the non-performing loans ratio. And Delis and Kouretas (2011) estimated a similar dynamic model and used the ratio of risk assets to total assets and the non-performing loans ratio as dependent variables that measure bank risk-taking. In our dynamic model, the firm characteristics and their interactions with domestic monetary policy (x_{it}) can be endogenous if they respond to past shocks in the firm's specific default probabilities. Technically, a variable x_{it} is endogenous if $E[x_{it}\varepsilon_{is}] \neq 0$ for $s \leq t$ and $E[x_{it}\varepsilon_{is}] = 0$ for all $s > t$. We use the estimation methodology of Arellano and Bond (1991) and use up to four lags of the firm characteristics and their interactions with the domestic monetary policy to instrument for these potentially endogenous variables.

In the US monetary region, models I to III confirm that the degree of foreign sales is an important source of foreign monetary policy exposure. In comparison, models I to III also confirm for the Eurozone that the foreign monetary policy exposure depends on

Table 4.8.: Panel regression for 5-year implied default probabilities on target interest rates at quarterly frequency.

Dependent variable	*logit* $(Q_{it}(5Y))$					
Monetary Region	US			EMU		
Model	(I	(II	(III	(I	(II	(III
Estimation	OLS	FGLS	Arellano and Bond (1991	OLS	FGLS	Arellano and Bond (1991
Cons.	-1.02	-5.44	-1.93	-10.59	-1.32	-2.66
	(0.33	(0.46	(0.00	(0.00	(0.49	(0.00
logit $(Q_{i,t\;1}(5Y))$			0.70			0.63
			(0.00			(0.00
Panel A.- US Monetary policy						
FIN$_i$×FEDTRG$_t$			-3.95			.
			(0.05			.
FIN$_i$×FEDTRG$_{t\;1}$	-15.94	-10.18		.	.	
	(0.06	(0.01		.	.	
LIQ$_{i,t}$×FEDTRG$_t$			0.68			1.19
			(0.84			(0.80
LIQ$_{i,t\;1}$×FEDTRG$_{t\;1}$	-6.23	-12.35		7.50	0.44	
	(0.51	(0.01		(0.38	(0.96	
CAP$_{i,t}$×FEDTRG$_t$			4.71			1.71
			(0.16			(0.76
CAP$_{i,t\;1}$×FEDTRG$_{t\;1}$	-1.46	-7.75		0.86	2.60	
	(0.89	(0.13		(0.93	(0.74	
SIZE$_{i,t}$×FEDTRG$_t$			-2.22			-0.81
			(0.00			(0.42
SIZE$_{i,t\;1}$×FEDTRG$_{t\;1}$	-4.63	-2.70		-3.15	0.33	
	(0.00	(0.00		(0.19	(0.83	
TFSALEP$_i$×FEDTRG$_t$			2.19			-14.77
			(0.31			(0.00
TFSALEP$_i$×FEDTRG$_{t\;1}$	5.05	4.25		-30.10	-29.35	
	(0.42	(0.24		(0.00	(0.00	
FORASS$_i$×FEDTRG$_t$						-7.58
						(0.18
FORASS$_i$×FEDTRG$_{t\;1}$				-22.13	-13.43	
				(0.14	(0.23	
FOREMP$_i$×FEDTRG$_t$						20.44
						(0.00
FOREMP$_i$×FEDTRG$_{t\;1}$				45.82	46.40	
				(0.00	(0.00	
Panel B.- EMU Monetary policy						
FIN$_i$×ECBMRO$_t$			7.40			.
			(0.03			.
FIN$_i$×ECBMRO$_{t\;1}$	26.44	9.22		.	.	
	(0.01	(0.14		.	.	
LIQ$_{i,t}$×ECBMRO$_t$			4.76			4.28
			(0.43			(0.62
LIQ$_{i,t\;1}$×ECBMRO$_{t\;1}$	31.66	32.78		6.72	-7.03	
	(0.05	(0.00		(0.71	(0.63	
CAP$_{i,t}$×ECBMRO$_t$			-2.92			13.84
			(0.61			(0.17
CAP$_{i,t\;1}$×ECBMRO$_{t\;1}$	18.33	21.89		50.86	29.55	
	(0.24	(0.01		(0.02	(0.03	
SIZE$_{i,t}$×ECBMRO$_t$			2.22			3.86
			(0.00			(0.03
SIZE$_{i,t\;1}$×ECBMRO$_{t\;1}$	1.89	-0.45		8.05	4.36	
	(0.24	(0.68		(0.00	(0.08	
TFSALEP$_i$×ECBMRO$_t$			-8.45			7.25
			(0.03			(0.36
TFSALEP$_i$×ECBMRO$_{t\;1}$	-26.91	-18.05		0.22	23.00	
	(0.00	(0.00		(0.99	(0.04	
FORASS$_i$×ECBMRO$_t$						17.66
						(0.07
FORASS$_i$×ECBMRO$_{t\;1}$				35.71	18.07	
				(0.07	(0.27	
FOREMP$_i$×ECBMRO$_t$						-21.41
						(0.02
FOREMP$_i$×ECBMRO$_{t\;1}$				-40.56	-42.72	
				(0.00	(0.00	
Panel C.- Firm controls						
LIQ$_{i,t}$			-1.05			-0.27
			(0.00			(0.22
LIQ$_{i,t\;1}$	-2.70	-2.26		-0.84	-0.46	
	(0.00	(0.00		(0.09	(0.29	
CAP$_{i,t}$			-0.93			-1.11
			(0.00			(0.00
CAP$_{i,t\;1}$	-3.16	-2.74		-2.75	-1.71	
	(0.00	(0.00		(0.00	(0.00	
SIZE$_{i,t}$			0.14			0.10
			(0.01			(0.13
SIZE$_{i,t\;1}$	0.19	0.18		0.48	0.33	
	(0.20	(0.00		(0.03	(0.00	
TFSALEP$_i$	-6.08	5.09	.	.	-4.38	.
	(0.00	(0.74	.	.	(0.00	.
FORASS$_i$				.	-3.24	.
				.	(0.11	.
FOREMP$_i$				.	-0.95	.
				.	(0.32	.
Panel D.- Unobservable effects						
Firm dummy	Yes	Yes	No	Yes	Yes	No
FIN dummy	Yes	Yes	Yes	Yes	Yes	Yes
Quarter dummy	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (Firm-quarter	2706	2706	2524	858	858	790
R^2-Adj	0.8256			0.8829		
Wald statistic		7347.47	13257.92		4805.00	8441.29
		(0.00	(0.00		(0.00	(0.00

Panel regressions for the 5-year cumulative risk neutral default probability. Here, i stands for firm, and t stands for time. The p-values are reported between parenthesis. In the OLS estimation, the p-values reported come from clustered standard errors by firm and by quarter, as suggested by Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The Feasible Generalized Least Squares (FGLS) estimation allows residuals to be heteroscedastic across firms and assumes a firm-specific AR(1) error structure. The dynamic model is estimated with the Arellano and Bond (1991) procedure by treating the firm characteristics and their interactions with the domestic monetary policy as endogenous. We use up to four lags to instrument for the endogenous variables. The sample consists of quarterly observations for US and EMU firms constituents of the CDX and iTraxx indexes. The sample period goes from Jan-2000 to Dec-2009.

the proportion of foreign employment.

Using the CDS prices to construct a measure of market implied default probabilities, we find evidence that *the firms' default risk exposure to foreign monetary policy depends on the firms' degree of internationalization.* This statement is relatively robust to numerous macroeconomic controls (exchange rate, business cycle, inflation, long-term interest rates, term spread), firm controls (liquidity, capital ratio, size, firm fixed effects), unobservable time-varying factors (time dummies), the geography (US or EMU), the frequency (monthly or quarterly), the definition of monetary policy (target interest rate, effective interest rate or Taylor-rule residuals), the type of forward default probability (market implied or real default probability), the horizon of the default probability (from 6 months up to 30 years), and the methodology (pooled panel data regression and dynamic panel data with endogenous domestic monetary policy).

4.4. Unexpected monetary policy shocks

So far, we have focused on the overall credit market relationship with a foreign monetary policy. This section focuses on the immediate impact of monetary policy the credit market. Understanding the direct links between monetary policy and asset prices is important for understanding the policy transmission mechanism (Bernanke and Kuttner, 2005).

The empirical approach summarized in equation (4.5) presents some obstacles in order to safely say that the foreign monetary policy indeed affects international firms' default probabilities. Among the main concerns are endogeneity, simultaneity, omitted foreign monetary policies, other omitted variables, stickiness of the monetary policy or non conventional monetary policies at near-zero interest rates. Furthermore, the asset markets are forward looking and tend to incorporate information about future monetary policy (Bernanke and Kuttner, 2005). These empirical issues make it difficult to safely disentangle the effect (if any) of foreign monetary policies on market implied default probabilities.

Most recent studies try to circumvent the previous concerns by measuring the unexpected changes in the target rate by the monetary authorities. They use the overnight interest rates futures market forecast errors as measures of exogenous, unforeseeable changes in the stance of monetary policy (Piazzesi and Swanson, 2008). To construct the unexpected changes in US and European monetary policy, we need futures contracts on effective short-term interest rates. For the US, we use the 30-Day Federal Funds Futures from the Chicago Board of Trade and for the Eurozone we use the EUREX One-Month EONIA Futures.[21] We follow the approach of Kuttner (2001) to construct the unexpected changes from futures on the interest rates controlled by the monetary authorities

$$\Delta i^u = \frac{D}{D-d}\left(f^0_{m,d} - f^0_{m,d-1}\right) \tag{4.5}$$

where $f^0_{m,d}$ is the current-month futures rate. The change in the futures price on day d is scaled by the number of days $D-d$ remaining in the month m.[22] Assuming that no further monetary policy changes are expected within the month, and that the premium embedded in the futures market does not change from one day to the next in the event of a monetary policy change, this method provides a good gauge of 1-day surprise target change (see Kuttner, 2001). As the risk premia embedded in the futures change at business-cycle frequencies, one-day changes in near-term futures on the day of a monetary policy announcement can be safely interpreted as a measure of monetary policy shock robust to the presence of risk premia (Piazzesi and Swanson, 2008; Hamilton, 2009).

[21] More information available at: http://www.cmegroup.com/trading/interest-rates/stir/30-day-federal-fund_contractSpecs_futures.html and http://www.eurexchange.com/exchange-en/products/int/mon/14664/

[22] Similarly to Kuttner (2001) and Bernanke and Kuttner (2005), we use the unscaled change in the futures rate to calculate the funds rate surprise when the change occurs within the last 3 days of the month. Also, in case of an event the first day of the month, I use the 1-month futures rate from the last day of the previous month $f^1_{m-1,D}$ instead of $f^0_{m,d-1}$. The monetary policy changes by the Fed, ECB and other central banks in September 17th, 2001 after the twin towers attack have been removed from the sample. We also exclude from the analysis October 8th, 2008 because the Bank of Canada, the Bank of England, the ECB, the Federal Reserve, Sveriges Riksbank and the Swiss National Bank simultaneously announced reductions in policy interest rates.

The vast majority of the empirical research on the reaction of financial markets to policy surprises is focused on the stock market. Bernanke and Kuttner (2005) documents that an unanticipated 25-basis-point cut typically leads to a 1% increase in the stock market index. They hypothesize that two main reasons might be behind this phenomenon. First, that tight money increases the risk-aversion of investors. And second, that tight money increases the firm's riskiness due to higher interest costs or weaker balance sheets. In order to identify the source of the reaction, Ehrmann and Fratzscher (2004) and Basistha and Kurov (2008) study the cross-sectional reaction of stocks that belong to the S&P500. They find that firms with higher credit and financial constraints are more affected by domestic monetary policy. Our empirical approach using ex-ante measures of default risk allows to better disentangle the asymmetric effects and focus on the default risk channel of monetary policy transmission.

The related literature has also studied the foreign stock market reactions to decisions by the Federal Reserve (eg. Wongswan, 2006; Ehrmann and Fratzscher, 2009). Wongswan (2009) and Hausman and Wongswan (2011) find that the cross-sectional response of the foreign equity indexes to surprise changes in the federal funds rate depends on the degree of financial integration with the United States, measured as the percentage of each country's equity market capitalization owned by U.S. investors. At firm level, Ammer et al. (2010) study foreign stocks and find stronger stock price reactions to U.S. monetary policy surprises for firms with higher ratio of foreign sales to total sales.

Following a similar approach to the literature on monetary policy surprises, we estimate the firms' default risk response to surprises in monetary policy rates as described in equation (4.6). More specifically, we conduct an event study where the daily change in the log-odds ratio reacts to unexpected changes of monetary policy the days that the Federal Reserve or the ECB decided to change interest rates

$$
\begin{aligned}
\Delta logit\left(PD_{i,t}(M)\right) &= \beta_0 + \beta_0' FedEvent + \beta_1 \mathrm{SALES}_{i,j} + \beta_2 Surprise_{j,t} \qquad (4.6)\\
&+ \beta_3 \mathrm{SALES}_{i,j} \times Surprise_{j,t}\\
&+ \beta_4 \mathrm{SALES}_{i,j} \times Surprise_{j,t} \times FedEvent\\
&+ \varepsilon_{it}
\end{aligned}
$$

Related research like Cenesizoglu and Essid (2012) and Zhu (2013) found that corporate bond yield indexes widen (narrow) following an unexpected tightening (easing) in monetary policy during periods of distress. In the equation (4.6) we measure the effect of domestic and foreign monetary policy shocks on firm level measures of default risk.[23] The regression (4.6) pools together the US and EMU firms. Both the surprises of the Fed and the ECB that happen at disjointed events are included in the variable $Surprise_{j,t}$ where j represents the monetary region. Next, we introduce two types of cross-sectional reaction in the default probabilities. First, the variable $\mathrm{DOI}_{i,j}$ introduces the different reaction depending on the firm's degree of internationalization. Second, the dummy variable $FedEvent$ distinguishes the Fed changes from the ECB changes of interest rates.

We have created the variable $SALES$ to proxy for the percentage of sales to the monetary region j that suffers a policy shock. This variable is measured as the percentage of foreign sales in the case of firms experiencing a shock in foreign monetary policy, and is measured as one less the foreign-to-total sales ratio in the case of firms experiencing a shock in domestic monetary policy. This definition of $SALES$ allows us to pool all the surprises into one single regression instead of doing the analysis separately for the US

[23] Gürkaynak et al. (2005) provide evidence that besides the target surprise introduced by Kuttner (2001), it is also needed the surprise on the expected path of future monetary policy (path surprise) to fully capture monetary policy surprises. For example, Wongswan (2009), Ammer et al. (2010) and Hausman and Wongswan (2011) measure the path surprise by running a regression of the daily change in 1-year-ahead Eurodollar interest rates futures and the target surprise measured as in equation (4.5) around FOMC's change in the target rate. However, we do not include the path surprises because they rarely exert a significant impact on credit spreads (Zhu, 2013). Moreover, due to data limitations we can only measure 17 ECB surprises, and the small sample would not allow us to construct the path surprises in the Eurozone.

and Europe.

The results showed in the Table 4.9 reinforce our previous statement that foreign monetary policy leads to higher default risk change for firms with a higher degree of internationalization. The firms with larger exposure to Europe experience a decrease in their default probability when facing an unexpected tightening event by the ECB. And firms with larger exposure to the US suffer an increase in their default probability when there is an unexpected tightening of the interest rate in a Fed event.

Table 4.9.: Panel regression for surprise events, US and EMU firms

Dependent variable	$\Delta logit(Q_{it}(T))$											$\Delta logit(EDF_{it}(T))$				
Model	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)	(XIII)	(XIV)	(XV)	(XVI)
	6M	1Y	2Y	3Y	4Y	5Y	7Y	10Y	15Y	20Y	30Y	1Y	2Y	3Y	4Y	5Y
Cons.	-0.01	-0.00	0.00	-0.00	-0.00	0.00	0.00	0.00	-0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
	(0.27)	(0.83)	(0.96)	(1.00)	(0.89)	(0.93)	(0.95)	(0.92)	(0.63)	(0.52)	(0.41)	(0.76)	(0.75)	(0.77)	(0.78)	(0.80)
FedEvent	-0.00	0.00	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	0.01	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.65)	(0.69)	(0.45)	(0.34)	(0.25)	(0.51)	(0.79)	(0.82)	(0.51)	(0.97)	(0.42)	(0.31)	(0.27)	(0.26)	(0.25)	(0.25)
$\text{SALES}_{i,j}$	0.00	-0.01	-0.01	-0.00	-0.01	-0.01	-0.01	-0.01	-0.00	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.77)	(0.07)	(0.22)	(0.23)	(0.00)	(0.02)	(0.03)	(0.01)	(0.37)	(0.01)	(0.03)	(0.21)	(0.20)	(0.22)	(0.24)	(0.26)
$\text{Surprise}_{j,t}$	-0.03	-0.02	-0.04	-0.04	-0.09	-0.05	-0.07	-0.03	-0.06	-0.05	-0.09	-0.10	-0.10	-0.09	-0.09	-0.08
	(0.55)	(0.67)	(0.31)	(0.27)	(0.08)	(0.17)	(0.08)	(0.40)	(0.08)	(0.05)	(0.08)	(0.23)	(0.23)	(0.22)	(0.23)	(0.23)
$\text{Surprise}_{j,t} \times \text{SALES}_{i,j}$	-0.49	-0.43	-0.38	-0.35	-0.33	-0.33	-0.31	-0.37	-0.05	-0.06	-0.21	-0.84	-0.83	-0.82	-0.80	-0.77
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.02)	(0.02)	(0.01)	(0.81)	(0.84)	(0.46)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
$\text{Surprise}_{j,t} \times \text{SALES}_{i,j} \times \text{FedEvent}$	0.54	0.47	0.45	0.41	0.42	0.41	0.39	0.40	0.13	0.16	0.34	1.00	0.98	0.97	0.94	0.89
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.52)	(0.59)	(0.21)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Obs. (Firm-event)	4130	4843	4779	4883	3196	4928	4866	4780	4496	4468	4197	2435	2435	2435	2435	2435
R^2-Adj	0.0019	0.0058	0.0182	0.0280	0.0813	0.0323	0.0303	0.0212	0.0023	0.0034	0.0022	0.1242	0.1307	0.1374	0.1391	0.1368

Panel regressions for the cumulative risk neutral and objective default probabilities. Here, i stands for firm, j stands for the monetary region, and t stands for time. The p-values reported come from clustered standard errors by firm and by time, as suggested by Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The sample consists of event observations for firms constituents of the CDX and iTraxx indexes with available information on foreign sales. The variable SALES is defined as the percentage of sales to the monetary region j that suffers a policy shock. The sample period goes from Jan-2000 to Dec-2009. During this period there are 40 changes of interest rates by the Federal Reserve and 27 changes of interest rates by the ECB. We can measure 40 Fed surprises and 17 ECB surprises with the futures data. The daily EDF measures are only available since June 2006.

4.5. The endogenous relationship between MP and aggregate default risk

This section discusses the endogenous relationship between monetary policy and the aggregate level of default risk. This section is divided into three subsections. In the first, we provide a brief review of the literature on systemic risk measurement. In the second, we describe our modeling framework to measure the probability of a systemic event. In the third subsection, we evaluate the sensitivity of our systemic risk measure to the impact of intervention rate shocks.

4.5.1. Measures of systemic risk

Previous empirical evidence in the Section 4.3 shows a significant effect of (external) monetary policies on the individual default risk. An interesting question is whether the monetary policy mechanisms are useful for handling the aggregate level of default risk in the economy. In this way, this section extends our study to broader aspects of credit risk.

The measurement of aggregate default risk constitutes a major issue for academics and regulators. On the regulatory side, the policy authorities have created specific institutions to monitor systemic risks as the Financial Stability Oversight Council in the US or the European Systemic Risk Board in the Eurozone. With regard to the academic side, one promising area of research is the analysis of systemic events.[24] Das and Uppal (2004) define systemic risk as the risk of infrequent events that are highly correlated across a large number of assets. They study the effects of this risk in portfolio diversification, concluding that systemic risk reduces the gains from international diversification and penalizes investors for holding levered positions. More recently, systemic risk has been associated with the common exposures of financial institutions. Acharya (2009)

[24] Classifying a certain event as systemic can be a judgment call at most times. For instance, the Federal Reserve rejected to bail out Lehman Brothers in September 2008, the largest bankruptcy in the US at the time. Two days after, the Fed rescued the insurance company AIG for its large exposition to the credit derivatives market, which could resulted in a collapse of the entire financial system.

defines systemic risk as the joint failure risk due to the endogenously chosen correlation across assets held by banks.

In parallel with that literature, the latest developments provide indicators of systemic risk. The recent measures of systemic risk have been defined as large losses in the in the financial system. For example, Lehar (2005) estimates a time series of bank asset values implied from the structural model of Merton (1974). Lehar (2005) uses simulation techniques to build an indicator of systemic risk as the probability that more than a certain fraction of all banks go bankrupt at the same time. Similarly, Huang et al. (2009) extract individual default probabilities and asset correlations from CDS and stock prices, respectively. Their systemic indicator represents the price for insuring a hypothetical portfolio of bank liabilities issued by a set of US banks.

Similarly, Acharya et al. (2010) consider that a systemic event takes place when the aggregate bank capital in the financial system falls below a certain threshold. They denote the Systemic Expected Shortfall (SES) as the contribution of each financial institution to systemic risk. Finally, Adrian and Brunnermeier (2011) posit the ΔCoVaR measure, which is becoming a standard in the systemic risk measurement. This measure captures the marginal contribution of a specific bank to the overall systemic risk. In particular, the ΔCoVaR is computed as the difference between the VaR of the entire financial system when the bank is in distress and the VaR of the entire financial system when the bank is not in distress.

4.5.2. Modeling framework and results

Macro-prudential supervision and monetary policy seek the stability of the banking system and the stability of firms that belong to other sectors also. Within the context of our modeling framework, we define systemic default risk as the instantaneous probability of an event that produces a market-wide default of firms. Under this definition of systemic risk, some recent crisis as the dot-com bubble with large default consequences could be considered as systemic, even though it was not originated by the financial system. Along these lines, our definition agrees with Das and Uppal (2004) or Longstaff and

Rajan (2008), who consider the possibility of an event that affects the entire economy, instead of focusing on a particular firm or sector.

We employ the model of Longstaff and Rajan (2008) to obtain a time-varying estimate of the probability of a market-wide event that affects the entire economy. Their model provides prices for a standard portfolio of CDSs.[25] The value of this portfolio depends on the default of its constituents, i.e. the higher the default probability, the higher the portfolio's value. Longstaff and Rajan (2008) captures the losses of the portfolio (L_t) with the unpredictable arrival of three independent Poisson processes

$$L_t = 1 - e^{-\overline{\gamma}_1 N_{1,t}} e^{-\overline{\gamma}_2 N_{2,t}} e^{-\overline{\gamma}_3 N_{3,t}} \tag{4.7}$$

representing the probability of an idiosyncratic, sector or market-wide impact in the portfolio, respectively. The independent Poisson processes $N_{i,t}$ have default intensities λ_{it}, with $i = 1, 2, 3$. The impact of the default arrival is captured by the constant $\gamma_i = 1 - e^{-\overline{\gamma}_i}$. Finally, the initial value of the portfolio is set to $L_0 = 0$, and $0 \leq L_t \leq 1$.

Using data from the CDS indexes and their tranches, Longstaff and Rajan (2008) provide an econometric approach for estimating the parameters of model (4.7). Contrary to other measures that rely on discretionary thresholds to define systemic events (see Lehar, 2005; Huang et al., 2009; Acharya et al., 2010; Adrian and Brunnermeier, 2011), our approach endogenously determines the time evolution of the systemic risk. The Table 4.10 displays the estimates of Longstaff and Rajan (2008) model. The results correspond to those with the best model fit. We run the optimization with different initial parameters until convergence. The parameter γ_3 has a size of approximately 50% to 60%. Roughly speaking, the estimated systemic default risk is the probability

[25] This credit derivative is known as Collateralized Debt Obligation (CDO). There are several liquid CDOs that are permanently traded in the market as the CDX NA IG index, which comprises the 125 most liquid CDS contracts of US firms. Similarly, the iTraxx index represents the 125 most liquid European CDS firms. The CDO issues claims with different priority against the cash-flows generated by the portfolio. These derivatives are named CDO tranches and they vary from high (equity tranche) to low (senior tranche) default risk of the payoffs. It is important to highlight that approximately a 30% of the firms contained in the iTraxx do not belong to the Eurozone. As we will explain later, we find a ubiquitous systemic risk measure in the CDX and iTraxx tranches, which diminishes the importance of European Non-EMU firms being included in the EMU systemic risk measure.

that approximately 50% to 60% of the debt in the portfolio defaults in a small time period. On average, in the period Jul/2005 to Dec/2009, there is a $0.007\Delta t$ conditional probability of a systemic event happening in a small time interval Δt.

Table 4.10.: Longstaff and Rajan (2008) estimates

Level	γ_i	$mean(\lambda_i)$	$med(\lambda_i)$	$std(\lambda_i)$	$min(\lambda_i)$	$max(\lambda_i)$	*Obs.*
Panel A.- Europe (iTraxx)							
Firm	0.0102	0.5011	0.4840	0.1131	0.3057	0.6674	54
Industry	0.0813	0.0385	0.0069	0.0549	0.0018	0.2088	54
Systemic (SYS-US)	0.5994	0.0071	0.0043	0.0073	0.0004	0.0274	54
Panel B.- United States (CDX.NA.IG)							
Firm	0.0152	0.5919	0.4861	0.2874	0.2705	1.0000	54
Industry	0.1021	0.0177	0.0046	0.0300	0.0010	0.1346	54
Systemic (SYS-EMU)	0.5295	0.0075	0.0039	0.0076	0.0004	0.0262	54

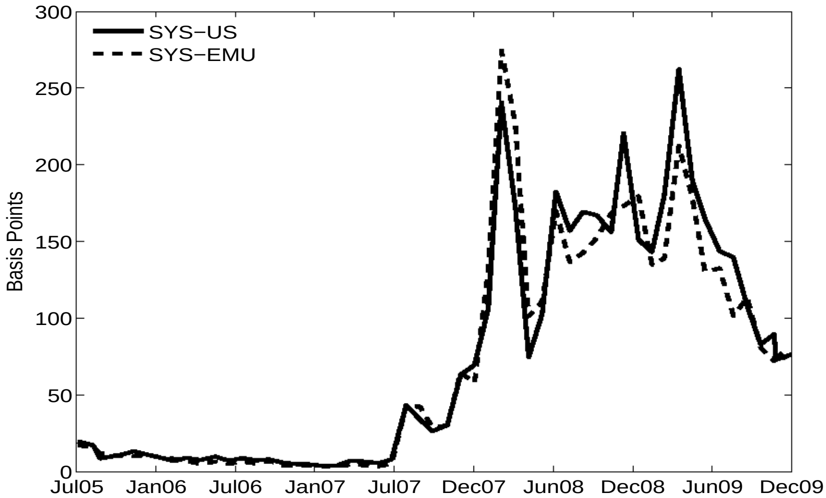
Estimates of systemic risk and summary statistics along time. We use monthly information from CDX.NA.IG and iTraxx indexes and their tranches from Jul/2005 to Dec/2009. We assume a risky duration of 3.75 to transform the upfront payments into running spreads, and a recovery rate of 40%.

The Figure 4.5 depicts the evolution through time of our proxies for the systemic default risk in the US (SYS-US) and in Europe (SYS-EMU). This Figure shows the ubiquitous nature of systemic risk. Even though we have employed data of different economic regions, the paths of systemic risk share a common trend behavior. This may suggest that systemic risk is highly transferable between regions.

4.5.3. Monetary policy and systemic default risk

We turn next to explore the endogenous relationship between the monetary policy and our measure of aggregate default risk. It is possible that monetary authorities react to shocks in the systemic default risk of the economy (Figure 4.1). And it is also possible that the monetary policy exerts power on the systemic risk undertaken by the economy. We test this endogenous relationship with a multivariate representation of the aggregate economy. This methodology is a common practice in the literature to assess the responses of aggregate variables to the stance of monetary policy. For instance, see the examples in

Figure 4.5.: Systemic risk in US and Europe.



Systemic risk measured as in Longstaff and Rajan (2008) with the CDX.NA.IG and iTraxx indexes and their tranches. End of month observations from Jul/2005 to Dec/2009

Bernanke and Blinder (1992), Bernanke and Gertler (1995) or Benati and Surico (2009).

In practice, the Vector Autoregressive representation in our data is not stable due to the presence of unit roots and the short time period – from Jul/2005 to Dec/2009. Instead, we use a Vector Error Correction Model (VECM) that includes inflation, unemployment, GDP growth and our proxy for the systemic default risk. Table 4.11 reports the estimates of a VECM for each monetary region separately. To better understand the results, we conduct an impulse-response analysis between the monetary policy rates and the systemic risk for each economic region.

Table 4.11.: VECM(p=2)

	Dependent variables									
	US					EMU				
	ΔFEDTRG$_t$	ΔINF$_t$	ΔUNEMP$_t$	ΔGDPG$_t$	ΔSYS$_t$	ΔECBMRO$_t$	ΔINF$_t$	ΔUNEMP$_t$	ΔGDPG$_t$	ΔSYS$_t$
ΔFEDTRG$_{t-1}$	.1215707	.1724546	.2518074	-.0353737	-.5180191					
	(0.393)	(0.509)	(0.001)	(0.763)	(0.000)					
ΔECMRO$_{t-1}$						.2053629	.2104173	-.1556729	.1503308	.8286968
						(0.216)	(0.490)	(0.020)	(0.027)	(0.001)
ΔINF$_{t-1}$	.0792435	.2497369	.0339298	-.0460244	.1204773	.0617904	.2846779	.0284242	-.0328674	-.4305667
	(0.240)	(0.043)	(0.323)	(0.409)	(0.084)	(0.530)	(0.115)	(0.472)	(0.415)	(0.004)
ΔUNEMP$_{t-1}$	.1469046	.594864	-.2313136	-.2098032	.1476751	-.3790251	.3402291	.0700869	-.0585883	1.003474
	(0.531)	(0.166)	(0.052)	(0.279)	(0.542)	(0.334)	(0.636)	(0.656)	(0.715)	(0.095)
ΔGDPG$_{t-1}$	-.1355633	1.695946	-.1475824	.9839854	-.4689536	-.035509	.3356734	-.263178	.8756678	-1.251063
	(0.392)	(0.000)	(0.067)	(0.000)	(0.004)	(0.878)	(0.427)	(0.004)	(0.000)	(0.000)
ΔSYS$_{t-1}$	.0515006	.0151556	-.0181794	.0336184	.5384386	.0156415	-.0594347	-.0780999	-.0020564	.6717417
	(0.708)	(0.952)	(0.795)	(0.767)	(0.000)	(0.863)	(0.720)	(0.032)	(0.956)	(0.000)
ce1	-.1685491	-.5180704	-.0887378	-.1295818	-.1799524	-.1175423	.0347172	-.0175441	-.0167986	-.9128113
	(0.017)	(0.000)	(0.013)	(0.026)	(0.013)	(0.249)	(0.853)	(0.668)	(0.687)	(0.000)
ce2	-.0318304	-.3749113	-.0056455	.000402	.0887246					
	(0.461)	(0.000)	(0.797)	(0.991)	(0.047)					
ce3	-.1027437	-.6277925	-.1853148	-.1583304	-.0797662					
	(0.196)	(0.000)	(0.000)	(0.016)	(0.331)					
	Cointegration equations									
ce1	$-.0478894 + FEDTRG_{t-1} + 1.11e-16 \cdot INF_{t-1} + 1.11e-16 \cdot UNEMP_{t-1} - .1601519 \cdot GDPG_{t-1} + 4.24777 \cdot SYS_{t-1}$					$-.2010974 + ECMRO_{t-1} - .4401526 \cdot INF_{t-1} + 2.002922 \cdot UNEMP_{t-1} + .3317606 \cdot GDPG_{t-1} + 1.084919 \cdot SYS_{t-1}$				
ce2	$.0339872 + INF_{t-1} - 1.118799 \cdot GDPG_{t-1} - 3.32196 \cdot SYS_{t-1}$									
ce3	$-.0745438 - 1.11e-16 \cdot FEDTRG_{t-1} - 1.11e-16 \cdot INF_{t-1} + UNEMP_{t-1} + .5829475 \cdot GDPG_{t-1} - 1.827868 \cdot SYS_{t-1}$									
Obs.			52					52		
SBIC			-43.52572					-50.06673		
R^2	0.3579	0.6572	0.7038	0.8021	0.5523	0.4092	0.1925	0.7058	0.9488	0.5164

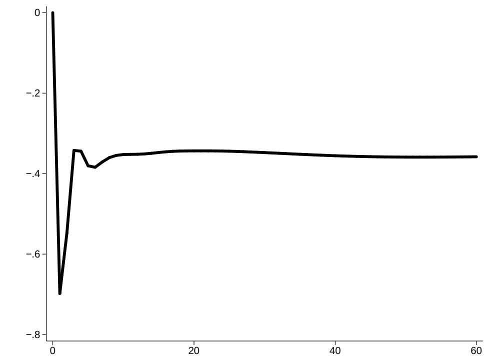
The lag of the VECM is selected according to the Schwarz Bayesian Information criterion. The number of cointegrated equations is chosen according to the Johansen's cointegration test. The estimation period goes from Jul/2005 to Dec/2009.

The Figure 4.6 depicts the results. On one side, a systemic default risk increment is followed by a loosening on the monetary policies gradually over time. The loosening of policy rates is not equal, being three times larger in the US than in the Eurozone. On the other side, a tightening of the monetary policy results in an asymmetric response of systemic risk in both areas. For example, a monetary tightening in the US leads to a permanent decrease of systemic risk at every subsequent month. In Europe, a monetary tightening leads to an increase of the systemic risk in the long term. Moreover, the US has more power to exert influence on the systemic risk, as can be seen from the larger responses of systemic risk. Unreported impulse-response simulations of a positive shock in the systemic risk measure predict reasonable economic consequences: an increase in the unemployment and a decrease of GDP growth.

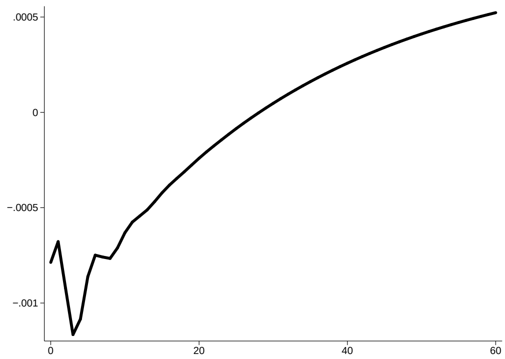
Theoretical research in a two-country world has evaluated the possibility of cooperation between a domestic and a foreign monetary authority. The theoretical work of Rogoff (1985) argues that under certain circumstances the monetary policy cooperation can be counterproductive and leads to higher inflation. Moreover, even in a world tightly linked with world productivity shocks, it is not necessarily problematic that countries unilaterally design their monetary policy in an inward-looking decision-making process (Obstfeld and Rogoff, 2002). On the contrary, Pappa (2004) concludes that for the Fed and ECB to cooperate, one has to assume high degree of trade links of the US and the Eurozone. Our results stress the importance of domestic and foreign central banks for the firms' credit stability during difficult episodes. Coordinated monetary policy might be a more appropriate mechanism to deal with large systemic events.

In summary, we document the existence of an endogenous relationship between monetary policy and systemic default risk. Although the monetary policy rates are not designed to fight against systemic risk, the last evidence suggests that monetary authorities have responded to an increase in systemic risk by lowering interest rates. However, we find an asymmetric impact of monetary policy on systemic risk. More long-term coordinated action in policy rates might be needed to solve a systemic crisis.

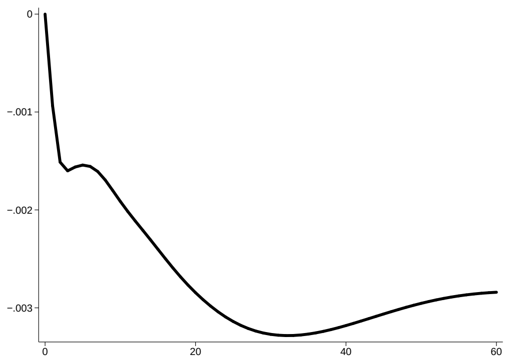
Figure 4.6.: Impulse-response graphs for the VECMs



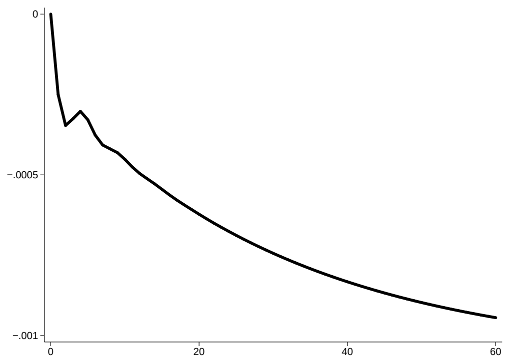
(a) Impulse(FEDTRG$_{t=0}$), Response(SYS-US)



(b) Impulse(ECBMRO$_{t=0}$), Response(SYS-EMU)



(c) Impulse(SYS-US$_{t=0}$), Response(FEDTRG)



(d) Impulse(SYS-EMU$_{t=0}$), Response(ECBMRO)

Orthogonalized impulse-response for the VECMs. The horizontal axis represents the months after the shock event. The lag of the VECM is selected according to the Schwarz Bayesian Information criterion. The number of cointegrated equations is chosen according to the Johansen's cointegration test.

4.6. Conclusions

We have used a new source of information to learn about the ex-ante default probability of a firm: the credit derivatives market. And we have paid attention to the possible influence of a foreign monetary policy on the firms' default risk. Furthermore, the data suggests that the monetary authorities have tried to attenuate the systemic events by using their monetary policy rates as a mechanism.

From a micro-perspective, the firms' default risk depends on the state of foreign monetary policy. Moreover, we document that a foreign monetary policy can have an important effect on international firms highly exposed to foreign countries.

Our findings suggest that, in general, *foreign monetary policy's influence of firms' default risk depends on the firms' degree of foreign operations.* And this result is quite robust to the definition of monetary policy, the type of default probability, the type of foreign operations, the horizon of cumulative default probability, the frequency, macroeconomic controls, unobservable firm and time effects, the geography (US and EMU), firm controls, and the empirical model. More interestingly, we find that firms facing a surprise tightening of the Fed's monetary policy or a surprise loosening of the ECB's monetary policy experience higher default probabilities than firms with lower foreign exposure to those economic areas.

From a macro-perspective we study how the monetary authorities have affected and reacted to the systemic risk. As we find evidence of non-stationary variables in the sample period, we perform a VECM. Systemic defaults are not frequent and predictable events, thus the results of the VECM that we find in our sample might be anecdotic, and highly model dependent. Due to the ubiquitous nature of the systemic default risk across countries that we find in our data, and the different regional specific monetary targets, the monetary policy might not be an effective tool to manage systemic risk. In the long term, we generally find a negative response of systemic risk to a monetary contraction in the US, but a positive response in the Eurozone. And this statement is generally robust to the VECM specification.

Chapter 5.

Final Remarks

The credit crunch has raised major concerns about the developed economies. The market-wide default events since 2007 have resulted in apprehensions about the creditworthiness of corporate and sovereign debts. Therefore, the understanding of the determinants of the rising credit spreads is becoming an important issue. Along these lines, this thesis commenced a search for the sources of credit risk at corporate, sovereign, and policy levels.

The understanding of the credit spreads during distressed conditions is at its origins. This thesis contributes to this understanding from asset pricing and policy perspectives. First, from an asset pricing perspective, the results evidence that corporate investors demand an excess return when the sovereign debt distress increases. Moreover, the findings suggest a risk transmission from distressed towards healthier sovereign debt through the price of risk. Second, from a policy perspective, we find an asymmetric response of systemic risk to the monetary policies undertaken by the Federal Reserve and the ECB. This suggests that a coordinated monetary policy might be more appropriate to deal with large systemic risks.

As a closing remark, there are important questions that need to be addressed regarding the transmission of risk during stressed scenarios, the regulation in the OTC credit markets, and the institutional role of the newly created systemic risk supervisors. Further research along these lines is needed to fight against large credit market disruptions.

Appendix A.

Risk-Neutral and actual estimates

A.1. Risk-Neutral intensity estimates

Appendix A.1 contains the maximum likelihood estimates for the risk-neutral intensity processes in Section 2.4. The Table A.1 exhibits the results for 85 companies. The sample period covers from 14/June/2006 until 31/March/2010.

Table A.1.: Risk-neutral intensity estimates

Maximum likelihood estimates for the Pan and Singleton (2008) model. Standard errors are in parenthesis. $\kappa^{\mathbb{Q}}$ and $\kappa^{\mathbb{P}}$ are the mean-reversion rates of default intensity process $\lambda^{\mathbb{Q}}$ under $\mathbb{Q}$ and $\mathbb{P}$ measures, respectively. Analogously, $\theta^{\mathbb{Q}}$ and $\theta^{\mathbb{P}}$ are the long-run mean. σ is the instantaneous volatility. Finally, σ_{1y} and σ_{5y} are the mispricing volatilities for CDS spreads with maturities 1- and 5-years. Data sample spans from 14/June/2006 until 31/March/2010.

Firm	$\kappa^{\mathbb{Q}}$	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	σ	$\kappa^{\mathbb{P}}$	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	σ_{1y}	σ_{5y}	LogLk
Anglo Amern plc	0.4063	-1.7000	1.1903	0.2654	-1.8750	0.0013	0.0013	1504.04
	(0.0134)	(0.0468)	(0.0204)	(0.2511)	(1.4565)	(0.0001)	(0.0001)	
Cr Agricole SA	-1.4844	4.0812	2.6625	4.8450	-28.1406	0.0011	0.0030	1501.91
	(0.1190)	(0.4856)	(0.2146)	(4.5890)	(27.7113)	(0.0001)	(0.0012)	
ACCOR	0.2000	-1.7000	1.8170	1.0730	-6.0000	0.0017	0.0014	1533.17
	(0.0268)	(0.1195)	(0.0487)	(1.2687)	(7.2627)	(0.0002)	(0.0002)	
Adecco S A	0.3750	-1.6844	1.1078	0.5442	-3.0625	0.0006	0.0026	1569.83
	(0.0165)	(0.0609)	(0.0143)	(0.3738)	(2.1968)	(0.0000)	(0.0023)	
Aegon N,V,	0.2313	-1.7000	1.7135	0.5315	-3.2500	0.0027	0.0014	1466.70
	(0.0244)	(0.0976)	(0.0252)	(0.5883)	(3.2439)	(0.0003)	(0.0002)	
Koninklijke Ahold N V	0.2313	-1.7000	1.6910	1.6121	-8.2500	0.0018	0.0021	1471.50
	(0.0328)	(0.1241)	(0.0539)	(1.5275)	(8.1627)	(0.0003)	(0.0004)	
AKZO Nobel N V	-1.4688	3.3469	3.1937	8.4856	-50.0000	0.0011	0.0050	1458.44
	(0.0930)	(0.2854)	(0.3374)	(6.0365)	(37.0095)	(0.0001)	(0.0129)	
ALSTOM	0.2000	-1.7000	1.7984	1.1482	-6.0000	0.0015	0.0015	1520.60
	(0.0224)	(0.0940)	(0.0485)	(1.1999)	(6.1340)	(0.0001)	(0.0001)	
Assicurazioni Generali S p A	-1.1875	1.6125	3.1000	5.1262	-29.5781	0.0011	0.0050	1465.38
	(0.0579)	(0.1362)	(0.2303)	(3.8444)	(22.8912)	(0.0001)	(0.0083)	
Aviva plc	0.3750	-1.8563	1.2387	0.2786	-1.8438	0.0008	0.0021	1541.59
	(0.0134)	(0.0559)	(0.0219)	(0.3077)	(1.7542)	(0.0000)	(0.0005)	
AXA	0.2500	-1.5438	1.3656	0.4583	-2.8125	0.0021	0.0011	1606.18
	(0.0276)	(0.1092)	(0.0181)	(0.4927)	(2.7964)	(0.0005)	(0.0002)	
EnBW Energie Baden Wuerttemberg AG	-1.1563	3.1437	2.1312	6.7512	-37.7813	0.0011	0.0050	1533.94
	(0.1010)	(0.4030)	(0.1721)	(4.3480)	(25.6617)	(0.0002)	(0.0208)	
BAE Sys PLC	0.2500	-1.5750	1.3266	0.6887	-3.9688	0.0011	0.0030	1624.22
	(0.0272)	(0.0919)	(0.0187)	(0.6492)	(3.7307)	(0.0002)	(0.0036)	
Brit Amern Tob plc	-0.2344	-0.5125	2.1156	3.5794	-20.4063	0.0011	0.0030	1547.16
	(0.0270)	(0.0696)	(0.0867)	(2.2010)	(11.9527)	(0.0001)	(0.0028)	
Bco Bilbao Vizcaya Argentaria S A	-1.2969	3.0812	2.7562	5.0012	-28.7656	0.0011	0.0030	1494.97
	(0.0734)	(0.2551)	(0.2035)	(4.2179)	(25.2262)	(0.0001)	(0.0011)	
Bay Motoren Werke AG	0.4219	-2.2313	1.5502	0.4046	-2.7656	0.0011	0.0013	1622.09
	(0.0203)	(0.0721)	(0.0244)	(0.5308)	(2.9757)	(0.0001)	(0.0002)	
BNP Paribas	-1.4063	3.6437	2.4750	5.5169	-31.4219	0.0011	0.0050	1521.33
	(0.1196)	(0.4453)	(0.2055)	(4.5622)	(27.3451)	(0.0001)	(0.0082)	
Brit Telecom PLC	0.2000	-1.7000	1.8326	1.0701	-6.0000	0.0012	0.0013	1574.13
	(0.0280)	(0.1040)	(0.0522)	(1.4601)	(8.1020)	(0.0001)	(0.0002)	
Bayer AG	-1.4063	3.0812	3.2250	8.2981	-50.0000	0.0011	0.0050	1470.14
	(0.0863)	(0.2667)	(0.2966)	(5.3243)	(34.3661)	(0.0002)	(0.0140)	
Carrefour	-0.9375	1.6125	2.6312	7.6731	-44.6563	0.0011	0.0050	1510.74
	(0.0600)	(0.1326)	(0.2136)	(4.5141)	(26.9364)	(0.0002)	(0.0110)	
Commerzbank AG	0.0000	-0.4344	1.2875	0.7512	-4.4375	0.0040	0.0011	1588.15
	(0.0189)	(0.0552)	(0.0230)	(0.8147)	(4.4135)	(0.0036)	(0.0003)	
Compass Gp PLC	0.0000	-0.1688	0.8812	2.0012	-10.9219	0.0011	0.0050	1570.97
	(0.0116)	(0.0328)	(0.0290)	(1.0780)	(5.7969)	(0.0002)	(0.0135)	
Deutsche Bk AG	0.0156	-1.0281	1.6469	1.1106	-6.3281	0.0011	0.0021	1581.64
	(0.0054)	(0.0426)	(0.0301)	(1.3566)	(7.0027)	(0.0001)	(0.0008)	
Diageo PLC	-0.6250	0.9875	2.1156	4.8762	-27.3750	0.0011	0.0050	1529.01
	(0.0495)	(0.0765)	(0.1566)	(3.8701)	(21.4474)	(0.0003)	(0.0153)	
Deutsche Post AG	-1.1875	2.8312	2.5062	8.8294	-50.0000	0.0011	0.0050	1507.53
	(0.1142)	(0.3274)	(0.2910)	(7.0280)	(41.0134)	(0.0003)	(0.0182)	
Deutsche Telekom AG	0.2500	-1.6844	1.4906	0.8020	-4.6094	0.0008	0.0030	1527.53
	(0.0293)	(0.1091)	(0.0309)	(1.0202)	(5.5410)	(0.0000)	(0.0032)	
Eurpn Aero Defence& Space Co Eads N V	0.3750	-2.0281	1.4320	0.4622	-2.9063	0.0022	0.0008	1604.47
	(0.0224)	(0.0782)	(0.0202)	(0.4294)	(2.5106)	(0.0005)	(0.0000)	
EDP Energias de Portugal SA	0.0000	-0.4812	1.2094	0.7669	-4.2031	0.0040	0.0011	1590.42
	(0.0171)	(0.0546)	(0.0286)	(0.8105)	(4.4568)	(0.0059)	(0.0002)	
ENEL S p A	0.3750	-2.0750	1.5023	0.4036	-2.5938	0.0021	0.0008	1618.88
	(0.0271)	(0.0977)	(0.0321)	(0.5249)	(2.7783)	(0.0006)	(0.0001)	
E,ON AG	-1.4688	3.7375	2.8500	8.5481	-50.0000	0.0011	0.0050	1480.80
	(0.1330)	(0.5400)	(0.2643)	(5.1030)	(31.7814)	(0.0001)	(0.0148)	

Table A.1 (Cont.).: Risk-neutral intensity estimates

Firm	$\kappa^{\mathbb{Q}}$	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	σ	$\kappa^{\mathbb{P}}$	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	σ_{1y}	σ_{5y}	LogLk
Bco Espirito Santo S A	0.5000	-3.2000	2.0219	0.5794	-3.6406	0.0050	0.0011	1495.57
	(0.0510)	(0.2656)	(0.0313)	(1.0529)	(5.5368)	(0.0036)	(0.0002)	
Edison S p A	-1.4219	3.0187	3.2875	7.9387	-47.9375	0.0011	0.0050	1465.31
	(0.0710)	(0.2754)	(0.2582)	(4.4691)	(28.4856)	(0.0001)	(0.0103)	
Finmeccanica S p A	0.2500	-1.6531	1.4398	0.6223	-3.6250	0.0011	0.0030	1581.81
	(0.0253)	(0.0942)	(0.0283)	(0.6410)	(3.5357)	(0.0001)	(0.0031)	
Fortum Oyj	-1.2969	2.8312	3.0062	8.0637	-48.9063	0.0011	0.0050	1496.30
	(0.0636)	(0.2312)	(0.2520)	(4.1865)	(27.6061)	(0.0002)	(0.0171)	
France Telecom	-0.2813	0.7063	1.2875	2.1106	-11.5156	0.0011	0.0030	1571.80
	(0.0208)	(0.0687)	(0.0530)	(2.0742)	(11.2534)	(0.0001)	(0.0044)	
Gas Nat SDG SA	0.2500	-1.6375	1.5453	0.4934	-3.0156	0.0011	0.0040	1529.75
	(0.0229)	(0.0834)	(0.0304)	(0.6059)	(3.5951)	(0.0000)	(0.0049)	
Casino Guichard Perrachon	0.2000	-1.7000	1.7921	1.3191	-7.0000	0.0015	0.0018	1504.79
	(0.0282)	(0.1164)	(0.0549)	(1.4936)	(7.7891)	(0.0002)	(0.0004)	
Hannover Ruck AG	-0.4531	-0.0438	2.2094	3.6106	-20.0000	0.0011	0.0050	1497.35
	(0.0411)	(0.0232)	(0.1244)	(2.5844)	(14.5074)	(0.0001)	(0.0123)	
Holcim Ltd	0.4219	-1.8250	1.3500	0.2981	-1.9844	0.0011	0.0050	1479.15
	(0.0176)	(0.0719)	(0.0301)	(0.3796)	(2.0249)	(0.0001)	(0.0053)	
Iberdrola S A	0.2500	-1.6063	1.3969	0.5559	-3.3438	0.0011	0.0030	1588.72
	(0.0296)	(0.1166)	(0.0349)	(0.6304)	(3.6305)	(0.0001)	(0.0058)	
Koninklijke DSM NV	-0.7969	0.8312	2.7250	8.6419	-49.5156	0.0011	0.0050	1500.41
	(0.0610)	(0.0955)	(0.2240)	(4.6141)	(27.3314)	(0.0003)	(0.0170)	
Koninklijke KPN N V	0.2000	-1.1844	1.3062	1.8762	-10.8281	0.0008	0.0013	1650.52
	(0.0244)	(0.1026)	(0.0331)	(1.2355)	(6.9918)	(0.0000)	(0.0002)	
Linde AG	-0.5000	-0.8094	2.9750	8.0481	-47.0781	0.0011	0.0050	1493.06
	(0.0729)	(0.1028)	(0.2015)	(3.6821)	(22.1354)	(0.0003)	(0.0105)	
Lanxess	0.2625	-1.7000	1.6207	1.1057	-6.0000	0.0022	0.0014	1489.61
	(0.0312)	(0.1136)	(0.0278)	(0.8826)	(4.6857)	(0.0002)	(0.0002)	
METRO AG	0.2000	-1.7000	1.7750	0.9895	-5.6875	0.0011	0.0013	1589.42
	(0.0285)	(0.1057)	(0.0296)	(0.9794)	(5.0869)	(0.0001)	(0.0002)	
Marks& Spencer p l c	0.2000	-1.7000	1.9269	0.9236	-5.3750	0.0021	0.0018	1461.33
	(0.0297)	(0.1156)	(0.0407)	(1.2186)	(6.5668)	(0.0002)	(0.0004)	
LVMH Moet Hennessy Louis Vuitton	-0.5156	-0.3875	2.7719	5.1731	-30.1719	0.0011	0.0050	1498.32
	(0.0468)	(0.0730)	(0.1942)	(3.4781)	(20.1488)	(0.0002)	(0.0121)	
Bca Monte dei Paschi di Siena S p A	-1.5000	3.3625	3.1625	6.3919	-37.9063	0.0011	0.0050	1447.86
	(0.0779)	(0.2854)	(0.2406)	(4.2011)	(26.5650)	(0.0001)	(0.0060)	
Natl Grid Plc	0.3750	-1.8719	1.2602	0.4251	-2.7500	0.0006	0.0028	1608.86
	(0.0175)	(0.0887)	(0.0354)	(0.3735)	(2.2733)	(0.0000)	(0.0057)	
Next plc	0.2313	-1.7000	1.8375	1.0515	-6.0000	0.0028	0.0022	1412.03
	(0.0351)	(0.1484)	(0.0383)	(1.2971)	(6.6134)	(0.0006)	(0.0006)	
Hellenic Telecom Org SA	0.2500	-1.6531	1.4984	0.8567	-4.7813	0.0008	0.0030	1559.55
	(0.0261)	(0.1078)	(0.0456)	(1.0287)	(5.7480)	(0.0000)	(0.0061)	
Koninklijke Philips Electrs N V	-1.1563	2.1125	3.0062	8.4075	-49.8438	0.0011	0.0050	1488.78
	(0.0568)	(0.1631)	(0.2616)	(4.6149)	(28.9831)	(0.0002)	(0.0131)	
PPR	0.5000	-1.7938	1.1156	0.2356	-1.6094	0.0011	0.0050	1396.47
	(0.0100)	(0.0435)	(0.0207)	(0.2310)	(1.2997)	(0.0000)	(0.0032)	
Pearson plc	0.0313	-0.6062	1.2875	1.9700	-10.9531	0.0011	0.0030	1588.16
	(0.0062)	(0.0424)	(0.0319)	(1.3576)	(7.2386)	(0.0001)	(0.0029)	
Royal Bk Scotland plc	0.1250	-1.7000	1.9682	0.7854	-4.8750	0.0021	0.0014	1520.32
	(0.0187)	(0.0957)	(0.0365)	(1.1428)	(6.3208)	(0.0001)	(0.0002)	
Reed Elsevier PLC	-1.0313	3.6125	1.6625	4.5012	-24.7344	0.0050	0.0011	1448.24
	(0.0575)	(0.2501)	(0.0860)	(3.0984)	(16.2568)	(0.0014)	(0.0001)	
Repsol YPF SA	0.3750	-1.9344	1.4086	0.4622	-2.8125	0.0008	0.0033	1522.51
	(0.0128)	(0.0613)	(0.0259)	(0.4554)	(2.7315)	(0.0000)	(0.0032)	
Rolls Royce plc	0.2500	-1.7000	1.4477	0.6419	-3.9219	0.0006	0.0016	1712.61
	(0.0183)	(0.0644)	(0.0202)	(0.6732)	(3.7022)	(0.0000)	(0.0011)	
RWE AG	-0.0938	0.2062	0.8500	1.1419	-6.5000	0.0011	0.0050	1599.82
	(0.0097)	(0.0304)	(0.0263)	(0.6917)	(3.8557)	(0.0001)	(0.0119)	
J Sainsbury PLC	0.1875	-1.7000	1.9965	1.3875	-8.5000	0.0022	0.0024	1410.93
	(0.0219)	(0.1122)	(0.0303)	(1.0886)	(6.4450)	(0.0002)	(0.0003)	

Table A.1 (Cont.).: Risk-neutral intensity estimates

Firm	$\kappa^{\mathbb{Q}}$	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	σ	$\kappa^{\mathbb{P}}$	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	σ_{1y}	σ_{5y}	LogLk
Svenska Cellulosa AB SCA	0.2000	-1.7000	1.7311	1.0242	-6.0000	0.0015	0.0013	1571.13
	(0.0271)	(0.1102)	(0.0364)	(1.3224)	(7.0017)	(0.0002)	(0.0002)	
Siemens AG	0.2500	-1.6375	1.4438	0.6106	-4.0000	0.0006	0.0030	1661.52
	(0.0272)	(0.1142)	(0.0376)	(0.7489)	(4.2979)	(0.0000)	(0.0064)	
Societe Generale	-0.4844	-0.0750	2.4438	2.2044	-12.8906	0.0011	0.0050	1498.38
	(0.0343)	(0.0416)	(0.1053)	(2.5742)	(14.1697)	(0.0001)	(0.0056)	
Cie de St Gobain	0.5000	-2.1844	1.3813	0.3450	-2.3281	0.0011	0.0030	1488.09
	(0.0166)	(0.0649)	(0.0241)	(0.4218)	(2.3416)	(0.0001)	(0.0006)	
Stmicroelectronics N V	0.2500	-1.6531	1.4789	0.6419	-4.0000	0.0011	0.0035	1606.48
	(0.0296)	(0.1298)	(0.0428)	(0.7175)	(4.1002)	(0.0003)	(0.0078)	
Swedish Match AB	0.3750	-1.7469	1.0531	0.5872	-3.5938	0.0023	0.0006	1671.96
	(0.0260)	(0.0985)	(0.0138)	(0.4290)	(2.6534)	(0.0003)	(0.0000)	
Technip	0.3750	-1.8250	1.2836	0.4739	-3.1875	0.0008	0.0022	1622.83
	(0.0150)	(0.0510)	(0.0178)	(0.3991)	(2.3860)	(0.0000)	(0.0006)	
Telefonica S A	0.2500	-1.5125	1.3617	0.8020	-4.4844	0.0011	0.0030	1539.96
	(0.0343)	(0.1251)	(0.0275)	(0.7814)	(4.1666)	(0.0001)	(0.0051)	
Telenor ASA	0.2500	-1.7000	1.5141	0.6575	-3.9844	0.0011	0.0030	1599.99
	(0.0308)	(0.1277)	(0.0478)	(0.8861)	(5.1444)	(0.0001)	(0.0071)	
Telecom Italia SpA	0.2313	-1.7000	1.8375	1.0891	-6.0000	0.0022	0.0013	1479.82
	(0.0298)	(0.1200)	(0.0337)	(1.0182)	(5.3458)	(0.0002)	(0.0002)	
Telekom Austria AG	0.2000	-1.5281	1.6109	1.3450	-7.8906	0.0008	0.0013	1680.33
	(0.0259)	(0.1152)	(0.0395)	(1.2130)	(7.0700)	(0.0001)	(0.0003)	
TeliaSonera AB	-0.4219	0.5188	2.0375	5.5012	-31.4844	0.0011	0.0030	1559.60
	(0.0465)	(0.0584)	(0.1431)	(4.0052)	(22.8826)	(0.0002)	(0.0046)	
TNT N,V,	-0.0469	-0.3719	1.3187	1.6731	-9.1094	0.0011	0.0030	1589.19
	(0.0115)	(0.0496)	(0.0353)	(1.4863)	(7.7720)	(0.0001)	(0.0045)	
Total SA	-1.4375	3.6125	2.5062	6.0169	-34.4375	0.0011	0.0050	1535.95
	(0.1038)	(0.3357)	(0.2016)	(4.2799)	(25.4443)	(0.0002)	(0.0127)	
Tesco PLC	-1.1406	2.3312	2.7562	5.0481	-29.4688	0.0011	0.0050	1497.80
	(0.0605)	(0.1635)	(0.2019)	(3.9559)	(24.4367)	(0.0002)	(0.0099)	
UBS AG	0.2000	-1.7000	1.7267	0.5369	-3.5000	0.0018	0.0013	1555.62
	(0.0238)	(0.0981)	(0.0318)	(0.8615)	(4.6244)	(0.0002)	(0.0001)	
Veolia Environnement	0.2500	-1.4500	1.2289	0.6731	-3.8906	0.0011	0.0030	1599.49
	(0.0290)	(0.1077)	(0.0289)	(0.5423)	(3.0888)	(0.0001)	(0.0053)	
Vinci	0.2000	-1.7000	1.7682	1.0647	-6.0000	0.0017	0.0014	1527.63
	(0.0264)	(0.1119)	(0.0433)	(1.2420)	(6.8712)	(0.0002)	(0.0003)	
Vivendi	0.2000	-1.7000	1.7862	1.1751	-6.3750	0.0012	0.0013	1570.72
	(0.0268)	(0.1107)	(0.0577)	(1.5270)	(8.3901)	(0.0001)	(0.0003)	
AB Volvo	0.5000	-2.0906	1.3344	0.2512	-1.6250	0.0011	0.0050	1400.70
	(0.0118)	(0.0572)	(0.0259)	(0.3350)	(2.0595)	(0.0001)	(0.0037)	
Vodafone Gp PLC	0.2500	-1.2781	1.0609	0.6223	-3.6406	0.0026	0.0011	1625.32
	(0.0250)	(0.0937)	(0.0124)	(0.5438)	(2.9169)	(0.0010)	(0.0002)	
Volkswagen AG	0.5000	-2.2781	1.3500	0.3450	-2.3594	0.0011	0.0021	1573.93
	(0.0174)	(0.0716)	(0.0218)	(0.3942)	(2.1572)	(0.0001)	(0.0008)	
Wolters Kluwer N V	-1.4063	3.8625	2.9437	8.3762	-50.0000	0.0011	0.0050	1466.67
	(0.1782)	(0.7289)	(0.3815)	(7.6445)	(47.1471)	(0.0002)	(0.0117)	
WPP 2005 Ltd	0.2000	-1.7000	1.9469	0.8299	-5.0000	0.0012	0.0014	1542.62
	(0.0284)	(0.0990)	(0.0381)	(1.1719)	(6.3440)	(0.0001)	(0.0002)	
Xstrata Plc	0.4375	-1.7000	1.2045	0.3040	-2.0000	0.0022	0.0025	1370.92
	(0.0135)	(0.0390)	(0.0111)	(0.2453)	(1.3577)	(0.0001)	(0.0001)	

A.2. Summary statistics for the EDF measure

Appendix A.2 shows the summary statistics for the 1-year EDF measure. The sample consists of biweekly EDF data for 75 European firms provided by Moody's, covering from 14/Jun/2006 to 31/Mar/2010.

Table A.2.: Summary statistics for 1-year EDF

	Mean (bps)	Median (bps)	Std (bps)	Skew	Kurt	Min (bps)	Max (bps)	$\overline{\Delta s}$ (bps)	Acorr(Δs) (1st lag)
					Panel A.- Basic Materials				
Mean	14.19	3.78	30.27	1.82	9.40	1.28	203.42	0.0586	-0.0707
Std	14.51	1.41	52.55	2.18	16.23	0.44	415.89	0.0496	0.1941
Min	2.38	1.40	1.55	0.50	1.53	1.00	5.28	-0.0036	-0.2842
Max	41.39	5.56	136.48	6.17	42.41	1.97	1050.67	0.1455	0.2797
					Panel B.- Consumer Goods				
Mean	6.63	5.14	4.17	0.65	2.39	1.65	17.20	0.0219	-0.2017
Std	1.26	1.48	1.20	0.16	0.52	0.57	2.08	0.0699	0.0275
Min	5.22	4.03	3.34	0.47	1.82	1.00	15.62	-0.0410	-0.2269
Max	7.65	6.82	5.55	0.78	2.85	1.99	19.56	0.0971	-0.1724
					Panel C.- Consumer Services				
Mean	8.40	6.36	5.39	1.04	3.91	2.64	24.80	-0.0070	-0.0528
Std	3.48	2.31	3.75	0.75	2.74	1.67	14.78	0.0765	0.1868
Min	2.19	1.21	1.34	0.20	1.78	1.00	6.33	-0.1814	-0.3855
Max	13.96	10.60	13.61	2.72	11.50	5.59	56.29	0.1399	0.2890
					Panel D.- Financials				
Mean	22.36	8.04	26.66	1.19	3.79	3.03	122.31	0.3434	-0.0950
Std	23.30	4.15	36.31	0.47	1.65	2.27	181.86	0.4914	0.1539
Min	5.56	4.06	2.83	0.21	1.69	1.00	15.65	-0.0364	-0.2954
Max	93.55	18.21	136.25	2.06	7.63	7.53	710.13	1.8821	0.2702
					Panel E.- Industrials				
Mean	33.76	15.76	34.03	0.95	2.93	5.78	135.76	0.4323	-0.0258
Std	47.60	18.57	67.02	0.37	1.07	7.86	261.33	1.2003	0.1419
Min	6.09	2.52	2.92	0.53	2.08	1.00	13.28	-0.2614	-0.2535
Max	171.11	68.28	243.58	1.89	5.89	29.05	951.46	4.2090	0.1946
					Panel F.- Telecommunications				
Mean	8.23	5.35	6.55	0.77	3.34	1.61	25.53	0.0773	-0.0400
Std	3.44	1.39	4.62	0.91	4.03	0.94	15.66	0.1971	0.1296
Min	3.70	3.45	1.80	-0.31	1.70	1.00	7.36	-0.3286	-0.2135
Max	13.89	7.55	15.32	3.25	15.44	3.32	51.22	0.4239	0.1484
					Panel G.- Utilities				
Mean	11.98	5.37	10.97	0.85	2.28	2.39	38.84	0.1974	-0.0844
Std	5.65	2.25	6.65	0.21	0.47	1.54	20.52	0.1133	0.1361
Min	6.24	2.06	3.69	0.54	1.67	1.00	19.12	0.0299	-0.2424
Max	26.82	8.88	26.49	1.16	3.06	4.72	84.67	0.4038	0.1206
					Panel H.- Others (Health Care, Oil and Gas, and Technology)				
Mean	15.89	8.31	17.76	1.01	3.64	2.61	79.77	0.0508	-0.0257
Std	21.05	8.58	29.65	0.76	2.37	2.53	133.39	0.0902	0.1629
Min	2.67	1.92	1.74	0.31	1.31	1.00	5.54	-0.0625	-0.2453
Max	52.53	22.72	70.34	2.27	7.43	6.85	315.95	0.1885	0.1663
					Panel I.- OVERALL				
Mean	16.59	7.79	17.91	1.03	3.79	2.88	81.68	0.1832	-0.0648
Std	23.86	8.62	35.95	0.84	5.03	3.65	180.67	0.5433	0.1521
Min	2.19	1.21	1.34	-0.31	1.31	1.00	5.28	-0.3286	-0.3855
Max	171.11	68.28	243.58	6.17	42.41	29.05	1050.67	4.2090	0.2890

Summary statistics for the 1-year EDF measures: the mean, median, standard deviation, skewness, kurtosis, minimum, maximum, mean of the differenced time series, and 1st lag autocorrelation coefficient for the differenced time series. The sample consists of biweekly EDF data for 75 European firms provided by Moody's, covering from 14/Jun/2006 to 31/Mar/2010.

A.3. Actual intensity estimates

Appendix A.3 contains the maximum Likelihood estimates for the actual intensity processes in Section 2.6. The Table A.3 exhibits the results for 75 European companies with available Expected Default Frequencies (EDF). The sample period covers from 14/June/2006 until 31/March/2010.

Table A.3.: Actual intensity estimates

Maximum likelihood estimates for the actual intensity process described in Section 6. Standard errors are in parenthesis. $\alpha^{\mathbb{P}}$, $\beta^{\mathbb{P}}$ and σ are the mean-reversion, long-run mean and instantaneous volatility of default intensity process $\lambda^{\mathbb{P}}$, respectively. Finally, σ_{3y} and σ_{5y} are the mispricing volatilities for EDF with maturities 3- and 5-years. Data sample spans from 14/June/2006 until 31/March/2010.

Firm	$\alpha^{\mathbb{P}}$	$\alpha^{\mathbb{P}}\beta^{\mathbb{P}}$	σ	σ_{3y}	σ_{5y}	LogLk
Anglo Amern plc	0 4516	-4 4730	1 1231	0 0001	0 0008	2035 79
	(0 0306)	(0 2011)	(0 0051)	(0 0000)	(0 0001)	
Cr Agricole SA	0 3659	-3 0544	0 8818	0 0006	0 0158	1713 11
	(0 0354)	(0 2790)	(0 0352)	(0 0007)	(0 0707)	
ACCOR	0 2005	-2 7079	0 8396	0 0000	0 0007	2103 71
	(0 0146)	(0 1030)	(0 0112)	(0 0000)	(0 0001)	
Adecco S A	0 4804	-5 0994	1 3018	0 0001	0 0008	2029 89
	(0 0240)	(0 1582)	(0 0043)	(0 0000)	(0 0001)	
Aegon N V	0 1663	-1 5362	0 8088	0 0008	0 0159	1650 96
	(0 0189)	(0 1415)	(0 0327)	(0 0014)	(0 0479)	
Koninklijke Ahold N V	0 5041	-4 7510	1 0721	0 0004	0 0000	1938 10
	(0 0458)	(0 3558)	(0 0454)	(0 0016)	(0 0000)	
AKZO Nobel N V	0 1043	-1 9307	0 8846	0 0000	0 0005	2249 68
	(0 0094)	(0 0805)	(0 0170)	(0 0000)	(0 0001)	
ALSTOM	0 5363	-6 2276	1 1881	0 0006	0 0021	1677 07
	(0 0513)	(0 3601)	(0 0446)	(0 0001)	(0 0033)	
Assicurazioni Generali S p A	0 0162	-0 9104	1 1995	0 0004	0 0001	1922 90
	(0 0013)	(0 0360)	(0 0390)	(0 0017)	(0 0000)	
Aviva plc	0 4537	-3 9030	1 7234	0 0009	0 0004	1570 60
	(0 0323)	(0 1815)	(0 0326)	(0 0019)	(0 0000)	
AXA	0 4517	-5 1579	2 1420	0 0001	0 0018	1812 19
	(0 0212)	(0 1275)	(0 0169)	(0 0000)	(0 0012)	
EnBW Energie Baden Wuerttemberg AG	0 1516	-2 2710	0 6867	0 0000	0 0007	2147 50
	(0 0100)	(0 0762)	(0 0141)	(0 0000)	(0 0001)	
BAE Sys PLC	0 3486	-3 7211	0 8013	0 0001	0 0004	2163 15
	(0 0351)	(0 2734)	(0 0125)	(0 0000)	(0 0001)	
Bco Bilbao Vizcaya Argentaria S A	0 0489	-1 2233	0 8451	0 0000	0 0007	2119 26
	(0 0054)	(0 0557)	(0 0251)	(0 0000)	(0 0001)	
Bay Motoren Werke AG	0 0623	-1 3959	0 7825	0 0000	0 0008	2094 40
	(0 0061)	(0 0604)	(0 0232)	(0 0000)	(0 0001)	
BNP Paribas	0 1825	-2 7679	1 6555	0 0000	0 0012	1961 31
	(0 0185)	(0 1185)	(0 0113)	(0 0000)	(0 0002)	
Brit Telecom PLC	0 4335	-4 3067	1 1937	0 0001	0 0010	2015 32
	(0 0481)	(0 3141)	(0 0077)	(0 0000)	(0 0001)	
Bayer AG	0 0943	-1 8508	0 8011	0 0000	0 0003	2336 15
	(0 0082)	(0 0776)	(0 0203)	(0 0000)	(0 0001)	
Carrefour	0 3891	-3 8826	0 9714	0 0004	0 0001	1977 60
	(0 0248)	(0 1929)	(0 0136)	(0 0003)	(0 0000)	
Commerzbank AG	0 3108	-3 5063	1 1852	0 0101	0 0197	1060 08
	(0 0244)	(0 2777)	(0 0522)	(0 0300)	(0 0654)	
Compass Gp PLC	0 1142	-1 9842	0 7924	0 0000	0 0004	2226 81
	(0 0103)	(0 0891)	(0 0195)	(0 0000)	(0 0001)	
Deutsche Bk AG	0 7278	-5 2945	1 2913	0 0009	0 0019	1442 08
	(0 0184)	(0 1115)	(0 0017)	(0 0001)	(0 0001)	
Deutsche Post AG	0 3145	-2 6306	0 8334	0 0368	0 0496	835 83
	(0 0258)	(0 2163)	(0 0264)	(0 0313)	(0 1226)	
Deutsche Telekom AG	0 0790	-1 4493	0 6788	0 0000	0 0007	2201 93
	(0 0070)	(0 0602)	(0 0183)	(0 0000)	(0 0001)	
Eurpn Aero Defence& Space Co Eads N V	0 4851	-4 1378	0 8909	0 0025	0 0002	1556 89
	(0 0251)	(0 1553)	(0 0215)	(0 0032)	(0 0000)	
EDP Energias de Portugal SA	0 4758	-4 6512	0 9629	0 0001	0 0007	2019 51
	(0 0474)	(0 3285)	(0 0108)	(0 0000)	(0 0001)	
E ON AG	0 4722	-4 8689	1 0878	0 0000	0 0007	2114 64
	(0 0234)	(0 1531)	(0 0047)	(0 0000)	(0 0001)	
Bco Espirito Santo S A	0 4930	-4 5802	1 7739	0 0006	0 0001	1811 88
	(0 0343)	(0 2300)	(0 0441)	(0 0015)	(0 0000)	
Edison S p A	0 1940	-2 7225	0 9233	0 0001	0 0006	2115 47
	(0 0143)	(0 1067)	(0 0105)	(0 0000)	(0 0000)	
Finmeccanica S p A	0 4478	-4 8100	1 0621	0 0000	0 0009	2033 81
	(0 0158)	(0 1018)	(0 0044)	(0 0000)	(0 0001)	

Firm	$\alpha^{\mathbb{P}}$	$\alpha^{\mathbb{P}}\beta^{\mathbb{P}}$	σ	σ_{3y}	σ_{5y}	LogLk
Fortum Oyj	0 3350	-3 4948	0 7806	0 0000	0 0005	2200 54
	(0 0272)	(0 2013)	(0 0049)	(0 0000)	(0 0001)	
France Telecom	0 1946	-2 4242	0 7703	0 0000	0 0006	2201 91
	(0 0092)	(0 0637)	(0 0055)	(0 0000)	(0 0001)	
Gas Nat SDG SA	0 4033	-4 2247	0 9858	0 0001	0 0006	2117 43
	(0 0350)	(0 2401)	(0 0075)	(0 0000)	(0 0001)	
Casino Guichard Perrachon	0 1683	-2 4124	0 8844	0 0000	0 0008	2100 17
	(0 0117)	(0 0861)	(0 0094)	(0 0000)	(0 0001)	
Hannover Ruck AG	0 6467	-5 4175	1 7874	0 0006	0 0002	1646 61
	(0 0487)	(0 3148)	(0 0516)	(0 0020)	(0 0000)	
Iberdrola S A	0 4213	-4 3868	0 9268	0 0001	0 0007	2103 62
	(0 0340)	(0 2301)	(0 0078)	(0 0000)	(0 0001)	
Koninklijke DSM NV	0 1194	-1 9719	0 7971	0 0000	0 0005	2245 84
	(0 0099)	(0 0774)	(0 0144)	(0 0000)	(0 0001)	
Koninklijke KPN N V	0 0917	-1 9503	1 0727	0 0000	0 0004	2240 00
	(0 0083)	(0 0738)	(0 0192)	(0 0000)	(0 0001)	
Linde AG	0 2432	-2 9699	0 7126	0 0000	0 0002	2453 48
	(0 0328)	(0 2728)	(0 0097)	(0 0000)	(0 0000)	
Lanxess	0 4501	-4 5737	1 3549	0 0002	0 0012	1868 86
	(0 0423)	(0 2575)	(0 0085)	(0 0000)	(0 0002)	
METRO AG	0 3407	-4 2310	1 4097	0 0000	0 0005	2126 88
	(0 0260)	(0 1705)	(0 0090)	(0 0000)	(0 0000)	
Marks& Spencer p l c	0 1775	-2 3630	0 8728	0 0000	0 0009	2081 91
	(0 0142)	(0 0972)	(0 0089)	(0 0000)	(0 0001)	
Bca Monte dei Paschi di Siena S p A	0 1988	-2 1903	0 8827	0 0004	0 0157	1779 11
	(0 0236)	(0 1667)	(0 0253)	(0 0034)	(0 1354)	
Natl Grid Plc	0 1279	-2 0683	0 7490	0 0000	0 0007	2153 00
	(0 0093)	(0 0735)	(0 0143)	(0 0000)	(0 0001)	
Next plc	0 3820	-3 9460	1 1672	0 0005	0 0000	1943 45
	(0 0177)	(0 1304)	(0 0328)	(0 0013)	(0 0000)	
Hellenic Telecom Org SA	0 1241	-1 9502	0 7581	0 0000	0 0011	2018 50
	(0 0106)	(0 0799)	(0 0149)	(0 0000)	(0 0001)	
Koninklijke Philips Electrs N V	0 0904	-1 8744	0 8332	0 0000	0 0005	2158 91
	(0 0071)	(0 0701)	(0 0236)	(0 0000)	(0 0001)	
PPR	0 4213	-4 4616	1 2420	0 0001	0 0008	2011 64
	(0 0217)	(0 1395)	(0 0052)	(0 0000)	(0 0001)	
Royal Bk Scotland plc	0 3968	-4 0453	1 5398	0 0028	0 0068	1404 04
	(0 0244)	(0 2012)	(0 0058)	(0 0004)	(0 0020)	
Repsol YPF SA	0 1327	-1 9957	0 6999	0 0000	0 0005	2251 37
	(0 0125)	(0 0984)	(0 0146)	(0 0000)	(0 0000)	
Rolls Royce plc	0 2915	-3 4255	0 8758	0 0006	0 0156	1706 46
	(0 0344)	(0 2804)	(0 0401)	(0 0009)	(0 0651)	
RWE AG	0 2083	-2 3834	0 9736	0 0004	0 0000	1826 23
	(0 0038)	(0 0183)	(0 0417)	(0 0016)	(0 0000)	
J Sainsbury PLC	0 1007	-1 9419	0 9177	0 0000	0 0004	2213 93
	(0 0094)	(0 0847)	(0 0190)	(0 0000)	(0 0001)	
Svenska Cellulosa AB SCA	0 2316	-2 8096	0 7784	0 0000	0 0004	2229 19
	(0 0185)	(0 1388)	(0 0073)	(0 0000)	(0 0001)	
Siemens AG	0 1855	-3 7972	1 8032	0 0000	0 0005	2100 92
	(0 0156)	(0 1216)	(0 0232)	(0 0000)	(0 0002)	
Societe Generale	0 2586	-2 4515	1 2072	0 0014	0 0002	1656 10
	(0 0056)	(0 0386)	(0 0151)	(0 0017)	(0 0000)	
Cie de St Gobain	0 2645	-2 9846	0 9106	0 0000	0 0007	2129 57
	(0 0152)	(0 1015)	(0 0044)	(0 0000)	(0 0001)	
Stmicroelectronics N V	0 4245	-4 3879	1 2703	0 0002	0 0009	1860 55
	(0 0359)	(0 2312)	(0 0080)	(0 0000)	(0 0001)	
Technip	0 3955	-4 1206	0 7575	0 0022	0 0028	1395 27
	(0 0306)	(0 2240)	(0 0209)	(0 0002)	(0 0036)	
Telenor ASA	0 3669	-4 2485	1 5434	0 0001	0 0008	1990 64
	(0 0339)	(0 2198)	(0 0084)	(0 0000)	(0 0001)	

Table A.3 (Cont.).: Actual intensity estimates

Firm	$\alpha^{\mathbb{P}}$	$\alpha^{\mathbb{P}}\beta^{\mathbb{P}}$	σ	σ_{3y}	σ_{5y}	LogLk	Firm	$\alpha^{\mathbb{P}}$	$\alpha^{\mathbb{P}}\beta^{\mathbb{P}}$	σ	σ_{3y}	σ_{5y}	LogLk
Telecom Italia SpA	0.0986	-1.6165	0.8261	0.0000	0.0009	2145.94	Veolia Environnement	0.3628	-3.7624	1.1333	0.0001	0.0015	1868.06
	(0.0072)	(0.0548)	(0.0094)	(0.0000)	(0.0001)			(0.0273)	(0.1610)	(0.0072)	(0.0000)	(0.0002)	
Telekom Austria AG	0.3345	-3.9930	1.5734	0.0001	0.0009	2052.87	Vinci	0.1113	-1.7969	0.7181	0.0000	0.0006	2174.51
	(0.0237)	(0.1489)	(0.0058)	(0.0000)	(0.0002)			(0.0111)	(0.0895)	(0.0158)	(0.0000)	(0.0001)	
TeliaSonera AB	0.2323	-2.8332	0.9239	0.0000	0.0004	2263.15	Vivendi	0.1007	-1.7615	0.6582	0.0000	0.0004	2261.05
	(0.0260)	(0.2051)	(0.0078)	(0.0000)	(0.0001)			(0.0098)	(0.0877)	(0.0224)	(0.0000)	(0.0001)	
TNT N,V,	0.2468	-2.9292	0.8437	0.0000	0.0005	2193.18	AB Volvo	0.5326	-5.2677	1.2414	0.0002	0.0011	1905.51
	(0.0263)	(0.1872)	(0.0091)	(0.0000)	(0.0001)			(0.0486)	(0.3057)	(0.0091)	(0.0000)	(0.0001)	
Total SA	0.3647	-3.9453	0.6732	0.0000	0.0003	2464.78	Vodafone Gp PLC	0.1993	-2.5641	0.8995	0.0000	0.0005	2199.48
	(0.0357)	(0.2905)	(0.0055)	(0.0000)	(0.0000)			(0.0161)	(0.1247)	(0.0072)	(0.0000)	(0.0001)	
Tesco PLC	0.3950	-4.3522	1.6290	0.0001	0.0000	2428.01	Wolters Kluwer N V	0.2734	-3.5763	1.6309	0.0002	0.0001	1957.85
	(0.0689)	(0.4719)	(0.0208)	(0.0001)	(0.0000)			(0.0444)	(0.3081)	(0.0376)	(0.0005)	(0.0000)	
UBS AG	0.2424	-2.0472	1.0523	0.0012	0.0005	1525.84	WPP 2005 Ltd	0.2864	-3.5411	1.0296	0.0001	0.0006	2046.24
	(0.0094)	(0.0672)	(0.0020)	(0.0001)	(0.0000)			(0.0266)	(0.1857)	(0.0114)	(0.0000)	(0.0001)	
Xstrata Plc	0.6540	-6.8750	1.6946	0.0232	0.0417	1052.56							
	(0.0565)	(0.4243)	(0.0545)	(0.0101)	(0.1190)								

A.4. Panel data model

Appendix A.4 contains a panel data model version of the Tables 2.7 and 2.10. The sample period covers from 14/June/2006 until 31/March/2010.

Table A.4.: Panel regression for distress risk premia

Dependent variable	$\Delta DRP_{i,t}$							
Model	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
	All period	<09/Aug/2007	≥ 09/Aug/2007 <15/Sep/2008	≥15/Sep/2008	All period	<09/Aug/2007	≥ 09/Aug/2007 <15/Sep/2008	≥15/Sep/2008
ΔBid Ask5y$_{i,t}$	1.1970***	0.4740**	0.9040***	1.2010***	1.1376***	0.4549*	1.0262***	1.1180***
ΔESTOXX50$_t$	0.0000**	0.0000***	0.0000	0.0000	0.0000*	0.0000***	0.0000	0.0000
ΔVIX$_t$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Δ SD/E R$_t$	0.0009	0.0005	0.0011	0.0007	0.0013	0.0004	0.0012	0.0000
ΔEONIA$_t$	0.0002	0.0000	0.0001	0.0002	0.0002	0.0001	0.0002	0.0001
ΔE RIBOR OIS$_t$	0.0004	0.0026***	0.0004	0.0002	0.0002	0.0026**	0.0005	0.0001
ΔSLOPE$_t$	0.0000	0.0000	0.0004	0.0005	0.0000	0.0001	0.0006	0.0005
ΔSOVPC1$_t$	0.0004***	0.0021**	0.0013**	0.0003**	0.0004***	0.0018*	0.0015***	0.0003**
ΔSOVPC2$_t$	0.0001	0.0060**	0.0048***	0.0002	0.0001	0.0067**	0.0044***	0.0002
Financial × ΔBid Ask5y$_{i,t}$					0.5377	0.3212	0.4882*	0.9221
Financial × ΔESTOXX50$_t$					0.0000	0.0000***	0.0000***	0.0000
Financial × ΔVIX$_t$					0.0000	0.0000***	0.0000***	0.0001
Financial × Δ SD/E R$_t$					0.0021	0.0000	0.0009	0.0047
Financial × ΔEONIA$_t$					0.0003	0.0001	0.0004**	0.0005
Financial × ΔE RIBOR OIS$_t$					0.0008	0.0001	0.0004	0.0016
Financial × ΔSLOPE$_t$					0.0006	0.0004	0.0012***	0.0003
Financial × ΔSOVPC1$_t$					0.0000	0.0009	0.0009**	0.0001
Financial × ΔSOVPC2$_t$					0.0001	0.0040*	0.0016**	0.0001
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial dummy	No	No	No	No	Yes	Yes	Yes	Yes
Obs.	8415	2550	2380	3485	8415	2550	2380	3485
R^2 Adj	0.2504	0.1780	0.4397	0.2410	0.2572	0.1815	0.4478	0.2534

OLS regressions of distress risk premium against different macro-financial variables. The table reports the estimated OLS coefficients and their significance, according to Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The date 09/Aug/2007 refers to the day that BNP Paribas froze three investment funds, and 15/Sep/2008 refers to the date that Lehman Brothers filed for bankruptcy. The sample period covers from 14/Jun/2006 to 31/Mar/2010. *, **, and *** denote the significance at 10%, 5% and 1%, respectively.

Table A.5.: Panel regression for jump-at-default risk premia

Dependent variable	$\Delta JAD_{i,t}$							
Model	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
	All period	<09/Aug/2007	$\geq$ 09/Aug/2007 <15/Sep/2008	$\geq$15/Sep/2008	All period	<09/Aug/2007	$\geq$ 09/Aug/2007 <15/Sep/2008	$\geq$15/Sep/2008
ΔBid Ask5y$_{i,t}$	2220.8849***	1008.7847**	2927.3078*	1977.7244***	2126.4277***	1032.9614**	3392.9802*	1860.7841***
ΔESTOXX50$_t$	0.0009	0.0001	0.0033	0.0029	0.0011	0.0001	0.0037	0.0029
ΔVIX$_t$	0.0477	0.0053	0.0317	0.0748	0.0514	0.0122	0.0195	0.0838
ΔUSD/EUR$_t$	2.9486	0.9929	1.1659	0.6171	2.1388	1.0185	0.2410	0.0062
ΔEONIA$_t$	0.1938	0.2908	0.0258	0.0350	0.1972	0.3438	0.1847	0.0476
ΔEURIBOR OIS$_t$	2.4607	2.9776*	1.3765	1.2671	2.5519	1.8168	1.8221	1.3557
ΔSLOPE$_t$	0.2346	0.7239	2.5280	1.6357	0.6559	0.6228	3.4041	1.2927
ΔSOVPC1$_t$	0.2586	5.3859***	2.8341	0.1784	0.3189	3.9610*	2.4945	0.2410
ΔSOVPC2$_t$	0.0319	8.6093*	18.0645***	0.2440	0.0271	9.3976*	17.7297***	0.2324
Financial $\times$ ΔBid Ask5y$_{i,t}$					760.8589	383.8721	2060.4151	1203.4123
Financial $\times$ ΔESTOXX50$_t$					0.0011	0.0002	0.0014	0.0006
Financial $\times$ ΔVIX$_t$					0.0197	0.0366***	0.0627***	0.0517
Financial $\times$ ΔUSD/EUR$_t$					3.7231	0.0735	6.1137*	4.1128
Financial $\times$ ΔEONIA$_t$					0.0336	0.2506	0.8492***	0.0217
Financial $\times$ ΔEURIBOR OIS$_t$					0.5567	5.8520**	1.9535	0.7858
Financial $\times$ ΔSLOPE$_t$					2.1834**	0.6011	3.6342**	1.7816
Financial $\times$ ΔSOVPC1$_t$					0.2920***	7.7782**	2.5063	0.2961***
Financial $\times$ ΔSOVPC2$_t$					0.0141	4.0558	0.2023	0.0654
Firm dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Financial dummy	No	No	No	No	Yes	Yes	Yes	Yes
Obs.	7421	2250	2100	3071	7421	2250	2100	3071
R^2 Adj	0.0561	0.0804	0.1546	0.0686	0.0587	0.0894	0.1606	0.0732

OLS regressions of jump-at-default risk premia against different macro-financial variables. The table reports the estimated OLS coefficients and their significance, according to Petersen (2009) to correct the fact that the residuals may be correlated across firms or across time. The date 09/Aug/2007 refers to the day that BNP Paribas froze three investment funds, and 15/Sep/2008 refers to the date that Lehman Brothers filed for bankruptcy. The sample period covers from 14/Jun/2006 to 31/Mar/2010. *, **, and *** denote the significance at 10%, 5% and 1%, respectively.

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