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PHD THESIS:

MARKET CRISES AND THE CONDITIONAL DISTRIBUTION OF FINANCIAL RETURNS: A DOWNSIDE RISK AND PRICING ERRORS ANALYSIS

A Thesis submitted by Lidia Sanchis-Marco for the degree of Doctor in Banking and Quantitative Finance at the University of Castilla la Mancha

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A mis padres, hermanos y sobrinos

Contents

Preface

This doctoral dissertation focuses on three important areas in Financial Economics: the downside risk modelling, pricing errors and tail financial spillover. These areas have aroused growing interest from recent episodes of financial crises. First, we are interested in some questions concerning the role of liquidity in forecasting downside risk measures using quantile regression approach. Second, we study if the sources of pricing errors are related with the credit market distress conditions. Finally, we analyze the tail financial spillover for banking system in different states of the economy using quantile regression methodology.

This dissertation consists in five chapters:

Chapter 1: Introduction. This chapter introduces the main areas of the dissertation and depicts the motivation and main contributions.

Chapter 2: On Downside Risk Predictability through Liquidity and Trading Activity. A Dynamic Quantile Approach. This chapter studies the value of liquidity and trading activity variables in forecasting Value at Risk using a quantile regression approach for different U.S. portfolios.

Chapter 3: Market Illiquidity and Pricing Errors in the Term Structure of CDS Spreads. This chapter explores the sources of the pricing errors in the term structure of CDS Spreads.

Chapter 4: Measuring Tail-Risk Cross-Country Exposures in the Banking Industry. This chapter analyzes the main transmission channels in the international banking system under adverse market conditions.

Chapter 5: Conclusions. This chapter presents the main results and future research in the different areas developed in the thesis.

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Resumen

Esta tesis está compuesta por tres artículos de investigación independientes en los que se analiza la modelización de *downside risk* (Capítulo 2), errores de valoración y medidas de *distress* (Capítulo 3) y medición de contagio financiero (Capítulo 4).

En el Capítulo 2, se analiza el contenido informativo de diferentes variables de liquidez y volumen en la predicción de rendimientos de diferentes carteras de mercado de acciones de Estados Unidos. Mientras que la mayoría de modelos que miden *downside risk* asumen que los rendimientos contienen suficiente información para predecir la distribución condicional de los rendimientos de una cartera, es posible que existan otras variables que tengan un papel importante. Así pues, el objetivo del primer capítulo es analizar si las variables relacionadas con liquidez y actividad negociadora contienen información relevante en la predicción de cuantiles de la distribución condicional de carteras de mercado representativas. La metodología utilizada se basa en regresión de cuantiles dinámica usando el modelo condicional autorregresivo CAViaR propuesto por Engle y Manganelli (2004). Los resultados muestran evidencia de la predicibilidad de la distribución condicional en términos de variables de liquidez y volumen. Realizando un análisis de *backtesting* usando diferentes metodologías, se obtienen mejores resultados de predicción, tanto dentro como fuera de muestra, que usando modelos basados únicamente en la información de los rendimientos. Los resultados son robustos para diferentes carteras representativas y medidas de liquidez y actividad negociadora consideradas de manera independiente y conjunta.

En el Capítulo 3, se estudia si los errores de valoración en la estructura temporal de *Credit Default swaps* (CDS) soberanos contienen información relevante acerca de características relacionadas con el *distress* en el mercado tales como la liquidez, cantidad de arbitrajistas, etc. Utilizando los residuos de diferentes modelos de valoración, se construye una medida de volatilidad de los errores de valoración llamada *Noise*. Se analiza entonces, si esta medida se puede considerar como un indicador de *distress* del mercado que puede reflejar fricciones de mercado

tales como la iliquidez. Mediante una aplicación para países del G20, obtenemos que una parte importante del riesgo sistemático no se valora utilizando modelos de valoración estándar. Utilizando la metodología de datos de panel se muestra evidencia de que las discrepancias en el precio observado y el estimado están relacionadas de forma sistemática con un mayor número de contratos negociados así como mayores *bid-ask spreads*. Los resultados sugieren que los flujos de capital de arbitraje disminuyen durante periodos de *distress*, lo cual es consistente con la segmentación del mercado entre inversores y arbitrajistas. Esta evidencia es robusta utilizando diferentes modelos de valoración de CDS de la industria como Pan y Singleton o Nelson y Siegel.

Finalmente, en el Capítulo 4, se analizan los efectos de contagio financiero entre diferentes regiones internacionales desarrolladas y emergentes aplicando la metodología de *State Dependent Sensitivity* (SDS) desarrollada por Adams, Füss y Gropp (2014). La mayoría de la evidencia existente sobre contagio financiero se basa en el análisis causal de la media de los rendimientos y de la volatilidad. En este capítulo, estudiamos si momentos de orden superior podrían aportar información relevante a la hora de medir posibles contagios. De esta forma, mediante el examen de contagio en la cola de la distribución condicional de los rendimientos de índices bancarios entre diferentes regiones, se pretende analizar si existe contagio en diferentes estados de la economía y en qué medida éste puede depender del estado. El objetivo es analizar la sensibilidad que caracteriza la vulnerabilidad del sector bancario de una determinada región ante shocks en otras regiones bajo diferentes estados de la economía. La hipótesis de partida se centra en que en momentos de gran volatilidad en los mercados los contagios serán mayores que en periodos de estabilidad. Los resultados obtenidos muestran evidencia de efectos de contagio más elevados y significativos durante periodos de crisis. La región con mayor capacidad de contagio es Estados Unidos y las regiones que muestran una mayor respuesta ante shocks en esta región son las europeas más desarrolladas. Por el contrario, Estados Unidos muestra mayor resistencia antes shocks en el resto de regiones, luego la baja concentración de prestatarios puede ser un factor determinante para limitar la propagación del riesgo sistémico entre instituciones financieras. [1]

[1] El resumen se presenta en castellano para cumplir con los requerimientos normativos de la Universidad de Castilla la Mancha. No obstante, al inicio de cada capítulo, se resume en inglés el contenido del mismo.

Chapter 1

Introduction

The recent market crises highlight the need to provide more accurate measurements of downside risk. The capacity to accurately identify, measure, control and forecast financial risk is crucial to ensure a stable financial system. Value at risk (VaR) is the most common downside risk measure popularized by the Basel Amendments. Regulators have encouraged banks and financial institutions to implement risk models based on this statistical measure. A number of methods can be found in the literature to compute this measure but they all rely solely upon returns. Recently, Kuester, Mittnik and Paolella (2006) showed that most of these procedures do not seem to perform successfully under current regulatory assessment rules for model adequacy. In this framework, is it possible to improve VaR performance using variables other than returns? Chapter 2 responds to this interesting and often overlooked question by providing an alternative downside risk measure which is not based only on returns information. Specifically, we analyze whether using trade-related variables and bid-ask spread measures yield improvements over standard approaches based on the returns solely when forecasting downside risk measures, such as the standard Value at Risk.

From an econometric perspective, the estimation and forecasting of the VaR involves certain additional challenges. We use quantile regression methodology (Koenker and Basset, 1978) that implies the assumption of no distribution of the portfolio returns. Additionally, an important issue is to analyze the capability of exogenous variables to measure downside risk measures better than some of the models previously proposed in the literature. The central idea is to model directly the dynamics of the conditional quantile by specifying a functional form that relates the time-varying dynamics of the (unobservable) conditional VaR process to the predictive variables, building on the so-called Conditional Autoregressive Value at Risk (CAViaR) model by Engle and Manganelli (2004). The model evaluation is based not only on the standard backtesting approaches but also on recent proposals such as a Dynamic Quantile (DQ) test from Engle and Manganelli (2004) and the quantile regression based test from Gaglianone, Lima, Linton and Smith (2011).

We consider data from different markets, size and book-to-market portfolios in the US market at the daily frequency and report that using variables such as relative spread or volume largely enhance the predictive ability of the risk models according to different measures. The empirical evidence suggests that there exist additional variables with predictive ability in downside risk measures. Our downside risk model outperforms the traditional models based on the return information using liquidity and volume related variables. Therefore, Chapter 2 of the dissertation proposes a new approach to VaR prediction. In contrast to existing methods, not only past returns but a structural time series model including observable state variables, which reflect market liquidity and trading activity, is used to forecast VaR. Both in-sample and out-of-sample evaluation are conducted. It is found that the method leads to a superior forecast performance compared to competing models.

Finding ways to improve market risk assessment has recently become an important topic, especially considering the failure of many popular quantitative models during the course of the recent financial crises. Indeed, many of the existing VaR prediction studies only focus on functions of past returns as conditioning information. The proposed extension in Chapter 2 towards variables that describe the trading environment seems promising. To the best of our knowledge, this question has not been addressed before, so this study adds empirical evidence supporting the existence of a link between returns and microstructure related variables. We strongly believe that the evidence presented is valuable for both future research and for practitioners that use quantitative methods to compute VaR measures.

Not only more involved downside risk requirements are consequence of recent instability periods but also the study of credit derivative innovations plays also a significant role in recent research. Furthermore, the financial crisis is mostly driven by the illiquidity of credit derivative products such as Credit Defaults Swaps (CDS). In Chapter 3, we focus on CDS market due to their tremendous growth in recent years and also to contribute to the literature about how CDS prices are formed. In this sense, many key aspects of this process remain unsolved in the literature, since active CDS trading is a relatively new phenomenon. Within this framework, Chapter 3 studies the residuals from different pricing models in terms of the structure of weekly sovereign CDS spreads. Our aim is examine the economic determinants that underlie CDS pricing errors as a consequence of market frictions reflected during periods of distress.

Specifically, we estimate from pricing errors a measure called Noise (see Hu, Pan and Wang, 2013 for a similar measure in the US bond market) and analyze whether it can be interpreted as a distress indicator that reflects market frictions such as illiquidity. The main research question is: Are CDS pricing errors related to market illiquidity? The empirical results reveal evidence that there exists a part of systematic risk that is not taken into account in default swaps spreads. We show how these discrepancies measured as the pricing error volatility by computing the Noise indicator are related with market illiquidity using panel data methodology.

Therefore, to analyze the informational content of CDS pricing errors, we have implemented different panel-data estimation techniques including two-way cluster errors, fixed-effects panel data, and instrumental-variable panel data on a broad sample of weekly sovereign default swap spreads from 16 countries in both advanced and emerging economies from the available dataset in the G20 group. We discover that pricing errors are higher during periods with high instability and panel data identifies bid-ask spreads and a higher level of offsetting transactions as the key determinants of these increased errors. In short, pricing errors can contain relevant information about credit market conditions.

Studying the sources of CDS pricing errors is important for several reasons. From a theoretical perspective, this study is useful to enhance the understanding of the operating price as these derivatives trade in a relatively opaque and decentralized market. From a practical perspective, the issue is important for the trading, pricing, hedging, and risk management of CDS. Finally, from a regulatory perspective, it is important given the potential systemic nature of the CDS market.

Another important topic arising from the recent global financial crisis is the growing interest in analyzing the spillover effects between different markets. The main aim is understand the contagion mechanisms and build efficient spillover measures in order to try to contain and mitigate contagion. Within this framework, Chapter 4 addresses the tail financial spillover effects between international regions in different states of the economy. The main research question of this Chapter is: Are financial spillover effects sensitive to the state of the economy? The analysis aims to identify the main transmission channels in the international banking system and provide a quantitative risk assessment of the size of contagion under adverse market conditions.

Furthermore, Chapter 4 is devoted to the estimation of financial spillover effects across international regions using a quantile regression approach based on a State Dependent Sensitivity (SDS) method. To this end, this chapter presents an efficient method in spillover measurement for carrying out this task. Firstly, the SDS model enables the calculation of the spillover for different states of the economy for different downside risk measurements, directly inspired by Adams, Füss and Gropp (2014). Secondly, we use as a downside risk measure the expected shortfall based on expectiles to estimate the risk from daily bank index returns. Finally, we also compute impulse response functions that determine the rapidity and persistence of contagion of a shock under different economic scenarios. In short, we study the size, direction and persistence of the tail spillover effects and study the tail spillover from different downside risk measures rather than volatility as in the main body of financial spillover literature.

Regarding the econometric approach, we estimate an SDS model using a two step quantile regression (2SQR) method over the expected shortfall from bank index returns using a maximum entropy algorithm for inference. This method allows us to quantify the tail spillover in different quantiles of this coherent measurement and obtain correct standard errors by correcting model endogeneity. Therefore, we compute spillover for all the regions simultaneously for different states of the economy and provide a complete picture of bilateral relationships that feature transmission channels. The general evidence shows that the contagion is higher, more significant and persistent during volatile periods than in tranquil ones. According to our study, the US banking sector is the greatest source of financial contagion in the international financial industry. However, the US tends to show more resilience in its banking system against foreign shocks.

The results in Chapter 4, provide evidence about the performance of an involved spillover method based on the higher moments of the returns distributions. The main advantage is about the computation of tail spillover in different economic states rather than traditional Granger causality in mean and volatility existing in the related literature. Moreover, our conclusions are not driven by any particular assumption on the returns distribution due to the use of expectiles in the expected shortfall estimation. This issue attract widespread attention from academics, policy makers and market participants endeavouring to understand the international spillover and thereby mitigate systemic risk.

The rest of the thesis is organized as follows. Chapter 2 studies the value of liquidity and trading activity in forecasting Value at Risk. Chapter 3 presents the CDS pricing errors determinants study. Chapter 4 analyzes the tail spillover effects across international regions. Finally, Chapter 5 summarizes the main conclusions and presents some further research related to the main topics developed in the thesis.

Chapter 2

On Downside Risk Predictability through Liquidity and Trading Activity: A Dynamic Quantile Approach

Most downside risk models implicitly assume that returns are a sufficient statistic with which to forecast the daily conditional distribution of a portfolio. In this chapter, we analyze if the variables that proxy for market-wide liquidity and trading conditions convey valid information to forecast the quantiles of the conditional distribution of several representative market portfolios, including volume- and value-weighted market portfolios, and several Book-to-Market- and Size-sorted portfolios. Using dynamic quantile regression techniques, we report evidence of conditional tail predictability in terms of these variables. A comprehensive backtesting analysis shows that this link can be exploited in dynamic quantile modelling to considerably improve the performance of day-ahead Value at Risk forecasts.

2.1 Introduction

Implementing risk control and monitoring systems requires quantitative procedures to capture the level of underlying uncertainty and make accurate predictions. The Basel Committee on Banking Supervision (BCBS) has popularized certain international standards in the financial services industry, known as Basel Accords, which entitle eligible institutions to use internal risk models based on the Value-at-Risk (VaR) framework for meeting market risk capital requirements. This statistical methodology has transcended the capital regulatory setting and is now routinely applied in risk management, investment assessing, and financial statement disclosing even by non-financial institutions. The recent crisis has shown the necessity of adequate risk-management protocols to achieve greater resilience and, hence, the need to improve the existing procedures for quantifying market risk. The present chapter is mainly motivated by this concern.

The extant literature has proposed a number of alternative methods for downside risk modelling, mainly VaR, which largely differ in the degree of sophistication: From the simple Exponential Weighting Moving Average (EWMA) popularized by RiskMetrics to the more advanced probabilistic settings based on the Extreme Value Theory (EVT); see McNeil, Frey and Embrechts (2005) for a review. Remarkably, several studies have revealed that most of these procedures do not perform successfully in practice under standard backtesting techniques (*e.g.,* Kuester, Mittnik and Paolella, 2006), which underlines the practical complexity that lies behind downside risk modelling. Why is accurate VaR forecasting so elusive? Whereas most of the previous literature has attempted to address this question on the grounds of model misspecification, in this chapter we adopt an alternative view within the framework of model risk and analyze the role played by the set of conditioning information. In spite of the large methodological differences, the existing methodologies to model market risk share a common characteristic: They all rely almost exclusively on historical returns. Naturally, this may turn out to be unnecessarily restrictive, since the conditional loss function of a portfolio may exhibit non-trivial links with the state variables that characterize the market environment and trading conditions, and which may help forecasting bursts in volatility and liquidity shocks, particularly, in times of stress.[1]

In this chapter, we analyze whether certain state variables related to the market trading process can predict the tail of the conditional loss distribution of returns and, consequently, be useful for risk management purposes. Although predictability is not necessarily limited to these variables, our main focus is on bid-ask spreads and volume measures. Our study is motivated by previous findings

[1]The implicit belief that returns subsume all the relevant information to forecast downside risk may be originated in a conservative interpretation of the Efficient Market Hypothesis. This forbids the systematic predictability of returns on the basis of the available information, *i.e.*, posits an orthogonal condition on the first-order conditional moment. However, it remains silent about higher-order moments, such as conditional volatility, or other distributional features, such as conditional percentiles. Furthermore, financial markets largely depart in practice from the complete-market and symmetric-information hypotheses that underlie a number of theoretical models in the asset pricing literature. In the presence of asymmetric or imperfect information and other frictions, even the conditional mean of returns may be predictable.

and theoretical considerations in the asset pricing and market microstructure literature, which jointly underline the link between returns and market liquidity, trading activity, and private information arrivals. Like returns, liquidity- and volume-related variables are available on the trading-basis and are highly sensitive to information flow. Like volatility, these variables are believed to reflect collective expectations, environmental conditions and market sentiments that have a major influence on investor decisions. In contrast to returns and volatility, however, trade-related variables seem to have been ignored in downside risk modelling, even though there exists previous evidence supporting the predictive power of trading activity and liquidity on volatility; see, for instance, Bollerslev and Melvin (1994) and Suominen (2001). The main aim of this chapter, therefore, is to address whether downside risk forecasts can be improved by using this kind of trade-related information.

In particular, we analyze predictability at different meaningful quantiles in the left tail of the conditional distribution of daily returns of several market portfolios, including volume- and value-weighted, Book-to-Market (B/M)- and Size-sorted market portfolios in the U.S. Stock Exchange. The predictive variables are different measures of market-wide liquidity and market-wide trading activity. These variables share a considerable degree of commonality and can be related to liquidity risk (Chordia, Roll and Subrahmanyam, 2001), but measure different facets of this magnitude. The simplest way to address predictability is through least squares-based regressions. Conditional quantiles are unobservable, however, and such an approach is infeasible. Fortunately, the Quantile Regression theory allows us to analyze tail-predictability without departing significantly from the intuitive spirit of predictive regressions; see Koenker (2005) for an overview. Applying this methodology, we model VaR dynamics through a functional form that relates this latent process to its own past as well as lagged predictors, building on the CAViaR model in Engle and Manganelli (2004). The main conclusion from the analysis on the significance of estimated coefficients in the predictive analysis is that bid-ask spreads and volume-related variables can predict the tail of the conditional distribution of daily returns.

The main practical purpose of VaR models is to construct accurate forecasts. Consequently, we also analyze the out-of-sample performance of daily VaR forecasts from risk models that account for microstructure variables in relation to restricted and alternative methodologies that build solely on return-based information. We consider the return-restricted CAViaR models originally proposed by Engle and Manganelli (2004), and alternative volatility-based risk models based on EWMA, EVT and Generalized Autoregressive Conditional Heteroscedastic (GARCH) modelling. Using these procedures, we construct a series of day-ahead forecasts in a period of market distress and apply a comprehensive battery of backtesting procedures including the likelihood-ratio tests in Christoffersen (1998), the conditional hit test in Engle and Manganelli (2004), and the quantile-regression test recently proposed by Gaglianone, Lima, Linton and Smith (2011). The overall picture that emerges from this exhaustive analysis agrees with the in-sample predictive results and suggests that trade-related variables can largely enhance the performance of return-based VaR risk models even in a stress scenario.

The analysis on B/M- and Size-sorted portfolios yields meaningful differences, both in the extent of predictability and the suitability of the different state variables. Quantiles in the left tail of the conditional distribution can be predicted accurately in portfolios formed by high B/M or small-cap stocks, using bid-ask spreads and trading activity variables, respectively. This evidence could be related to how discovery price takes place and to the existence of investment clienteles. Chordia, Sarkar and Subrahmanyam (2011) argue that informed investors have preferences for large-cap stocks. Since noise trading activity is the main cause of volatility in small-cap stocks, this may explain why using volume-related variables enhances VaR forecasts in this particular portfolio. In short, the main conclusion that consistently emerges from our analysis is that liquidity and trading activity convey incremental information to forecast daily conditional tail dynamics at different quantiles. We show that this property can be used for applied purposes to greatly enhance the forecasting performance of suitable downside risk models.

This chapter can be related to different streams of previous research. First, it belongs to the literature devoted to VaR modelling in the general context of quantile regression. Previous papers have addressed predictability using different types of variables and methodologies. Taylor (1999) forecasted VaR at different horizons in linear quantile regressions, using GARCH-type volatility estimates and deterministic functions of the forecasting horizon involved. Similarly, Chernozhukov and Umantsev (2001) used lagged values of stock and market returns to characterize daily VaR in an individual stock. Engle and Manganelli (2004) use return-restricted CAViaR models at the daily horizon. Cenesizoglu and Timmerman (2008) analyzed tail predictability in monthly returns using equity premium predictors, such as valuation and corporate ratios, bond yields, and default and market risk measures. Adrian and Brunnermeier (2011) model weekly VaR dynamics similarly, aiming to characterize systemic risk; see, also, Taylor (2000, 2008b), Kouretas and Zarangas (2005), Bao, Lee and Salto (2006), Kuester *et al.* (2006), and López-Espinosa, Moreno, Rubia and Valderrama (2012) for related work. In addition, our study is related to return predictability and, more precisely, to the literature devoted to the analysis of the links between volatility, liquidity and trading activity; see, among many others, Clark (1973), French and Roll (1986), Tauchen and Pitts (1983), Stoll (1989) and Kalimipalli and Warga (2002).

This chapter contributes to these strands of literature in different ways. Our analysis formally uncovers the existence of a Granger-type causal predictive relationship that links trade-related variables to the conditional distribution of daily market returns. An immediate practical application is downside risk modelling. We report consistent evidence that VaR risk models that exploit this link can exhibit a considerably enhanced out-of-sample performance with respect to return-restricted alternatives. Hence, this chapter also contributes to expanding the literature on CAViaR modelling. This general class of models was developed recently, so only a limited number of specifications constructed in the spirit of GARCH-type models have been analyzed. We show that the conditional tail of daily returns exhibits similar stylized features to those characterizing conditional volatility, but also more complex dynamics that are captured by liquidity and trading activity variables. The class of CAViaR models discussed in this chapter, in which trade-related variables are distinctively incorporated, produces more accurate VaR forecasts than the specifications studied in the extant literature.

The remaining part of the chapter is organized as follows. Section 2.2 describes the dataset used in the paper and its main characteristics. Section 2.3 reviews the basic elements in VaR modelling, specifically in CAViaR modelling. Section 2.4 carries out the main empirical analysis, focusing on the returns of a volume-weighted market portfolio, using both in-sample predictive and out-of-sample backtesting techniques. Section 2.5 discusses the robustness of the results and analyzes predictability in others characteristic market portfolios. Section 2.6 summarizes the main results and concludes. Appendix A briefly summarizes the main features of the alternative risk models used in this chapter.

2.2 Data

We analyze tail-predictability in the returns of several representative portfolios in the U.S. Stock Exchange. The choice of portfolio data allows us to eliminate the idiosyncratic noise that may affect the main conclusions in a study on individual stocks and it is coherent with real practices, since VaR is normally computed over portfolio returns. Data are obtained from different sources. The main analysis in Section 2.4 is conducted on daily continuously compounded returns of the volume-weighted portfolio obtained from Center for Research in Security Prices (CRSP). The sample spans the period 01-04-1988 to 12-31-2002, totaling 3,782 observations. This period is particularly interesting for risk management purposes, because it includes a stress scenario originated during the burst of the technological bubble in 2000. This particular sub-sample shall be used to backtest the different risk models under market stress conditions. In addition, Section 2.5 checks the robustness of the main conclusions of this analysis under different modelling considerations and analyzes predictability in other representative market portfolios. We focus on daily log returns of the value-weighted portfolio as well as several B/M- and Size-sorted portfolios in the same period. These data are obtained, respectively, from CRSP and Kenneth French's website.

The most distinctive feature of this chapter is the analysis of the predictive power of microstructure variables on daily VaR of several market portfolios, which requires representative measures of market-wide liquidity and trading activity in the period of interest. Chordia *et al.* (2001) constructed several variables in this spirit which have been widely used in a series of subsequent papers to address different issues. In particular, market-wide liquidity and market-wide trading activity measures are computed by cross-averaging individual measures at the stock level on each trading day using a comprehensive sample of NYSE stocks after applying standard filtering rules. The individual measures of liquidity are constructed by averaging intraday observations from the

Trade and Quote (TAQ) database over the day. The readers are referred to Chordia *et al.* (2001) for further details.

The set of market trade- and order-based variables used as VaR predictors in this chapter, which we shall collectively refer to as $\mathscr{M}\mathscr{T}_T$ hereafter, is available at Avanadir Subrahmanyam's website and includes the following measures of market-wide trading activity and bid-ask spread measures in the period of interest:

i) Market trading activity (or volume-related) variables: Trading Volume (TV) measured in thousands of shares; Number of Trades (NT) calculated as the sum of sell and buy trades; Number of Sell trades (NS); Number of Shares Sold in thousands (NSS) and Traded Volume in Dollars (TVD). The variables in this group are trade-based measures and, therefore, deemed as *indirect* measures of liquidity. Trading activity induces price volatility and, hence, a greater likelihood of large price movements. Consequently, we expect large trading activity reacting to news and anticipating increments in the VaR level of the portfolio.

ii) Market bid-ask spreads (or liquidity-related) variables: Quoted Spread (QS) measured as the dollar difference between ask and bid prices; Effective Spread (ES) given by the signed difference between trade price and bid-ask midpoint (MP); Relative Quoted Spread (RQS) defined as the ratio QS/MP, and Relative Effective Spread (RES) defined as the ratio ES/MP. Bid-ask spreads measure transaction costs and, as such, are order-based measures widely considered as *direct* measures of liquidity. When market liquidity dries out, transaction costs increase and prices become more volatile. Hence, we expect large bid-ask spreads levels anticipating a greater likelihood of a large market movement.

Table 2.1 shows the usual descriptive statistics for the time-series of daily demeaned returns, computed as the residuals from a first-order autoregressive process, and all the predictive variables (in logarithms) used in our analysis. Note that the log-transform yields strictly positive (negative) series when applied on trading-activity (bid-ask spreads) variables. Returns exhibit the characteristic stylized features in daily samples: Excess kurtosis, mild degree of skewness and negligible autocorrelation. Liquidity- and volume-related variables are known to be persistent processes, and the most salient feature of the predictors is the strong degree of persistence as measured by the first-order autocorrelation coefficient. The daily conditional quantile of returns is a persistent process as well because so is volatility. Hence, lagged values of these state variables can be expected to be good predictors of the VaR process. Returns are contemporaneously correlated to all the variables analyzed.

Correlations are shown in Table 2.2. We observe that absolute returns are positively correlated with the variables in the volume group, exhibiting an average correlation around 39%, and negatively correlated to bid-ask spreads, with an average correlation around -25%. A number of empirical papers have documented a positive correlation between volume and absolute price change, while Pastor and Stambaugh (2003) find that periods experiencing adverse liquidity shocks generally coincide with high market volatility. As usual, the variables within each group are strongly correlated among themselves, and largely and negatively correlated with the variables in the other group. Cross-correlations range from -79%, for TVD and QS, to -88%, for TVD and RES.

Table 2.1: Descriptive statistics of the demeaned return for the portfolios

Panel A.- Returns								
	Mean	Median	Max.	Min.	Var	Skew.	Kurt.	$\rho_{(1)}$
$r_{t,Vol}$	0.00	0.01	5.54	-6.70	0.98	-0.20	7.78	-0.06
$r_{t,Value}$	0.02	0.06	4.97	-6.11	0.49	-0.35	10.84	-0.07
$r_{1t},_{LowB/M}$	0.01	0.02	6.65	-7.85	1.22	-0.11	7.29	-0.07
$r_{2t},_{HighB/M}$	0.00	0.02	4.81	-6.32	0.67	-0.43	8.36	-0.05
$r_{1t,LowSize}$	0.00	0.05	6.02	-7.56	0.66	-0.71	11.06	-0.05
$r_{2t,HighSize}$	0.00	0.01	5.73	-6.89	1.05	-0.16	7.39	-0.06
Panel B.- Predictive variables								
	Mean	Median	Max.	Min.	Var	Skew.	Kurt.	$\rho_{(1)}$
TV	7.39	7.21	9.69	5.52	0.73	0.36	1.86	0.96
NT	6.85	6.69	8.76	5.07	0.65	0.30	1.64	0.98
NS	6.09	5.94	8.02	4.24	0.65	0.29	1.67	0.98
NSS	6.51	6.33	8.80	4.50	0.73	0.35	1.86	0.96
TVD	11.10	11.04	13.00	9.13	0.76	0.17	1.66	0.96
QS	-1.89	-1.74	-1.20	-3.40	0.21	-1.64	4.79	0.99
ES	-2.29	-2.11	-1.50	-3.80	0.20	-1.53	4.48	0.99
RQS	-5.39	-5.39	-4.80	-6.90	0.20	-1.02	3.23	0.99
RES	-5.96	-5.76	-5.20	-7.20	0.20	-0.96	3.08	0.99

Descriptive statistics (mean, median, maximum, minimum, variance, skewness and kurtosis) of the demeaned returns for the volume- and value- weighted market portfolio, B/M- and Size-sorted portfolios corresponding to Low30 and High30 portfolios. Panel B shows the descriptive analysis for the predictive variables involved in the analysis (in logarithms). The last column indicates the first-order autocorrelation of the variables. The variables included are TV (Trading Volume); NT (Number of Trades); NS (Number of Sell trades); NSS (Number of Shares Sold in thousands); TVD (Traded Volume in Dollars); QS (Quoted Spread); ES (Effective Spread); RQS (Relative Quoted Spread) and RES (Relative Effective Spread).

Table 2.2: Correlation variables matrix involved in the analysis between absolute demeaning log-returns for volume portfolio and liquidity variables in logarithms.

	r_t	TV	NT	NS	NSS	TVD	QS	ES	RQS	RES
r_t	1.00									
TV	0.40	1.00								
NT	0.39	0.98	1.00							
NS	0.39	0.98	0.99	1.00						
NSS	0.40	0.99	0.98	0.98	1.00					
TVD	0.39	0.99	0.98	0.98	0.98	1.00				
QS	-0.25	-0.83	-0.82	-0.82	-0.82	-0.79	1.00			
ES	-0.26	-0.85	-0.85	-0.85	-0.84	-0.81	0.993	1.00		
RQS	-0.24	-0.86	-0.87	-0.87	-0.86	-0.86	0.957	0.95	1.00	
RES	-0.25	-0.88	-0.89	-0.89	-0.88	-0.88	0.948	0.95	0.99	1.00

2.3 Modelling and forecasting VaR

Let r_t, $t = 1,...,T$, be the daily log-return time-series of a portfolio, and let $\mathscr{F}_t$ be the natural filtration including all the available information at time t. This includes the lagged and current values of any observable variable up to time t, as well as measurable transformations of these. For ease of exposition, we assume that $\{r_t\}$ is stationary martingale difference sequence (MDS), verifying $E(r_t|\mathscr{F}_{t-1}) = 0$, with bounded moments $E\left(|r_t|^{\delta}\right) < \infty$ for some $\delta > 2$ large enough. This assumption comes with no practical loss of generality, since in practice it is customary to demean returns previous to the VaR modelling; see, for instance, Taylor (2008b).

For a certain probability level $\lambda \in (0,1)$, we define the $\lambda \times 100\%$ VaR of a financial portfolio as the maximum loss over a horizon of $h \geq 1$ days which is expected at the $(1-\lambda) \times 100\%$ confidence level given $\mathscr{F}_t$, *i.e.,* the λ-quantile of the conditional loss distribution of the portfolio. Formally, we denote:

$$VaR_{\lambda,t}(h) = -\{\inf z \in \mathbb{R} : \Pr(r_t(h) \leq z|\mathscr{F}_t) \geq \lambda\} \tag{2.1}$$

where $r_t(h) = \log P_{t+h} - \log P_t$ is the h-period return, and the negative sign on the right-hand side turns the magnitude of the expected loss into a positive measure following standard reporting practices. In market risk management, h typically ranges from 1 to 10 days, and λ usually takes values no greater than 0.05; see Section 2.4 for details. Since our empirical analysis refers specifically to a one-day holding period, $h = 1$, we shall suppress the h reference for notational convenience.

The extant literature has suggested different methodologies with which to model and forecast VaR dynamics. The following subsection discusses the main characteristics of the quantile regression approach used in this Chapter. The main features of several alternative procedures that shall be used together with quantile regression in Section 2.4.2 are sketched in Appendix A.

2.3.1 Dynamic conditional quantile modelling: CAViaR

Quantile regressions, introduced by Koenker and Bassett (1978), are well suited to estimating conditional VaR dynamics; see, Chernozhukov and Umantsev (2001) for an overview and an empirical application on this field. This semiparametric technique allows the direct modelling of the time-varying dynamics of conditional quantiles without imposing strong assumptions about the distribution function of observations. Engle and Manganelli (2004), EM hereafter, proposed a general class of nonlinear quantile regression models, the so-called Conditional Autoregressive Value at Risk (CAViaR), and discussed a number of particular cases which are specifically intended for VaR modelling at the daily horizon.

The main intuition behind CAViaR models is that the λ-th conditional quantile is treated as a latent autoregressive process, possibly depending on a number of lagged covariates, according to the general specification

$$VaR_{\lambda,t+1} = \beta_{\lambda,0} + \sum_{j=1}^{p} \beta_{\lambda,j} VaR_{\lambda,t+1-j} + \sum_{l=1}^{q} \gamma_{\lambda,l} f\left(X_{t+1-l}\right) \tag{2.2}$$

where $\theta_\lambda = \left(\beta_{\lambda,0}, \beta_{\lambda,1}, ..., \gamma_{\lambda,q}\right)'$ is a vector of unknown parameters, possibly depending on λ, X_t is a m-vector of covariates, and $f(\cdot) : \mathbb{R}^m \to \mathbb{R}$ is a measurable transform of the data. This specification embeds a large degree of flexibility and generality. Under the restriction $\beta_{\lambda,1} = ... = \beta_{\lambda,p} = 0$, model (2.2) can be reparameterized linearly and renders the well-known quantile regression model proposed by Bassett and Koenker (1982), widely used to model conditional quantiles directly. Also, CAViaR models are related to the autoregressive quantile models proposed by Koenker and Zhao (1996) and Koenker and Xiao (2006), but differ from these in which the autoregressive process is not directly observable and can depend nonlinearly on θ_λ. More recently, De Rossi and Harvey (2009) have proposed an iterative Kalman filter method that can be applied to characterize suitable CAViaR models. These may provide a reasonable approximation to the filtered estimators of time-varying quantiles that come from signal plus noise state-space models; see De Rossi and Harvey (2006) for further details.

As remarked by EM, a natural choice of X_t in (2.2) is lagged returns. In this chapter, we consider market returns and trade-related variables in two models with functional forms nested in (2.2). First, we consider a first-order autoregressive covariate-extended CAViaR model,

$$VaR_{\lambda,t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_{\lambda,t} + \gamma_{\lambda,1} |r_t| + \gamma_{\lambda,\mathscr{M}} x_{it}^{*} \tag{2.3}$$

with $x_{it}^* \equiv \log(x_{it})$, and $x_{it} \in \mathscr{MT}_T$, denoting the trading-activity and bid-ask spread covariates described in Section 2.2. Under the restriction $\gamma_{\lambda,\mathscr{M}} = 0$, EM dubbed the model Symmetric Absolute Value (SAV), so we shall refer to the unrestricted specification as SAV-CAViaR similarly. Also, we denote $\gamma_{\lambda,\mathscr{M}}$ to emphasize that, although this coefficient is related to a state variable, it belongs to $\mathscr{MT}_T$, a set of microstructure variables different from returns. The log transform is routinely applied to smooth the underlying series, reducing the statistical problems related to outliers and heteroskedasticity in financial time-series.

In addition, the dynamics of conditional quantiles in daily returns are strongly related to volatility, which displays asymmetric responses to the sign of lagged returns. This stylized feature, known as leverage effect, may feed into the tails of the conditional distribution. Therefore, we consider a direct extension of (2.3), say ASYM-CAViaR model, given by

$$VaR_{\lambda,t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_{\lambda,t} + \gamma_{\lambda,1}|r_t| \times \mathbb{I}_{(r_t \geq 0)} + \gamma_{\lambda,2}|r_t| \times \mathbb{I}_{(r_t < 0)} + \gamma_{\lambda,\mathscr{M}} x_{it}^* \tag{2.4}$$

to account for this possibility, where $\mathbb{I}_{(\cdot)}$ is an indicator function that takes values equal to one if the condition in brackets is fulfilled and zero otherwise.

Our main aim is to determine if there exists predictability in the conditional tail of returns, and if a risk model accounting for trade-related market state variables may lead to enhanced forecasting performance. The CAViaR framework seems particularly well adapted for this purpose for several reasons. First, model (2.3) and its generalization (2.4) have a clear economic interpretation, since VaR dynamics are allowed to depend on market risk, via $|r_t|$, and other factors generally related to market-wide liquidity risk, proxied by $x_{it} \in \mathscr{MT}_T$. Second, the suitability of these state variables can be analyzed straightforwardly by addressing $\mathrm{H}_0 : \gamma_{\lambda,\mathscr{M}} = 0$. Hence, this testing approach can be seen as a Granger-type test of causality, since the latent VaR process is linearly predicted with its own lags and the lags of other covariates. The problem that VaR is not directly observable is circumvented by endogenizing the estimation of the process. Third, dynamic quantile models are intended to construct VaR forecasts, so this framework allows the simultaneous analysis of in-sample predictability and out-of-sample performance. Finally, autoregressive models extended with microstructure variables can be seen as a particular class of models in the general CAViaR framework. The models originally proposed in EM adopt an ARMA-type functional form in the spirit of GARCH-type equations. While GARCH models are highly successful in volatility forecasting, conditional quantiles may exhibit more complex dynamics. Therefore, we analyze a straightforward variation of these models which may lead to large forecasting improvements.

Some additional comments are in order. Models (2.3) and (2.4) attempt to capture the statistical information conveyed by the past of the VaR process, returns, and other potential covariates. The autoregressive structure ensures that the dynamics of the conditional quantile change smoothly over time. Following EM, we consider a single lag, noticing that Kuester *et al.* (2006) showed the good performance of this parsimonious specification in relation to higher-order alternatives. As mentioned previously, the process $|r_t|$ introduces a source of stochastic short-term variation related to the arrival of news (*i.e.*, the information flow) and is a natural proxy for the unobservable volatility, a major driver of market uncertainty and downside risk at the daily frequency. Since $VaR_{\lambda,t+1}$ is a $\mathscr{F}_t$-measurable function, the similarities between the parametric structures of CAViaR and GARCH-type models are fully evident at this point and, in fact, both settings can be related upon certain restrictions.[2]

In addition to lagged returns, VaR could be related to other covariates, noting that there does not exist a specific theory indicating which state variables are more appropriate to this end. As discussed previously, the literature in market microstructure and asset pricing provide some guidance. In imperfect markets, security prices are sensitive to environmental factors that characterize transaction costs and which determine liquidity and trading activity conditions. Therefore, these variables may be useful in forecasting conditional quantiles. Since absolute-valued market returns proxy for volatility, it seems natural to include other variables to proxy for the remaining environmental factors, noting that liquidity is not directly observable and cannot be linked to a single dimension of the market. Liquidity generally denotes the ability of investors to trade large volumes quickly, at low cost, and without substantially moving prices. Therefore, we can observe a number of interrelated variables that capture different aspects of market-wide liquidity risk (directly or indirectly), such as those in $\mathscr{M}\mathscr{T}_T$, and which, in practice, may exhibit different predictive power.

We follow two different approaches to deal with this issue. Firstly, in Section 2.4 we analyze a sequence of conditional quantile models relying on individual covariates $x_{it} \in \mathscr{M}\mathscr{T}_T$, as stated in (2.3) and (2.4). Any of the resulting models can be seen as a low-order individual autoregressive distributed lag model, which are known to be particularly effective in the forecasting analysis (*e.g.,* Rapach and Strauss 2009). This allows us to examine how different trade- and order-based extended models perform in practice. We expect a robust picture to emerge from this analysis because all these state variables share a strong degree of commonality (Chordia, Roll and Subrahmanyam, 2000). Additionally, in Section 2.5, we analyze the combined predictive power of multiple regressors and, furthermore, take advantage of the underlying commonality in these variables, using Principal Component Analysis (PCA) to identify the main latent factors driving these series. This makes the overall analysis less sensitive to model specification considerations and may simplify the practical implementation of the procedure. The overall picture that emerges from this analysis is remarkably similar and leads us to robust conclusions.

2.3.2 Estimation and inference in CAViaR models

Building on Koenker and Bassett (1978), assume that returns obeys a data generating process such that $r_t - VaR_{\lambda,t}(\theta_0) = \varepsilon_{\lambda,t}$, where $VaR_{\lambda,t}(\theta_0)$ is a $\mathscr{F}_{t-1}$-measurable conditional quantile function,

[2] For instance, under the assumption that returns obey the GARCH-type model suggested by Taylor (1986), $r_t = \sigma_t \eta_t$ with $\sigma_t = \omega + \alpha|r_{t-1}| + \delta\sigma_{t-1}$ and $\eta_t \sim iid\mathscr{N}(0,1)$, then $VaR_{\lambda,t} = -\mathscr{Z}_\lambda \sigma_t$, where $\mathscr{Z}_\lambda$ is the λ-quantile of the standard normal distribution. In this case, the volatility process leads conditional quantiles to obey SAV dynamics characterized by $VaR_{\lambda,t} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_{\lambda,t-1} + \gamma_{\lambda,1}|r_{t-1}|$, with $\beta_{\lambda,0} = -\mathscr{Z}_\lambda \omega$, $\beta_{\lambda,1} = \delta$ and $\gamma_{\lambda,1} = -\alpha\mathscr{Z}_\lambda$.

$\theta_0 \in \mathbb{R}^n$ is the true (unknown) parameter vector, and $\varepsilon_{\lambda,t}$ is a stationary innovation term with continuous density satisfying the usual zero-quantile restriction $\text{Quant}\left(\varepsilon_{\lambda,t}|\mathscr{F}_{t-1}\right) = 0$. Since the dependence on the λ quantile is now agreed, in the sequel we shall suppress the λ subscript for notational convenience whenever there is no risk of confusion. For an arbitrary n-vector θ, define $u_t(\theta) = r_t - VaR_t(\theta)$. Then, the unknown parameters that characterize the CAViaR model can be estimated consistently as

$$\widehat{\theta}_\lambda : \arg\min_{\theta\in\mathbb{R}^n} \left\{ \sum_{t=1}^{T} \lambda \left|u_t(\theta)\right| \, \mathbb{I}_{(u_t(\theta)\geq 0)} + \sum_{t=1}^{T} (1-\lambda) \left|u_t(\theta)\right| \, \mathbb{I}_{(u_t(\theta)<0)} \right\} \tag{2.5}$$

under standard regularity conditions which do not impose a particular distribution on the data; see EM (Thm.1) for details, and Chernozhukov and Umantsev (2001) and Koenker (2005) for a more general discussion of nonlinear quantile regression models.

Similarly, under fairly general conditions, it is shown that

$$\sqrt{T}(\widehat{\theta}_\lambda - \theta_0) \xrightarrow{d} \mathscr{N}(0,V) \tag{2.6}$$

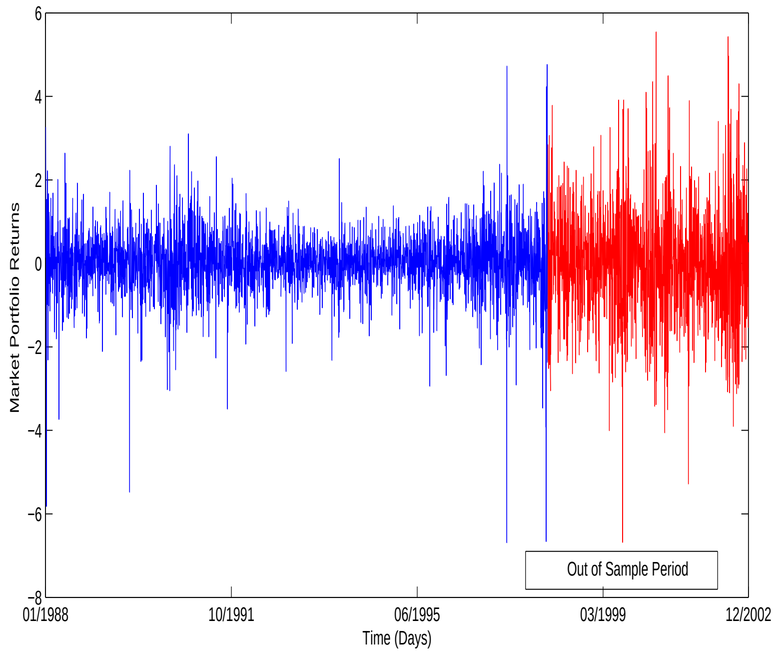
as the sample size is allowed to grow unbounded. The asymptotic covariance matrix takes the sandwich-type representation that generally characterizes the variance of extremum estimators, $V \equiv D^{-1}AD^{-1}$. In this context, $A = \lim_{T\to\infty}\mathrm{E}\left[\lambda(1-\lambda)\sum_{t=1}^{T}\xi_t\xi_t'/T\right]$ is mainly given by the expected value of the outer product of the gradient $\xi_t \equiv \nabla_\theta VaR_t(\theta_0)$, and $D = \lim_{T\to\infty}\mathrm{E}\left[\sum_{t=1}^{T} f_{\varepsilon_t}(0|\mathscr{F}_{t-1})\,\xi_t\xi_t'/T\right]$, with $f_{\varepsilon_t}(\cdot)$ denoting the conditional density of ε_t evaluated at zero; see EM (Thm. 3). Hence, V can be estimated consistently using the sample analogous of the matrices involved given $\widehat{\theta}_\lambda$. In particular, the estimation of A is straightforward, say $\widehat{A}_T = \lambda(1-\lambda)\sum_{t=1}^{T}\widehat{\xi}_t\widehat{\xi}_t'/T$, while D requires dealing with the unknown conditional density of innovations. A consistent estimator, based on kernel estimation, is generally given by $\widehat{D}_T = (Th_T)^{-1}\sum_{t=1}^{T}\mathscr{K}(\widehat{u}_t/h_T)\,\widehat{\xi}_t\widehat{\xi}_t'$, where h_T is a bandwidth parameter satisfying $h_T \to 0$ and $\sqrt{T}h_T \to \infty$, and $\mathscr{K}(\cdot)$ is a suitable weighting function. We shall discuss this issue in greater detail in the following section.

2.4 Downside risk analysis on volume-weighted returns

In this section, we analyze the predictive ability of trade- and order-based covariates at different quantiles of the left tail of the volume-weighted portfolio. The focus on day-ahead estimation is consistent with the holding period considered for internal risk control by most financial firms; see, among others, Taylor (2008b). The Basel framework requires the 1% conditional percentile to determine regulatory capital adequacy, but higher quantiles are also applied for different purposes. For instance, traders in the banking industry are often constrained by the rule that the 5% daily VaR of their position should not exceed a given bound (McNeil *et al.*, 2005). Furthermore, publicly traded firms are required to disclose quantitative market risk measures in their financial statements under Securities and Exchange Commission (SEC) rules, being VaR one out of three possible disclosing formats entitled. The SEC rule, effective since June 1998, states a 5% VaR or lower risk level, but also permits higher rates provided economic justification. Hence, we are particularly interested in the quantiles $\{0.01, 0.05\}$, but shall analyze more generally the VaR probabilities $\Theta_\lambda = \{0.01, 0.025, 0.05, 0.075\}$ to characterize predictability along the left tail.

Figure 2.1 shows the time series of volume-weighted returns. The beginning of the sample corresponds to the period that followed the market crash in October 1987. After the extraordinary crash, the volatility of the market decreased progressively and reverted to normal levels. In 1998, Long-Term Capital Management failure in the hedge-fund industry led to a massive bailout by other major banks and investment houses that, in turn, generated an excess of volatility in the market and which preceded the burst of the dot-com firms in 2000. Finally, the data from 2000 to 2002 show the large excess of volatility that characterized the market after the burst of the technological bubble. This period is particularly interesting for backtesting purposes.

Figure 2.1: Daily returns of the volume-weighted market portfolio



2.4.1 Predictive analysis

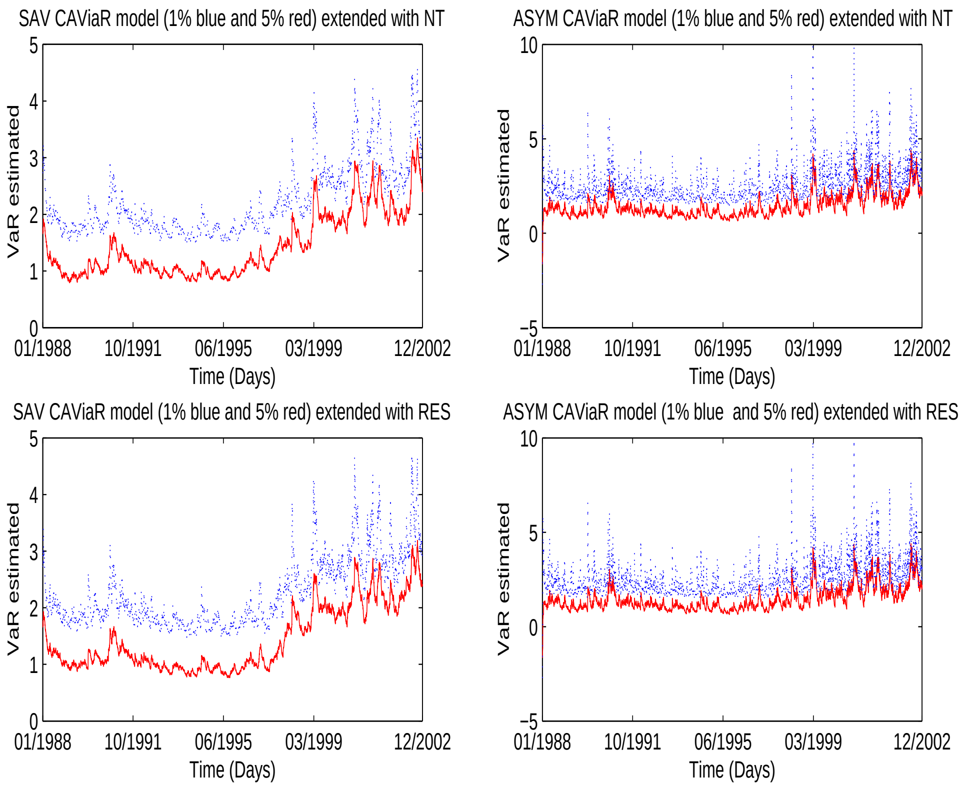
We first analyze tail-predictability in the intuitive spirit that characterizes predictive regressions, assuming quantile dynamics given by $VaR_{t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_t + \gamma_{\lambda,1} |r_t| + \gamma_{\lambda,\mathscr{M}} x_{it}^*$ and its asymmetric generalization (2.4), given any of the market trade-related variables $x_{it} \in \mathscr{M}\mathscr{T}_T$, and using the entire sample. Our main aim is to test $\mathrm{H}_0 : \gamma_{\lambda,\mathscr{M}} = 0$ for any $\lambda \in \Theta_\lambda$, since rejections of this test provides formal evidence of predictability at the λ quantile for the state variable involved.

Parameter estimates are obtained by minimizing (2.5) by means of the Simulated Annealing optimization algorithm (Goffe, Ferrier and Rogers, 1994). This local random-search search algorithm accepts values that increase the objective function (rather than lower it) with a probability that decreases as the number of iterations increases. The main purpose is to prevent the search process from becoming trapped in local optima, which in addition provides low sensitivity to the choice of the initial values. To minimize the possibility of getting convergence to local optima, the optimization process was repeated $1,000$ times over the whole sample. We also applied the simplex algorithm described in EM taking the solution from the Simulating-Annealing algorithm as the initial value, obtaining no significant difference.

The asymptotic covariance matrix V in (2.6) is inferred combining kernel-density estimation with heteroskedasticity-consistent covariance matrix estimation, as discussed in Section 2.3.2. Following EM, we implement a k-nearest neighbor (kNN) kernel setting to estimate D, say, $\widehat{D}_{1T} = \left(2Td_{[k]}\right)^{-1} \sum_{t=1}^{T} \mathbb{I}_{\left(d_t < d_{[k]}\right)} \widehat{\xi}_t \widehat{\xi}_t'$, where $d_{[k]}$ is the k-th order statistic of the Euclidean distances $d_t = |\widehat{u}_t|$, and $\widehat{u}_t$ is the quantile-regression residual estimates given the optimizer of (2.5). Consistency in kNN density estimation requires the bandwidth-type parameter k to diverge as does T also such that $k/T \to 0$; see, for instance, Devroye and Wagner (1977). A common rule of thumb sets $k = \sqrt{T}$ and, therefore, we follow this convention. In addition, we implement a kernel-based estimator $\widehat{D}_{2T} = (Th_T)^{-1} \sum_{t=1}^{T} \mathscr{K}\left(\widehat{u}_t / h_T\right) \widehat{\xi}_t \widehat{\xi}_t'$, where $\mathscr{K}(\cdot)$ is the Gaussian density and h_T is optimally selected according to Silverman's rule, *i.e.,* $h_T = 0.9 \times \min\left(\widehat{\sigma}_u, IQR_u\right) \times T^{-1/5}$, where $\widehat{\sigma}_u$ and IQR_u denote, respectively, the sample standard deviation and the sample interquartile of the estimated residuals.

Figure 2.2 shows the 1% and 5% conditional VaR estimates from the SAV- and ASYM-CAViaR models as a function of Relative Effective Spread (RES) and Number of Trades (NT).

Figure 2.2: Estimated VaR functions over the entire sample from covariate-extended SAV- and ASYM-CAViaR model at 1% (dashed blue line) and 5% (red solid line) quantiles using the variables NT (Number of Trades) and RES (Relative Effective Spread) as predictors for the volume-weighted market portfolio



We aim to discuss certain empirical features in these estimates that are common across the different variables and quantiles considered, so we only present VaR estimates for two representative variables and those quantiles, noting that complete results are available upon request. Conditional VaR estimates seem to exhibit the strong persistence that characterizes daily volatility, with VaR levels increasing considerably in the final part of the sample as consequence of the burst of the technological bubble. The estimates from the asymmetric models tend to be more volatile owing to the discontinuous path introduced by the dummy threshold. Finally, the monotonic property of quantiles, requiring $VaR_{\lambda_1,t} < VaR_{\lambda_2,t}$ for any $\lambda_1 > \lambda_2$ uniformly on t given definition (2.1), holds for all the models and quantiles $\lambda \in \Theta_\lambda$ analyzed. This is an important feature because conditional quantile models are estimated independently and shows that the CAViaR setting is generally well suited for empirical downside risk modelling. Should it be necessary, monotonicity may be empirically reinforced by imposing optimization constraints (see, for instance, Fan and Fan, 2006 for a discussion), but we remark that a significant number of observations at which this property is violated may be taken as evidence of model misspecification.

Table 2.3 reports the estimated coefficients for all the state variables analyzed. We report results for $\lambda \in \{0.01, 0.05\}$ in the in-sample analysis, noting that complete results are available. The table shows parameter estimates and one-sided robust p-values of individual significance tests based on covariance-matrix estimates given kNN- and kernel-based estimators, as described before. According to estimations in Table 2.3, there exists a strong degree of persistence in the VaR dynamics as measured by the autoregressive estimate, $\widehat{\beta}_{\lambda,1}$. The reason is that daily downside risk measures are driven by volatility, which characteristically exhibit long-range dependence at this horizon. Persistence tends to be weaker as λ decreases, particularly, in the asymmetric specification. This is not surprising, since extreme movements are likely driven by the jumping component of daily returns, which is generally expected to exhibit a more irregular pattern. Accordingly, volatility is a major driver of the empirical VaR process, with its influence becoming more important as λ decreases. In addition, we observe strong evidence of volatility-induced asymmetric patterns, since the estimates of $\gamma_{\lambda,2}$, associated to negative shocks, largely exceed those of $\gamma_{\lambda,1}$ in the asymmetric model (2.4). The estimates of $\gamma_{\lambda,1}$ are sometimes not significantly different from zero and tend to be negative and significant at $\lambda = 0.01$, so the restriction $\mathrm{H}_0 : \gamma_{\lambda,1} = \gamma_{\lambda,2}$ that gives rise to the SAV-CAViaR in the generalized asymmetric specification is strongly rejected through a standard F-type test (not reported here), particularly, at lower quantiles. The overall picture that emerges completely agrees with the qualitative evidence discussed, for instance, in EM.

We carried out a more comprehensive analysis for any $\lambda \in \Theta_\lambda$ and $k \in \{10, 30, 50, 70, 90\}$. Also we applied quantile-dependent values of k, setting $k = 40$ and $k = 60$ for the 1% and 5% quantiles, as in EM. The main statistical conclusions from this analysis are similar in every way to those discussed in the main test and show that the reported results are not particularly sensitive to the choice of the bandwidth-type parameter k, observing no qualitative difference. Complete results, particularizing in the symmetric model, are showed in 2.4.

Table 2.3: Inference results from predictive quantile regressions in the covariate-extended SAV-CAViaR and ASYM-CAViaR models for the volume-weighted market portfolio

	SAV-CAViaR								ASYM-CAViaR									
	$\lambda=5\%$				$\lambda=1\%$				$\lambda=5\%$					$\lambda=1\%$				
x_{it}	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,2}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,2}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$
TV	**-0.04**	**0.96**	**0.05**	**0.01**	**0.02**	**0.92**	**0.11**	**0.01**	**-0.07**	**0.93**	**-0.02**	**0.16**	**0.02**	**-0.12**	**0.84**	**-0.13**	**0.43**	**0.05**
pv_1	(0.00)	(0.00)	(0.00)	(0.00)	(0.34)	(0.00)	(0.06)	(0.14)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)	(0.01)	(0.01)
pv_2	[0.01]	[0.00]	[0.00]	[0.00]	[0.35]	[0.00]	[0.00]	[0.10]	[0.01]	[0.00]	[0.25]	[0.00]	[0.00]	[0.07]	[0.00]	[0.01]	[0.00]	[0.00]
NT	**-0.03**	**0.96**	**0.05**	**0.01**	**0.03**	**0.92**	**0.11**	**0.01**	**-0.05**	**0.93**	**-0.02**	**0.16**	**0.02**	**0.02**	**0.85**	**-0.11**	**0.43**	**0.03**
pv_1	(0.00)	(0.00)	(0.00)	(0.00)	(0.18)	(0.00)	(0.04)	(0.14)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.01)	(0.00)
pv_2	[0.01]	[0.00]	[0.00]	[0.00]	[0.21]	[0.00]	[0.00]	[0.12]	[0.01]	[0.00]	[0.24]	[0.00]	[0.00]	[0.05]	[0.00]	[0.01]	[0.00]	[0.00]
NS	**-0.02**	**0.96**	**0.05**	**0.01**	**0.03**	**0.92**	**0.11**	**0.01**	**-0.05**	**0.93**	**-0.02**	**0.16**	**0.02**	**-0.06**	**0.85**	**-0.12**	**0.42**	**0.05**
pv_1	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	(0.04)	(0.13)	(0.01)	(0.00)	(0.11)	(0.00)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)
pv_2	[0.01]	[0.00]	[0.00]	[0.00]	[0.16]	[0.00]	[0.00]	[0.11]	[0.01]	[0.00]	[0.24]	[0.00]	[0.00]	[0.12]	[0.00]	[0.01]	[0.00]	[0.00]
NSS	**-0.03**	**0.96**	**0.05**	**0.01**	**0.03**	**0.92**	**0.11**	**0.01**	**-0.05**	**0.93**	**-0.02**	**0.16**	**0.02**	**-0.09**	**0.84**	**-0.12**	**0.44**	**0.05**
pv_1	(0.01)	(0.00)	(0.00)	(0.00)	(0.17)	(0.00)	(0.00)	(0.15)	(0.01)	(0.00)	(0.17)	(0.00)	(0.00)	(0.11)	(0.00)	(0.01)	(0.00)	(0.00)
pv_2	[0.01]	[0.00]	[0.00]	[0.00]	[0.18]	[0.00]	[0.00]	[0.11]	[0.01]	[0.00]	[0.26]	[0.00]	[0.00]	[0.11]	[0.00]	[0.01]	[0.00]	[0.00]
TVD	**-0.06**	**0.96**	**0.05**	**0.01**	**-0.01**	**0.92**	**0.12**	**0.01**	**-0.11**	**0.93**	**-0.01**	**0.15**	**0.02**	**0.01**	**0.88**	**-0.09**	**0.39**	**0.01**
pv_1	(0.00)	(0.00)	(0.00)	(0.00)	(0.42)	(0.00)	(0.05)	(0.12)	(0.00)	(0.00)	(0.18)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.01)	(0.01)
pv_2	[0.00]	[0.00]	[0.00]	[0.00]	[0.42]	[0.00]	[0.00]	[0.11]	[0.00]	[0.00]	[0.33]	[0.00]	[0.00]	[0.01]	[0.00]	[0.01]	[0.00]	[0.00]
QS	**-0.01**	**0.97**	**0.05**	**-0.01**	**0.07**	**0.92**	**0.14**	**-0.01**	**0.01**	**0.93**	**0.00**	**0.17**	**-0.02**	**0.15**	**0.82**	**-0.03**	**0.50**	**-0.05**
pv_1	(0.05)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.31)	(0.24)	(0.00)	(0.44)	(0.01)	(0.10)	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)
pv_2	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.26]	[0.15]	[0.00]	[0.45]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ES	**0.00**	**0.97**	**0.05**	**-0.00**	**0.08**	**0.91**	**0.15**	**-0.01**	**0.00**	**0.93**	**-0.01**	**0.17**	**-0.02**	**0.06**	**0.85**	**-0.12**	**0.51**	**-0.07**
pv_1	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.26)	(0.47)	(0.00)	(0.43)	(0.01)	(0.11)	(0.14)	(0.00)	(0.00)	(0.00)	(0.04)
pv_2	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.24]	[0.45]	[0.00]	[0.44]	[0.00]	[0.00]	[0.07]	[0.00]	[0.01]	[0.00]	[0.00]
RQS	**-0.04**	**0.97**	**0.05**	**-0.01**	**0.04**	**0.92**	**0.14**	**-0.01**	**-0.11**	**0.92**	**-0.01**	**0.20**	**-0.03**	**-0.12**	**0.89**	**-0.10**	**0.38**	**-0.05**
pv_1	(0.00)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.10)	(0.06)	(0.00)	(0.40)	(0.00)	(0.02)	(0.08)	(0.00)	(0.00)	(0.00)	(0.01)
pv_2	[0.00]	[0.00]	[0.00]	[0.00]	[0.41]	[0.00]	[0.00]	[0.09]	[0.00]	[0.00]	[0.43]	[0.00]	[0.00]	[0.01]	[0.00]	[0.02]	[0.00]	[0.00]
RES	**-0.08**	**0.96**	**0.05**	**-0.02**	**--0.03**	**0.91**	**0.15**	**-0.03**	**-0.12**	**0.92**	**0.00**	**0.18**	**-0.03**	**-0.02**	**0.86**	**-0.12**	**0.50**	**-0.04**
pv_1	(0.00)	(0.00)	(0.00)	(0.00)	(0.25)	(0.00)	(0.00)	(0.07)	(0.01)	(0.00)	(0.36)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.01)
pv_2	[0.00]	[0.00]	[0.00]	[0.00]	[0.24]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.35]	[0.00]	[0.00]	[0.01]	[0.00]	[0.02]	[0.00]	[0.00]

This table shows the estimated parameters in bold and robust p-values in brackets (pv_1 and pv_2 indicates the p-value for the kNN density estimator and kernel-based estimator, respectively) using the entire sample and given $\lambda = 0.05$ and $\lambda = 0.01$. SAV-CAViaR assumes $VaR_{\lambda,t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_{\lambda,t} + \gamma_{\lambda,1}|r_t| + \gamma_{\lambda,\mathscr{M}} x_{it}^*$ and ASYM-CAViaR generalizes nonlinearly assuming $VaR_{\lambda,t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_{\lambda,t} + \gamma_{\lambda,1}|r_t| \times \mathbb{I}_{(r_t \geq 0)} + \gamma_{\lambda,2}|r_t| \times \mathbb{I}_{(r_t<0)} + \gamma_{\lambda,\mathscr{M}} x_{it}^*$, where $x_{it}^* \equiv \log x_{it}$ with $x_{it} \in \mathscr{M}\mathscr{T}_T$.

Table 2.4: Sensitivity analysis of p-values to different k-bandwidth

λ		TV	NT	NS	NSS	TVD	QS	ES	RQS	RES	$\lvert r_t \rvert$
10%	$\hat{\gamma}_\lambda$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**-0.01**	**-0.00**	**-0.01**	**-0.02**	**0.06**
	10	0.04	0.00	0.00	0.00	0.01	0.00	0.05	0.00	0.02	0.00
	30	0.00	0.00	0.00	0.00	0.05	0.03	0.00	0.00	0.05	0.00
k	50	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.07	0.00	0.00
	70	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.08	0.00	0.00
	90	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.04	0.01	0.00
7.5%	$\hat{\gamma}_\lambda$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**-0.02**	**-0.00**	**-0.01**	**-0.02**	**0.06**
	10	0.00	0.00	0.00	0.00	0.24	0.00	0.02	0.00	0.13	0.00
	30	0.00	0.01	0.00	0.00	0.00	0.00	0.04	0.07	0.02	0.00
k	50	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.06	0.06	0.00
	70	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.07	0.04	0.00
	90	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.04	0.02	0.00
5.0%	$\hat{\gamma}_\lambda$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**-0.01**	**-0.00**	**-0.01**	**-0.02**	**0.05**
	10	0.02	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.16	0.00
	30	0.00	0.01	0.00	0.00	0.00	0.04	0.00	0.00	0.06	0.00
k	50	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.04	0.00
	70	0.00	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.07	0.00
	90	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.01	0.05	0.00
2.5%	$\hat{\gamma}_\lambda$	**0.02**	**0.02**	**0.02**	**0.03**	**0.02**	**-0.01**	**-0.00**	**-0.00**	**-0.03**	**0.07**
	10	0.04	0.14	0.43	0.00	0.00	0.04	0.34	0.39	0.46	0.01
	30	0.03	0.17	0.10	0.04	0.07	0.10	0.29	0.36	0.08	0.11
k	50	0.02	0.08	0.06	0.02	0.04	0.12	0.26	0.35	0.11	0.09
	70	0.03	0.03	0.04	0.02	0.02	0.11	0.27	0.35	0.06	0.07
	90	0.03	0.03	0.03	0.02	0.02	0.07	0.28	0.35	0.04	0.07
1.0%	$\hat{\gamma}_\lambda$	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.03**	**0.14**
	10	0.04	0.02	0.05	0.11	0.03	0.24	0.03	0.30	0.00	0.03
	30	0.15	0.16	0.12	0.15	0.14	0.34	0.33	0.38	0.24	0.05
k	50	0.12	0.12	0.11	0.14	0.11	0.33	0.28	0.38	0.15	0.03
	70	0.14	0.15	0.14	0.16	0.10	0.28	0.24	0.30	0.16	0.03
	90	0.11	0.13	0.11	0.12	0.10	0.28	0.24	0.32	0.15	0.03

This table shows the estimated coefficients in bold $\hat{\gamma}_{\lambda,1}$ and $\hat{\gamma}_{\lambda,\mathscr{M}}$ and robust p-values of the test for individual significance from model (2.3) and the entire sample when the robust asymptotic covariance matrix is estimated with a kernel-based estimator with values of $k \in \{10, 30, 50, 70, 90\}$ in the covariance matrix estimation process for a larger set of quantiles. The $\hat{\gamma}_{\lambda,1}$ estimates (last column) are from model (2.3) with $x_{it} = TV$.

Turning our attention to microstructure-related predictors, the predictive analysis in Table 2.3 suggests that increments in trading activity (which can generally be related to greater volatility) and bid-ask spreads (related to greater illiquidity) generate larger VaR levels, as expected from the previous discussion. The overall statistical evidence of predictability tends to be greater for volume-related variables. More specifically, in the asymmetric specification, we find strong evidence of predictability through significant estimates at any of the quantiles involved and for any of the predictive variables. Similarly, $\mathrm{H}_0 : \gamma_{\lambda,\mathscr{M}} = 0$ is largely rejected in the SAV-CAViaR model for any of the variables analyzed at the 5% VaR level. At $\lambda = 0.01$, results are more sensitive to the estimation of the covariance matrix and the predictor involved. While kNN-based inference tends to reject predictability at conventional levels, kernel density-based inference finds marginal evidence for this hypothesis, particularly, for variables in the trading activity group, and some liquidity variables. It is possible that a variable has predictive power at a given quantile yet not at another, so these results may indicate a heterogeneous ability to predict the tail of the distribution. Alternatively, the discrepancies at $\lambda = 0.01$ may arise from potential misspecification biases (since this model neglects meaningful asymmetric patterns in the in-sample fitting), and/or efficiency problems which are distinctively related to the estimation of the asymptotic covariance matrix at extreme quantiles. The characteristic low density of observations near these percentiles compromises accurate estimation, with covariates possibly amplifying this problem; see Chernozhukov and Umantsev (2001). Therefore, conclusions in near-extreme quantiles should always be interpreted with caution.

It is also possible to implement non-regular asymptotic approximations that accommodate extremal or rare data considerations, yet at the cost of a more complex analysis; see, for instance, Chernozhukov and Umantsev (2001) and Chernozhukov (2005). Owing to the statistical difficulties in dealing with these percentiles, empirical studies often avoid the analysis for values of λ close to boundaries; see, for instance, Cenesizoglu and Timmerman (2008). Nevertheless, in the risk modelling context we have alternative methods with which to study the forecasting ability of the predictive variables. Indeed, since the main purpose of VaR modelling is to generate accurate forecasts of market risk, in practice the most important question refers to whether liquidity and activity-extended risk models show improved out-of-sample predictability or not. Consequently, the backtesting analysis provides us with a more appropriate framework with which to judge predictability in this context.

2.4.2 Out-of-sample analysis: backtesting analysis

In this section we address the day-ahead out-of-sample performance of covariate-extended models. Following EM and Alexander and Sheedy (2008) we consider a rolling-window estimation period formed with the most recent $2,700$ observations available at any day to initialize the risk models and generate VaR forecasts for any of the target probabilities $\lambda \in \Theta_{\lambda}$. This allows us to construct a series of $N = 1,000$ one-day ahead daily VaR predictions that can be compared with returns realized in the stress period that followed the burst of the technological bubble in 2000.

Table 2.5 reports the average values of the parameters estimates of equation (2.3) over the out-of-sample period for $\lambda \in \{0.01,\ 0.025,\ 0.05,\ 0.075\}$ using volume and spread variables. As with the whole sample, the average estimates reveal a strongly persistent process and the positive effect of volatility.

Table 2.5: Averaged estimates out-of-sample analysis for SAV-CAViaR model.

VOLUME EXTENDED CAViaR						LIQUIDITY EXTENDED CAViaR				
x_{it}	λ	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\hat{\gamma}_{\lambda,1}$	$\hat{\gamma}_{\lambda,\mathscr{M}}$	x_{it}	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\hat{\gamma}_{\lambda,1}$	$\hat{\gamma}_{\lambda,\mathscr{M}}$
TV	7.5%	-0.047	0.955	0.056	0.009	QS	-0.018	0.956	0.061	-0.016
	5.0%	-0.055	0.960	0.046	0.011		-0.018	0.970	0.046	-0.017
	2.5%	-0.099	0.934	0.076	0.023		-0.036	0.952	0.068	-0.042
	1.0%	-0.003	0.822	0.331	0.028		0.044	0.836	0.349	-0.065
NT	7.5%	-0.047	0.955	0.055	0.010	ES	-0.032	0.954	0.062	-0.020
	5.0%	-0.034	0.965	0.045	0.008		-0.032	0.968	0.046	-0.021
	2.5%	-0.052	0.952	0.058	0.015		-0.044	0.955	0.064	-0.036
	1.0%	0.051	0.784	0.399	0.029		0.028	0.844	0.308	-0.060
NS	7.5%	-0.041	0.954	0.056	0.010	RQS	-0.054	0.959	0.059	-0.012
	5.0%	-0.037	0.962	0.046	0.010		-0.053	0.971	0.044	-0.012
	2.5%	-0.079	0.937	0.065	0.025		-0.115	0.960	0.054	-0.027
	1.0%	-0.060	0.778	0.382	0.056		-0.086	0.851	0.300	-0.043
NSS	7.5%	-0.042	0.954	0.056	0.010	RES	-0.088	0.954	0.062	-0.017
	5.0%	-0.041	0.963	0.045	0.010		-0.062	0.971	0.043	-0.012
	2.5%	-0.118	0.920	0.084	0.033		-0.079	0.963	0.052	-0.019
	1.0%	-0.167	0.775	0.369	0.073		-0.006	0.838	0.348	-0.026
TVD	7.5%	-0.074	0.956	0.054	0.008					
	5.0%	-0.039	0.969	0.044	0.005					
	2.5%	-0.072	0.956	0.058	0.010					
	1.0%	0.059	0.789	0.435	0.015					

This table shows the average value of the out-of-sample parameters from model (2.3) estimates with volume-extended and liquidity variables for volume weighted portfolio. The column labelled as x_{it} denotes the volume-related and liquidity variables analyzed.

To appraise the relative performance of trade-extended risk models, we consider return-restricted CAViaR models and alternative VaR procedures that rely solely on returns, such as the well-known EWMA model (VaR-EWMA), the Gaussian GARCH(1,1) model (VaR-GARCH), and a hybrid approach that combines GARCH estimation with block-maxima estimation in the Extreme Value Theory (VaR-EVT). The main characteristics of these procedures are sketched in Appendix A; see also McNeil *et al.* (2005) for further details.

2.4.2.1 Backtesting procedures

Backtesting is a crucial stage in the validation process of an internal risk model. It simply compares forecasts from a given risk model against realized returns. Most backtesting techniques analyze the stochastic properties of an indicator variables, say $\{H_t\}_{t=1}^{N}$, signalling the occurrence of an exception, *i.e.,* taking value one whenever $r_t < -VaR_t$ and zero otherwise. Risk models must exhibit the property known as reliability, or correct unconditional coverage, which implies that the realized number of exceptions, $N_\lambda = \sum_{t=1}^{N} H_t$, should represent approximately a $\lambda \times 100\%$ of the total number of out-of-sample forecasts, N. This suggests the testable restriction $\mathrm{H}_{0,UC} : \mathrm{E}(H_t) = \lambda$. In addition, $\{H_t\}_{t=1}^{N}$ should ideally exhibit i.i.d.-type dynamics, since the risk of bankruptcy is not evenly distributed otherwise. The conjunction of both characteristics determines the crucial property of perfect conditional coverage, which posits the testable restriction $\mathrm{H}_{0,CC} : \mathrm{E}(H_t|\mathscr{F}_{t-1}) = \lambda$. We apply several testing procedures to address both hypotheses, as is briefly described in the sequel.

The most popular and widely used backtesting approach is the sequence of likelihood ratio tests proposed by Christoffersen (1998). These are intended to test $i)$ correct unconditional coverage, $ii)$ first-order serial independence, and $iii)$ perfect conditional coverage. In particular, $i)$ the test for unconditional coverage is the so-called Kupieck's test, which analyzes $\mathrm{H}_{0,UC}$ through the test statistic,

$$\mathscr{L}\mathscr{R}_{UC} = 2(N-N_\lambda)\left[\log(1-\widehat{\lambda}_H) - \log(1-\lambda)\right] + 2N_\lambda\left[\log\widehat{\lambda}_H - \log\lambda\right] \tag{2.7}$$

where $\widehat{\lambda}_H = N_\lambda/N$. Under the null hypothesis, this test is distributed asymptotically as a Chi-squared distribution with one degree of freedom, here denoted $\chi^2_{(1)}$; see Kupiec (1995) for details. In addition, $ii)$ analyzes if exceptions are serially uncorrelated assuming that H_t takes values in its support according to a binary first-order Markov chain with transition probabilities $\pi_{ij} = \Pr(H_t = j \mid H_{t-1} = i),\ \ i,j \in \{0,1\}$. The joint likelihood of H_t conditional on H_1 is $\mathscr{L}_H(\pi_{ij}|H_1) = (1-\pi_{01})^{n_{00}}\pi_{01}^{n_{01}}(1-\pi_{11})^{n_{10}}\pi_{11}^{n_{11}}$, with n_{ij} representing the number of transitions from state i to state j. Under the null hypothesis of first-order independence, $\pi_{01} = \pi_{11} \equiv \pi_0$, and the likelihood function reduces accordingly to $\mathscr{L}_H(\pi_0|H_1) = (1-\pi_0)^{n_{00}+n_{10}}\pi_0^{n_{01}+n_{11}}$. Hence, the test statistic

$$\mathscr{L}\mathscr{R}_{IND} = 2\left[\log\mathscr{L}_H(\widehat{\pi}_{ij}|H_1) - \log\mathscr{L}_H(\widehat{\pi}_0|H_1)\right] \xrightarrow{d} \chi^2_{(1)} \tag{2.8}$$

determines whether differences between the theoretical and empirical likelihood functions are significant, with $\widehat{\pi}_{01} = n_{01}/(n_{00}+n_{01})$, $\widehat{\pi}_{11} = n_{11}/(n_{10}+n_{11})$ and $\widehat{\pi}_0 = \widehat{\lambda}_H$. Finally, *iii*) tests $H_{0,CC}$ analyzing whether VaR violations are independent and occur with probability λ, *i.e.,* the joint restriction $\pi_{01} = \pi_{11} = \lambda$, which can be addressed through the test statistic

$$\mathscr{LR}_{CC} = \mathscr{LR}_{UC} + \mathscr{LR}_{IND} \xrightarrow{d} \chi^2_{(2)}. \tag{2.9}$$

The $\mathscr{LR}_{CC}$ test has been criticized arguing that it does not have power to detect higher-order dependence in H_t because it only focuses on first-order correlations. EM introduced a conditional test that accounts for a more general form of dependence to test $H_{0,CC}$ and which, therefore, exhibits better properties. In particular, define $\widetilde{H}_t = H_t - \lambda$ and let $Z_{t-1} = (\widetilde{H}_{t-1}, ..., \widetilde{H}_{t-p}, VaR_{t-1}, ..., VaR_{t-q})'$ be a vector of instruments, where $p, q \geq 1$ are predetermined lag values. The property $\mathrm{E}[H_t|\mathscr{F}_{t-1}] = \lambda$ implies that $\widetilde{H}_t$ is a MDS, which suggests a testable hypothesis using Z_{t-1} as a proxy of the set of available information. In the empirical implementation of this test, we follow EM, setting $p = 4, q = 1$ and analyze the MDS property of $\widetilde{H}_t$ through the test statistic

$$\mathscr{DQ} = \frac{\widehat{\beta}' \left(\sum_{t=2}^{N} Z_{t-1} Z'_{t-1}\right) \widehat{\beta}}{\lambda(1-\lambda)} \xrightarrow{d} \chi^2_{(p+q)} \tag{2.10}$$

where $\widehat{\beta}$ is the least-square estimate of β in the auxiliary regression $\widetilde{H}_t = Z'_{t-1}\beta + \varepsilon_t$, $t = 2, ..., N$. Note that $\mathscr{DQ}$ is no less than the joint test of significance for $H_0 : \beta = 0$ in this equation.

Finally, Gaglianone *et al.* (2011) have recently suggested a Mincer-Zarnowitz type test to analyze the optimality of the VaR forecasts. The test is asymptotically equivalent to $\mathscr{DQ}$, but these authors argued that it may exhibit better properties in finite samples. In particular, the test addresses $H_{0,CC}$ on the basis of an auxiliary quantile regression $r_t = \alpha_0 + \alpha_1 VaR_t + \varepsilon_t$, $t = 1, ..., N$. The hypothesis that VaR_t is an optimal forecasts of the λ-th conditional of r_t implies the joint restriction $H_0 : \alpha_0 = 0, \alpha_1 = -1$ or, equivalently, $H_0 : \beta = 0$ with $\beta \equiv (\alpha_0, \alpha_1 + 1)'$. Hence, under the null hypothesis, and provided standard regularity conditions, it follows that

$$\mathscr{VQR} = N\,[\widehat{\beta}\Omega^{-1}\widehat{\beta}] \xrightarrow{d} \chi^2_{(2)} \tag{2.11}$$

as the number of forecasts is allowed to diverge, with $\widehat{\beta}$ and Ω denoting the quantile regression estimate of β and its asymptotic covariance matrix, respectively. In the implementation of this test, we used a robust estimation of the asymptotic covariance matrix Ω, as described previously, based on a Gaussian kernel-based estimation of the unknown density with bandwidth parameter selected according to Silverman's rule. Using alternative procedures, such as the kNN estimator, did not lead to different results.

2.4.2.2 Backtesting results

We first analyze the backtesting results for returns-based risk models, focusing on volatility-based models (VaR-GARCH, VaR-EWMA, and VaR-EVT), and the return-restricted SAV-CAViaR and ASYM-CAViaR models resulting from imposing the restriction $\gamma_{\lambda,\mathscr{M}} = 0$ in (2.3) and (2.4). Table 2.6 reports the main outcomes from this analysis, showing the empirical frequency of exceptions for each model, $\widehat{\lambda}_H = \sum_{t=1}^{N} H_t/N$, the test statistics $\mathscr{LR}_{UC}$, $\mathscr{LR}_{IND}$, $\mathscr{LR}_{CC}$, $\mathscr{DQ}$ and $\mathscr{VQR}$ and their respective p-values.

Table 2.6: Backtesting analysis for return-restricted VaR models in the volume-weighted market portfolio

VaR Model	λ	Exc.	$\mathscr{LR}_{UC}$	$\mathscr{LR}_{IND}$	$\mathscr{LR}_{CC}$	$\mathscr{DQ}$	$\mathscr{VQR}$
EWMA	7.5%	8.9%	2.68(0.10)	0.67(0.41)	3.38(0.18)	23.45(0.00)	14.11(0.00)
	5.0%	5.5%	0.51(0.47)	0.00(0.99)	0.52(0.77)	11.40(0.07)	23.54(0.00)
	2.5%	1.5%	4.78(0.02)	0.46(0.49)	5.21(0.07)	18.48(0.00)	84.25(0.00)
	1.0%	0.5%	3.09(0.08)	0.05(0.82)	3.13(0.21)	3.45(0.74)	177.84(0.00)
GARCH(1,1)	7.5%	11.3%	18.22(0.00)	0.29(0.59)	18.59(0.00)	44.21(0.00)	20.85(0.00)
	5.0%	7.4%	10.63(0.00)	0.46(0.49)	11.15(0.00)	29.44(0.00)	31.05(0.00)
	2.5%	2.8%	0.35(0.55)	0.08(0.78)	0.44(0.80)	22.51(0.00)	60.93(0.00)
	1.0%	0.9%	0.10(0.75)	0.16(0.69)	0.27(0.87)	11.40(0.07)	23.54(0.00)
EVT-BM	7.5%	10.4%	10.85(0.00)	0.58(0.45)	11.49(0.00)	18.24(0.00)	14.91(0.00)
	5.0%	6.1%	2.36(0.12)	0.51(0.48)	2.89(0.23)	9.31(0.15)	10.10(0.01)
	2.5%	2.4%	0.04(0.83)	0.31(0.58)	0.35(0.84)	3.32(0.76)	46.30(0.00)
	1.0%	0.5%	3.10(0.08)	0.04(0.84)	3.13(0.21)	3.64(0.72)	74.36(0.00)
SAV-CAViaR	7.5%	10.1%	8.86(0.00)	0.46(0.49)	8.74(0.01)	28.14(0.00)	9.53(0.01)
	5.0%	7.4%	10.63(0.00)	0.50(0.48)	11.19(0.00)	28.91(0.00)	9.63(0.01)
	2.5%	3.2%	1.85(0.17)	0.00(0.99)	1.86(0.39)	10.86(0.09)	11.77(0.00)
	1.0%	1.3%	0.83(0.36)	0.31(0.57)	1.15(0.56)	14.05(0.02)	27.28(0.00)
ASYM-CAViaR	7.5%	10.0%	8.21(0.00)	0.00(0.94)	7.65(0.02)	23.12(0.00)	11.62(0.00)
	5.0%	7.6%	12.36(0.00)	0.08(0.77)	11.62(0.00)	41.88(0.00)	33.88(0.00)
	2.5%	4.8%	17.17(0.00)	1.22(0.26)	18.44(0.00)	54.69(0.00)	100.06(0.00)
	1.0%	2.9%	24.12(0.00)	3.82(0.05)	27.98(0.00)	102.03(0.00)	64.43(0.00)

This table shows the backtesting analysis for the one-day forecasts of the VaR given the EWMA, Gaussian GARCH, EVT and the return-restricted CAViaR models (SAV-CAViaR and ASYM-CAViaR with $\gamma_{\lambda,\mathscr{M}} = 0$) on the volume-weighted market portfolio. The column Exc. shows the estimated frequency of empirical exceptions, while the columns $\mathscr{LR}_{UC}$, $\mathscr{LR}_{IND}$, $\mathscr{LR}_{CC}$, $\mathscr{DQ}$ and $\mathscr{VQR}$ show the test statistics of the respective tests (p-values in brackets).

For the group of volatility-based VaR models, the empirical unconditional coverages tend to be greater than the respective nominal level at quantiles $\lambda \geq 0.05$, with $\widehat{\lambda}_H$ significantly departing from λ in most cases. Consequently, $\mathrm{H}_{0,UC}$ and $\mathrm{H}_{0,CC}$ are mostly rejected. Similar evidence has been reported previously, for instance, in Taylor (2008b) and Gaglianone *et al.* (2011). Turning our attention to return-restricted CAViaR models, we observe similar biases, which are considerably larger for the asymmetric specification, particularly, at lower probabilities. EM and Kuester *et al.* (2006) also report similar biases. On the other hand, for $\lambda < 0.05$, the distortions in unconditional coverages are considerably reduced for all but the EWMA and ASYM-CAViaR models and, therefore, $\mathrm{H}_{0,UC}$ tends not to be rejected. The overall evidence for $\mathrm{H}_{0,CC}$, however, is mixed. Whereas the conservative $\mathscr{LR}_{CC}$ test tends to accept the perfect coverage hypothesis, the more powerful $\mathscr{DQ}$ and $\mathscr{VQR}$ tests largely reject it. Among the different return-restricted risk models analyzed, EVT yields the best performance but, overall, none of these models seem able to pass the backtesting requirements convincingly. The $\mathscr{VQR}$ test largely rejects the correct performance of *all* the returns-based models at *any* of the conditional quantiles analyzed.

Table 2.7 displays the main backtesting results for the covariate-extended CAViaR models, now allowing $\gamma_{\lambda,\mathscr{M}} \neq 0$. We first discuss the evidence from the SAV-CAViaR model (2.3). Whereas its return-restricted counterpart exhibits large biases, the inclusion of trade-related variables largely improves the out-of-sample performance. The estimated VaR dynamics are shifted (see Figure 2.3 below) in the correct direction such that most of the empirical departures from the theoretical coverage are removed. The empirical exception rates tend to stabilize around the nominal levels without generating clusters in the exception variable. As a result, all covariate-extended SAV-CAViaR models are able to amply pass Christoffersen's (1998) backtests at any of the usual confidence levels. Similarly, the $\mathscr{DQ}$ test tends to largely support the suitability of the extended models, showing sizeable statistical gains with respect to the restricted case. The $\mathscr{VQR}$ test now yields supportive evidence for $\mathrm{H}_{0,CC}$, which is in sharp contrast to returns-restricted models, particularly for the set of variables in the volume group and for quantiles larger than 1%. At $\lambda = 0.01$, however, $\mathscr{VQR}$ still rejects the perfect coverage hypothesis.[3]

[3]Hence, none of the different models analyzed are able to pass the backtest at the 1% VaR level. Gaglianone *et al.* (2011) analyzed the small-sample properties of the test through Monte Carlo simulation, finding that $\mathscr{VQR}$ tends to overreject for small quantiles. At extreme quantiles and finite samples, the evidence based on quantile regression should be interpreted with some caution.

Table 2.7: Backtesting VaR analysis for covariate-extended SAV-CAViaR model in the volume-weighted market portfolio. See details in 2.6.

	λ	Exc.	$\mathscr{LR}_{UC}$	$\mathscr{LR}_{IND}$	$\mathscr{LR}_{CC}$	$\mathscr{DQ}$	$\mathscr{VQR}$
TV	7.5%	8.1%	0.51(0.48)	0.06(0.80)	0.43(0.81)	8.03(0.24)	1.72(0.42)
	5.0%	5.5%	0.51(0.47)	0.36(0.55)	0.88(0.64)	7.98(0.23)	1.69(0.43)
	2.5%	2.2%	0.38(0.53)	0.94(0.33)	1.32(0.51)	6.02(0.42)	5.36(0.07)
	1.0%	0.7%	1.02(0.31)	0.08(0.77)	1.09(0.58)	1.38(0.96)	29.78(0.00)
NT	7.5%	8.1%	0.51(0.48)	0.06(0.80)	0.43(0.81)	7.50(0.27)	1.10(0.58)
	5.0%	6.0%	1.98(0.16)	0.61(0.43)	2.61(0.27)	10.92(0.09)	3.15(0.21)
	2.5%	2.3%	0.17(0.68)	1.03(0.30)	1.20(0.55)	4.02(0.67)	2.13(0.34)
	1.0%	0.9%	0.10(0.75)	0.14(0.70)	0.25(0.88)	2.30(0.88)	33.69(0.00)
NS	7.5%	8.2%	0.69(0.41)	0.03(0.85)	0.55(0.76)	7.06(0.31)	1.42(0.49)
	5.0%	5.5%	0.51(0.47)	0.36(0.55)	0.88(0.64)	7.63(0.26)	1.56(0.46)
	2.5%	2.0%	1.10(0.29)	0.78(0.38)	1.87(0.39)	5.24(0.51)	5.29(0.07)
	1.0%	0.6%	1.89(0.17)	0.06(0.81)	1.94(0.38)	1.99(0.92)	32.95(0.00)
NSS	7.5%	8.0%	0.35(0.55)	0.01(0.91)	0.25(0.88)	6.29(0.39)	1.72(0.42)
	5.0%	5.6%	0.73(0.39)	0.28(0.59)	1.03(0.60)	9.53(0.16)	3.39(0.18)
	2.5%	1.9%	1.61(0.20)	0.70(0.40)	2.29(0.32)	5.63(0.46)	7.44(0.02)
	1.0%	0.6%	1.89(0.17)	0.06(0.81)	1.94(0.38)	2.15(0.90)	53.83(0.00)
TVD	7.5%	8.3%	0.89(0.34)	0.01(0.91)	0.71(0.69)	6.96(0.32)	2.50(0.29)
	5.0%	6.1%	2.39(0.12)	1.44(0.23)	3.86(0.14)	13.58(0.03)	3.97(0.14)
	2.5%	2.8%	0.36(0.55)	0.08(0.78)	0.44(0.80)	4.47(0.61)	2.13(0.34)
	1.0%	1.2%	0.38(0.54)	2.45(0.12)	2.83(0.24)	21.14(0.00)	47.69(0.00)
QS	7.5%	8.6%	0.51(0.48)	0.06(0.80)	0.43(0.81)	8.21(0.22)	5.53(0.06)
	5.0%	5.3%	0.18(0.67)	0.55(0.46)	0.75(0.69)	10.34(0.11)	5.39(0.07)
	2.5%	2.1%	0.69(0.40)	0.86(0.35)	1.54(0.46)	8.57(0.19)	21.89(0.00)
	1.0%	1.0%	0.00(1.00)	0.18(0.67)	0.18(0.91)	14.68(0.02)	95.41(0.00)
ES	7.5%	8.0%	0.35(0.55)	0.10(0.75)	0.34(0.84)	9.02(0.17)	5.26(0.07)
	5.0%	5.0%	0.00(1.00)	0.92(0.34)	0.92(0.63)	8.89(0.17)	4.56(0.10)
	2.5%	2.2%	0.38(0.53)	0.94(0.33)	1.32(0.51)	7.96(0.24)	23.53(0.00)
	1.0%	0.9%	0.10(0.75)	0.14(0.70)	0.25(0.88)	13.84(0.03)	37.52(0.00)
RQS	7.5%	8.6%	1.67(0.19)	0.09(0.75)	1.50(0.47)	0.08(0.08)	3.93(0.14)
	5.0%	5.5%	0.51(0.47)	0.36(0.55)	0.88(0.64)	12.46(0.05)	2.68(0.26)
	2.5%	2.4%	0.04(0.84)	1.13(0.28)	1.17(0.55)	13.43(0.03)	12.78(0.00)
	1.0%	0.7%	1.02(0.31)	0.08(0.28)	1.09(0.58)	1.56(0.95)	32.18(0.00)
RES	7.5%	7.9%	0.23(0.63)	0.00(0.97)	0.13(0.93)	9.02(0.17)	5.46(0.07)
	5.0%	5.5%	0.51(0.47)	0.36(0.55)	0.88(0.64)	10.94(0.09)	1.44(0.46)
	2.5%	2.4%	0.04(0.84)	1.13(0.29)	1.17(0.56)	7.53(0.27)	4.71(0.10)
	1.0%	1.0%	0.00(1.00)	0.18(0.67)	0.18(0.91)	12.59(0.05)	38.64(0.00)

Turning to the ASYM-CAViaR model, allowing for $\gamma_{\lambda,\mathscr{M}} \neq 0$ considerably improves results over the return-restricted specification, but the overall performance is not as good as that from the SAV-CAViaR model. This is not surprising in view of the poor performance of the return-based models. Table 2.8 shows the results of backtesting for Asymmetric extended model. As discussed in EM, the asymmetric CAViaR model tends to overfit in-sample, which may partially offset the potential out-of-sample gains from using further covariates; see also Kuester *et al.* (2006) for similar findings. Note that similar evidence has been reported in the literature related to volatility forecasting, which is relevant in this context because conditional quantiles are tied to volatility dynamics. Whereas asymmetric generalizations of the GARCH(1,1) model overperform in-sample, the simpler GARCH model tends to show a superior performance out-of-sample; see, for instance, Hansen and Lunde (2005).

Table 2.8: Backtesting VaR analysis for covariate-extended ASYM-CAViaR model in the volume-weighted market portfolio. See details in 2.6.

	λ	Exc.	$\mathscr{LR}_{UC}$	$\mathscr{LR}_{IND}$	$\mathscr{LR}_{CC}$	$\mathscr{DQ}$	$\mathscr{VQR}$
TV	7.5%	7.8%	0.12(0.72)	0.82(0.36)	0.88(0.64)	9.89(0.12)	11.47(0.00)
	5.0%	5.2%	0.08(0.77)	0.06(0.79)	0.08(0.95)	9.59(0.14)	30.89(0.00)
	2.5%	3.3%	2.38(0.12)	2.75(0.09)	4.61(0.09)	18.83(0.00)	82.02(0.00)
	1.0%	2.0%	7.82(0.01)	3.86(0.05)	10.35(0.01)	49.15(0.00)	46.56(0.00)
NT	7.5%	7.9%	0.23(0.63)	0.94(0.33)	1.07(0.58)	8.91(0.17)	10.01(0.01)
	5.0%	5.1%	0.02(0.88)	0.10(0.74)	0.10(0.94)	10.34(0.11)	31.59(0.00)
	2.5%	3.4%	2.99(0.08)	2.49(0.11)	4.89(0.08)	20.95(0.00)	75.74(0.00)
	1.0%	1.8%	5.22(0.02)	4.46(0.03)	9.70(0.00)	47.86(0.00)	52.92(0.00)
NS	7.5%	7.9%	0.22(0.63)	0.94(0.33)	1.07(0.58)	8.34(0.21)	9.51(0.01)
	5.0%	5.1%	0.02(0.88)	0.10(0.74)	0.10(0.94)	10.75(0.09)	34.36(0.00)
	2.5%	3.4%	2.99(0.08)	2.49(0.11)	4.89(0.08)	20.99(0.00)	77.83(0.00)
	1.0%	2.0%	7.82(0.01)	0.80(0.37)	7.29(0.02)	34.83(0.00)	70.12(0.00)
NSS	7.5%	7.8%	0.12(0.72)	2.02(0.15)	2.08(0.35)	11.54(0.07)	9.29(0.01)
	5.0%	5.2%	0.08(0.77)	0.06(0.79)	0.08(0.95)	9.83(0.13)	39.82(0.00)
	2.5%	3.0%	0.96(0.32)	1.24(0.26)	1.87(0.39)	10.60(0.10)	82.50(0.00)
	1.0%	2.1%	9.28(0.00)	3.50(0.06)	11.35(0.00)	51.95(0.00)	57.93(0.00)
TVD	7.5%	10.2%	0.89(0.34)	1.50(0.22)	2.20(0.33)	12.75(0.04)	13.22(0.00)
	5.0%	5.5%	0.51(0.47)	0.00(0.95)	0.33(0.84)	13.45(0.03)	35.11(0.00)
	2.5%	3.8%	5.99(0.01)	1.59(0.20)	6.78(0.03)	28.65(0.00)	78.78(0.00)
	1.0%	2.3%	12.48(0.00)	0.44(0.50)	11.30(0.00)	35.54(0.00)	36.63(0.00)
QS	7.5%	7.5%	0.00(1.00)	0.50(0.48)	0.52(0.77)	16.81(0.01)	9.89(0.01)
	5.0%	5.6%	0.52(0.77)	0.00(0.98)	0.52(0.77)	19.28(0.00)	34.48(0.00)
	2.5%	3.1%	1.37(0.24)	1.07(0.30)	2.05(0.35)	15.93(0.01)	97.51(0.00)
	1.0%	1.4%	1.43(0.23)	0.34(0.55)	1.17(0.55)	15.92(0.01)	36.27(0.00)
ES	7.5%	7.4%	0.01(0.90)	0.42(0.51)	0.47(0.78)	17.68(0.00)	12.09(0.00)
	5.0%	5.2%	0.08(0.77)	0.06(0.80)	0.08(0.95)	16.76(0.01)	34.62(0.00)
	2.5%	2.9%	0.62(0.43)	1.33(0.25)	1.96(0.37)	16.25(0.01)	97.75(0.00)
	1.0%	1.6%	3.07(0.08)	1.51(0.22)	3.71(0.15)	28.86(0.00)	37.09(0.00)
RQS	7.5%	8.1%	0.50(0.47)	1.20(0.27)	1.57(0.45)	15.21(0.02)	12.15(0.00)
	5.0%	6.0%	1.98(0.15)	0.07(0.77)	1.71(0.42)	21.99(0.00)	34.36(0.00)
	2.5%	3.3%	2.38(0.12)	0.78(0.37)	2.65(0.26)	20.54(0.00)	67.46(0.00)
	1.0%	1.9%	6.47(0.01)	0.95(0.32)	6.19(0.04)	34.28(0.00)	31.73(0.00)
RES	7.5%	7.5%	0.00(1.00)	1.53(0.21)	1.54(0.46)	12.99(0.04)	7.68(0.02)
	5.0%	5.6%	0.73(0.39)	0.00(0.98)	0.52(0.77)	19.17(0.00)	19.17(0.00)
	2.5%	3.0%	0.96(0.32)	1.24(0.26)	1.87(0.39)	15.65(0.02)	91.13(0.00)
	1.0%	2.8%	21.98(0.00)	4.35(0.03)	24.31(0.00)	93.32(0.00)	38.23(0.00)

2.4.3 Discussion

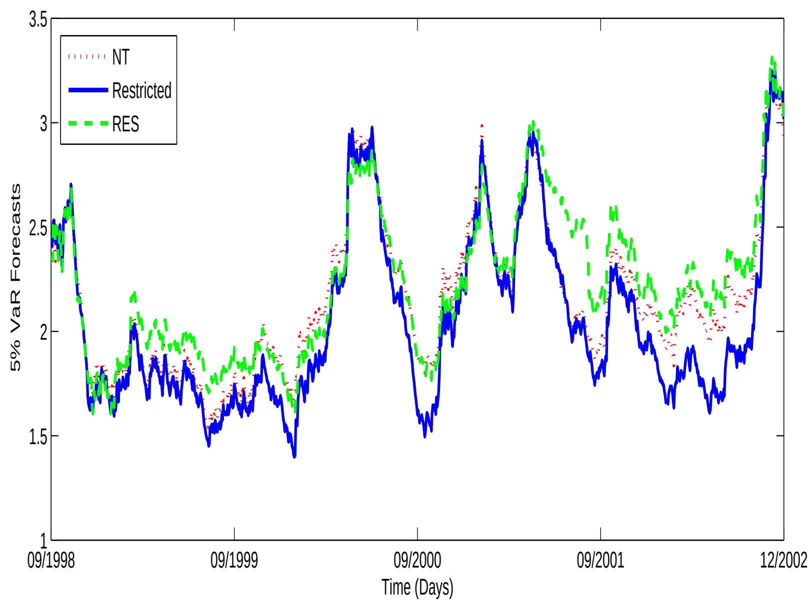
According to our analysis, return-restricted risk models for VaR forecasting show a poor out-of-sample performance. This feature can probably be explained by the fact that the out-of-sample period corresponds to a backdrop of greater market volatility in relation to the in-sample period, leading return-based risk models estimated in a lower-volatile period to generate conservative estimates. Obviously, it is precisely during periods of market distress when risk models are most needed to ensure correct risk management. The VaR framework has largely been criticized because it may produce a good risk assessment in 'normal' periods, but generates wrong estimates in times of distress. The new dispositions in Basel III attempt to correct this shortcoming in different ways. Financial institutions are now required to validate the accuracy and consistency of their internal risk models periodically, especially, whenever a significant structural change occurs in the market. In addition, financial institutions must compute the so-called stressed VaR under conditions of significant financial stress, which, together with the standard VaR estimates, jointly determine the total regulatory capital surcharge.

In sharp contrast with return-restricted risk models, dynamic quantile risk models that simultaneously account for volatility and trade-related conditions seem to capture downside risk dynamics more accurately, producing risk forecasts that exhibit a considerably enhanced performance in a stressed scenario. Liquidity and trading activity are highly sensitive to the flow of information that conditions investment decisions and determines prices. According to our analysis, these variables prove able to anticipate dynamics of the conditional tail which are not entirely captured by market volatility. The empirical links between market conditions and large market swings have been noticed in different contexts. For instance, the SEC and the Commodity Futures Trading Commission (CFTC) staff carried out a joint investigation to analyze the causes of the so-called flash crash, a market event that, on May 6th 2010, led to the biggest one-day point decline in the history of the Dow Jones Industrial Average index. The report issued by the federal agencies on September 2010 remarks that the market conditions that immediately preceded this extreme event were characterized by "*...unusually high volatility and thinning liquidity*", and stresses the major role played by a conjunction of microstructure factors, among which large trading activity of institutional investors and high-frequency traders played a fundamental role; see SEC (2010) for further details. More generally, large shocks in the stock market have historically been related to poor market-wide liquidity conditions, and trading activity is known to generate volatility, see, for instance, French and Roll (1986).

Whereas the link between price changes and liquidity and activity conditions have long been noted in asset pricing and market microstructure, this feature has not been exploited for risk management purposes. The main conclusion from our analysis, therefore, is that liquidity and trading activity conditions, as proxied by the different variables analyzed, are predictors of the tail of the daily conditional distribution of market returns and, consequently, can be used to considerably improve the out-of-sample forecasting performance of a suitably extended risk model.

It is interesting to illustrate and discuss in greater detail the differences between returns-restricted and unrestricted CAViaR forecasts. To this end, Figure 2.3 displays the series of one-day 5% VaR forecasts from the SAV-CAViaR model restricted with $\gamma_{\lambda,\mathscr{M}} = 0$ in the out-of-sample period against the respective forecasts of unrestricted models extended with either RES or NT. As discussed previously, the actual proportion of VaR exceptions from the return-restricted model is much higher than the expected 5% and, consequently, it is biased towards underestimating the actual level of market risk. This is consistent with the notion that the risk model is mainly calibrated in a low-volatility regime, yet it has to produce VaR forecasts in a high-volatility regime. By contrast, including market liquidity or trading activity in the model generates an upward shift in the dynamics of the predicted VaR process and introduces further variability in the forecasts, see Figure 2.3, since VaR forecasts now reflect further dynamics which were not entirely captured by volatility dynamics in absolute returns. The main result is that the gap between the expected and the actual ratio of exceptions is eliminated, without generating clusters or patches in the exception process, as is formally demonstrated by the backtesting analysis. In view of the combined results from the predictive and backtesting analyses, we must conclude that the SAV-CAViaR model extended with trade-related variables are able to track the dynamics followed by true VaR process more closely than its return-restricted counterpart, largely improving the predictive performance.

Figure 2.3: Forecasts VaR at nominal level 5% of Restricted SAV-CAViaR model (blue solid line) and Unrestricted CAViaR model extended with Number of Trades (NT) and Relative effective Spread (RES) variable (red dotted and green dashed line respectively) in the volume-weighted portfolio



2.5 Robustness checks

2.5.1 Dealing with liquidity and activity simultaneously

In the previous section, we adopted a univariate perspective to uncover the predictive ability of the individual variables $x_{it} \in \mathscr{M}\mathscr{T}_T$. This analysis has shown a pattern of predictability in the conditional tail of the market portfolio that can be successfully captured in the quantile-regression setting. It is remarkable that these results are not particularly sensitive to the choice of the variable used to proxy for liquidity or trading activity, although the best results are observed for variables in the volume group.

More generally, it may be possible to apply different predictors in a multivariate analysis attempting to improve univariate results. We addressed this question combining different variables of the liquidity and trading activity groups as a direct extension of (2.3) and (2.4). We discuss the main evidence from this analysis without reporting results in tables, mentioning that complete results are available upon request. The in-sample predictive analysis on the entire sample shows that volume-related variables tend to be significant at most quantiles, while bid-ask spreads are either significant or add little incremental power in relation to volume-related variables, particularly, at lower VaR levels. Nevertheless, the out-of-sample analysis reveals that none of the models in which multiple variables were included was able to improve the out-of-sample results discussed previously. This is not particularly surprising, since the predictive variables are largely correlated among themselves, as discussed in Section 2.2, and adding unnecessary information reduces efficiency and the forecasting ability of the model.

An alternative approach to combine parsimoniously the information provided by trading activity and liquidity is to extract the common source of variation from the data. The strong correlation in the variables suggests the existence of common underlying systematic influences, (or "risk drivers" or "factors"), as noted by Chordia *et al.* (2000); see also Hasbrouck and Seppi (2001). PCA is an appealing procedure because it allows us to obtain latent factors that subsume the relevant information in a simply way and facilitates the practical implementation of the procedure. However, we note that this is not the only possible approach. The literature has suggested more sophisticated alternatives, which may provide a more efficient analysis, at the cost of greater complexity; see, for instance, the generalized dynamic factor model proposed by Hallin, Mathias, Pirotte, and Veredas (2011) to capture commonality in volume-related and liquidity measures.

We applied PCA because of its simplicity, proceeding as follows. First, paralleling the predictive analysis in Section 2.4.1, we identified the main latent factor in the system of predictors using the whole sample, replacing the individual predictors in the CAViaR models in (2.3) and (2.4) with this factor. The principal components matrix is given by $P = E' \times Z'_{\mathscr{M}}$, with $Z_{\mathscr{M}}$ denoting the matrix with demeaned and standardized predictors x_{it}, and E being the eigenvector matrix. The first principal component is the row of P corresponding to the largest eigenvalue in the system, and explains the greatest portion of joint variability. Second, paralleling Section 2.4.2, we implemented a dynamic version of PCA in a rolling-window approach to avoid the possibility of forward-looking biases in the out-of-sample analysis. We computed the main latent factor given the most recent $2,700$ observations at any time, then estimated the CAViaR models given the resultant series, and finally generated a day-ahead VaR forecast at the target probabilities $\lambda \in \Theta_{\lambda}$, repeating the whole process in the rolling-window approach.

As expected, the PCA analysis revealed a strong degree of commonality in the covariates, with the first component roughly explaining 90% of joint variability. Recall that the state variables are cross-averages from individual stocks measures and, hence, are free of idiosyncratic noise, which facilitates identifying a common factor with a high explanatory power. The results in the predictive analysis were remarkably similar to those reported in Section 2.4. Apart from strong persistence, volatility dependence, and significant asymmetric patterns, the latent factor, most likely related to liquidity risk, emerged as a significant predictor of the left tail of the distribution. Whereas this evidence was particularly strong at most of the quantiles, statistical significance at the 1% VaR level was only marginally accepted. Similarly, the backtesting analysis revealed the same out-of-sample performance described previously. Table 2.9 depics the results for both symmetric and asymmetric CAViaR extended specifications. The symmetric specification largely overperformed its asymmetric generalization, with all backtests supporting the suitability of this model at all quantiles, except the $\mathscr{VQR}$ at test at lower quantiles. The overall evidence based on the latent factor is similar to that of the individual analysis and supports the hypothesis that the conditional tail of market returns is driven by market and liquidity risk sources.

Table 2.9: Predictive quantile regressions results and forecasting analysis in the SAV-CAViaR and ASYM-CAViaR model using the first principal component of the predictors. See details in 2.6.

Panel A.- Predictive regressions

	SAV-CAViaR								ASYM-CAViaR									
	$\lambda=5\%$				$\lambda=1\%$				$\lambda=5\%$					$\lambda=1\%$				
	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,2}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$	$\hat{\beta}_{\lambda,0}$	$\hat{\beta}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,1}$	$\widehat{\gamma}_{\lambda,2}$	$\widehat{\gamma}_{\lambda,\mathscr{M}}$
PC1	**0.02**	**0.96**	**0.04**	**0.00**	**0.09**	**0.93**	**0.10**	**0.00**	**0.07**	**0.92**	**-0.02**	**0.17**	**0.01**	**0.26**	**0.83**	**-0.12**	**0.46**	**0.02**
pv_1	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)
pv_2	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.09]	[0.00]	[0.00]	[0.18]	[0.00]	[0.00]	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]

Panel B.- Out-of-Sample analysis

	SAV-CAViaR						ASYM-CAViaR					
λ	Exc.	$\mathscr{LR}_{UC}$	$\mathscr{LR}_{IND}$	$\mathscr{LR}_{CC}$	$\mathscr{DQ}$	$\mathscr{VQR}$	Exc.	$\mathscr{LR}_{UC}$	$\mathscr{LR}_{IND}$	$\mathscr{LR}_{CC}$	$\mathscr{DQ}$	$\mathscr{VQR}$
7.5%	7.1%	0.23(0.62)	0.00(0.96)	0.35(0.83)	7.20(0.30)	1.46(0.48)	6.70%	0.95(0.32)	0.53(0.46)	1.73(0.42)	12.55(0.05)	10.77(0.00)
5.0%	4.3%	1.08(0.29)	0.02(0.88)	1.08(0.58)	9.01(0.17)	2.01(0.36)	4.10%	1.81(0.17)	0.99(0.31)	2.79(0.24)	11.74(0.07)	36.14(0.00)
2.5%	1.6%	3.80(3.80)	0.48(0.48)	4.27(0.12)	6.88(0.33)	21.26(0.00)	2.50%	0.00(1.00)	2.30(0.12)	2.34(0.31)	10.15(0.11)	87.40(0.00)
1.0%	0.5%	3.09(0.07)	0.04(0.84)	3.12(0.21)	2.80(0.83)	115.69(0.00)	1.60%	3.07(0.07)	5.38(0.02)	8.47(0.01)	46.88(0.00)	75.95(0.00)

This table shows in panel A) the estimated parameters in bold and robust p-values (pv_1 and pv_2 from kNN and Kernel based estimator with gaussian density respectively) for the entire sample and the quantile regression model (2.3) and (2.4),

$$VaR_{\lambda,t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_t + \gamma_{\lambda,1}|r_t| + \gamma_{\lambda,2} PC1_{1,t}$$

$$VaR_{\lambda,t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR_{\lambda,t} + \gamma_{\lambda,1}|r_t| \times \mathbb{I}_{(r_t \geq 0)} + \gamma_{\lambda,2}|r_t| \times \mathbb{I}_{(r_t<0)} + \gamma_{\lambda,3} PC1_{1,t}$$

given $\lambda = 0.05$ and $\lambda = 0.01$. The first column shows the volume-related and liquidity variables survey based in the principal components of the total variables analyzed. In panel B) this table shows the out-of-sample analysis for both CAViaR specifications.

2.5.2 Other representative market portfolios

We also analyzed predictability in other market representative portfolios, still using the same market-wide predictors. We firstly addressed predictability in a value-weighted market portfolio, finding no remarkable differences with the previous results. Similarly, we analyzed predictability for B/M- and Size-sorted market portfolios. Fama and French (1992) point out that these characteristics seem to capture most of the cross-section of average stock returns, and it is usual that investors consider risk profiles based in growth/value and large-cap/small-cap stocks to make financial decisions. Consequently, we analyzed predictability in Low30 and High30 B/M-sorted and Size-sorted portfolios.

We briefly summarize the main results in the most interesting context of out-of-sample predictability. Table 2.10 shows the backtesting results of the SAV-CAViaR model particularizing in the High30 B/M and Low30 Size portfolios, for which the evidence of predictability is stronger. A detailed analysis for all the portfolios with all the variables is available in a working paper with a previous version of this chapter.

The out-of-sample backtesting shows that the tail of the conditional distribution is predictable, noting that meaningful differences arise depending on the portfolio characteristics. For the High30 B/M portfolio (formed by the stocks with higher value profile), the evidence of out-of-sample predictability is considerably stronger than that discussed for the market portfolio: All the back tests, including $\mathscr{VQR}$, suggest that bid-ask spreads and, particularly, Effective and Relative Effective Spread, predict the tail of the distribution at the quantiles analyzed; see 2.10 for details. Similarly, for the Low30 Size portfolio (formed by stocks with smaller capitalization), we observe that volume-related variables exhibit a remarkable good predictive performance. All the back tests, including $\mathscr{VQR}$, accept perfect conditional coverage at all quantiles, showing that tail movements in small-cap stocks can be predicted accurately. In contrast, the results (not reported) for the Low30 B/M and High30 Size portfolios are much more conservative. While the $\mathscr{LR}_{UC}$ and $\mathscr{LR}_{CC}$ tests tend to accept the correct performance of covariate-extended models, the $\mathscr{DQ}$ and, particularly, the $\mathscr{VQR}$ test led to a conservative picture, rejecting at the 1% VaR level. Similarly, forecasts from return-restricted models lead to large biases according to the backtesting analysis. Whereas volatility-based model do a better job in the case of the Low30 Size portfolio (particularly, EVT), the $\mathscr{VQR}$ test rejects the suitability of any of these models at any of the quantiles analyzed.

Table 2.10: Backtesting VaR analysis for covariate-extended SAV-CAViaR model on High30 B/M and Low30 Size portfolios. See details in 2.6.

	λ	Exc.	$\mathscr{LR}_{UC}$	$\mathscr{LR}_{CC}$	$\mathscr{DQ}$	$\mathscr{VQR}$
High30 B/M Portfolio						
QS	7.5%	8.6%	1.67(0.19)	1.89(0.38)	2.69(0.84)	3.54(0.17)
	5.0%	6.1%	2.38(0.12)	2.91(0.23)	7.51(0.27)	4.89(0.09)
	2.5%	2.8%	0.35(0.55)	0.43(0.80)	17.05(0.01)	1.11(0.57)
	1.0%	0.8%	0.43(0.51)	0.55(0.75)	12.28(0.06)	0.14(0.93)
ES	7.5%	8.2%	0.68(0.40)	1.49(0.47)	2.83(0.83)	2.56(0.28)
	5.0%	5.7%	0.98(0.32)	1.99(0.36)	6.58(0.36)	3.92(0.14)
	2.5%	2.4%	0.04(0.83)	0.34(0.83)	4.76(0.57)	2.62(0.27)
	1.0%	0.9%	0.10(0.74)	0.26(0.87)	20.00(0.00)	0.18(0.91)
RQS	7.5%	8.9%	2.67(0.10)	3.07(0.21)	4.40(0.62)	5.45(0.07)
	5.0%	6.3%	3.29(0.06)	3.65(0.16)	7.16(0.31)	7.67(0.02)
	2.5%	2.9%	0.62(0.42)	0.67(0.71)	16.10(0.01)	3.41(0.18)
	1.0%	1.0%	0.00(1.00)	0.18(0.91)	21.14(0.00)	6.25(0.04)
RES	7.5%	8.8%	2.31(0.12)	2.87(0.23)	4.09(0.66)	3.67(0.16)
	5.0%	6.3%	3.29(0.06)	4.44(0.11)	7.06(0.32)	8.77(0.01)
	2.5%	2.4%	0.04(0.83)	0.34(0.84)	11.77(0.07)	4.37(0.11)
	1.0%	1.3%	0.83(0.36)	1.15(0.56)	19.21(0.00)	2.53(0.28)
Low30 Size Portfolio						
TV	7.5%	7.2%	0.13(0.71)	0.29(0.86)	3.77(0.71)	1.41(0.49)
	5.0%	3.8%	3.29(0.06)	3.50(0.17)	8.75(0.19)	1.90(0.39)
	2.5%	2.3%	0.16(0.68)	1.24(0.53)	2.00(0.92)	1.90(0.39)
	1.0%	1.4%	1.43(0.23)	1.84(0.39)	2.84(0.83)	6.13(0.05)
NT	7.5%	7.4%	0.50(0.47)	0.51(0.77)	7.10(7.11)	2.65(0.27)
	5.0%	3.9%	2.74(0.09)	2.90(0.23)	7.79(0.25)	2.75(0.25)
	2.5%	2.2%	0.38(0.53)	1.36(0.50)	2.25(0.89)	6.01(0.05)
	1.0%	1.2%	0.37(0.53)	0.67(0.71)	1.19(0.98)	3.99(0.14)
NS	7.5%	7.3%	0.05(0.80)	0.17(0.91)	4.25(0.64)	4.72(0.09)
	5.0%	3.8%	3.29(0.06)	3.50(0.17)	8.72(0.19)	2.80(0.25)
	2.5%	2.2%	0.38(0.53)	1.36(0.50)	2.26(0.90)	2.80(0.25)
	1.0%	1.2%	0.37(0.53)	0.67(0.71)	1.16(0.98)	7.95(0.02)
NSS	7.5%	7.3%	0.05(0.80)	0.17(0.91)	3.36(0.76)	5.89(0.05)
	5.0%	3.8%	3.29(0.06)	0.62(0.17)	8.75(0.19)	3.26(0.20)
	2.5%	2.1%	0.69(0.40)	1.58(0.45)	2.68(0.85)	6.16(0.05)
	1.0%	1.3%	1.17(0.55)	1.17(0.55)	1.93(0.92)	1.92(0.38)
TVD	7.5%	7.5%	0.00(1.00)	0.04(0.97)	5.15(0.52)	5.10(0.08)
	5.0%	3.6%	4.55(0.03)	4.92(0.08)	9.62(0.14)	2.29(0.32)
	2.5%	2.3%	0.16(0.68)	1.24(0.53)	2.00(0.92)	7.17(0.03)
	1.0%	1.2%	0.37(0.53)	0.67(0.71)	1.16(0.98)	1.01(0.60)

The overall evidence suggests that the extent of tail-predictability varies according to different portfolio characteristics and that certain predictors may be more appropriate than others. Interestingly, both features may be related to differences in which price discovery occurs and the existence of investment preferences. At the daily horizon, Chordia *et al.* (2011) argue that information is firstly traded upon in the large-cap sector, and subsequently incorporated into prices of small-cap stocks with a lag, with large-cap returns driving small-cap returns. The existence of lagging effects makes the conditional distribution of small-cap stocks more predictable, which explains why even return-restricted models show a better performance in this portfolio. The existence of clienteles helps to explain why including trading activity variables leads to further improvements. Chordia *et al.* (2011) argue that, while institutional investors prefer to trade large-cap stocks, small-cap trading is mostly dominated by retail investors, who are mostly deemed as unsophisticated, noise traders. Since return volatility in this class of stocks is mainly related to trading activity, adding information about this variable boosts the performance of conditional quantile regression models in the Low30 Size portfolio. Our findings are consistent with this notion and, more generally, with the hypothesis that more illiquid stocks (such small-cap stocks) exhibit more predictability patterns; see Chordia *et al.* (2011).

2.5.3 Further checks

We conducted a number of further analyses focused on the volume-weighted market portfolio. Because the CAViaR setting is so general, it is possible that other functional forms of the conditional quantile model may lead to better results. Of course, the question then turns to which alternative specification may be better than the linear specification analyzed in Section 2.4. Given that conditional quantiles of daily returns are tied to volatility, and motivated by the success of the GARCH(1,1) model to forecast volatility, EM proposed the so-called Indirect GARCH-CAViaR specification, which characterizes VaR dynamics as $VaR^2_{t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR^2_t + \gamma_{\lambda,1} r^2_t$. Here, the (squared) VaR process obeys the characteristic GARCH equation. We estimated univariate covariate-extended versions of this model, namely, $VaR^2_{t+1} = \beta_{\lambda,0} + \beta_{\lambda,1} VaR^2_t + \gamma_{\lambda,1} r^2_t + \gamma_{\lambda,\mathscr{M}} x^*_{it}$, as in Section 2.4.1, and analyzed their out-of-sample performance, as in Section 2.4.2. While the predictive analysis showed that parameter estimates associated to the covariates were highly significant, even at lower quantiles, the out-of-sample performance of these models was considerably worse than those of covariate-extended SAV-CAViaR models. While the former suggests that VaR dynamics depend on trading variables associated to liquidity risk, the latter indicates that the underlying relation that links conditional VaR to this source of uncertainty is better captured by a linear functional form.

Additionally, we studied the performance of alternative VaR models based on different parametric specifications of the volatility process, σ_t. Among these, it is of particular interest the linear GARCH-type model proposed by Taylor (1986), which assumes that volatility evolves according to the equation $\sigma_{t+1} = \omega + \alpha |r_t| + \beta \sigma_t$, $\omega > 0$; $\alpha, \beta \geq 0$. The reason is that if returns are driven by this volatility process, then the conditional quantile function of the series is necessarily driven by SAV-CAViaR dynamics – although the converse is not necessarily true. Consequently, we aim to shed light on the extent in which the forecasting gains reported previously can be related to the precise specification of the volatility process, or if they arise as a consequence of including state variables in the direct modelling of the conditional quantile, as discussed previously. To this end, we implemented two different econometric techniques to estimate the unknown parameters that characterize the linear GARCH model. In a similar spirit as the remaining volatility-based models considered in the previous section, we firstly used quasi-maximum likelihood (QML) to estimate $(\omega,\alpha,\beta)'$, generating subsequent VaR forecasts without imposing normality in that stage (see Appendix A for a general description). Alternatively, we also implemented the two-step quantile-regression estimation of this model as proposed by Xiao and Koenker (2009). This procedure is much more demanding from a computational perspective, as it involves estimation at different quantiles, but it has the advantage of producing estimates and forecast which are robust against outliers. Furthermore, estimation can be carried out without making any particular assumption on the distribution of the data.[4] None of the resulting VaR forecasts was able to improve the results discussed previously. These results are consistent with the previous evidence reported in Xiao and Koenker (2009) for different international stock indexes. In addition, we also estimated a covariate-extended specification of the linear GARCH(1,1) model, namely, $\sigma_{t+1} = \omega + \alpha |r_t| + \beta \sigma_t + \gamma x^*_{it}$, using QML. Again, this approach did not lead to improvements over the results reported previously. This analysis shows that using covariates in the modelling of dynamic quantiles is the key to improve VaR forecasts.

Similarly, we analyzed the performance of covariate-extended VaR-GARCH(1,1) models, allowing the volatility process to depend on trade-related variables, *e.g.*, $\sigma^2_{t+1} = \omega + \alpha r^2_t + \beta \sigma^2_t + \gamma x^*_{it}$. Including covariates in the GARCH equation led to a considerable improvement of the unconditional performance of the model, making the unconditional frequency of rejections closer to the nominal levels. However, the $\mathscr{DQ}$ and $\mathscr{VQR}$ conditional tests largely rejected the correct forecasting performance of these models, in contrast to dynamic quantile regression models. The main conclusion, therefore, is that modelling directly VaR dynamics in dynamic quantile models using variables related to the trading process largely improves the out-of-sample performance in relation to other alternatives.

2.6 Concluding remarks

In this chapter, we have analyzed the predictability of the tail of the conditional distribution of daily market returns. The most distinctive feature of our analysis is that we use different variables which are related to market-wide measures of trading activity and liquidity building on the general nonlinear CAViaR quantile regression setting proposed by Engle and Manganelli (2004). This strategy allows us to study in a simple and direct way the forecasting ability of a number of risk models extended with trade-related variables in relation to return-restricted models, using both predictive regressions and out-of-sample backtesting techniques.

The overall evidence suggests that the tail of the conditional distribution of portfolio returns is predictable on a basis of observable information not necessarily limited to returns. Quantitative downside measures, such as VaR, may largely be improved by using liquidity and trading activity variables. Models constructed in this spirit may be used, for instance, to comply with SEC financial disclosing rules or to produce improved VaR forecasts. This evidence is robust against the choice of different representative market portfolios and different testing procedures, both in the in-sample and the out-of-sample analysis. The extent of predictability may vary along the different quantiles in the left tail and the particular portfolio involved. Our analysis suggests

[4] In the implementation of this procedure, we set a bandwidth-type parameter $m = \log T$ following Xiao and Koenker (2009), and considered the estimation of the parameters that characterize the model using a cross-section of quantile-regression estimates at the deciles. VaR forecasts where generated at the quantiles $\lambda \in \Theta_\lambda$.

that volume-related variables are particularly good predictors of well-diversified portfolios, such as the market portfolio, and small-cap stocks, while market liquidity seems to be the best option when forecasting the tail of value portfolios.

This chapter extends the models in Engle and Manganelli (2004) and complement previous findings in the previous literature. Our analysis also provides empirical support to the literature in market microstructure concerned with the relation between market environmental variables and large price movements. For instance, Easley, Lopez de Prado and O'Hara (2011) argue that the flash-crash on May 2010 arose as a consequence of a market liquidity problem that was slowly developing in the hours and days before the collapse. The central point is that by tracking liquidity and activity conditions, large movements may be predictable. The findings in this chapter support this hypothesis and suggest that, at the daily horizon, the information provided by liquidity and activity is useful to determine a greater likelihood of large price movements.

The methodological approach used in this chapter could be used to address a number of questions in future research. The increasing availability of high-frequency data allows the use of quantitative models based on information on a real time basis which may be useful to design risk controls and to implement investment rule decisions. The procedures discussed in this chapter can be implemented to forecast intraday VaR. While previous papers dealing with this issue have focused on standard volatility models (see, for instance, Ergün and Jun, 2010), the evidence in this chapter suggests that quantile regression-based risk models that account for volatility and other market conditions may easily overperform these approaches. More generally, tail predictability may vary across different horizons involving several days. Characterizing the term predictability pattern seems an interesting topic for further research. Finally, although our analysis has focused on quantiles, thereby allowing us to obtain direct conclusions for the VaR risk methodology, the main conclusions may be extrapolated to other quantile-based downside risk measures, among which expected shortfall (conditional VaR) is the most representative. If the dynamics of conditional quantiles are predictable, trivial transformations such as the mean of quantiles, should be predictable as well. The formal analysis of this interesting issue is left for future research.

Chapter 3

Market Illiquidity and Pricing Errors in the Term Structure of CDS Spreads

This chapter studies the informational content of the pricing errors in the term structure of sovereign CDS spreads. The residuals from a non-arbitrage model are employed to construct a price discrepancy estimate, or noise measure. The noise estimate is understood as an indicator of market distress and reflects frictions such as illiquidity. Empirically, the noise measure is computed for an extensive panel of CDS spreads. Our results reveal an important fraction of systematic risk is not priced in default swap contracts. When projecting the noise measure onto a set of financial variables, the panel-data estimates show that greater price discrepancies are systematically related to a higher level of offsetting transactions of CDS contracts. This evidence suggests that arbitrage capital flows exit the marketplace during times of distress, and this is consistent with a market segmentation among investors and arbitrageurs where professional arbitrageurs are particularly ineffective at bringing prices to their fundamental values during turbulent periods. Our empirical findings are robust for the most common CDS pricing models employed in the industry.

3.1 Introduction

The literature in asset pricing has discussed the crucial role played by arbitrage capital in removing price deviations from fundamental values. Trading frictions, such as illiquidity and information asymmetries, can lead transaction prices to depart substantially from their theoretical counterparts; see, among others, Merton (1987), Brunnermeier and Pedersen (2009), and Duffie (2010). Although price discrepancies are mostly a transient phenomenon, they can be systematically related to the latent forces that characterize the market environmental conditions to which investors in general, and arbitrageurs in particular, are extremely sensitive. The recent literature has provided empirical evidence of these links, placing particular emphasis on the term-structure of fixed-income securities. Hu, Pan and Wang (2013) show that deviations from a smooth zero-coupon yield curve in sovereign bonds are associated to illiquidity in the US Treasury bond market. Similarly, Berenguer, Gimeno and Nave (2013) find that differences in the liquidity of bonds with the same creditworthiness lead to yields that may depart from their expected level in a theoretical liquidity-free term structure of interest rates.

In this chapter, we examine the informational content of pricing errors from non-arbitrage models in the term structure of sovereign Credit Default Swaps (CDS). Default swaps are a well-known class of over-the-counter (OTC) derivatives traded for investing and speculating single name default risk at different maturities. The CDS market has undergone tremendous growth over recent years, now accounting for more than two thirds of all outstanding credit derivatives (Goldstein, Li and Yang, 2013). In parallel to the increasing importance of this market, significant effort has been devoted to understand how CDS prices are formed. However, many key aspects of this process remain unsolved in the literature, since active CDS trading is a relatively new phenomenon.

The main aim of this chapter is to examine the economic determinants that underlie CDS pricing errors as a consequence of market frictions, seeking to characterize the existence of systematic patterns generally related to illiquidity and transaction costs in temporary price deviations. The central hypothesis is that a decline in capital arbitrage, typically observed during periods of distress, increases market-wide illiquidity and leads to greater deviations from fundamental values. As discussed by Garman and Ohlson (1981), Tuckman and Vila (1992), or Schleifer and Vishny (1997), arbitrage is an inherently risky and costly activity due to market inefficiencies. Professional arbitrageurs are reluctant to trade under circumstances in which the cost of identifying and successfully implementing arbitrage operations can be prohibitive. In turn, the lack of sufficient arbitrage capital limits the strength of arbitrage, breaking the general agreement about pricing and enabling assets to be traded in equilibrium at prices significantly different from their fundamental values. Accordingly, the observable variables that generally capture trading and holding costs and which are expected to have a sharp influence on arbitrage capital could be used to explain and even predict fundamental-value discrepancies. The empirical evidence may be particularly significant in markets which are usually characterized by intense professional arbitrage activity, such as the CDS market.

To analyze the informational content of CDS pricing errors we implement robust panel-data techniques (including two-way cluster errors, fixed-effect panel data, and instrumental-variable panel data) on a broad sample of weekly sovereign default swap spreads from 16 countries in both advanced and emerging economies in the period 2008 to 2012. A suitable measure of CDS term-structure price discrepancy is regressed on either contemporaneous or lagged illiquidity-related variables at the country level. The right-hand side variables in this analysis capture transaction costs which may proxy for changes in arbitrage capital after controlling for other potential drivers. The dependent variable is the log-transform of a price-discrepancy statistical measure, adapted from Hu *et al.* (2013), and defined as the root mean square deviation between the market and model-implied CDS term structure spreads. While this measure was originally implemented in Treasury bond markets, its foundations are so general that it can be extrapolated directly to the CDS market. For robustness, we consider a number of theoretical CDS pricing models that vary considerably in complexity and the underlying assumptions behind them to generate pricing errors, all of which are widely used by applied researchers and practitioners. Although the main discussion follows under the arbitrage-free default-intensity model in Pan and Singleton (2008), we also implement the spline-type model suggested by Nelson and Siegel (1987), and a deterministic quadratic function for the conditional default probability curve as in Houweling and Vorst (2005) .[1]

The evidence from this analysis allows us to draw several important conclusions. The most important result is that there exists a strong empirical connection between market-wide illiquidity factors and sovereign CDS missvaluation as is generally predicted by the arbitrage-capital hypothesis. Accordingly, bid-ask spreads –the most usual proxy for illiquidity and transaction costs in asset pricing and market microstructure– and the outstanding net notional position –defined as the net funds transference between sellers and buyers, a measure of effective trading activity– are major drivers of pricing errors and significant short-term predictors of their variability. More specifically, larger bid-ask spreads and increments in the number of CDS offsetting transactions can systematically be related to larger CDS pricing errors, both contemporaneously and in one-week ahead periods. The rationale for this finding lies in the existence of a link that ties arbitrage activity to market illiquidity and, hence, greater price discrepancies, as discussed previously. Consequently, the main empirical evidence in this chapter provides empirical support for the general theoretical claims of this literature in the specific context of CDS markets.

In addition, the analysis provides a clear insight into the systematic patterns –both in the time-series and in the cross-section– that characterize pricing errors in sovereign CDS markets over the period analyzed. As expected under the arbitrage capital hypothesis, CDS price deviations

[1] There exists several methods for pricing default swaps. On the one hand, a common practice in the industry is to bootstrap the survival probabilities from the observed quotes. To this end, both nonparametric (piecewise constant hazard rates) and parametric (Nelson and Siegel, 1987) interpolation methods are commonly used in practice. On the other hand, the intensity modeling approach has been extensively accepted among researches for pricing fixed income instruments such as corporate bonds (Lando 1998, Duffie and Singleton, 1999 or Duffee, 1999) and default swaps (Longstaff, Mithal and Neis, 2005, Berndt, Douglas, Duffie, Ferguson and Schranz, 2005, Pan and Singleton, 2008 and Longstaff, Pan, Pedersen and Singleton, 2011).

substantially increase during periods of financial distress such as Lehman's collapse in September 2008, or the Greek bailout in March 2010. Furthermore, pricing errors exhibit strong cross-country commonalities that can be captured by market-wide factors, more prominently, illiquidity- and volatility-related factors. This evidence strongly suggests the existence of global trends that lead to systematic mispricing in the CDS market. A simple principal component analysis reveals that about 50% of the total variation in pricing errors can be explained by two principal components. The projection of the first component on different proxies of global market-wide illiquidity and volatility results in statistically significant coefficients and R^2 measures of about 26%. The panel-data analysis shows that the noise measure significantly covariates with local illiquidity measures after controlling for other potential drivers, leading to R^2 measures of about 95%. Similarly, heterogeneity in creditworthiness between advanced and emerging economies lead to systematic differences in pricing errors. The immediate implication of all this evidence is that CDS prices must be driven by different risk factors which include, at least, a time-varying source of non-diversifiable illiquidity risk. This interpretation is consistent with the increasing evidence about the existence of an illiquidity component in credit markets in general, and CDS in particular. The main conclusions hold after controlling for a number of macroeconomic and financial state variables, using different estimation techniques, and different pricing models.

This chapter belongs to the increasing stream of literature devoted to CDS pricing and illiquidity. A non-exhaustive review of this literature includes the papers by Longstaff *et al.* (2005), Chen, Cheng and Wu (2005), Chen, Cheng, Fabozzi and Liu (2008), Pan and Singleton (2008), Tang and Yan (2008), Bühler and Trapp (2009), Lin, Liu and Wu (2009), Bongaerts, Jong and Driessen (2011), Nashikkar, Subrahmanyam and Mahanti (2011), Arakelyan, Rubio and Serrano (2013), and Coro, Dufour and Varotto (2013); see also Xing, Zhang and Zhou (2007), Bao, Pan and Wang (2011), Lin, Wang and Wu (2011), and Acharya, Amihud and Bharath (2013) for related work. Earlier studies in this field argued that CDS prices may not be significantly affected by liquidity because their specific contractual nature makes it possible to easily trade large notional amounts compared to bond markets, implying that CDS spreads may better reflect default risk premium; see, for instance, Longstaff *et al.* (2005) and Blanco, Brennan and Marsh (2005). However, the recent literature largely supports the hypothesis that CDS prices are not just driven by a default risk factor, but also by (at least) a component related to illiquidity risk; see, for instance, Berndt *et al.* (2005), Pan and Singleton (2008), Tang and Yan (2008), and Bongaerts *et al.* (2011). In a recent analysis on corporate CDS spreads, Coro *et al.* (2013) conclude that liquidity risk is even more important than firm-specific credit risk regardless of market conditions. The empirical evidence in the current chapter largely supports the claims of this branch of the literature. The additional compensation required for market maker risk seems to play a crucial role in CDS transaction prices, particularly during periods of distress. As a result, illiquidity-related factors are largely responsible of pricing errors in non-arbitrage default intensity models.

This chapter also belongs to the literature centered on the analysis of the economic determinants of pricing errors from arbitrage-free pricing models and its diverse implications, particularly in derivative markets. Jarrow, Li and Ye (2011) characterize arbitrage opportunities from a non-arbitrage pricing model under a Cox, Ingersoll and Ross (CIR) specification, showing how to implement profitable strategies in this context; see also Duffie (1999). This chapter adopts a different approach and examines the systematic sources of CDS mispricing. The idea of comparing market prices with theoretical prices obtained from a non-arbitrage model to inform about market liquidity is implicitly contained in Nashikkar *et al.* (2011), who construct an estimate of the CDS-bond basis by computing the difference between market and a hypothetical CDS spread. While we are not aware of other papers dealing with mispricing in CDS markets, several studies in the extant literature have analyzed the drivers of pricing errors in other derivative exchanges. Peña, Rubio and Serna (1999) characterize the determinants of the implied volatility function in European options under the Black-Scholes (BS) model. The distinctive U-shaped pattern that emerges, known as 'smile', suggests that the BS model systematically misprices deep in-the-money and out-of-the-money options. Since none of the generalizations of the BS formula can remove this pattern completely, Peña *et al.* (1999) argue that the apparent failure of the BS model is (partially) due to transaction costs and liquidity effects, as proxied by bid-ask spreads. These authors show that the curvature of the implied-volatility function increases on the size of bid-ask spreads, which implies a clear link between pricing errors and transaction costs in the BS setting. Similar results have been reported for other derivative products, such as interest-rate options; see Deuskar, Gupta and Subrahmanyam (2008) and references therein. The evidence in Deuskar *et al.* (2008) is particularly relevant for our paper because, like CDS contracts, interest-rate options are traded in OTC markets, where liquidity-providers are more sensitive to market conditions. Although our methodological approach differs substantially, the overall results in this chapter completely agree with the evidence reported in these studies, suggesting that pricing errors in derivative contracts are generally sensitive to market-wide illiquidity. Finally, this chapter builds on the price discrepancy measure of Hu *et al.* (2013) and complements their paper in two main ways. First, by discussing the generality and suitability of this measure, originally implemented in the context of Treasury bond exchanges, in other markets. Secondly, by reporting evidence showing that this measure does indeed correlate with market-wide liquidity conditions from a different methodological approach. While Hu *et al.* (2013) use the measure in an asset-pricing analysis, we analyze the determinants that ultimately underlie greater price discrepancies.

The rest of the chapter is organized as follows. Section 3.2 introduces the noise or pricing discrepancy measure and discusses its suitability for the CDS market. Section 3.3 presents the dataset employed in this chapter and explores its main statistical features. Section 3.4 presents the econometric framework and discusses the main results that characterize the noise measure. Section 3.5 analyzes the determinants of pricing errors, considering a broad set of market-wide indicators. Section 3.6 conducts several robustness checks. Finally, Section 3.7 summarizes and concludes.

3.2 Pricing errors in the CDS term structure

This section formalizes the theoretical relation between pricing errors and market frictions with the main purpose of introducing the notation and the main concepts used throughout the chapter. It also examines the link between arbitrage capital and pricing errors in CDS markets, introducing the discrepancy or noise measure proposed by Hu *et al.* (2013) and a discussion on its general suitability in the context of this chapter.

3.2.1 Mispricing and arbitrage opportunities

The theoretical arguments used here are primarily taken from Jarrow *et al.* (2011), who provide a formal demonstration on how the residuals from a term structure pricing model can be related to the existence of arbitrage opportunities. The central point is to construct a portfolio immune to changes in the underlying asset, longing a given maturity contract (e.g., 5-year) and shorting other different maturities (for example, the 3- and 7-year).[2] Under standard arbitrage arguments, this strategy is self-financed and the prices of the credit instruments must be consistent across maturities. Consequently, the (expected) value of this portfolio is zero when employing suitable weights whose composition is detailed in Jarrow *et al.* (2011). As a result, whenever the value of the portfolio differs from zero, an arbitrage opportunity emerges.

To introduce the notation and outline the formal demonstration, consider the price at time t of a CDS with maturity m, denoted $CDS_t(m)$, defined as certain function of the risk-neutral default probability, $\lambda_t^{\mathbb{Q}}$, say $CDS_t(m) = f_t^m(\lambda_t^{\mathbb{Q}})$. Under usual assumptions, a second-order Taylor expansion of the theoretical CDS price function at time $s = t + \Delta t$ yields

$$f_t^m(\lambda_s^{\mathbb{Q}}) = f_t^m(\lambda_t^{\mathbb{Q}}) + (\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})H_{1t}^m + \frac{1}{2}(\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})^2 H_{2t}^m + O\left(\left(\widetilde{\lambda}_s^{\mathbb{Q}}\right)^3\right), \tag{3.1}$$

where Δt denotes a short period of time, $\widetilde{\lambda}_s^{\mathbb{Q}}$ is a midpoint in the line that joins $\lambda_s^{\mathbb{Q}}$ and $\lambda_t^{\mathbb{Q}}$, and $O(\cdot)$ is a (bounded) remaining term. The terms H_{1t}^m and H_{2t}^m are the first- and second-order derivatives of the pricing function with respect to the default probability, respectively.

According to Jarrow *et al.* (2011), the current price of a CDS at time s approximates its price at time t, i.e. $f_s^{m-\Delta t}(\lambda_s^{\mathbb{Q}}) \approx f_t^m(\lambda_s^{\mathbb{Q}})$, with $m - \Delta t$ denoting the correction for the maturity time lapse. This assumption enables a connection between the future price of a CDS contract with its current price and certain correcting terms. In particular,

$$f_s^{m-\Delta t}(\lambda_s^{\mathbb{Q}}) \approx f_t^m(\lambda_t^{\mathbb{Q}}) + (\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})H_t^m + \frac{1}{2}(\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})^2 H_{2t}^m. \tag{3.2}$$

[2] The default probability of the reference entity is essentially the underlying asset of a default swap contract. Nevertheless, the results of Jarrow *et al.* (2011) are also extensible to other term structure derivatives such as interest rate options or commodity futures.

and, hence, investors could build a delta and gamma-neutral hedging portfolio formed by three default swaps with different maturities, say m_0, m_1 and m_2, such that

$$f_t^{m_0}(\lambda_t^{\mathbb{Q}}) + n_{1t} f_t^{m_1}(\lambda_t^{\mathbb{Q}}) + n_{2t} f_t^{m_2}(\lambda_t^{\mathbb{Q}}) \approx f_s^{m_0-\Delta t}(\lambda_s^{\mathbb{Q}}) + n_{1t} f_s^{m_1-\Delta t}(\lambda_s^{\mathbb{Q}}) + n_{2t} f_s^{m_2-\Delta t}(\lambda_s^{\mathbb{Q}}), \quad (3.3)$$

where the portfolio weights n_{1t} and n_{2t} are explicitly chosen to form the market neutral portfolio. On average, the theoretical value of portfolio (3.3) must equal the market price of the portfolio, from which the following relation emerges:

$$\begin{aligned} & \left(f_t^{m_0}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_0)\right) + n_{1t}\left(f_t^{m_1}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_1)\right) + n_{2t}\left(f_t^{m_2}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_2)\right) \\ \approx \ & \varepsilon_t^{m_0} + n_{1t}\varepsilon_t^{m_1} + n_{2t}\varepsilon_t^{m_2}, \end{aligned} \quad (3.4)$$

with $CDS_t(m_i)$ denoting the observed market prices, and $\varepsilon_t^{m_i} = f_t^{m_i}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_i)$ defined implicitly.

Apart from the tracking error of the strategy, equation (3.4) shows that discrepancies between the observed and theoretical prices in the CDS curve are directly informative of arbitrage opportunities in the CDS market. Similarly, Duffie (1999) shows that the condition of no arbitrage binds the value of a CDS contract to the prices of a risky bond and a riskless par bond of the same maturity. In the absence of market frictions, the yield of the risk-free bond must be equal to the difference between the yield of the risky bond and the value of the CDS contract, expressed as a percentage of the risky bond nominal value. Consequently, arbitrageurs can trade in the CDS market when they detect profitable opportunities involving mispricing in bond markets, since buying a CDS contract is similar to shorting the underlying bond. Indeed, a great deal of professional arbitrage activity, such as that of hedge funds and proprietary trading desks of investment banks, is concentrated in the bond and CDS markets; see, for instance, Nashikkar *et al.* (2011), Goldstein *et al.* (2013) and Oehmke and Zawadowsky (2013).

3.2.2 Market frictions and prices discrepancies

The differences between observed and theoretical prices may not necessarily appear as a consequence of a temporary misappraisal of the fundamental value, but also as a consequence of market frictions. Among others, Schleifer and Vishny (1997) argue that arbitrage is often a risky investment activity that requires capital. These authors show that professional arbitrageurs are reluctant to trade under extreme market circumstances as the cost of identifying or successfully implementing arbitrage operations can be prohibitive. The main reason is that volatility increases informational asymmetries and exposes arbitrageurs to unwind their positions prematurely, possibly incurring substantial losses. As a result, risk-averse specialized arbitrageurs avoid extremely volatile markets, which reduces the market effectiveness in eliminating differences between fundamental and transaction prices.[3] It is worth mentioning that, while many well-known theoretical asset pricing models do not acknowledge the impact of transaction costs on prices, in practice these may have substantial effects. This seems to be particularly true in OTC markets, as these are characterized by a high degree of illiquidity, irregular trading, asymmetric information, and greater counterparty-search costs relative to stock markets; see Tang and Yan (2008) for a discussion. For instance, search costs largely affect market liquidity and market prices, as theoretically discussed by Duffie, Garleanu and Pedersen (2005), leading to higher transactions costs and preventing potential liquidity providers from participating in the market.

The existence of a relationship between market frictions and pricing deviations brings up the issue of capturing these discrepancies empirically. With the purpose of aggregating all the information provided by the CDS curve, let us define $m_1, m_2, ..., m_N$ as an increasing sequence of maturities, and denote as $CDS_t(m_i)$ and $CDS^*_t(m_i)$ the observed CDS spread for the i-th maturity and the corresponding model-implied theoretical price at time t, respectively. Let $CDS_t = (CDS_t(m_1), ..., CDS_t(m_N))'$ be a (N×1) vector collecting the observed CDS spreads representative of the CDS term structure at time t, and define CDS^*_t analogously. The most natural measure for the existence of pricing discrepancies is given by the Euclidean distance between both curves, $\delta_t = ||CDS^*_t - CDS_t||$, namely,

$$\delta_t = \sqrt{\sum_{i=1}^{N} \left(CDS_t\left(m_i\right) - CDS^*_t\left(m_i\right)\right)^2} \tag{3.5}$$

such that $\delta_t = 0$ if and only if all the prices along the curve CDS_t match with the fundamental values, and $\delta_t > 0$ captures the distance between both curves otherwise. While a number of transformations can be defined on the norm δ_t, in this chapter we shall consider the log-transformation of the re-scaled distance $noise_{CDS,t} \equiv \delta_t/\sqrt{N}$ proposed in Hu *et al.* (2013). Note that $noise_{CDS,t}$ may also be seen as a sample-based measure of the mean cross-sectional dispersion of the pricing error at time t. The term *noise* was coined by Hu *et al.* (2013) since, in the fixed-income literature, it is usual to refer to deviations from a given pricing model as noise.

Some comments on (3.5) follow. First, Hu *et al.* (2013) originally proposed the noise measure in the different context of Treasury bonds. The main premise is that the abundance of arbitrage capital during normal times helps smooth out the Treasury yield curve and keep the average dispersion low. In periods of stress, arbitrage capital vanishes and, hence, the average dispersion increases. On the basis of the corresponding noise measure, say $noise_{TBond,t}$, these authors show indeed that the deviations between market yields on Treasury bonds and their model-based yields are characteristically low –and liquidity correspondingly high– in normal periods, but generally tend

[3] Goldstein *et al.* (2013) argue that in highly segmented markets, such as the CDS market, the existence of investors with fairly heterogeneous trading opportunities can lead to multiplicity of equilibria, causing instability in prices. This feature may explain jumps and excess volatility in the CDS markets.

to increase during crises, as arbitrage capital exits the marketplace. The noise measure successfully captures, therefore, an empirical link between price deviations and arbitrage capital.[4]

Second, the Euclidean norm δ_t depends on the prices generated by a theoretical term-structure pricing model, and so does $noise_{CDS,t}$. Although we shall consider different approaches, we focus initially on the continuous-time, arbitrage-free CDS pricing model of Pan and Singleton (2008). The distinctive characteristic of this model is that it yields a full theoretical term structure of CDS spreads consistent with the no arbitrage condition that overperforms other alternative approaches; see, for example, Longstaff *et al.* (2011). A priori, it seems reasonable to expect that sensible choices of alternative pricing models would lead to similar patterns in the resultant pricing errors. However, since this is ultimately an empirical issue, we shall address the robustness of the main conclusions based on Pan and Singleton (2008) by focusing on alternative term structure pricing models that differ in complexity and underlying assumptions. This will be extensively discussed in Section 3.6.2.

3.3 The data

CDS are contracts where one party (protection seller) shorts credit risk to another (protection buyer) against the default of a certain bond (reference entity). The CDS spread represents the annual percentage over the total amount of the bond (notional) paid to the insurer for obtaining protection in case of a credit event. The dataset analyzed in this chapter consists of an unbalanced panel of weekly sovereign CDS spreads from 16 economies of the G-20 group: Argentina, Australia, Brazil, China, France, Germany, Indonesia, Italy, Japan, Mexico, Saudi Arabia, South Africa, South Korea, Spain, the UK and the US. The final composition of this sample was solely dictated by the availability of the data. The choice of the weekly frequency aims to avoid potential caveats related to the low trading activity at daily frequency of most sovereign CDS contracts.[5] The sample initially available spans the period from January 1st, 2006 to November 9th, 2012 and includes 358 weekly observations for most of these countries. The data for some countries (Saudi Arabia, the UK, and the US) is available on a shorter period and includes a smaller number of observations,

[4]This measure has been used subsequently in a number of applied studies; see, for instance, Filipovic and Trolle (2013). Because the price of sovereign CDS contracts are not independent of the price of a Treasury bond of the same maturity (Duffie, 1999), and since professional arbitrageurs such as hedge funds and proprietary trading desks of investment banks are particularly active in CDS markets, we may expect that arbitrage capital features $noise_{CDS,t}$ in a similar way as it does with $noise_{TBond,t}$. Therefore, the average dispersion of CDS spreads should be expected to be low during normal periods, when arbitrage capital actively contributes to align CDS spreads, and high in turmoil periods, when arbitrage capital exits the market. In that case, abnormally high values of $noise_{CDS,t}$ may be related to episodes of market illiquidity and local or global shortage of arbitrage capital. This is the central hypothesis analyzed in this Chapter.

[5]Chen, Fleming, Jackson, Li and Sarkar (2011) analyze the distribution of total trading frequency of sovereign CDS contracts across all maturities. From a total of 74 reference entities, just 4 are actively traded on average 30 times daily; and 14 out of 74 are less actively traded, at 15 times per day on average. The remaining sovereign references are infrequently traded at an average of twice daily.

ranging from 228 (Saudi Arabia) to 257 (US) data. The maturity spectrum of CDS contracts in the sample comprises all available maturities from one to ten years. All contracts are denominated in US dollars and written under the Complete Restructuring (CR) clause. Data have been provided by Credit Market Analysis (CMA), a quote provider integrated in the Datastream platform.[6]

Together with CDS spreads, we observe different variables related to trading activity and liquidity. These variables are provided by the Depository Trust & Clearing Corporation (DTCC), which reports public information about real transactions of CDS contracts since November 2008. In particular, we observe both the gross and net notional CDS positions, and the number of outstanding contracts in the CDS market. The gross notional value is the aggregate sum of the CDS contracts bought or sold for a single reference entity. The net notional values represents the aggregate net funds transference between protection sellers and buyers that could be required upon the occurrence of a credit event relating to a particular reference entity. Finally, the number of contracts reports the outstanding number of contracts for a given reference.

3.3.1 Descriptive analysis

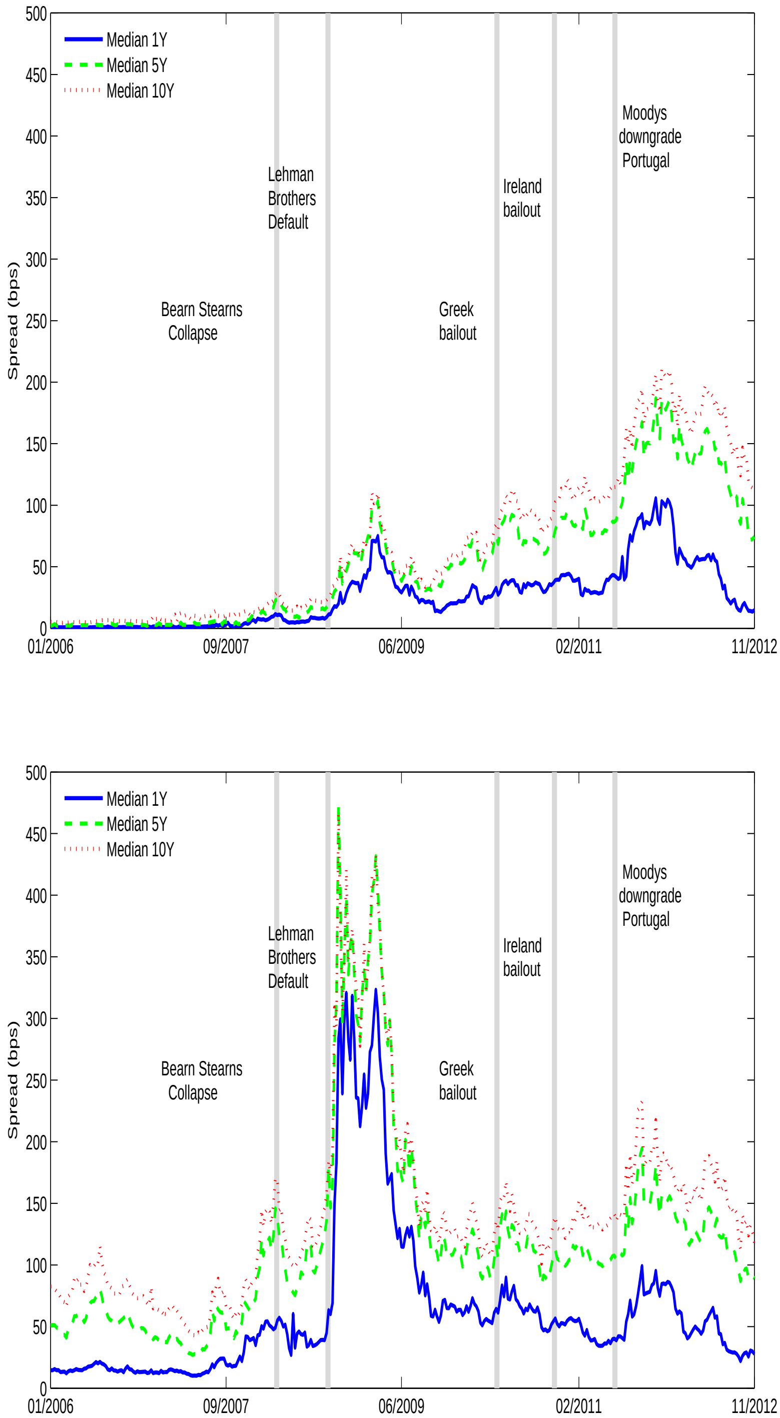
3.3.1.1 CDS spreads

Figure 3.1 shows the time series dynamics of the cross-sectional medians of the sovereign CDS spreads at 1-, 5- and 10-year maturities over the total available sample, from January 1st, 2006 to November 9th, 2012. To account for likely structural differences across countries, we split the total sample into two subsamples. A first group is characterized by Advanced Economies (henceforth AE) and includes Australia, France, Germany, Italy, Japan, Spain, the UK, and the US. A second group is characterized by Emerging Economies (henceforth EE) and is formed by the remaining countries in the sample.

For both subsamples, the cross-sectional medians increase monotonically from 1- to 10-year maturities, thereby revealing an upward slope in the CDS spreads term-structure over the period. In addition, CDS spreads exhibit time-varying dynamics with considerable sensitivity to episodes of financial distress. More specifically, CDS spreads show similar responses to the largest systemic shocks over the period, peaking after the defaults of Bear Stearns (March 2008) and Lehman Brothers (September 2008). Although this pattern is clearly visible for both AE and EE groups, there are idiosyncratic patterns across countries that can be related to creditworthiness differences and that are worth discussing in detail. In particular, while the average CDS spreads in the AE group exhibit moderate values before the default of Bear Stearns at the different maturities, they increase steadily until mid 2011 as a consequence of the European debt crisis. These series exhibit a mean-

[6]The CMA database collects daily CDS spreads from a robust consortium that consists of approximately 40 members from the buy-side community (hedge funds, asset managers, and major investment banks), which are active participants in the CDS market. Daily reports on bid, ask and mid-quotes are available to us. Mayordomo, Peña and Schwart (2013) state that the quoted CDS spreads provided by CMA led the credit risk price discovery process with respect to the quotes provided by other databases.

Figure 3.1: Cross-sectional median of sovereign CDS for different maturities



Cross-sectional medians of sovereign CDS spreads of different maturities for advanced (upper graph) and emerging (lower graph) economies. Advanced economies are Australia, France, Germany, Italy, Japan, Spain, the UK and the US. The maturities of CDS contracts are 1-, 5- and 10-year, respectively. Vertical bars denote some crisis events. The sample period spans from January 2006 to November 2012. Data frequency is weekly.

reverting behavior in the final part of the sample, when the concerns in the Eurozone dissipated and default probabilities reverted to lower levels. On the other hand, while CDS spreads in the EE group largely increased around the collapse of Lehman Brothers, they show resilience against the idiosyncratic shocks that featured the European debt crisis. Lastly, CDS spreads in the AE group have a lower median and lower volatility than CDS spreads in EE group. The maximum cross-sectional median value rose to 450 basis points for emerging countries after Lehman Brother's collapse, while the peak in advanced economies was around 200 basis points in the midst of the European crisis.

Table 3.1 reports the usual descriptive statistics (mean, median and standard deviation) of CDS spreads for each country in the sample. For the ease of exposition, we report these statistics for the representative cases of 1-, 5-, and 10-year maturities, noting that a complete analysis is available upon request. As expected from the previous discussion, there are significant differences in average spreads across maturities, consistent with the upward slope of the term structure discussed previously. Argentina is the economy with the lowest creditworthiness in the sample. Accordingly, the mean 5-year maturity CDS spread is 964.41, considerably greater than the spread of any other country in the sample. This series also exhibits a massive degree of volatility, given by a standard deviation of 897.20, which is caused by extreme observations in the upper tail recorded after the Lehman Brother's collapse. As discussed previously, there is a meaningful mean-volatility pattern in CDS spreads such that countries with higher spreads tend to consistently exhibit higher volatility levels as well. This result suggests that investors are more sensitive to news affecting default probabilities when creditworthiness is low. Not surprisingly Germany, widely seen as the safe haven by investors, is the economy with the overall best credit creditworthiness in the sample. The mean spread values for the 5-year German CDS contract is 33.20, with a standard deviation of 30.68, the smallest among the different countries analyzed.

Table 3.1: Descriptive statistics of sovereign CDS spreads

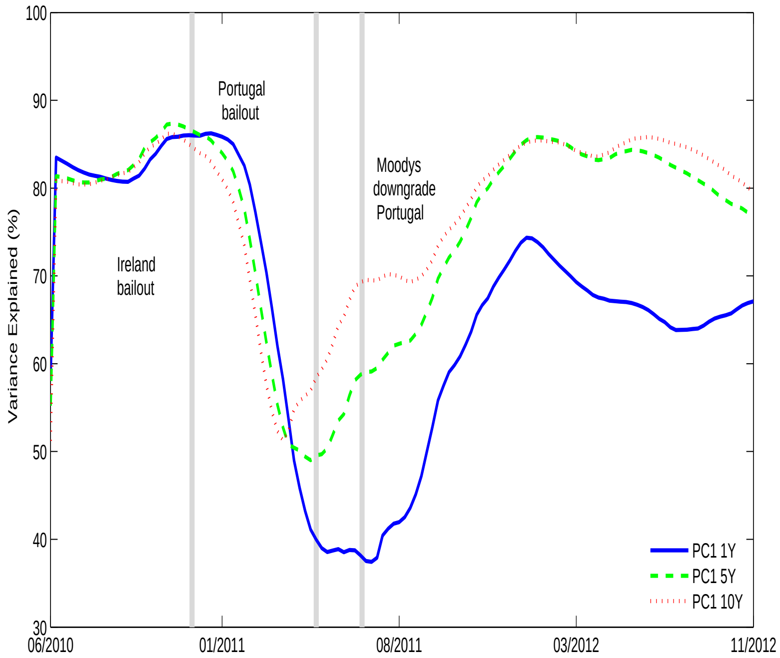
	1 Year			5 Year			10 Year			
Country	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.	Obs.
Argentina	855.99	417.60	1213.68	964.41	741.90	897.20	971.81	752.33	818.27	358
Australia	25.28	23.26	21.34	44.44	44.12	33.31	52.83	49.86	38.42	358
Brazil	66.68	54.89	58.44	145.45	125.15	68.66	183.24	159.82	65.94	358
China	36.40	28.02	34.56	75.08	70.66	52.20	91.33	85.87	56.96	358
France	28.43	18.64	34.56	58.68	36.59	63.73	67.95	40.01	72.10	358
Germany	13.70	10.12	14.09	33.20	30.34	30.68	41.87	32.98	38.59	358
Indonesia	115.81	69.65	135.04	220.09	174.77	146.64	267.99	227.39	134.62	358
Italy	105.96	51.38	136.00	148.06	99.36	157.39	152.20	103.43	149.60	358
Japan	18.74	13.78	18.48	51.68	49.84	40.56	67.74	61.69	53.23	358
Mexico	65.23	43.25	70.05	126.82	113.81	83.61	152.74	144.02	82.71	358
Saudi Arabia	80.46	78.08	33.46	115.66	105.33	52.18	126.61	116.90	54.03	228
South Africa	76.68	50.83	95.17	145.58	140.81	97.30	168.30	162.69	90.91	358
South Korea	72.14	45.62	90.36	107.71	97.71	91.43	122.58	115.01	89.50	358
Spain	115.71	61.41	130.30	154.04	93.08	163.13	153.47	94.36	154.73	358
UK	30.17	25.57	22.86	63.16	65.95	30.81	72.70	77.96	31.32	261
US	18.72	19.23	13.90	38.34	40.25	16.72	40.09	42.00	22.50	334

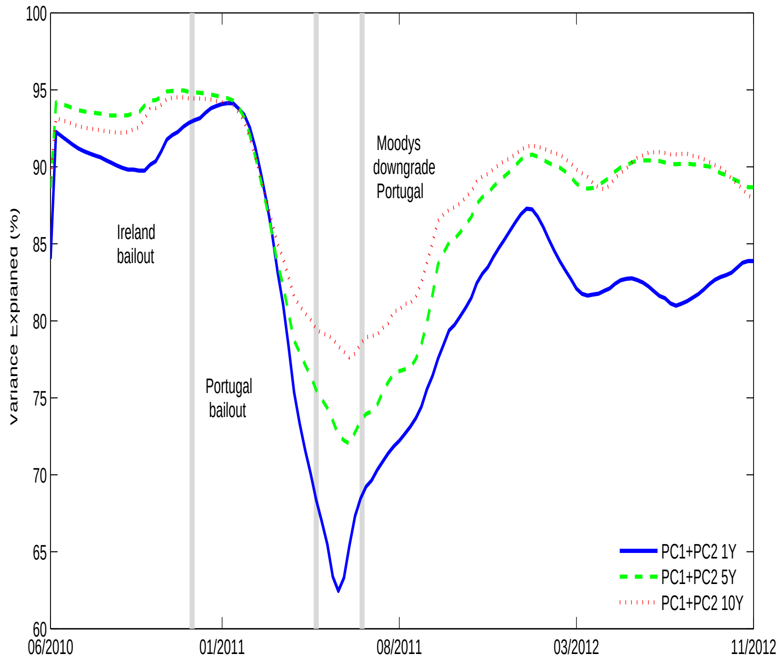
Summary of the main descriptive statistics of CDS spreads in levels for each country. Maturities are 1-, 5- and 10-year, respectively. Sample comprises from January 2006 to November 2012, with the exception of Saudi Arabia, the UK and the US, which covers from December 2007 to November 2012. Data frequency is weekly.

Previous literature on CDS have put forward the existence of a strong degree of commonality in sovereign CDS spreads. Principal Component Analysis (PCA) on the standardized CDS spread series confirms the existence of a strong commonality in the behavior of sovereign spreads. In particular, the first principal component (PC1) of the system explains approximately 74% of the total cross-country variation, which increases to nearly 88% when a second principal component (PC2) is included. Interestingly, the previous literature has not discussed whether the degree of commonality tends to be stable over time or exhibits time-varying patterns. Note that, for instance, a sharp reduction in the explanatory power of the first principal component will be indicative of idiosyncratic patterns that would likely lead to greater pricing errors. Because this question is particularly relevant in the context of this chapter, we perform a dynamic PCA analysis, computing the principal components on the basis of the 100 most recent observations at any time in the sample on the basis of a rolling-window approach.

Figure 3.2 shows the time series dynamics of the proportions of explained cross-country variability which are related to either the conditional PC1, or PC1 and PC2, given the 1-, 5- and 10-year maturities. Some interesting results emerge from this analysis. First, the share of variability explained by PC1 sharply declined from 90% to approximately 40% during the summer of 2011. This sheer decay affected all maturities and can be related to the European sovereign debt crisis. Adding a second factor reduces the magnitude of this decline, allowing the share total variability explained to reach about 65%, but still far from the average level achieved before this episode. Figure 3.2 also shows that the proportion of explained variance over the total tends to be higher as the maturity increases, especially after August 2011. Finally, the levels of total variability explained by the first two principal components eventually reverted to the level observed before July 2011, with the exception of the 1-year maturity. Overall, this simple descriptive analysis suggests that a single factor (roughly corresponding with PC1) may not be able to consistently capture the full variation in the term structure of sovereign CDS spreads over time. Furthermore, there are important differences across the maturities that characterize the term structure, with the 1-year CDS contract exhibiting a more idiosyncratic behavior. As discussed in Pan and Singleton (2008), the most likely reason being that liquidity is lower at this maturity.

Figure 3.2: Time series dynamics of the proportions of variance explained related to either the conditional PC1, or PC1 and PC2, given the 1-, 5- and 10-year maturities.





Evolution of the aggregated explained variance of first (upper graph) and first and second (lower graph) principal components using a rolling window scheme. Each window contains 100 observations.

3.3.1.2 Trading activity and liquidity-related data

The sovereign CDS market has become one of the most active markets in the aftermath of the financial crisis. The relative volume of the sovereign CDS contracts traded is particularly sizeable. According to DTCC, the gross notational outstanding ranges from USD 0.71 trillions in November 14th, 2008 to USD 1.70 trillions in November 9th, 2012, showing the sharp increase in trading activity in CDS markets over recent years as a consequence of the financial crisis. Similarly, the net notional outstanding ranges from USD 0.08 trillions to USD 0.15 trillions over the same period. These series show a considerably degree of commonality across countries, reflecting the existence of common world-wide trends. For instance, the PC1 on either the gross or net notional outstanding series accounts for nearly 76% of the total variation of these series (a complete analysis is available upon request). Because the central premise in this chapter is that mispricing in CDS markets can be related to illiquidity, Tables 3.2 and 3.3 report descriptive statistics on trading activity and liquidity based on these variables.

Table 3.2 provides a summary of the weekly increments of the number of outstanding contracts, and the gross and net notional positions of the sovereign CDS written on the countries under study. For comparative purposes, we also include the relative position of the contracts with respect to the remaining G20 countries, i.e., the ratio of each country over the total G-20 group. The sample available spans the period November 14th, 2008 to November 9th, 2012. Note that, since trade-related information is not available for Saudi Arabia, this country has been excluded from the analysis. The weekly average increment in the number of contracts over the sample period is of approximately 20 contracts, with the mean gross and net position sizes reaching USD 318.23 and 20.63 millions, respectively. Trading activity is far from being homogeneous across the different countries in the period analyzed. In particular, Italy and Spain show the highest increments in the number of contracts and gross outstanding volumes, reflecting the financial tensions of these countries during the European debt crisis. Similarly, the overall net position on CDS has largely increased for other advanced economies in the EMU area, particularly, France, suggesting effects related to financial contagion. The average of net notional CDS positions over the period is negative for Argentina and Spain, and tends to exhibit larger positive values for the economies with better creditworthiness in the sample. Negative values of this variable can be related to offsetting transactions in the CDS market. In this way, the net volume can be taken as a crude proxy for professional arbitrage activity and will play a major role in the analysis of determinants in Section 3.5.

Table 3.2: Trading activity statistics

	Absolute measures (in differences)						Relative measures (in levels)						
	Contracts		Gross vol. (USD mill.)		Net vol. (USD mill.)		Contracts (%)		Gross vol. (%)		Net vol. (%)		
Country	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Obs.
Argentina	-8.10	139.49	-65.41	1131.25	-4.67	88.93	7.68	2.05	4.59	1.10	1.72	0.48	208
Australia	19.52	57.22	199.93	490.71	22.82	91.42	1.85	1.16	1.21	0.70	1.99	1.17	185
Brazil	-8.47	332.03	41.30	3331.37	27.03	287.98	15.80	3.90	13.56	2.16	11.55	0.61	208
China	30.75	143.53	267.06	1132.89	35.12	146.53	5.66	1.34	3.45	0.58	3.84	1.43	208
France	33.45	219.88	739.41	3401.11	58.43	388.13	4.57	2.19	6.74	2.02	11.27	2.54	208
Germany	24.66	114.78	548.28	2375.90	34.98	277.43	3.48	1.04	7.05	0.80	12.05	0.77	208
Indonesia	6.30	142.31	49.67	1056.35	6.57	76.64	6.52	1.25	3.22	0.64	1.98	0.26	208
Italy	45.14	309.60	1123.34	6169.96	16.49	473.74	9.59	1.14	22.28	1.14	18.95	4.54	208
Japan	35.61	173.52	345.55	1593.84	46.36	118.10	4.61	2.52	3.14	1.33	4.46	1.66	208
Mexico	10.54	185.17	212.91	1656.96	23.71	145.28	12.77	2.76	9.65	1.22	5.87	0.55	208
South Africa	10.96	92.52	98.21	670.39	1.58	78.67	6.37	1.19	3.60	0.53	1.87	0.44	208
South Korea	21.05	238.28	152.41	2063.22	6.86	149.90	9.43	1.58	5.53	1.20	3.68	0.93	208
Spain	38.53	320.06	697.09	5201.09	-8.15	334.01	7.03	1.61	10.76	0.95	12.03	2.24	208
UK	20.42	100.69	280.22	1357.33	31.60	194.12	3.95	1.57	3.96	0.98	6.48	1.92	208
US	4.09	39.39	83.46	640.63	10.74	127.24	0.90	0.40	1.39	0.37	2.49	0.52	208

Summary of the main descriptive statistics of CDS volumes in increments for each country. Relative measure includes the ratio of each country value with respect to the remaining G20 countries. Sample comprises from November 2008 to November 2012. Data frequency is weekly.

Table 3.3 reports descriptive statistics (mean, median, and standard deviation) for the bid-ask spreads of CDS contracts for each country. For conciseness, we report these descriptives at 1-, 5- and 10-year maturities, noting that a complete study on all maturities is available upon request. In addition, Table 3.3 reports descriptive statistics for the so-called veracity index, an indicator of data reliability at each maturity elaborated directly by the data provider. The analysis on bid-ask spreads essentially reveals the same features discussed previously. Clearly, there exists a negative relationship between bid-ask spread and creditworthiness. Countries with lower default probabilities exhibit smaller bid-ask spreads uniformly over the maturities. Similarly, and consistent with the previous discussion, the CDS with higher average bid-ask spreads are also the more volatile, showing a greater disagreement on fundamental values. In particular, while Germany and France are the countries with the lowest bid-ask averages and standard deviations, Argentina and Saudi Arabia in the EE group exhibit the highest values of these statistics in the sample. Interestingly, the average bid-ask spreads are higher at the 1-year maturity, suggesting that sovereign CDS investors seem to incorporate their liquidity concerns about a country in the short-term maturities of the curve, as pointed out by Pan and Singleton (2008). Finally, the analysis on the veracity index reveals similar values with no particular pattern across countries, indicating that the CDS sample is representative of the real trade quotes finally traded in the market.

Table 3.3: Liquidity and veracity index of CDS spreads

	Bid-ask spread									Veracity index			
	1-Year			5-Year			10-Year			All maturities			
Country	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.	Obs.
Argentina	79.03	28.82	139.30	36.75	12.48	83.41	39.37	15.00	86.89	1.71	1.80	0.22	358
Australia	6.63	5.63	5.39	4.81	3.39	3.59	5.03	3.96	3.16	1.91	1.90	0.03	358
Brazil	7.01	5.01	5.75	3.54	2.58	2.93	5.03	4.00	2.73	1.71	1.80	0.21	358
China	6.94	5.20	6.77	4.64	3.90	3.91	5.00	4.24	2.88	1.84	1.90	0.14	358
France	3.49	3.06	2.86	3.11	2.92	1.74	4.50	3.29	2.70	1.83	1.80	0.09	358
Germany	2.60	2.00	2.38	2.65	2.62	1.32	3.55	3.12	2.16	1.85	1.80	0.09	358
Indonesia	18.11	10.54	20.55	9.07	5.18	10.40	10.64	8.06	9.69	1.78	1.90	0.21	358
Italy	9.44	6.70	9.36	4.52	3.70	3.31	6.72	4.41	4.66	1.80	1.80	0.12	358
Japan	3.88	2.00	4.66	3.88	3.00	2.40	4.47	3.58	2.63	1.92	1.90	0.07	358
Mexico	7.28	5.67	5.64	3.77	3.00	2.59	4.96	4.00	2.53	1.77	1.80	0.17	358
Saudi Arabia	24.83	16.65	21.05	15.58	10.01	13.58	13.52	9.36	10.31	1.92	1.90	0.04	228
South Africa	13.68	7.01	17.75	6.45	4.32	7.55	8.03	5.19	7.03	1.77	1.80	0.17	358
South Korea	10.01	6.23	12.09	5.09	4.00	4.51	5.31	4.29	3.50	1.77	1.80	0.17	358
Spain	9.56	7.41	10.03	4.87	3.71	3.04	6.31	4.48	5.37	2.05	1.80	0.49	358
UK	4.98	3.82	4.14	4.20	3.73	2.12	5.03	4.13	2.69	1.82	1.80	0.06	261
US	6.20	5.90	3.21	5.15	4.94	2.08	5.56	4.90	2.53	1.85	1.80	0.06	334

Descriptive statistics of bid-ask spreads and veracity index for available G20 countries. Maturities for bid-ask spreads are 1-, 5- and 10-year, respectively. Veracity index is computed across all available maturities. Sample comprises from January 2006 to November 2012, with the exception of Saudi Arabia, the UK and the US, which covers from December 2007 to November 2012. Data frequency is weekly.

3.4 Estimating the noise measure

3.4.1 Theoretical CDS spreads and econometric estimation

The empirical implementation of the noise measure requires model-implied theoretical prices. Most of the pricing models for CDS spreads in the extant literature strive essentially to capture default risk and the potential loss upon default, similarly to that of credit spreads for corporate bonds. The intensity framework of Duffie and Singleton (1999) and Lando (1998) seems to be the most popular pricing framework. Under this approach, the default event is modeled as the first jump of a Poisson process with stochastic default intensity $\lambda_t^{\mathbb{Q}}$, where $\mathbb{Q}$ denotes the risk-neutral measure. Then, the (annualized) price of a CDS contract for maturity m at time t obeys the relation:

$$\frac{1}{4}CDS_t(m)\sum_{i=1}^{4m}E_t^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+\frac{i}{4}}(r_s+\lambda_s^{\mathbb{Q}})ds\right)\right]=(1-\mathbb{R}^{\mathbb{Q}})\int_t^{t+m}E_t^{\mathbb{Q}}\left[\lambda_u^{\mathbb{Q}}\exp\left(-\int_t^{u}(r_s+\lambda_s^{\mathbb{Q}})ds\right)\right]du, \tag{3.6}$$

where r_t and $\mathbb{R}^{\mathbb{Q}}$ denote, respectively, the risk-free interest rate and the recovery of face value (in percentage) of the referenced bond under the risk-neutral measure; see Longstaff, *et al.* (2005) and Pan and Singleton (2008), among others. The left-hand side of this equation represents the premium on the sum of expected discounted cash-flows paid by the protection buyer under the risk-neutral measure. This premium is the CDS spread and is quarterly. The right-hand side accounts for the expected discounted payoff received by the protection buyer in case of a default event. Single-name CDS contracts are written without up-front payments, which equals both sides of expression (3.6).

In this setting, Pan and Singleton (2008) propose an intensity model, referred to as PS in the sequel, which presents remarkable advantages over other affine pricing models for CDS spreads. While the CIR process has been extensively employed for modeling the default intensity $\lambda_t^{\mathbb{Q}}$, as it provides closed-form formulas (e.g., Duffee, 1999, Driessen, 2005 or Longstaff *et al.*, 2005), the Feller condition bounds the long-term mean of the CIR-based intensity to the square-root of its long-term variance, a requirement frequently violated in practice. The PS model not only overcomes this drawback, but also provides a good compromise between model parsimony and performance in a comparison of several one-factor intensity models; see, for instance, Berndt (2006) for a discussion on a related approach. For these reasons, and although we stress that we shall consider alternative modeling approaches later on, the arbitrage-free PS model is the pricing benchmark chosen for characterizing empirically price discrepancies in CDS markets. We provide a brief discussion on the implementation of this model below.

The PS model assumes that the logarithm of the risk-neutral default intensity $\lambda_t^{\mathbb{Q}}$ follows an Ornstein-Uhlenbeck diffusion process characterized by

$$d\ln\lambda_t^{\mathbb{Q}}=\kappa^{\mathbb{P}}\left(\theta^{\mathbb{P}}-\ln\lambda_t^{\mathbb{Q}}\right)dt+\sigma^{\mathbb{Q}}dW_t^{\mathbb{P}}, \tag{3.7}$$

where $\kappa^{\mathbb{P}}$ and $\theta^{\mathbb{P}}$ are the long-run mean, and mean-reversion rate of the process under the actual or historical measure $\mathbb{P}$, respectively, with $\sigma^{\mathbb{Q}}$ denoting the volatility of the process and $W_t^{\mathbb{P}}$ a standard Wiener process. The model also characterizes the dynamics of (3.7) under the risk-neutral measure $\mathbb{Q}$,

$$d\ln\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{Q}}\left(\theta^{\mathbb{Q}} - \ln\lambda_t^{\mathbb{Q}}\right)dt + \sigma^{\mathbb{Q}}dW_t^{\mathbb{Q}}, \tag{3.8}$$

and the market price of risk, say Λ_t, can be defined through the affine function $\varphi_0 + \varphi_1 \ln\lambda_t^{\mathbb{Q}}$, where φ_0 and φ_1 denote constant parameters. The process (3.8) ensures the positiveness of risk-neutral default intensity. However, the expectations in CDS formula (3.6) are not in closed-form, so numerical techniques as the Crank-Nicholson scheme are required.

The parameters that characterize the PS model can be estimated by maximum likelihood, given a number of additional assumptions. The reader is referred to the original paper for details, but we briefly sketch the main steps involved in the estimation of this model in the sequel. In particular, the PS procedure requires the assumption that CDS contracts at a certain maturity are priced with no error, whereas prices at the remaining maturities can be freely determined. Since the 5-year CDS contract is widely considered as the more liquid maturity, we make the same assumption as Pan and Singleton (2008) and consider this contract is free of pricing errors. Then, a series of the probability of default $\lambda^{\mathbb{Q}}$ can be obtained by solving the pricing formula (3.6) for this coefficient. This involves non-linear numerical techniques, using the 3-, 6-, 9- and 12-month USD Libor and 2-, 3-, 4-, 5-, 7- and 10-year USD interest rate swaps to construct the risk-free curve that characterizes (3.6). The remaining CDS contract maturities are assumed to be priced with random errors $\varepsilon_{m,t}$ that obey a normal multivariate distribution with zero mean vector and covariance matrix $\sigma_M^2 I_{N-1}$, where I_{N-1} denotes the $N-1$ dimensional identity matrix and N is the number of different maturities. For parsimony and computational tractability, we assume that σ_M is constant across maturities, noting however that results do not qualitatively differ from more general specifications.[7] The estimation of the model also requires the discretization of $\lambda^{\mathbb{Q}}$ in expression (3.7), for which we adopt the Euler's approach setting $\Delta t = 1/52$. The unknown parameters of the model $\psi = (\psi^{\mathbb{P}}, \psi^{\mathbb{Q}}, \sigma_M)'$, with $\psi^{\mathbb{P}} = (\kappa^{\mathbb{P}}, \theta^{\mathbb{P}})'$, $\psi^{\mathbb{Q}} = (\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma^{\mathbb{Q}}, \mathbb{R}^{\mathbb{Q}})'$, can be estimated by maximizing the conditional log-likelihood function $\sum_{t=2}^{T} \ln f^{\mathbb{P}}(\varepsilon_{m,t}|\psi, \mathscr{F}_{t-1})$, with $\mathscr{F}_{t-1}$ denoting the set of available information up to t, and

$$f^{\mathbb{P}}(\varepsilon_{m,t}|\psi,\mathscr{F}_{t-1}) = \phi^{\mathbb{P}}(\varepsilon_{m,t}|\sigma_M,\mathscr{F}_{t-1}) \times \phi^{\mathbb{P}}(\ln\lambda_t^{\mathbb{Q}}|\psi^{\mathbb{P}},\sigma^{\mathbb{Q}},\mathscr{F}_{t-1}) \times \left|\frac{\partial CDS^{\mathbb{Q}}(\lambda^{\mathbb{Q}}|\psi^{\mathbb{Q}},\mathscr{F}_{t-1})}{\partial\lambda_t^{\mathbb{Q}}}\right|^{-1} \tag{3.9}$$

[7]The assumption of homoskedasticity of the pricing errors across maturities is introduced to reduce the number of parameters of the model and simplify the computational estimation. The existence of an average level of common volatility across maturities can be expected not to have a major effect on the estimations. This observation has been confirmed by conducting the estimations of the model assuming heteroskedasticity in the pricing errors across maturities. These results are not presented for the sake of conciseness, but are available upon request. In Section 3.6 we shall consider alternative specifications that do not impose assumptions on the distribution of pricing errors.

where $\phi^{\mathbb{P}}(\cdot)$ denotes the probability density function of the Normal distribution, $\lambda_t^{\mathbb{Q}}$ as given by expression (3.7), and $CDS^{\mathbb{Q}}(\cdot)$ in formula (3.6).

Table 3.4 reports the maximum-likelihood estimates of ψ (robust standard errors in parenthesis). The mean-reversion speed estimates under the actual measure, $\kappa^{\mathbb{P}}$, are higher than the mean-reversion speed coefficients under the risk-neutral measure, $\kappa^{\mathbb{Q}}$, indicating that the arrival of credit events last longer under this measure. Moreover, the long-run mean estimates are also higher under the risk-neutral measure ($\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}} > \kappa^{\mathbb{P}}\theta^{\mathbb{P}}$), suggesting that the arrival of events in the risk-neutral scenario is more probable than in the actual one. In other words, a positive risk premium related to changes in the credit environment seems to be priced in the CDS market. Finally, the recovery rate $\mathbb{R}^{\mathbb{Q}}$ is closely related to the creditworthiness of the country: South Korea, South Africa, Germany, France and the UK exhibit the highest value (around 80%), in contrast to Argentina and Spain (around 3%). Overall, the model yields reasonable estimates that are coherent with related studies in the extant literature; see, for instance, Pan and Singleton (2008) and Longstaff *et al.* (2011).

Table 3.4: Maximum likelihood estimates

Firm	$\kappa^{\mathbb{Q}}$	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	σ	$\kappa^{\mathbb{P}}$	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	σ_G	$R^{\mathbb{Q}}$	LogLk
Argentina	0.0977	-0.3111	1.1515	0.4100	-1.3947	0.0158	0.0100	10055.49
	(0.0109)	(0.0345)	(0.0054)	(0.4271)	(1.4933)	(0.0000)	(0.0032)	
Australia	-0.1576	0.5665	0.8519	2.0488	-9.7753	0.0006	0.6568	14361.35
	(0.0055)	(0.0253)	(0.0086)	(1.0181)	(4.9049)	(0.0000)	(0.0246)	
Brazil	-0.0372	0.3160	0.9967	1.4271	-6.0946	0.0015	0.7120	18082.42
	(0.0046)	(0.0235)	(0.0058)	(0.5463)	(2.2478)	(0.0000)	(0.0065)	
China	-0.0725	0.2836	1.0452	0.6028	-3.2016	0.0010	0.6741	19873.02
	(0.0051)	(0.0270)	(0.0048)	(0.5508)	(2.7026)	(0.0000)	(0.0124)	
France	-0.3077	1.2479	0.7489	0.7476	-3.9226	0.0008	0.7792	20549.94
	(0.0044)	(0.0180)	(0.0026)	(0.2650)	(1.4954)	(0.0000)	(0.0050)	
Germany	-0.3294	1.4366	0.7977	0.3122	-1.8284	0.0006	0.7966	21590.77
	(0.0049)	(0.0226)	(0.0046)	(0.4622)	(2.6673)	(0.0000)	(0.0075)	
Indonesia	0.0262	-0.0780	1.0802	0.8218	-3.6363	0.0026	0.3690	16292.05
	(0.0029)	(0.0152)	(0.0064)	(0.5350)	(2.2836)	(0.0000)	(0.0129)	
Italy	-0.1439	0.4858	0.8729	0.0935	-0.3948	0.0016	0.7069	18222.76
	(0.0065)	(0.0231)	(0.0044)	(0.3268)	(1.2389)	(0.0000)	(0.0049)	
Japan	-0.2444	1.0591	1.0024	0.6477	-3.9007	0.0008	0.4715	20608.46
	(0.0037)	(0.0181)	(0.0060)	(0.5088)	(3.3369)	(0.0000)	(0.0139)	
Mexico	-0.0637	0.3664	0.9337	0.1722	-0.8381	0.0009	0.7454	19782.02
	(0.0031)	(0.0140)	(0.0050)	(0.3099)	(1.2314)	(0.0000)	(0.0030)	
Saudi Arabia	-0.1952	0.6712	0.6739	0.9137	-3.8040	0.0007	0.5927	13230.57
	(0.0027)	(0.0093)	(0.0068)	(1.0620)	(4.2584)	(0.0000)	(0.0124)	
South Africa	0.2871	-1.2749	1.9191	0.5267	-2.9677	0.0012	0.7046	18922.40
	(0.0061)	(0.0393)	(0.0076)	(0.5213)	(2.6152)	(0.0000)	(0.0061)	
South Korea	-0.0087	0.1557	0.8793	0.3607	-1.6318	0.0011	0.8246	19178.13
	(0.0017)	(0.0066)	(0.0019)	(0.2136)	(0.7573)	(0.0000)	(0.0015)	
Spain	-0.0720	0.0833	0.8929	0.1361	-0.8052	0.0014	0.0335	18550.07
	(0.0018)	(0.0063)	(0.0039)	(0.1944)	(1.1928)	(0.0000)	(0.0066)	
UK	0.2227	-1.2409	1.7872	0.4324	-2.8469	0.0008	0.7695	14987.91
	(0.0236)	(0.1769)	(0.0105)	(0.8604)	(4.8489)	(0.0000)	(0.0350)	
US	0.0176	-0.1397	0.8465	0.2009	-1.1237	0.0005	0.7390	15755.24
	(0.0028)	(0.0151)	(0.0047)	(0.3980)	(2.1537)	(0.0000)	(0.0138)	

Maximum likelihood estimates for the Pan and Singleton (2008) model. Standard errors are in parenthesis. $\kappa^{\mathbb{Q}}$, $\theta^{\mathbb{Q}}$ and $\sigma^{\mathbb{Q}}$ denote the mean-reversion, long-run mean and instantaneous volatility of default intensity process $\lambda^{\mathbb{Q}}$ under the $\mathbb{Q}$ probability measure, respectively. Similar convention applies for the parameters of the objective measure $\mathbb{P}$. σ_M is the standard deviation mispricing errors, and $R^{\mathbb{Q}}$ the recovery rate. LogLk is the log-likelihood. Data frequency is weekly and it comprises from January 2006 to November 2012, with the exception of Saudi Arabia, the UK and the US, which covers from December 2007 to November 2012.

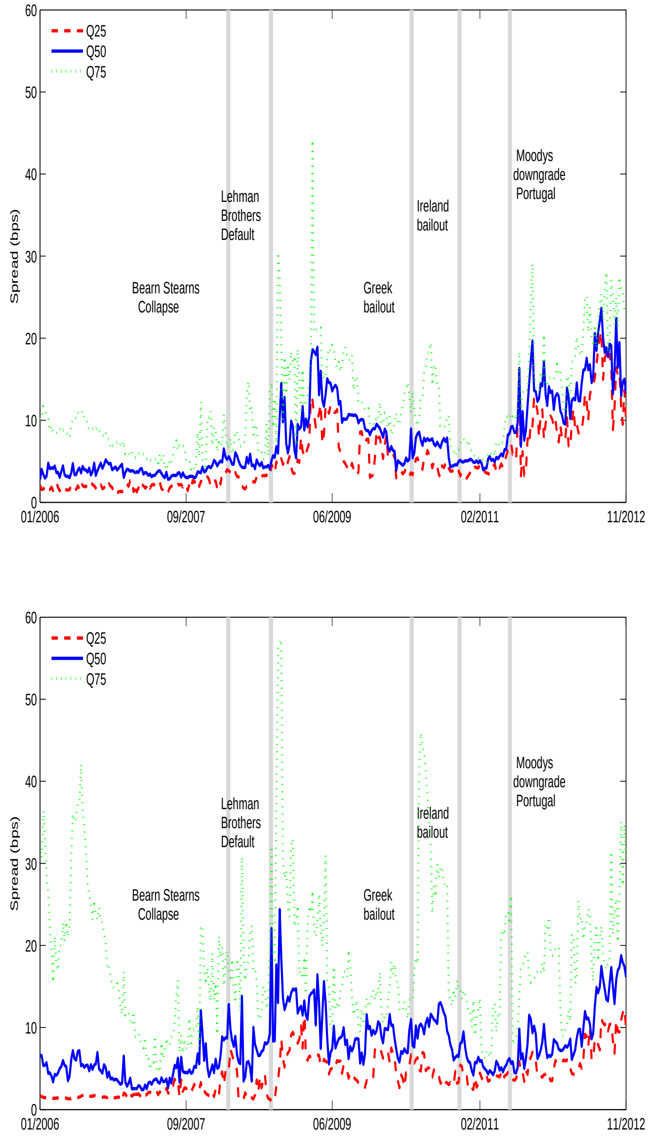
3.4.2 Main results

Given the maximum-likelihood estimates of ψ, we can readily determine the theoretical prices implied by the PS model and the resultant estimates of the noise measure, $noise_{CDS,t}$. Figure 3.3 shows the time series variation of the 25%, 50%, and 75% percentiles of $noise_{CDS,t}$ given the sovereign CDS belonging to either the AE or EE groups. The median time-series tend to be relatively low during normal periods, consistent with a low dispersion in the CDS spread term structure. Nevertheless, the noise measure largely increases during stress periods, showing a sharp increment in price dispersion. Note, for instance, that the median time-series for both AE and EE groups peak after systemic episodes such as the collapse of Lehman Brothers in September, 2008, or the Greek bailout in March, 2010. Clearly, the average values of $noise_{CDS,t}$ in both groups is characterized by a strongly non-linear, globally mean-reverting pattern which can be associated to latent dynamics that determine whether the economy is a normal or stressed regime. This evidence completely agrees with the results reported by Hu *et al.* (2013) for the noise measure in the US Treasury bond market.[8] Although, on average, pricing discrepancies tend to be greater and much more volatile in the EE group (thereby suggesting the existence of an idiosyncratic component in the series), it is clear that the AE and EE noise measures exhibit common patterns and follow a similar trend, which strongly suggests the existence of a source of global commonalities in mispricing.

Table 3.5 reports standard descriptive statistics of the estimates of the noise measure for any of the sovereign CDS analyzed. The overall mean value is 13.08 basis points, but there is a strong heterogeneity across countries. The individual averages range from 4.52 (Germany) to 85.70 basis points (Argentina). Furthermore, the volatility of $noise_{CDS,t}$ largely varies from distressed to resilient economies, showing the largest differences for Argentina, Indonesia, Italy and Spain. In contrast, solid economies, such as the US or Germany, show the smallest degree of average dispersion in pricing errors. The largest value of the noise measure in Argentina reaches 1111.39 basis points, whereas the US peaks at 17.22 basis points. Clearly, the noise measure is related to the factors that characterize whether the CDS spread has a large mean value and high dispersion or not.

[8] The non-linear, mean-reverting path of the noise series is even more evident in the analysis of $noise_{TBond,t}$ in Hu *et al.* (2013) because the sample analyzed therein spans a longer period, from 1987 through 2011. Over this period, $noise_{TBond,t}$ is shown to spike prominently as a consequence of shocks related to crises, and revert to the mean level afterwards.

Figure 3.3: The noise measure



This Figure displays the evolution of different percentiles of the noise measure using Pan and Singleton (2008) model model as pricing model. The noise measure is computed for advanced (upper graph) and emerging (lower graph) economies. Advanced countries comprise Australia, France, Germany, Italy, Japan, Spain, the United Kingdom and the US. The sample period spans from January 2006 to November 2012. Data frequency is weekly.

Table 3.5: Descriptive statistics of the noise measure

						Percentiles		
Country	Mean	Median	Std	Min	Max	5%	95%	N
Argentina	85.70	43.87	136.40	4.41	1111.39	7.84	472.10	358
Australia	4.42	2.66	4.67	0.33	21.44	1.28	17.47	244
Brazil	12.11	10.78	9.46	1.06	57.31	2.54	32.18	358
China	7.44	4.96	6.10	0.40	27.90	1.22	18.76	358
France	5.80	3.80	5.89	0.42	28.09	1.18	19.51	358
Germany	4.52	3.11	4.37	0.37	18.75	0.61	15.08	358
Indonesia	17.79	12.47	19.06	1.39	219.45	4.77	59.08	358
Italy	11.37	5.85	11.13	1.62	66.65	2.88	59.08	358
Japan	5.80	4.66	4.91	0.41	26.19	0.82	15.18	358
Mexico	7.87	6.68	4.93	1.49	56.84	2.36	16.25	358
Saudi Arabia	5.58	4.92	3.91	0.85	18.24	1.05	14.62	228
South Africa	9.91	7.90	7.01	2.02	56.34	3.01	21.92	358
South Korea	9.48	7.80	6.45	2.21	43.66	2.97	21.58	358
Spain	10.11	6.33	10.19	1.09	62.43	1.60	30.39	358
UK	6.84	5.33	3.83	1.40	17.75	2.52	13.65	261
US	4.57	3.87	2.73	0.53	17.22	1.12	10.52	257

Main descriptive statistics of the noise measure. Sample period comprises from January 2006 to November 2012, with the exception of Australia, Saudi Arabia, the UK and the US, which covers from December 2007 to November 2012.

Since, as discussed previously, short-term maturities exhibit larger idiosyncratic patterns, an important question is whether CDS maturities contribute equally to the noise measure. This is an economically important concern because the existence of a systematic mispricing of CDS contracts of a given maturity could indicate the existence of pricing factors not captured by the model (Pan and Singleton, 2008). To address this question, we can define the relative contribution of maturity m_τ to the noise measure as $\omega_t(m_\tau) = |CDS_t(m_\tau) - CDS_t^*(m_\tau)|/\delta_t$, $\tau = 1,...,10$, with δ_t as defined in (3.5), noting that $0 \leq \omega_t(m_\tau) \leq 1$, and $\sum_{\tau=1}^{10} \omega_t(m_\tau) = 1$. Recalling that the PS model assumes no pricing error at the 5-year maturity by initial assumption, it follows by construction $\omega_t(5) = 0$, and it should be understood that the relative contributions of the remaining maturities are conditional to this assumption.

Table 3.6 reports basic time-series statistics (mean, median and standard deviations) of $\omega_t(m_\tau)$ for each maturity and each country in the sample, and the maturity for which the relative contribution $\omega_t(m_\tau)$ is the largest. According to these results, the 1-year contract systematically exhibits the highest contribution to the noise measure.[9] The relative contributions of the pricing errors to the total range from 26.93% in the US to 59.20% in Argentina. Larger mispricing errors in the 1-year maturity suggest the existence of common factors across countries that are driving the dynamics of the residuals at shortest maturities. A possible interpretation of this behavior is pointed out by Pan and Singleton (2008), who suggest that large institutions might employ short-term CDS contracts as primary trading vehicles for expressing their views on sovereign bonds, inducing illiquidity or trading pressures in these maturities. These authors argue that 1-year (and perhaps 10-year) contracts include an idiosyncratic liquidity component due to the short/long-term nature of these instruments. The main evidence from this simple analysis supports this claim.

Before a more formal analysis is conducted, it is worth analyzing the existence of commonalities in pricing errors. The PCA on the standardized noise series across countries reveals that the first principal component is able to capture approximately 33% of the total variation of these series. The share of explained variance increases to 56% and 65% when second and third components are included, respectively. In order to gain insight into the economic interpretation of these latent components, Figure 3.4 shows the loadings of PC1 and PC2. Clearly, PC1 can be interpreted as a world-wide market trend, since all the countries except Brazil and China exhibit positive loadings. These are uniformly distributed across advanced economies, pivoting around an average coefficient of 0.70. On the other hand, the loadings of emerging markets are significantly smaller, but still positive in most cases. Turning our attention to the loadings of PC2, these exhibit a heterogeneous behavior that, once more, can be related to creditworthiness heterogeneity in the sample. In particular, the estimated loadings tend to be positive or mildly negative for the countries in which the noise measure exhibits low mean values and low volatility, such as Australia, France, Germany, UK, and US. Conversely, loadings are mostly negative for countries in which pricing errors have a relatively high mean and high volatility, such as most countries in the EE group and distressed economies in Southern Europe such as Spain.

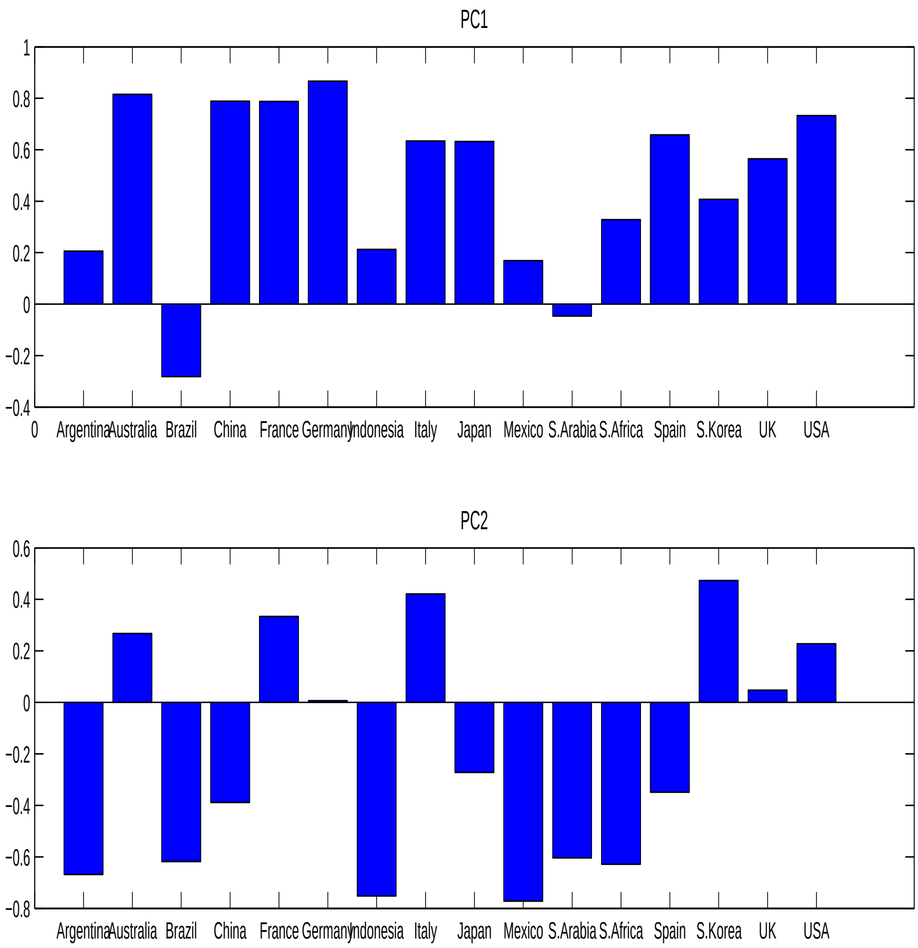
[9] Australia, China and the US seem to be rare exceptions. Even though the noise is concentrated at longer maturities for these countries, the standard deviation of the noise contribution to the 1-year maturity is still the highest across maturities.

Table 3.6: Contribution of maturities to the noise measure

	Maturity (years)									Rank		
Country	1	2	3	4	6	7	8	9	10	mean	median	std
Argentina	59.20 [64.57]	39.44 [43.48]	26.28 [25.96]	12.86 [10.96]	9.63 [8.29]	16.62 [14.41]	20.82 [19.09]	23.33 [21.70]	25.03 [22.06]	1	1	1
	(25.81)	(17.12)	(14.46)	(8.64)	(5.99)	(10.94)	(13.58)	(15.45)	(17.18)			
Australia	32.54 [30.35]	33.99 [36.81]	29.68 [31.98]	18.34 [18.85]	19.84 [22.82]	29.79 [33.45]	35.43 [40.18]	35.42 [38.99]	36.84 [38.73]	10	8	1
	(19.37)	(13.36)	(12.13)	(5.16)	(6.52)	(8.81)	(10.74)	(13.34)	(16.91)			
Brazil	45.51 [46.10]	38.02 [39.11]	29.17 [29.16]	19.19 [18.09]	12.34 [12.82]	23.07 [23.98]	27.54 [30.13]	31.48 [34.35]	34.65 [37.58]	1	1	1
	(20.02)	(16.35)	(15.08)	(9.89)	(5.44)	(9.97)	(11.48)	(12.46)	(15.00)			
China	32.38 [34.97]	30.05 [31.72]	26.99 [25.91]	14.22 [14.35]	13.20 [13.62]	25.63 [25.53]	32.53 [34.76]	39.17 [42.11]	43.48 [42.66]	10	10	1
	(20.41)	(17.18)	(17.10)	(8.72)	(4.65)	(9.74)	(13.62)	(13.70)	(15.45)			
France	51.69 [56.95]	38.86 [40.00]	26.43 [26.19]	14.83 [15.18]	12.67 [12.14]	21.10 [20.01]	26.06 [25.56]	29.84 [30.26]	33.23 [34.31]	1	1	1
	(23.13)	(13.49)	(13.11)	(7.31)	(6.33)	(10.28)	(11.89)	(13.07)	(14.98)			
Germany	49.90 [48.16]	34.25 [36.11]	27.66 [27.80]	16.30 [16.30]	13.11 [11.94]	20.94 [20.13]	26.09 [27.57]	30.20 [31.35]	34.33 [36.45]	1	1	1
	(24.23)	(14.19)	(13.62)	(8.32)	(8.97)	(12.58)	(13.34)	(13.56)	(16.91)			
Indonesia	49.28 [52.52]	39.09 [42.88]	32.23 [33.74]	16.00 [15.08]	11.43 [10.67]	19.19 [18.37]	23.36 [24.69]	27.70 [29.56]	33.67 [35.59]	1	1	1
	(20.69)	(15.39)	(14.46)	(10.57)	(5.71)	(11.18)	(12.34)	(14.60)	(17.32)			
Italy	56.68 [62.50]	38.35 [40.10]	23.07 [20.12]	10.55 [9.43]	9.94 [9.05]	15.84 [15.53]	20.30 [17.83]	25.74 [19.83]	31.62 [25.89]	1	1	1
	(25.15)	(15.63)	(12.34)	(6.89)	(7.21)	(11.01)	(13.82)	(17.64)	(22.43)			
Japan	50.76 [51.81]	31.10 [32.09]	23.50 [24.07]	15.25 [14.62]	13.70 [12.44]	20.94 [20.40]	26.14 [27.52]	30.73 [33.80]	36.03 [39.31]	1	1	1
	(23.04)	(17.87)	(14.59)	(10.50)	(9.37)	(12.80)	(13.69)	(14.66)	(17.26)			
Mexico	54.74 [60.15]	31.38 [33.05]	22.05 [20.11]	12.71 [12.02]	10.24 [10.10]	18.80 [17.59]	24.04 [24.48]	29.20 [29.36]	37.42 [39.57]	1	1	1
	(23.02)	(18.31)	(15.47)	(8.80)	(6.15)	(12.05)	(13.29)	(14.58)	(18.26)			
Saudi Arabia	45.83 [49.00]	42.25 [51.60]	29.08 [30.30]	14.18 [14.85]	14.26 [11.00]	21.43 [8.74]	23.37 [15.14]	23.34 [23.76]	26.08 [30.92]	1	2	1
	(23.54)	(20.42)	(14.94)	(6.90)	(12.41)	(20.54)	(17.26)	(14.96)	(17.48)			
South Africa	51.74 [53.49]	43.14 [44.69]	28.56 [29.00]	12.90 [12.43]	10.93 [10.94]	18.72 [18.02]	23.76 [24.78]	27.86 [29.52]	32.05 [32.61]	1	1	1
	(20.47)	(17.55)	(13.49)	(8.34)	(5.49)	(9.47)	(11.32)	(12.83)	(15.97)			
South Korea	42.58 [46.70]	33.18 [38.94]	24.65 [23.62]	13.73 [10.74]	11.50 [11.11]	21.41 [20.69]	28.55 [27.83]	34.73 [33.22]	39.56 [35.31]	1	1	1
	(24.95)	(19.33)	(15.63)	(9.97)	(6.97)	(9.16)	(11.69)	(14.52)	(17.28)			
Spain	53.61 [53.09]	38.12 [35.18]	26.17 [26.45]	13.42 [11.47]	11.38 [10.33]	17.79 [18.63]	22.64 [21.77]	26.79 [25.95]	32.24 [28.97]	1	1	1
	(23.56)	(17.66)	(11.36)	(8.32)	(6.94)	(10.92)	(14.08)	(16.75)	(19.69)			
UK	44.92 [43.98]	43.73 [50.74]	36.82 [35.30]	17.47 [15.47]	12.07 [11.30]	19.81 [18.64]	24.12 [22.98]	26.39 [26.30]	27.64 [27.88]	1	2	1
	(23.48)	(17.42)	(18.84)	(9.36)	(5.79)	(8.74)	(10.43)	(11.69)	(13.49)			
US	26.93 [22.47]	32.76 [32.93]	26.99 [26.16]	13.86 [14.21]	12.71 [13.68]	22.44 [25.36]	32.78 [35.99]	41.59 [45.79]	48.62 [53.52]	10	10	1
	(21.19)	(14.90)	(14.31)	(6.82)	(5.36)	(8.77)	(10.31)	(11.53)	(13.63)			

Main descriptive statistics for the contribution (in percentage) of different maturities to the noise measure. The Table reports the mean, median (in brackets) and standard deviation (in parenthesis) statistics, respectively. The contribution $\omega_t(m_i)$ is defined as $|CDS_t(m_i) - CDS^*_t(m_i)|/\delta_t$. The contribution $\omega_t(5)$ is zero by construction and has been omitted. Column Rank reports the maturity with highest value in mean, median and standard deviation, respectively.

Figure 3.4: Loading coefficients for principal components of the noise measure



The strong degree of commonality in the residuals of the pricing model strongly suggests the existence of risk factors which are not properly captured by the model but which, nevertheless, are systematically priced in the CDS market. To gain further insight into the sources of commonality and their economic interpretation, we project the time series increments of PC1 and PC2, denoted as ΔPC1 and ΔPC2, respectively, on the increments of a set of market-wide global state variables sampled from the US market over the period December 2007 to November 2012. Using variables from the US market to proxy for global conditions in this preliminary analysis seems reasonable because of the strong degree of globalization in financial markets, and the predominance of the US economy (see, among others, López-Espinosa, Moreno, Rubia and Valderrama, 2012 and Rapach, Strauss and Zhou, 2013). Nevertheless, we stress that a more detailed analysis, building on country-specific variables, shall be conducted in the next section. The explanatory variables used in this preliminary analysis are the changes in the volatility index of the Chicago Board Options Exchange (VIX), used as an indicator of global uncertainty; the change in Moody's bond spread index between AAA and BBB bonds (Default), used as a proxy for corporate default spread; the return of the Dow Jones Index (DJIndex), used as a natural indicator of stock market performance and market risk; the change in the first PC of net notional volumes (PC1netvol), and the first PC of bid-ask spreads at 5-year maturity (PC1BA5y), both of which are used as proxies of aggregate market liquidity. All these variables are sampled weekly.

Table 3.7 reports the OLS estimates for the individual regression of ΔPC1 (Panel A) and ΔPC2 (Panel B) on a constant and any of the state variables. The Table also reports the main outcomes from the OLS regression on all these variables. For conciseness, we only discuss the results for the regressions involving ΔPC1, since this factor captures the main source of common variation in cross-country mispricing, and the results of ΔPC2 follow along the same lines. In individual regressions, all the state variables are highly significant, with the sole exception of the first principal component of net volumes (PC1netvol). Hence, the global trend that seems to underlie PC1 is positively related to market-wide increments in volatility and default probabilities, and it is negatively related to market-wide returns and liquidity. The joint regression of ΔPC1 on all the explanatory variables simultaneously yields a significantly and positive association with VIX, and a significantly and negative association with returns and the principal component of net volume. The remaining variables (Default and PC1BA5y) no longer provide incremental information over these variables. The adjusted-R^2 in this regression is approximately 26%.

Table 3.7: OLS regressions of principal components of the noise measure

Constant	VIX	Default	DJIndex	PC1netvol	PC1BA5y	Adj-R^2	N
			Panel A.- PC1 vs Global variables				
0.0397	0.0616***					18.20	227
(0.0353)	(0.0086)						
0.0413		1.8627***				5.00	227
(0.0381)		(0.5188)					
0.0415			-0.0027***			21.79	227
(0.0346)			(0.0003)				
0.0426				-0.4468		1.38	185
(0.0410)				(0.2366)			
0.0371					-0.2316***	10.99	227
(0.0369)					(0.0431)		
0.0633	0.0366*	-0.0273	-0.0016*	-0.4358*	-0.1173	25.75	185
(0.0364)	(0.0183)	(0.7145)	(0.0007)	(0.2107)	(0.0778)		
			Panel B.- PC2 vs Global variables				
0.0074	-0.0676***					10.59	227
(0.0527)	(0.0128)						
0.0032		-3.3799***				8.35	227
(0.0534)		(0.7273)					
0.0062			0.0024***			8.06	227
(0.0535)			(0.0005)				
0.0113				0.1716		-0.17	185
(0.0356)				(0.2058)			
0.0108					0.4195***	17.96	227
(0.0505)					(0.0590)		
0.0033	-0.0128	0.2222	0.0010	0.1786	0.0030	4.56	185
(0.0356)	(0.0179)	(0.6990)	(0.0007)	(0.2061)	(0.0761)		

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

OLS estimates for the first (PC1) and second (PC2) principal components of the noise measure against a set of regressors. Panels A and B report the beta estimates for the individual and jointly regressions of PC1 and PC2, respectively. Last column includes the adjusted R-squared. Sample period spans from July 2008 to November 2012.

The main conclusions from the preliminary analysis conducted in this section allows us to conclude that price discrepancies exhibit a strong time-varying pattern which increases substantially during distress periods. Pricing errors are mainly contributed by discrepancies at the 1-year maturity, so they must be related to short-term fluctuations. Furthermore, the PCA analysis reveals a strong source of commonality that can be related to market-wide stress conditions, with a first component able to explain nearly 33% of the total variability that can be related to state variables that define a scenario of high volatility, negative market performance, and liquidity withdraws. This evidence shows a characteristic scenario which fits squarely with the theoretical predictions in Schleifer and Vishny (1997), showing that larger pricing errors can systematically be related to adverse economic scenarios. These conclusions, based on a simple and direct analysis, shall be confirmed in a more rigorous analysis based on panel-data regressions in the next section.

3.5 Determinants of pricing errors in CDS markets

The main objective of this chapter is to examine the economic determinants of pricing errors in the CDS term structure. To this end, we implement different estimation procedures within the panel-data methodology that regress a log-transform of the noise measure on either contemporaneous or lagged values of illiquidity-related variables. Our main aim is to parsimoniously address the existence of an empirical relationship between price discrepancies and market-wide illiquidity, considering mainly country-specific variables that capture local information on the liquidity conditions in the CDS market as well as other potential global control variables.

3.5.1 State variables

We consider a panel of country-specific and global variables that can be grouped into the categories of market-wide illiquidity and market uncertainty. The set of illiquidity-related variables include *i*) the 5-year maturity bid-ask spreads (*Bidask*), *ii*) Number of Traded CDS contracts (*Contracts*), and *iii*) Net Notional Outstanding Volume (*Netvol*). All these variables are country-specific and are availabe from DTCC. The set of of market uncertainty-related variables include *iv*) a local proxy of market volatility (*Marketvol*), as measured by the absolute value of the weekly market index return, and *v*) a global indicator of default premium (*Default*), characterized as the price spread between AAA and BBB rated US investment. This set of variables suffices to explain a remarkably large proportion of variability, since price discrepancies turn out to be strongly related to country-specific drivers which characterize liquidity. As discussed in the robustness section, taking further macroeconomic and financial variables into account, most of which are only available at the global level, does not seem to improve results nor lead to qualitative differences in the main results. We discuss the variables used in the panel-data regressions in the remainder of this subsection.

All the variables in the liquidity group are strongly correlated and share a considerable degree of commonality. Although they all can be related to liquidity risk, they measure different facets of this magnitude (Chordia, Roll and Subrahmanyam, 2001). In particular, *Bidask*, the most popular indicator of illiquidity in security markets, is a measure of the tightness of asset prices. According to the literature in market microstructure, bid-ask spreads include two components. One is the compensation required by market-makers for inventory costs, clearing fees, and/or monopoly profits. The second one results from a characteristic adverse-selection problem faced by market-makers in a context of asymmetric information. It mainly represents the additional compensation for the expected costs caused by informed-trading activity. Hence, in periods of greater price uncertainty in which informed investors can profit from their superior information, bid-ask spreads tend to widen and lead to greater transaction costs. Acharya and Johnson (2007) report evidence of informed-trading activity in the CDS market. Furthermore, this information flows to equity markets in response to negative credit news, suggesting that price discovery for those events tends to happen in CDS markets. Consequently, we expect a positive relation with mispricing, since liquidity providers can exit the market when transaction costs are high; see Longstaff *et al.* (2005), Chen *et al.* (2007), and Tang and Yan (2008).

The variable *Contracts* is a measure of market-wide trading activity and, therefore, can be deemed to be an indirect measure of liquidity; see Berg and Streitz (2012). In general terms, trading activity induces price volatility, so the number of trades has been often related to noise trading. Furthermore, Tang and Yan (2008) use this variable to proxy for the overall inventory in the CDS market, which could also be related to holding costs. In the inter-dealer market, inventory control may be a major concern for dealers under funding constraints, as this may impair the capacity for dealers to take sides in additional contracts and thereby affect the liquidity of the related contracts; see Brunnermeier and Pedersen (2009). Finally, Oehmke and Zawadowsky (2013) argue that the illiquidity of the bond market increases the amount of CDSs outstanding, since CDS contracts should be more heavily used when the underlying bond is illiquid – and thus hard or expensive to trade. According to all these considerations, we should expect a positive relation with the noise measure.

The variable *Netvol* reflects the net total amount exchanged in case of default. In contrast to the gross notional outstanding volume, which increases with every trade, the net notional volume adjusts the gross notional amount for offsetting positions; see Berg and Streitz (2012). In this way, the net notional turns out to be an excellent indicator of the overall amount of credit risk transfer in the CDS market. As discussed by Oehmke and Zawadowsky (2013), an intuitive way to interpret the *Netvol* variable is to consider it as the maximum amount of payments that need to be made between counterparties in the case of a credit event on a particular reference entity. As in other derivative markets, such as the futures market, entering offsetting trades in the CDS markets is a more common way to reduce exposures than canceling an existing CDS contract. Because arbitrageurs unwind positions during extreme circumstances, effective reductions in net traded volumes should be related to larger pricing errors. This variable could inversely proxy for the unobservable holding costs (including, for example, the opportunity cost of capital, the opportunity cost of not receiving full interest on short-sale proceeds, and idiosyncratic risk exposures), with arbitrageurs closing positions when these costs increase excessively.

Together with these variables, we consider the country-specific variable *Marketvol* to capture market-wide volatility in the local stock market. Market volatility is a latent factor particularly sensitive to the information flow which subsumes information relative to collective expectations, environmental conditions, and market sentiment. Consistent with the results reported in the previous section and the theoretical considerations in Schleifer and Vishny (1997) and others, we expect volatility to be a natural driver of the noise measure. For instance, asset volatility is a key driver of default probabilities according to Merton (1974) model. Accordingly, larger levels of volatility lead to greater pricing errors. Additionally, the variable *Default* is a global proxy to control for default premium. This variable is calculated using the Moody's bond spread index for 3-5 year maturity bonds; see Hu *et al.* (2013). A greater default is naturally associated with greater pricing errors.

3.5.2 Analysis of determinants

Let $\ln noise_{CDS,it}$ denote the natural logarithm of the sample estimate of the $noise_{CDS}$ measure for the i-th country at time t. We model the conditional mean of this process as a linear function of the state variables building on a panel-data model specification. Acharya and Johnson (2007), Tang and Yan (2008), Pires, Pereira and Martins (2013) use a similar approach to identify the main determinants of CDS spreads, rather than CDS spread pricing errors; see also Peltonen, Scheicher and Vuillemey (2013) and Chiaramonte and Casu (2013). The specification is similar in spirit to the determinant models used, for instance, in Peña *et al.* (1999) and Deuskar *et al.* (2008), although our approach builds on direct estimates of pricing errors. In particular, we consider the following regression specification, referred to as Model I in the sequel,

$$\begin{aligned} \ln noise_{CDS,it} &= \alpha + \phi \ln Bidask_{it} + \beta_1 \ln Contracts_{it} + \beta_2 \ln Netvol_{it} \\ &+ \beta_3 Marketvolatility_{it} + \beta_4 Default_t + \eta_i + \varepsilon_{it} \end{aligned} \tag{3.10}$$

or, using a more convenient notation,

$$\ln noise_{CDS,it} = \alpha + \phi \ln Bidask_{it} + X_{it}'\beta + \eta_i + \varepsilon_{it}, \tag{3.11}$$

where η_i represents country-specific effects that are constant over time but can vary across countries, $\theta = (\alpha, \phi, \beta')'$, with $\beta = (\beta_1, ..., \beta_4)'$, denotes the vector of unknown parameters, ε_{it} is a disturbance assumed to obey standard assumptions, and X_{it} is a vector of explanatory variables defined implicitly.

Some brief comments follow. While bid-ask spreads are stationary series, the vector X_{it} includes strongly-persistent variables which may be driven by stochastic or deterministic trends, such as ln*Contracts*, ln*Netvol*, *Marketvolatility* and *Default*. In order to ensure that this feature does not impose any meaningful distortion in the main conclusions from (3.11), we will consider an alternative specification in which these variables are differentiated. The log-transform is applied to reduce the effects of outliers and heteroskedasticity in the series. Note that, as a result, the coefficients associated to regressors in logarithms can be interpreted as the elasticity of $noise_{CDS,it}$ with respect to the related variable. Finally, this specification does not include gross volume, available in DTCC, because this variable has a correlation coefficient of 85% with $Contracts$. We exclude that variable to avoid colinearity-related concerns, noting that $Contracts$ shows a greater sample correlation to the dependent variable (36%), and a smaller correlation to the other explanatory variables than gross contracts.

Since X_{it} is a strongly persistent vector process with high first-order autocorrelation coefficients, for the sake of robustness, we consider an alternative specification to (3.11) in which persistent variables are plugged in differences, namely,

$$\ln noise_{CDS,it} = \alpha^* + \phi^* \ln Bidask_{it} + \Delta X_t' \beta^* + \eta_i + u_{it} \tag{3.12}$$

with $\Delta X_{it} = X_{it} - X_{it-1}$. Since bid-ask spreads and the dependent variable are stationary, they are left in levels. The resultant model shall be referred to as Model II in the sequel.

The parameters that characterize equations (3.11) and (3.12) are estimated using three different procedures aiming to control for cluster errors, unobservable individual heterogeneity and endogeneity. In particular, we first consider pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. This methodology allows us to carry out statistical inference which is robust to fairly general simultaneous dependences of unknown form in both the cross-sectional and time-series dimensions of the panel; see Petersen (2009), Gow, Ormazabal and Taylor (2010), Cameron, Gelbach and Miller(2011) and Thompson (2011). Furthermore, this methodology seems particularly useful in the empirical context of this chapter, characterized by a panel with a larger number of time-series observations than individuals, because we can readily control for unobservable heterogeneity using individual dummies to estimate the coefficients η_i, since the Haussman test largely favors fixed-effect over random errors. Second, consistent with model specification testing, and as is common in the related literature, we consider fixed-effects panel-data regressions with robust errors to autocorrelation and heteroskedasticity.[10] The resultant estimates are remarkably similar to those obtained under the first

[10] Panel data with random errors can be seen as a more general specification than fixed errors. We implemented both approaches, noticing no qualitative difference in the main conclusions discussed below. However, since the Haussman test largely favors fixed-effect over random errors in our sample, we report and discuss the resultant estimates from this model.

approach. Lastly, we consider instrumental variables in the fixed-effects panel data, using a single lag of the variables as an instrument in order to mitigate concerns related to endogeneity.

In addition, we analyze the predictive ability of the variables in Model I and II to forecast the dependent variable. To this end, we regress $\ln noise_{CDS,it}$ on lagged values of all the right-hand side variables in equations (3.11) and (3.12), i.e., we consider predictive panel-data regressions. We adopt this approach for two main reasons. First, the analysis on the parameters estimates from these regressions allows us to determine whether the state variables are useful to predict price discrepancies given the set of available information. Second, since the dependent variable is regressed on predetermined variables in this analysis, endogeneity can no longer be a serious concern. Of course, this form of robustness comes at the expense that parameter significance may be considerably weakened , but the comparative analysis between contemporaneous and predictive regressions allows us to determine whether endogeneity introduces significant biases. Consequently, and paralleling equations (3.11) and (3.12), we consider the following predictive specifications

$$\ln noise_{CDS,it} = \alpha_l + \phi_l \ln Bidask_{it-1} + X'_{it-1}\beta_l + \eta_i + v_{it} \tag{3.13}$$

and

$$\ln noise_{CDS,it} = \alpha_l^* + \phi_l^* \ln Bidask_{it-1} + \Delta X'_{t-1}\beta_l^* + \eta_i + w_{it} \tag{3.14}$$

with $\theta_l = \left(\alpha_l, \phi_l, \beta_l'\right)'$ and $\theta_l^* = \left(\alpha_l^*, \phi_l^*, \beta_l^{*\prime}\right)'$ denoting the main parametes of interest, and v_{it} and w_{it} being random disturbances. For ease of exposition, we shall present and discuss the parameter estimates from the two-way cluster methodology with country dummies and robust standard errors to unknown heteroskedasticity and correlation. Because (3.13) and (3.14) are trivial variations of Models I and II, respectively, we shall simply refer to this approach as predictive two-way cluster when reporting the main results.

3.5.3 Main results

Table 3.8 reports the main outcomes from the regression analysis (estimated parameters, robust p-values of the t-statistic for individual significance, and R^2), using the different estimation techniques discussed previously and the model specifications (3.11) to (3.14). Let us first discuss the results for Model I and its predictive variation, corresponding to equation (3.11) and (3.13), respectively. These are reported in the top part of the table (Panel A). Independently of the estimation technique, the results show that larger bid-ask spreads, greater trading activity, and greater netting activity within counterparties are systematically related to greater pricing errors. A relative increment of 100 basis points in the bid-ask spread leads, on average, to an increment of nearly 50 basis points in the dispersion of pricing error, everything else being equal. Similarly, the noise measure has a elasticity coefficient of 0.58 and -0.32 with respect to the number of contracts and net notional CDS positions, respectively. These estimates are both statistically and economically significant, and confirm a unmitigated influence of liquidity-related factors on pricing errors in the CDS markets. Owing to the importance of this result, we shall discuss its implications in detail later on, after presenting the remaining estimates.

As expected, the proxy variables for local market volatility in stock markets, used mainly as controls in our analysis, are positively related to price discrepancies in the CDS markets. The evidence of statistical significance of these coefficients is marginal in the contemporaneous regression, and non-significant in the predictive model. While using a robust, but noisy proxy of the unobservable volatility based on absolute-valued weekly returns is likely to increase the standard error of the resultant estimate, the apparent lack of significance is actually related to the (positive) correlation that volatility shows with the *Bidask* variable. If the latter is omitted from the analysis (results not presented for the sake of saving space), then the coefficient on market volatility is positive and strongly significant in all cases, suggesting the *Bidask* partially overrides the information conveyed by volatility. Similarly, *Default* is positively related to the noise measure, as expected, but the statistical evidence supporting the inclusion of this variable is considerably weaker. The tests of significance cannot be rejected in most cases. This result probably indicates that the potential information conveyed by this variable is subsumed in the remaining variables, which is not particularly surprising in view that *Default* is a global variable. The analysis on the predictive regression shows that illiquidity-related variables can be used as short-term predictors of future mispricing. The strong similarity in the main conclusions shows that endogeneity does not cause meaningful distortions on the least-squares based estimates of model (3.11). Finally, the analysis of the R^2 shows that the models are extremely parsimonious, since a reduced number of country-specific variables, mainly related to market-wide illiquidity, are able to achieve a R^2 of approximately 95% of price discrepancies.

The main results from the estimation of Model II are reported in the bottom part of Table 3.8, see Panel B. Recall that the only difference with respect to the previous models is that the dependent variable is regressed on $Bidask_{it}$ and ΔX_{it} in the contemporaneous regression, and on $Bidask_{it-1}$ and ΔX_{it-1} in the predictive regression. The resultant estimates show that relative increments in bid-ask spreads, as well as relative reduction in net notional CDS volumes, can be consistently related to larger dispersion in the CDS curve. Once more, *Bidask* turns out to be a particularly significant determinant. However, $Netvol$ tends to be marginally significant in this context. The variables *Contracts* and *Default* do not seem to play any role, and market volatility is positively but not significantly related to the noise measure. As in Panel A, this evidence is robust to different estimation techniques and remains valid even when considering lagged values of these state variables in a predictive regression.

Table 3.8: Panel-data estimates of noise determinants

	Two-way cluster			**Panel-data Fixed-Effects**			**Instrumental Fixed Effects**			**Predictive Two-way cluster**		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
						Panel A.- Model I						
logBidaskspread5Y	0.5251	0.0766	0.00	0.5251	0.0718	0.00	0.5330	0.0318	0.00	0.5104	0.0842	0.00
logContracts	0.5780	0.1596	0.00	0.5780	0.1554	0.00	0.5650	0.0417	0.00	0.5593	0.1598	0.00
logNetvolume	-0.3193	0.1338	0.02	-0.3193	0.1325	0.03	-0.2970	0.0522	0.00	-0.2823	0.1296	0.03
Marketvolatility	0.7383	0.4554	0.11	0.7383	0.3617	0.06	0.7372	0.4698	0.12	0.1310	0.2811	0.64
Default	0.1223	0.1044	0.24	0.1222	0.0990	0.24	0.1338	0.0276	0.00	0.1477	0.1067	0.17
Constant	-5.4617	2.4059	0.02	-4.9798	2.3723	0.05	-5.4003	0.8978	0.00	-6.1473	2.2953	0.01
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3131	3131	3131	3131	3131	3131	3101	3101	3101	3101	3101	3101
R^2-coefficient	0.9418	0.9418	0.9418	0.9418	0.9418	0.9418	-	-	-	0.9417	0.9417	0.9417
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
						Panel B.- Model II						
logBidaskspread5Y	0.5740	0.0611	0.00	0.5740	0.0587	0.00	0.5835	0.0207	0.00	0.5604	0.0612	0.00
ΔlogContracts	-0.2468	0.3914	0.53	-0.2468	0.3522	0.49	-0.2549	0.3100	0.41	-0.2123	0.3634	0.56
ΔlogNetvolume	-0.8498	0.5392	0.12	-0.8498	0.4878	0.10	-0.9074	0.3436	0.01	-1.0404	0.5328	0.05
ΔMarketvolatility	0.2862	0.3600	0.43	0.2862	0.2764	0.32	0.2153	0.3742	0.57	0.0917	0.2950	0.76
ΔDefault	-0.2199	0.4621	0.63	-0.2199	0.3897	0.58	-0.0563	0.1950	0.77	-0.2178	0.4554	0.63
Constant	-8.6457	0.1042	0.00	-7.3340	0.0961	0.00	-7.3464	0.0347	0.00	-8.6218	0.1051	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3115	3115	3115	3115	3115	3115	3099	3099	3099	3099	3099	3099
R^2-coefficient	0.9355	0.9355	0.9355	0.9355	0.9355	0.9355	-	-	-	0.9349	0.9349	0.9349

Panel data estimates for noise measure using different standard estimation methods. The mispricing errors have been computed using the Pan and Singleton (2008) model model. Panel A shows the results for variables in levels and Panel B for variables in differences. First column corresponds with pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. Second column shows the fixed effect with robust standard errors to autocorrelation and heteroskedasticity. The last two columns present the estimation for fixed effects and two-cluster using lagged regressors.

In short, the price discrepancies of observed CDS spreads with respect to the theoretical prices implied by the PS model do significantly covariate with state variables that characterize illiquidity in the CDS market. This relation is so strong that illiquidity-related variables can be used even as reliable predictors of mispricing in the short-term. The evidence is particularly significant for bid-ask spreads, as generally expected from the theoretical and empirical considerations in the previous literature. In addition, our analysis reveals a significant relation with outstanding net volumes, a variable at our disposal which has not been used in previous literature. This evidence merits a special mention because a significant relation of CDS pricing errors with *Netvol* reinforces the empirical suitability of the arbitrage-capital hypothesis in Schleifer and Vishny (1997). The estimates of the elasticity coefficient on this variable are negative and highly significant in most cases, implying that a relative reduction in net volume is systematically associated with increments in the variability of pricing errors. This result is particularly meaningful because reductions in net volume can be interpreted as increments of offsetting transactions, which is consistent with a greater number of market participants unwinding positions, particularly, during times of distress. Hence, consistent with the theoretical claims in Schleifer and Vishny (1997), larger price discrepancies can be caused by the temporary exit of market participants.

This result provides empirical support to the generality of the measure proposed by Hu *et al.* (2013) in the context of CDS markets, as it essentially agrees with the main conclusions drawn by these authors in the context of Treasury bonds. Finally, it should be noted that the overall evidence reported in this section strongly suggests that single-factor intensity models, specifically intended to capture default risk, may systematically lead to large pricing errors in a distress scenario characterized by high illiquidity risk; as these neglect the influence of this risk-factor. As in the case of the BS model discussed in Peña *et al.* (1999), extensions of this models that do not accommodate liquidity risk may lead to substantial pricing errors.

3.6 Robustness checks

This section shows the results from various robustness checks grouped into two main categories. On the one hand, we discuss the general suitability of the model specifications when taking into account various considerations. We firstly analyze if the overall evidence can be extended to both AE and EE, or if there are heterogeneous patterns attending to creditworthiness. We also discuss if the estimated models could be improved significantly by adding further variables, or if the results are robust to alternative definitions of the main proxy variables involved in the analysis. On the other hand, we analyze whether using alternative pricing models could lead to substantial changes in the main qualitative results discussed previously. The main conclusion from this analysis is that the overall evidence is robust to all these considerations.

3.6.1 Model specification

A) Differences between advanced and emerging economies

Paralleling the analysis in the main section, Table 3.9 reports the main outcomes from the panel-data analysis on the subsamples of emerging countries (Panel A) and advanced economies (Panel B). The main aim of this analysis is to determine if the conclusions apply uniformly over all the countries, of if there are differences attending to this consideration. For conciseness, we display the results corresponding to Model II, in which the dependent variable is regressed against *Bidask* and ΔX_{it}. The main qualitative conclusions are fairly similar for the remaining models, but we report the results for a specification that tends to yield more conservative results.

For both groups of countries, the bid-ask spread variable is always positive and strongly significant, independently of the estimation technique. Interestingly, the coefficient on net volume, *Netvol*, is negative and remains highly significant in statistical terms, but only for the countries in the advanced economies groups (see Panel B). The estimates for emerging markets are highly non-significant. In our view, this evidence shows important differences in CDS pricing in advanced and emerging contracts during the sample period analyzed which is consistent with the fragmentation hypothesis in the CDS market suggested by Goldstein *et al.* (2013). CDS are contracts used essentially for either speculative or hedging purposes. The evidence that relative changes in net volume is not significant on the group of emerging markets over the period analyzed suggests that trading activity on these markets is primarily intended for hedging purposes. Conversely, the evidence of illiquidity-related mispricing in the CDS written on the AE group, mostly composed of European countries, would be consistent with speculative activity. This interpretation is also consistent with the view of the European banking crisis as a 'carry trade' behavior of banks; see Acharya and Steffen (2013).

Table 3.9: Panel-data estimates of noise determinants separated by economic group

	Two-way cluster			Panel-data Fixed-Effects			Instrumental Fixed Effects			Predictive Two-way cluster		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel A.- EE Group												
logBidaskspread5Y	0.6416	0.0507	0.00	0.6416	0.0489	0.00	0.6467	0.0239	0.00	0.6218	0.0564	0.00
ΔlogContracts	0.3284	0.6903	0.63	0.3284	0.7094	0.66	0.3184	0.4928	0.52	0.0445	0.6934	0.95
ΔlogNetvolume	0.1331	0.5286	0.80	0.1331	0.5253	0.81	0.1501	0.4365	0.73	-0.0350	0.4765	0.94
ΔMarketvolatility	0.5541	0.3534	0.12	0.5541	0.3433	0.15	0.4677	0.4836	0.33	0.0962	0.2813	0.73
ΔDefault	-0.9532	0.4837	0.05	-0.9532	0.4734	0.08	-0.8947	0.2665	0.10	-0.8658	0.5152	0.09
Constant	-7.9771	0.0509	0.00	-6.5870	0.0881	0.00	-6.5979	0.0438	0.00	-7.9609	0.0579	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1482	1482	1482	1482	1482	1482	1474	1474	1474	1474	1474	1474
R^2-coefficient	0.9658	0.9658	0.9658	0.9658	0.9658	0.9658	-	-	-	0.9651	0.9651	0.9651

	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel B.- AE Group												
logBidaskspread5Y	0.4221	0.1103	0.00	0.4221	0.1034	0.01	0.4367	0.0378	0.00	0.4221	0.1082	0.00
ΔlogContracts	-0.2773	0.4491	0.54	-0.2773	0.3619	0.47	-0.2589	0.4047	0.52	-0.0834	0.3974	0.83
ΔlogNetvolume	-1.8605	0.8315	0.03	-1.8605	0.7169	0.04	-2.0425	0.5312	0.00	-2.1216	0.7097	0.00
ΔMarketvolatility	0.0004	0.6135	1.00	0.0004	0.4051	1.00	-0.0644	0.5644	0.91	0.0881	0.5208	0.87
ΔDefault	0.5519	0.6724	0.41	0.5519	0.5276	0.33	0.8290	0.2797	0.00	0.4654	0.6965	0.50
Constant	-8.3786	0.1808	0.00	-7.8933	0.1504	0.00	-7.9065	0.0574	0.00	-8.3794	0.1770	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1633	1633	1633	1633	1633	1633	1625	1625	1625	1625	1625	1625
R^2-coefficient	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	-	-	-	0.3437	0.3437	0.3437

Panel data estimates for noise measure using different standard estimation methods considering two groups of countries and variables in differences. The mispricing errors have been computed using the Pan and Singleton (2008) model model. Panel A shows the results for Emerging economies (EE) and Panel B for advanced (AE) ones. First column corresponds with pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. Second column shows the fixed effect with robust standard errors to autocorrelation and heteroskedasticity. The last two columns present the estimation for fixed effects and two-cluster using lagged regressors.

B) Additional explanatory variables.

Together with the set of variables discussed previously, we included a number of additional explanatory variables. Most of these variables are global, i.e., variables that are common for all the countries, and that reflect major trends in the global economy. These variables include *i*) the 1-day LIBOR, since this represents the unsecured rate at which banks lend to each other and it is sensitive to default conditions; *ii*) the slope of the US term structure of interest rates, calculated as the difference between the 10- and 2- year constant maturity Treasury bond yields; *iii*) the noise measure of Hu *et al.* (2013), representative of illiquidity proxy of the US sovereign bond market; *iv*) the local stock market index returns, as a measure of short-term market performance; *v*) the spread between the three-month LIBOR rate and the Overnight Index Swap rates, as a proxy of counterparty risk, since this variable captures the market expectations of future official interest rates set by central banks, and aggregates the perceptions of counterparty risk in credit markets. There exists a strong degree of correlation between these variables. Not surprisingly, therefore, in the estimation of Model I and II extended with these variables, most of the related coefficients were not significant, which suggests that a simpler model that mainly exploits local information is parsimonious enough and subsumes all the relevant information to explain systematic trends in CDS mispricing. The main results, underlining the crucial role played by illiquidity-related variables on price biases, remain unaltered. We do not present these results for the sake of saving space, noting that they are available upon request.

C) Financial distress-related deterministic indicators.

We include time dummies signaling the occurrence of major sovereign events in the sample, such as the Greek and Ireland bailouts, and the downgrade of Portugal. The main aim is to isolate the estimates of the main parameters from the influence of these events. To this end, we considered an extended model with dummies in the unconditional mean and cross-effects with all the local variables in our model. The main qualitative results from the analysis do not differ substantially from those discussed previously, suggesting that bid-ask spreads and net volumes are major drivers and even predictors of the noise measure in the sample. Interestingly in this analysis, some variables such as trading activity and default seem to gain statistical significance, with the crossing-effects being particularly significant for the bid-ask spreads, net volumes and default in nearly all model specifications. As a further check, we repeated this exercise by extending the time window effect of the dummies until one, two, three and four weeks after the event, noting that the main qualitative conclusions are essentially the same as those reported previously.

D) Definitions of proxy variables.

We also analyzed the sensitivity of the results to the way in which the main proxy variables were constructed. In particular, the bid-ask is defined as the 5-year maturity bid-ask. This particular choice was motivated by a criterion of homogeneity, since the trading-related variables facilitated by DTCC mainly refer to this maturity. Nevertheless, since bid-ask spreads are available at different maturities, we analyzed the sensitivity of the results to this consideration, considering bid-ask spreads at any of the available maturities and even a sample average. Additionally, we consider a different proxy for market-wide volatility in the stock market, using a measure of realized volatility defined as the weekly sum of absolute-valued daily returns. The evidence discussed previously is not affected in any significant way by these considerations.

3.6.2 Alternative pricing models

The main results discussed in the previous sections build on the PS pricing model. Other pricing approaches are possible, since the definitive functional form of the default process $\lambda^{\mathbb{Q}}$ remains an open question in this literature. Consequently, we consider two alternative pricing models, namely, a quadratic intensity function (QIF) suggested by Houweling and Vorst (2005), and the semi-parametric (NS) model suggested by Nelson and Siegel (1987). Like PS, these alternative approaches rely on CDS spreads to directly measure the credit risk attributable to default risk and do not explicitly accommodate other risk factors, such as liquidity risk. The main methodological difference, however, is that the theoretical term-structure is characterized on cross-sectional estimates at a particular date, whereas PS uses maximum-likelihood in the time-series context. The advantage is that QIF and NS build on flexible semi-parametric specifications that do not impose distributional assumptions on the data. This feature allows us to ensure that the main qualitative conclusions are not driven by the assumptions implied in Pan and Singleton (2008).

The QIF approach builds on a second-order degree polynomial to model the term-structure of the risk-neutral default intensity at maturity m_τ at time t, namely,

$$\lambda_t^{\mathbb{Q}}(m_\tau) = l_t + s_t m_\tau + c_t m_\tau^2, \tag{3.15}$$

where the parameters l_t, s_t and c_t capture the level, slope and curvature of the default term structure, respectively, with m_τ denoting the time to maturity. Houweling and Vorst (2005) argue that this approach works reasonably in practice. The main advantage of this specification lies on its methodological tractability, but some readers may deem it as excessively simplistic.

The NS approach is a more sophisticated pricing model that attempts to capture the default spread term structure at time t by parsimoniously fitting a smooth curve to the cross-sectional data, namely,

$$\lambda_t^{\mathbb{Q}}(m_\tau) = \xi_{1t} + \xi_{2t}\frac{1-e^{-\gamma_t m_\tau}}{\gamma_t m_\tau} + \xi_{3t}\frac{1-e^{-\gamma_t m_\tau}}{\gamma_t m_\tau} - \exp\left(-\gamma_t m_\tau\right), \tag{3.16}$$

where the parameters $(\xi_{1t}, \xi_{2t}, \gamma_t)'$ are latent dynamic factors that admit a precise economic interpretation. In particular, ξ_{1t} can be viewed as the long-term mean of the default intensity; ξ_{2t} is related to the slope of the spread term-structure, since $-\xi_{2t} = \lambda_t^{\mathbb{Q}}(\infty) - \lambda_t^{\mathbb{Q}}(0)$; ξ_{3t} is closely related to the curvature of the shape. Finally, γ_t is related to the convexity of the curve and controls the position, magnitude and direction of the hump of the spread curve. Remarkably, the NS approach provides the corresponding default rate for a continuous of maturities, so additional interpolation is not necessary. Moreover, this modeling approach avoids the over-parametrization, allowing for monotonically increasing or decreasing and hump shaped default term curves. Jankowitsch, Pullirsch and Veza (2008) set an extensive comparison of the pricing properties in the bond market for several parametrizations of the default intensity, concluding that the Nelson and Siegel (1987) specification turned out to be optimal.

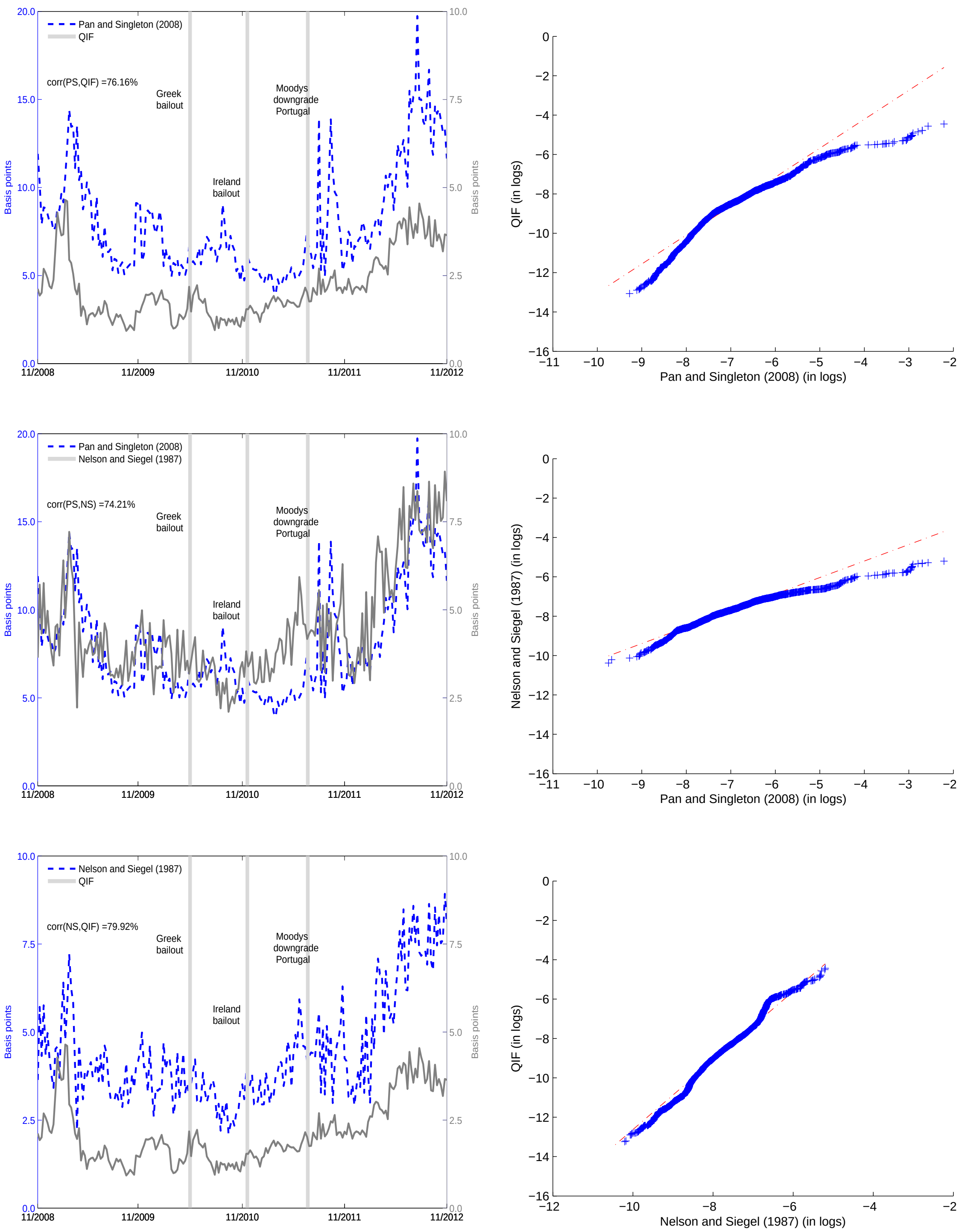
Recalling that the (annualized) price of a CDS contract for maturity m at time t obeys (3.6), we can use the following discretized version of this formula for computing the spreads under both the QIF and NS approaches,

$$\frac{1}{4}\sum_{j=1}^{4m} e^{-\frac{j}{4}\left(r_t+\lambda_t^{\mathbb{Q}}(j)\right)} CDS_t(m) = (1-\mathbb{R}^{\mathbb{Q}}) \sum_{j=1}^{4m} e^{-\frac{j}{4}r_t}\left[e^{-\frac{(j-1)}{4}\lambda_t^{\mathbb{Q}}(j)} - e^{-\frac{j}{4}\lambda_t^{\mathbb{Q}}(j)}\right], \tag{3.17}$$

where $\lambda_t^{\mathbb{Q}}(m_\tau)$ denotes the risk-neutral default intensity at maturity m_τ, and $\mathbb{R}^{\mathbb{Q}}$ is the recovery rate. Consistent with previous literature, we set the risk-neutral recovery rate to 40%; see, for instance, Berndt and Obreja (2010). We also assume a constant default intensity $\lambda_t^{\mathbb{Q}}$, which results in $CDS_t^*(m_\tau) \approx \lambda_t^{\mathbb{Q}}(m_\tau)(1-\mathbb{R}^{\mathbb{Q}})$. The parameters $(l_t, s_t, c_t)'$ and $(\xi_{1t}, \xi_{2t}, \xi_{3t}, \gamma_t)'$ that characterize the QIF and NS models are estimated using linear and non-linear least squares, respectively, given the observable curve CDS_t; see, for instance, Okane and Turnbull (2003) and Houweling and Vorst (2005). Since γ_t in the NS model should be positive in order to assure convergence to the long-term value ξ_{1t}, we impose the constraints $\xi_{1t} > 0$, $\xi_{1t} + \xi_{2t} > 0$ and $\gamma_t > 0$ in the numerical optimization of the objective loss-function of this model. Given the resultant estimates, it is straightforward to compute theoretical term-structure CDS prices and, hence, determine the noise measure with respect to the observed prices CDS_t.

Figure 3.5 shows the time series of the cross-country median of the theoretical CDS spreads implied by the three different pricing models considered in this chapter. For comparative purposes, the figure also reports the qq-plots of these series in logarithms. Clearly, all these model-implied CDS spreads tend to exhibit similar time series features on average. The pairwise correlation between the model-implied prices from PS and those from QIF and NS are about 76% and 74%, respectively. Similarly, the correlation between the theoretical prices generated with the QIF and NS models is nearly 80%. Note that the CDS spreads implied by PS and NS have a similar level and tend to overlap, but the latter display a considerably degree of additional volatility. Theoretical prices from the QIF model exhibit similar time series properties as the other two methodologies, but the average is downward shifted, i.e., prices are systematically smaller.

Figure 3.5: Cross-sectional median of sovereign CDS and qq-plots for different models



Cross-sectional medians (left column) and qq-plots (right column) of sovereign CDS spreads. Each row compares the different models. The first row shows the Pan and Singleton (2008) model model against the quadratic intensity model (QIF). The second row contains the Pan and Singleton (2008) model model against the Nelson and Siegel (1987) model. The third row depicts the QIF model against the Nelson and Siegel (1987) model.

Table 3.10 reports the main results from the analysis of determinants of the QIF- and NS-based noise measures. For ease of exposition, we report the estimates of Table 3.10 noting that the dependent variable $\ln noise_{CDS,it}$ is now computed according to the residuals of either the QIF or the NS models. Not surprisingly, the strong correlation between the theoretical prices generated by these pricing methodologies is consistent with the main qualitative evidence discussed in Section 3.5.2, and it is not affected in qualitative terms. Independently of the pricing framework, all the different proxy variables for market-wide liquidity in the CDS market exhibit the expected signs and are statistically significant. Broadly speaking, the estimates in the QIF-implied noise equation are closer to those reported previously, as should be expected in view of the correlation between these series. The main conclusion, therefore, is that pricing errors from default single-factor models can be consistently related to market-wide illiquidity variables as well as other indicators of financial distress.

Table 3.10: Panel-data estimates of noise determinants for alternative pricing models

	Two-way cluster			Panel data Fixed Effects			Instrumental Fixed Effects			Predictive Two-way cluster		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel A.- QIF Model												
logBidaskspread5Y	0.3695	0.1049	0.00	0.3793	0.1005	0.00	0.3863	0.0233	0.00	0.3471	0.1015	0.00
ΔlogContracts	0.2102	0.9473	0.82	0.1503	0.4234	0.72	0.0009	0.7996	0.99	-0.2421	1.1060	0.83
ΔlogNetvolume	-2.9275	1.3588	0.03	-2.9305	1.2655	0.02	-3.0072	0.8787	0.00	-2.6033	1.2017	0.03
ΔMarketvolatility	0.2438	0.4459	0.58	0.2440	0.1639	0.14	0.2848	0.4204	0.50	0.1338	0.4581	0.77
ΔDefault	1.2566	0.5448	0.02	1.2603	0.3937	0.00	1.5150	0.2191	0.00	1.1011	0.5106	0.03
Constant	-9.8490	0.1759	0.00	-9.0103	0.2426	0.00	-8.9705	0.0389	0.00	2.7646	0.1597	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3168	3168	3168	3168	3168	3168	3152	3152	3152	3152	3152	3152
R^2-coefficient	0.6218	0.6218	0.6218	0.6218	0.6218	0.6218	-	-	-	0.6178	0.6178	0.6178
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel B.- NS Model												
logBidaskspread5Y	0.1550	0.0916	0.09	0.1634	0.0933	0.08	0.1659	0.0231	0.00	0.1446	0.0922	0.12
ΔlogContracts	-0.1028	0.8326	0.90	-0.1247	0.7723	0.87	-0.2073	0.7914	0.79	-0.0557	0.8174	0.95
ΔlogNetvolume	-2.4881	1.0928	0.02	-2.4662	1.0574	0.02	-2.4301	0.8697	0.01	-1.9586	0.9333	0.04
ΔMarketvolatility	-0.0499	0.3436	0.88	-0.0499	0.2936	0.87	-0.0715	0.4161	0.86	0.0746	0.3060	0.81
ΔDefault	0.4474	0.3876	0.25	0.4438	0.3069	0.15	0.5519	0.2168	0.01	0.5448	0.3800	0.15
Constant	-8.5070	0.1573	0.00	-8.0439	0.1640	0.00	-8.0039	0.0385	0.00	-8.4916	0.1563	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3168	3168	3168	3168	3168	3168	3152	3152	3152	3152	3152	3152
R^2-coefficient	0.2651	0.2651	0.2651	0.2651	0.2651	0.2651	0.2631	0.2631	0.2631	0.2631	0.2631	0.2631

Panel data estimates for alternative noise measure using different standard estimation with variables in differences. The mispricing errors have been computed using a quadratic intensity (Panel A) and Nelson-Siegel (Panel B) model. First column corresponds with pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. Second column shows the fixed effect with robust standard errors to autocorrelation and heteroskedasticity. The last two columns present the estimation for fixed effects and two-cluster regressors.

3.7 Concluding remarks

The term structure of fixed-income derivative products must be consistently priced across maturities under the absence of arbitrage opportunities. In practice, however, temporary discrepancies between observed prices and theoretical values can arise as a consequence of market frictions such as illiquidity. While the extant literature has documented both theoretically and empirically the unmitigated influence of illiquidity-related costs on arbitrage-free option pricing models, the evidence for other derivative markets is generally scarce, and plainly nonexistent for CDS. The main objective of this chapter has been to contribute to this literature by documenting the existence of systematic illiquidity-related patterns in the pricing errors implied by some of the most popular pricing models used to value CDS spreads. To this end, we have implemented different panel-data estimation techniques on a broad sample of sovereign CDS in 16 countries.

The main evidence in this chapter is remarkably robust and suggests that price discrepancies in CDS markets can systematically be related to illiquidity factors. Pricing errors tend to be greater during periods of significant distress, such as the collapse of Lehman Brothers or the European debt crisis, as expected under the general arbitrage capital hypothesis. The panel-data analysis identifies bid-ask spreads and a higher level of offsetting transactions as key economic determinants, and even predictors, of greater pricing errors. The overall evidence is largely consistent with the hypothesis that arbitrage capital exits the market during times of distress, causing assets to be traded at prices significantly different to their fundamental value. Accordingly, theoretical pricing models that fail to properly accommodate the additional compensation required for market maker risks can systematically lead to pricing errors in this context.

This evidence is important for different agents, including investors who trade in the CDS market and supervisory organisms that use CDS transaction prices as reliable indicators of the underlying economic conditions. On the one hand, most investors trade in the CDS market for either speculative or hedging purposes. For both types of agents, the evidence that state-of-the-art CDS pricing models can generate prices that systematically depart from real prices is particularly relevant for its economic implications. Investment decisions based on the theoretical prices generated by these models may lead to suboptimal results in a distress scenario. On the other hand, regulators and supervisory organisms often closely monitor financial and economic time series looking for signals that may anticipate a financial weakening. The CDS market provides natural indicators for this end, since CDS spreads convey information on market expectations of creditworthiness. However, if CDS spreads are wrongly assumed to solely reflect default risk, the severity of the underlying market conditions could be largely overestimated, particularly, during periods of distress. In this context, transaction prices may no longer reflect fundamental values, but also include large illiquidity-risk premiums, as directly suggested by the recent literature on the field, and confirmed from the empirical findings in this chapter. The case of peripheral European countries in the midst of the European sovereign crisis perhaps illustrates this point accurately, since sovereign CDS contracts were traded at excessively high prices to solely reflect credit default risk premiums.

Chapter 4

Measuring Tail-Risk Cross-Country Exposures in the Banking Industry

In this chapter we analyze the state-dependent risk-spillover in different economic areas. To this end, we apply the quantile regression-based methodology developed in Adams, Füss and Gropp (2014) approach to examine the spillover in conditional tails of daily returns of indices of the banking industry in the US, BRICs, Peripheral EMU, Core EMU, Scandinavia, the UK and Emerging Markets. This methodology allow us to characterize size, direction and strength of financial contagion in a network of bilateral exposures to address cross-border vulnerabilities under different states of the economy. The general evidence shows as the spillover effects are higher and more significant in volatile periods than in tranquil ones. There is evidence of tail spillovers of which much is attributable to a spillover from the US on the rest of the analyzed regions, specially on European countries. In sharp contrast, the US banking system show more financial resilience against foreign shocks.

4.1 Introduction

Financial contagion has received considerable attention in empirical finance, particularly, after the recurrent episodes of financial crisis that have followed the October 1987 stock market crash. The main interest in this literature is to analyze how shocks to prices of certain financial assets are transmitted into prices of other financial assets. Early papers analyzed the existence of Granger-type causal relationships in the conditional mean of returns during periods of distress; see, for instance, Eun and Shim (1989) and Becker, Finnerty and Gupta (1990); see also Longstaff (2010) and Cheung, Fung and Tsai (2010) for recent analyses. In a similar vein, a considerable body of research has analyzed causality in variance and time-varying conditional correlations aiming to characterize the existence of volatility spillovers; see, among others, Hamao, Masulis and Ng (1990), Engle, Ito and Lin (1990), King and Wadhwani (1990), Susmel and Engle (1994), Baele (2005), and Dungey, Gonzalez-Hermosillo and Martin (2005). More recently, the severity of the global recession has motivated a considerable interest in understanding the linkages that interconnect financial losses during periods of distress, particularly, in financial institutions. This systemic crisis, albeit initiated in the US subprime mortgage-backed securities market, resulted in the collapse of major financial institutions, bankruptcies, declines in credit availability, and sharp drops in global real Gross Domestic Product (GDP). This has motivated a new regulatory setting in the banking industry in the aftermath of the crisis, and a rapidly-growing literature devoted to systemic risk and tail-spillover modelling; see, among others, Segoviano and Goodhart (2009), Acharya, Pedersen, Philippon and Richardson (2010), Adrian and Brunnermeier (2011), Brownlees and Engle (2012), López-Espinosa, Moreno, Rubia and Valderrama (2012), Diebold and Yilmaz (2012), Kim and Hwang (2012), and Rodríguez-Moreno and Peña (2013).

In this chapter, we characterize the existence of state-dependent risk-spillovers in the daily returns of representative indices of the banking industry in different economic areas. The main aim is to appraise the sensitivity that characterizes the local vulnerability of domestic banking sectors to shocks originated in or transmitted by banks in a foreign area under different (stressed and non-stressed) characteristic scenarios. This analysis allows us to formally identify the main transmission channels in the international banking system and provide a quantitative risk assessment of the size of contagion. Cross-country contagion in the banking industry typically occurs because large-scale banks usually hold an important proportion of claims on foreign borrowers over total assets in their balance sheets. A shock in a foreign counterparty that decreases the market value of these claims leads to a balance-sheet contraction which may be further transmitted (and even amplified) into the domestic system through the local interbank network. In this context, we can assess the vulnerability to cross-country shocks in foreign countries by measuring the sensitivity of expected losses in domestic banks to *contemporaneous* changes in the expected losses of foreign banks. In this study, we consider different economic scenarios, all of which are endogenously determined by the empirical distribution of expected losses in the local industry. Our main interest is to analyze contagion under adverse market conditions.

To this end, we focus on representative indices of the banking industry in the US, the UK, peripheral and non-peripheral countries in Europe, and emerging-country economies. All these data, focused on most of the major financial areas of the world, are directly available from Datastream. The sample spans December 1999 through November 2013 and includes periods of expansion and financial recession that caused considerable distress in the banking sector, more prominently, during the 2007-2009 global recession, and the 2010 European sovereign debt crisis. Using these data, we characterize the empirical links in the lower tails of the bank-industry portfolio returns building on a variant of the two-stage quantile-regression methodology (henceforth 2SQR) implemented in Adams, *et al.* (2014). The most distinctive feature of this methodology is that it generates state-dependent estimates that are robust to endogeneity bias. Hence, we can consistently estimate the coefficients that characterize the direction and the strength of financial contagion in a network of bilateral exposures using a contemporaneous equation system. Based on these estimates, we address the existence of significant cross-border vulnerabilities whose intensity can vary as a function of the underlying economic conditions. Furthermore, we characterize impulse-response functions that determine the rapidity and persistence of contagion of a shock under different economic scenarios.

Analyzing tail-interdependences requires suitable estimates of conditional expected losses, a latent process that cannot be observed directly. While the analysis in Adams *et al.* (2014) is conducted on GARCH-type based estimates of the VaR process of US institutions, we rely on estimates of the Expected Shortfall (ES henceforth) process in our international sample. In the financial industry, VaR is an important measure because it is normally computed to meet regulatory capital. However, it has been widely criticized because it is not a coherent measure of risk (Artzner, Delbaen, Eber and Heath, 1999) and, more importantly, it may be completely insensitive to extreme, but infrequent market movements. In contrast, ES is a coherent risk measure that overcomes all these critiques. We proceed to estimate ES at the usual 1% shortfall probability using the expectile-based approach suggested by Taylor (2008a). Although other alternative estimation procedures are available, expectile-based modelling does not require specification of the underlying distribution of the data. This property is particularly appealing in the current context because it preserves the semi-parametric nature of the 2SQR methodology. As a result, the main conclusions from our analysis are not driven by any particular assumption concerning the formally unknown distribution of returns.

Our analysis provides specific insight into the degree of vulnerability of the banking industry in the main economic areas in a global context. While previous studies have shown the existence of tail-interconnections between individual banks and the global financial system (e.g., López-Espinosa *et al.* 2012), our analysis provides a complete picture of bilateral relationships that feature transmission channels. Consistent with the previous literature, the main results from our analysis suggest that the degree of interconnectedness and, hence, financial vulnerability, largely increases during periods of distress; see also King and Wadhwani (1990) and Ang, Chen and Xing (2006). For instance, under normal market conditions, a one percent increase in the expected losses in the US banking system increases the ES of core EMU banks by approximately 0.01 percentage points.

Under adverse market circumstances, however, the same shock increases the expected losses by nearly 0.072 percentage points. Similar results hold consistently on the remaining areas, showing that cross-border contagion increases systematically and significantly during periods of distress.

This study also reveals directionality in cross-border contagion. According to our estimates, the US banking sector is the greatest source of financial contagion in the financial industry. In a stressed scenario, the largest estimates of cross-country spillover coefficients are systematically related to this country. While previous literature in contagion agrees that shocks that originate in the US are larger and more persistent (Hamao *et al.,* 1990), and that the US is a major exporter of volatility in financial markets (Theodossiou and Lee, 1993), there are specific reasons that explain the systemic relevance of the US banking industry. The global vulnerability to the US stems from the fact that large-scale local banks with a specific weight in the local sector are typically internationally-diversified institutions for which, characteristically, a large portion of their foreign exposures and cross-border activities over total assets are held on US-issued financial instruments; see, among others, Weistroffer and Möbert (2010) and Degryse, Elahi and Penas (2010). Hence, write-downs can have a direct impact on the balance sheets of these banks, which are further transmitted to other domestic banks through the local network. As a result, most financial sectors are particularly vulnerable to idiosyncratic shocks originating either directly or indirectly in the US.

On the other hand, and in sharp contrast, the US banking system tends to show more financial resilience against foreign shocks. When compared to European banks, the characteristic business model in US banks is featured by a combination of low foreign lending to total assets ratio and low borrower concentration (Weistroffer and Möbert 2010). As a result, US banks use local lending more intensively than European banks and, simultaneously, their foreign lending activities are more diversified across different countries. While our analysis makes clear that the US banking sector is vulnerable to shocks in European countries (particularly, the UK) as well as emerging-market economies, this characteristic business model would make the system more resilient to these shocks. This evidence seems particularly relevant for central banks and international supervisors concerned with macroprudential policies to mitigate systemic risk, since low borrower concentration could be a determinant factor to limit the systemic importance of financial institutions. This issue merits attention in further research.

The remainder of this is chapter organized as follows. Section 4.2 introduces the methodology implemented to estimate ES and characterize risk spillovers through 2SQR. Section 4.3 presents the data and discusses the main stylized features. Section 4.4 discusses the estimation of the ES process on the data. Section 4.5 presents the main results from the 2SQR analysis. Finally, Section 4.6 summarizes and concludes.

4.2 Measuring tail interdependences

We start our analysis by introducing mathematical notation and technical definitions in order to characterize risk spillovers. Since our modelling approach relies mainly on the expectile-based methodology proposed by Taylor (2008a) to estimate ES, we first introduce this semi-parametric procedure. We then discuss the main features of the 2SQR methodology used to characterize tail spillovers in the global banking industry.

4.2.1 Estimating Expected Shortfall: an expectile-based approach

VaR, defined as the conditional quantile of the loss-function of a portfolio at a certain horizon, is a fundamental tool for downside-risk measurement and risk management in the financial industry. However, this statistic has been widely criticized because is not a coherent measure of risk. It is not sub-additive and, more importantly, is insensitive to the magnitude of extreme losses as it only accounts for their probability; see, among others, Artzner *et al.* (1999) and Acerbi and Tasche (2002). The ES, proposed by Artzner *et al.* (1999), constitutes a valid alternative to VaR which has gained increasing prominence.

Formally, ES is defined as the conditional expectation of the return of certain portfolio, r_t, when it exceeds the VaR threshold $VaR_t(\lambda)$ associated to a certain shortfall probability $\lambda \in (0,1)$, i.e.,

$$ES_t(\lambda) = E\left(r_t \mid r_t < VaR_t(\lambda)\right) \tag{4.1}$$

noticing that $VaR_t(\lambda)$ denotes the λ-quantile of the conditional distribution of r_t, i.e., it verifies $\Pr\left(r_t \leq VaR_t(\lambda) \mid \mathscr{F}_{t-1}\right) = \lambda$, where $\mathscr{F}_t$ is the set of available information up to time t.

The estimation of the ES process can be more demanding than VaR and typically requires explicit assumptions on the conditional distribution of the data; see McNeil, Frey and Embrechts (2005). Taylor (2008a) introduced a procedure based on the expectile theory developed by Aigner, Amemiya and Poirier (1976) and Newey and Powell (1987) that seems well suited for modelling both ES and VaR. The distinctive characteristic of this methodology is that it builds on estimates of the conditional dynamics of expectiles, a quantile-related statistic that can be related to ES. The main advantage of this procedure is that it yields estimates of the ES process without relying on a particular distribution; see Kuan, Yeh and Hsu (2009), and De Rossi and Harvey (2009) for related approaches. In the remainder of this subsection, we review the concept of expectiles and its connection with ES, introducing the procedure suggested by Taylor (2008a).

Let $\{y_t\}$, $t = 1, ..., T$, be a stochastic process with finite moments $E\left(|y_t|^{\kappa}\right)$ for some positive large enough κ. For ease of exposition, we assume that $\{y_t\}$ is a martingale difference sequence (MDS) such that $E\left(y_t \mid \mathscr{F}_{t-1}\right) = 0$. This assumption implies no loss of generality in practice, since we can consider the residuals from a demeaned process otherwise, as is customary in the literature devoted to downside risk modelling. For certain constant parameter $\theta \in (0,1)$, the population θ-

expectile can be defined as the minimizer of an asymmetrically-weighted sum of squared errors, namely,

$$\min_{m_\theta \in \mathbb{R}} \sum_{t=1}^{T} \left[\theta (y_t - m_\theta)^2 \mathbb{I}(y_t \geq m_\theta) + (1-\theta)(y_t - m_\theta)^2 \mathbb{I}(y_t < m_\theta)\right] \tag{4.2}$$

where $\mathbb{I}(\cdot)$ denotes the indicator function.[1] It is easy to see that when $\theta = 1/2$, the so-called Asymmetric Least-Squares (ALS) estimate of m_θ reduces to the sample mean. Therefore, in the same way in which quantiles generalize the median for $\theta \neq 1/2$ (in the sense that the θ-quantile specifies the position below which $100\theta\%$ of the probability mass of the random process Y lies), expectiles generalize the mean for $\theta \neq 1/2$. In particular, the expectile function (4.2) determines the value point such that $100\theta\%$ of the mean distance between this value and Y comes from the mass below it; see Yao and Tong (1996). Kuan *et al.* (2009) provide an additional economic interpretation for expectiles in a financial risk setting. According to these authors, m_θ can be seen as the ratio of expected margin shortfall to the expected total cost of the capital requirement and, hence, represents the relative cost of the expected margin shortfall in the derivative contracts framework.

Expression (4.2) can be generalized straightforwardly to allow for time-varying conditional dynamics, considering a measurable function, say $m(x_t;\beta_\theta)$, with x_t denoting a k-dimensional vector of covariates and β_θ a conformable vector of unknown parameters. Setting $m(x_t;\beta_\theta) = x_t'\beta_\theta$, Newey and Powell (1987) show the consistency and asymptotic normality under the i.i.d condition of the ALS estimator $\widehat{\beta}_\theta$, defined as the solution of

$$\min_{b \in \mathbb{R}^k} \sum_{t=1}^{T} \left[\theta\ u_t^2(b)\ \mathbb{I}(u_t(b) \geq 0) + (1-\theta) u_t^2(b)\ \mathbb{I}(u_t(b) < 0)\right] \tag{4.3}$$

with $u_t(b) := y_t - m(x_t;b)$. Kuan *et al.* (2009) generalize this setting, permitting stationary and weakly-dependent data under suitable regularity conditions.

As pointed out by Koenker (2005), linear conditional quantile functions in a location-scale setting imply linear conditional expectile functions, and so there is a convenient rescaling of the expectiles to obtain the quantiles and vice versa. The existence of a one-to-one mapping implies that the conditional θ-expectile is equivalent to the, say, λ_θ-quantile, where the latter is characterized by the probability with which observations would lie below the conditional expectile, noting that typically $\theta < \lambda_\theta$ for values in the lower tail (Efron 1991). Because any expectile is also a quantile, conditional expectile functions can be used to estimate VaR functions given a suitable choice of θ that ensures the desired λ-coverage level; see, for example, Taylor (2008a) and Kuan *et al.* (2009). The advantage of conditional expectile regressions over quantile regressions is that the ALS loss-function (4.3) is absolutely differentiable, so computing conditional expectiles is considerably

[1] Note the similitude between expectiles m_θ and quantiles, say q_θ, since the latter arise as the solution of the objective function $\min_{q_\theta} \sum_{t=1}^{T} \left[\theta |y_t - q_\theta|\ \mathbb{I}(y_t \geq q_\theta) + (1-\theta)|y_t - q_\theta|\ \mathbb{I}(y_t < q_\theta)\right]$.

simpler. More importantly, as shown by Newey and Powell (1987), the asymptotic covariance matrix of the parameters can be determined without estimation of the density function of the errors.

Newey and Powell (1987) and Taylor (2008a) discuss the theoretical relationship between expectiles and ES. In particular, for a MDS process, it follows that

$$ES_t(\lambda_\theta) = \left(1 + \frac{\theta}{(1-2\theta)\lambda_\theta}\right) m_t(\theta) \tag{4.4}$$

where the short-hand notation $m_t(\theta) := m(x_t; \beta_\theta)$ shall be conveniently used in the sequel to simplify notation. Hence, the ES at certain shortfall level λ_θ is proportional to the λ_θ-th empirical quantile, which in turn could be estimated as the θ-*th* conditional expectile. The fact that ES can be seen as a simple rescaling of a suitable expectile is not surprising since, as pointed out by Newey and Powell (1987), $m_t(\theta)$ is determined by the properties of the expectation of the random variable Y conditional on Y being in a tail of the distribution. Consequently, expression (4.4) allows us to generate estimates of the ES process without making any explicit assumption on the particular distribution of the data, only specifying the functional form that characterizes $m_t(\theta)$ as a function of (unknown) parameters. More generally, Yao and Tong (1996) have discussed non-parametric techniques to infer this process.

In the same spirit as the class of non-linear quantile models introduced by Engle and Manganelli (2004), Taylor (2008a) considers a non-linear autoregressive-type specification for the conditional expectile function. In this class of models, $m_t(\theta)$ varies smoothly over time and depends on the lagged values of the volatility process as proxied by $|y_t|$. For instance, the so-called Symmetric Absolute Value (SAV) model assumes

$$m_t(\theta) = \beta_0 + \beta_1 m_{t-1}(\theta) + \beta_2 |y_{t-1}| \tag{4.5}$$

which implies that the ES process is driven by

$$ES_t(\lambda_\theta) = \gamma_0 + \gamma_1 ES_{t-1}(\lambda_\theta) + \gamma_2 |y_{t-1}| \tag{4.6}$$

with $\gamma_1 = \beta_1$, and $\gamma_i = \beta_i \left[1 + \frac{\theta}{(1-2\theta)\lambda_\theta}\right]$, $i \in \{0, 2\}$.

This parametric specification is strongly reminiscent of the characteristic GARCH-type equation used to model the conditional variance of returns, widely known because of its parsimony and superior forecasting power in practice. In fact, if $\{y_t\}$ is an MDS with conditional volatility σ_t driven by the linear GARCH model of Taylor (1986) (namely, $\sigma_t = \omega_0 + \omega_1 \sigma_{t-1} + \omega_2 |r_{t-1}|$; $\omega_0 > 0$, $\omega_1, \omega_2 \geq 0$), then both the conditional quantile and the expectile functions are driven by SAV-type dynamics, and so is the ES process, although the contrary is not necessarily true. Because of the simplicity, we shall estimate ES using (4.6), noting that the main conclusions are not qualitatively different from other alternative specifications that involve further parameters such as asymmetric expectile-based model.

4.2.2 Two-stage quantile regression

Given the shortfall probability λ, let $ES^*_{it}(\lambda)$ $t = 1,...,T$, $i \in \mathscr{S}$, denote the estimates of the ES process related to the banking sector in the economic area i, with $\mathscr{S}$ representing a certain set of such areas. The superscript emphasizes that we build on feasible estimates of the unobservable latent process obtained, for instance, by applying the procedures described in the previous section. Recall that our main interest is to characterize the bilateral relationships that may arise contemporaneously between the tails of the conditional distributions of the domestic indices included in $\mathscr{S}$.

To this end, we may run a system of linear regressions. Thus, for any $i \in \mathscr{S}$, we may regress $ES^*_{it}(\lambda)$ on the estimates of the remaining ES processes in $\mathscr{S}$, possibly accounting for persistence through lags of the dependent variable, and additionally including a number of controlling variables, say $(z_{1t},...,z_{kt})'$. For instance, if we assume first-order autoregressive dynamics, our interest is to estimate the system of equations:

$$ES^*_{it}(\lambda) = \alpha_i + \phi_i ES^*_{it-1}(\lambda) + \sum_{\substack{s\in\mathscr{S} \\ s\neq i}} \delta_{i|s} ES^*_{st}(\lambda) + \sum_{l=1}^{k} \xi_{il} z_{lt} + \varepsilon_{it} \tag{4.7}$$

for all $i \in \mathscr{S}$, where ε_{it} is a random error term, and the parameters $\delta_{i|s}$ would capture the intensity of the tail spillover in portfolio i given portfolio s. Note that the analysis recognizes bidirectionality in tail spillovers, since it may generally follow that $\delta_{i|j} \neq \delta_{j|i}$, for any $i, j \in \mathscr{S}$, $i \neq j$.

In the estimation of this system, two important features should be noted. First, the size of the cross-border risk-spillover coefficients $\delta_{i|s}$ are likely to vary depending on the underlying economic conditions. During normal or tranquil periods, tail-interrelations may be of little or no economic importance, yet become largely significant in periods of financial distress, particularly when dealing with portfolios related to the banking industry; see, for instance, Adrian and Brunnermeier (2011), López-Espinosa *et al.* (2012). More importantly, the ES processes involved in (4.7) are generated simultaneously, so least-squares (LS) and other standard estimation procedures may not render consistent estimates in this context owing to endogeneity.

While a number of alternative procedures are possible, the 2SQR methodology implemented in Adams *et al.* (2014) overcomes both challenges in a simple and particularly tractable way. First, the procedure builds on the quantile-regression (QR) methodology at different quantiles $\tau \in (0,1)$ of the distribution of the left-hand side ES process in (4.7) to endogenously capture state-related effects on the coefficients $\delta_{i|s}$; see Koenker (2005) for an outstanding overview of the QR methodology.[2] Note that, while the shortfall probability λ that defines the ES process is fixed in our analysis (e.g.,

[2]The LS methodology is useful to characterize the conditional mean of the dependent variable in a (linear) regression given the set of regressors. When the series take values that depart from the center of the distribution, LS-based estimates may not capture accurately the underlying relationship between the dependent variable and the regressors, leading to misleading conclusions. When the main interest is to characterize the relationship during extreme or 'abnormal' periods, the quantile-regression methodology is better suited, as it is specifically intended to characterize parameters at any quantile of the conditional distribution of the data.

$\lambda = 0.01$), we can consider a sequence of quantiles $\{\tau_n\}$ that characterize the sample distribution of $ES^*_{it}(\lambda)$ to capture the effects of different economic scenarios on the coefficients $\delta_{i|s}$. Normal and tranquil periods would feature the upper tail of the conditional distribution of $ES^*_{it}(\lambda)$, whereas low percentiles in the left tail would be determined by the excess of volatility observed during periods of financial distress. Second, the 2SQR procedure uses the same estimating strategy as the well-known two-stage least squares (2SLS) in order to correct the endogeneity bias. In particular, the endogenous right-hand side variables, $ES^*_{st}(\lambda)$, are replaced with suitable predictions from ancillary equations based on (weakly) exogenous variables; see, Amemiya (1982), Powell (1983), and Kim and Muller (2004).

Consequently, in the spirit of Adams *et al.* (2014), we consider the system of quantile-regression equations

$$ES^*_{it}(\lambda) = \alpha_i(\tau) + \phi_i(\tau) ES^*_{it-1}(\lambda) + \sum_{\substack{s\in\mathscr{S}\\ s\neq i}} \delta_{i|s}(\tau) ES^*_{st}(\lambda) + \sum_{l=1}^{k} \xi_{il}(\tau) z_{lt} + \varepsilon_{it} \tag{4.8}$$

for all $i \in \mathscr{S}$, and estimate the parameters involved in these equations using the 2SQR procedure. Note that the size of all parameters may vary on the τ quantile. While we shall consider a broad range of quantiles $\tau \in [0.1, 0.9]$ in a general estimation of this equation system, for the sake of conciseness we shall report and discuss the results focusing on the *representative* quantiles $\tau = 0.15$, $\tau = 0.5$, and $\tau = 0.85$. These quantiles in the left, center, and right tail of the empirical distribution of $ES^*_{it}(\lambda)$ characterize the local banking sector during volatile (or excited), normal (or average), and tranquil (or low-volatile) periods, respectively.

The 2SQR methodology proceeds as follows. In the first stage, the right-hand side variables $ES^*_{st}(\lambda)$ that characterize the i equation in (4.8), $s \in \mathscr{S}$, $s \neq i$, are regressed on a set of instruments to generate predicted values, say $ES^{**}_{st}(\lambda)$, which are computed as the fitted values from LS instrumental estimation. Following standard practices, we take a constant and a number of lags from the right-hand side variables $ES^*_{st}(\lambda)$ as instruments. Note that, in order to ensure that the system is identified, the set of instruments does not include lags from the left-hand side variable, $ES^*_{it-l}(\lambda)$, $l \geq 1$; see Adams *et al.* (2014).[3]

In the second stage, the set of equations (4.8) are estimated individually using QR, treating the first-stage predicted values $ES^{**}_{st}(\lambda)$ as regressors. Under sufficient conditions, this procedure yields consistent and asympotically-normal distributed estimates of the main coefficients in (4.8); see, for instance, Powell (1983) and Kim and Muller (2004). The estimation of the covariance matrix in this context, however, may not be trivial, because it depends on a number of nuisance terms that characterize both the variability of the main parameter estimates in the main equation as

[3]This restriction implies that lags of the dependent variable only affect the ES of the i region. In other words, after controlling for contemporaneous spillovers from other areas, there is no additional spillover effect in a certain area related to the lagged values of the ES in other areas.

well as the parameter uncertainty stemming from the first-stage estimation. To deal with this issue, we implement a bootstrapping scheme based on the maximum entropy algorithm proposed in Vinod and López-de-Lacalle (2009); see also Chevapatrakul and Paez-Farrel (2014) for related work.

4.3 Data

The dataset used in this chapter is formed by daily continuously compounded returns from value-weighted portfolios representative of the local banking industry in different economic regions. The choice of portfolio data allows us to eliminate the idiosyncratic noise that may affect the main conclusions in a study on individual firms. The sample comprises the period from 31/12/1999 through 07/11/2013, with 3,596 daily observations. Data are directly available from Datastream, which provides closing prices of different banking-industry indices in the following economic regions: US, UK, Peripheral EMU area (PE), Core EMU area (CE), Scandinavia area (SC), the so-called BRICs area (BR), and Emerging Markets (EM). Together with this regions, we consider a Global Banking index (GB) to control for exposures to global shocks. All these indices are formed by the main banks which are publicly traded in the countries that make up the different economic areas. In turn, publicly-traded banks are usually bank-holding companies characterized by a representative size in the local industry, sophisticated business models, and intense cross-border activities. All these characteristics are commonly associated to systemic importance. As in other studies concerned with systemic risk in the global banking industry, returns are computed from prices denominated in US dollars; see López-Espinosa *et al.* (2012).

The PE index, referred to as PIIGS index in Datastream, is formed by the main banks in Greece, Ireland, Italy, Portugal, and Spain. The CE index includes the main banks in countries that belong to the EMU, but not to the PE area, namely, Austria, Belgium, Cyprus, Finland, France, Germany, Luxembourg, Malta, Netherlands, and Slovenia. Scandinavia is formed by banks based in Denmark, Finland, Norway, and Sweden. We distinguish between PE and CE because both areas are characterized by different macroeconomic drivers and because these areas exhibited a considerable heterogeneity in response to the systemic shocks. The Scandinavian countries and the UK have local currencies, which provides them with an invaluable tool to handle an adverse economic scenario through currency devaluation.[4] The BR index is formed by banks in the so-called BRIC area, namely, Brazil, China, India, and Russia. It represents a subarea of emerging economies that has undergone remarkably strong development over the recent years. The EM is a global banking index formed by 300 banks operating in emerging-market economies, mainly, Central and Eastern Europe, Asia, and Latin America. Similarly, the GB is an index representative of the global banking industry. It pools data from 536 banks around the world. Appendix B provides a list with the banks included in any of these areas.

[4]Note that the SC index includes Finland, a country in the EMU area. Nevertheless, this country contributes with two banks to the total index. In our view, this is unlikely to introduce any form of bias.

Table 4.1 reports the usual descriptive statistics on the returns of all these indices. Returns at the daily frequency exhibit the usual stylized features, such as time-varying volatility, skewness, and excess kurtosis. Analysis of the (annualized) mean and volatility reveals the consequences of the financial crises in the banking sector, particularly, in advanced economies. Returns in the banking industry of the US and EMU areas over the period analyzed are characterized by large levels of volatility –mainly, in the second half of the sample– and low average returns. More specifically, the annualized mean return is approximately zero in the US (0.09%), and negative in the CE (-3.50%) and the UK (-4.02%). Countries in the peripheral EMU area have suffered the consequences of the crises more intensely, and exhibit the lowest mean annualized return (-5.04%) in the sample. On the other hand, banks in emerging countries have shown more resilience to the global financial recession and the subsequent European sovereign debt crisis. The returns in emerging countries over the period are characterized by lower volatility levels and higher mean returns.[5]

Table 4.1: Descriptive statistics for daily returns of representative indices of the local banking-industry in different economic regions

Region	Mean_a	Median_a	Std._a	Min.	Max.	Skew.	Kurt.
US	0.0960	0.9463	32.4195	-0.1774	0.1602	0.0903	17.1664
BR	12.1923	25.9466	26.7714	-0.1062	0.1434	0.0154	9.7893
PE	-5.0453	4.4639	31.2875	-0.1061	0.1860	0.1738	10.0923
CE	-3.5099	12.0845	34.2854	-0.1338	0.1641	0.0716	9.9634
UK	-4.0268	12.0845	33.8417	-0.2161	0.1954	-0.1537	16.0296
SC	7.1017	4.6113	32.2620	-0.1462	0.1489	0.1792	10.6774
EM	8.2132	25.4218	20.4843	-0.0928	0.1130	-0.3839	10.9448
GB	0.9145	16.3191	20.5831	-0.0865	0.1244	-0.0792	16.0296

This table shows the main descriptive statistics for bank portfolio daily returns in the set of regions considered: US (United States), BR (BRICs), PE (Peripheral EMU), CE (Core EMU), UK (United Kingdom), SC (Scandinavia), EM (Emerging Markets), GB (Global Banking). Mean, median and standard deviation are computed by annualizing return data. Minimum, maximum, skewness, kurtosis and sample size are computed from daily return data.

4.4 Estimating Expected Shortfall

To estimate the ES process of the returns, we set $\lambda = 0.01$, the regulatory shortfall probability level required by Basel disposals and the most common choice in downside-risk analysis. The daily

[5] Some caution should be applied when comparing the mean-variance profile across these areas because of the influence of cross-country diverisfication. Whereas the US- and UK-related ones are country specific indices, the other series represent the banking industries in different countries, which introduces a certain level of diversification.

frequency is consistent with the holding period targeted for internal risk control by most financial firms; see, among others, Taylor (2008b). Consistent with standard procedures in downside-risk analysis, we compute ES on demeaned returns, $\widetilde{r}_t$, determined as the residuals from a first-order autoregression; see, for instance, Poon and Granger (2003). The ES processes are then estimated individually for any of the economic areas using the expectile-based model discussed in the previous section. In particular, given $\lambda = 0.01$, the latent conditional expectile in the i-th area is assumed to obey time-varying dynamics given by $m_{it}(\theta) = \beta_{i0} + \beta_{i1} m_{it-1}(\theta_i) + \beta_{i2} |\widetilde{r}_{it-1}|$, $t = 1, ..., T$. In the same spirit as Engle and Manganelli (2004), we initialize $m_{i0}(\theta_i)$ to the empirical θ_i-expectile based on the first 300 observations in the sample for each series. Giving θ_i, the unknown parameters $(\beta_{i0}, \beta_{i1}, \beta_{i2})'$ that characterize the time-varying dynamics of ES are determined as the numerical solution of the ALS problem (4.3). Following Efron (1991) and Taylor (2008a), $\widehat{\theta}_i$ is optimally determined as the value for which the proportion of in-sample observations lying below the conditional expectile, say $\widehat{\lambda}_{i,T}$, matches the shortfall probability $\lambda = 0.01$ that characterizes exceptions in the ES. To this end, we estimated the model for different values of this parameter, using the optimization procedure described in Engle and Manganelli (2004) and Taylor (2008a)[6], in a trial-and-error algorithm with stopping rule $|\lambda_i - \widehat{\lambda}_{i,T}| < 10^{-06}$. Note, therefore, that the estimates of $\zeta_i = (\beta_{i0}, \beta_{i1}, \beta_{i2}; \theta_i)'$ are determined simultaneously in this context, and the values ensure that the empirical coverage probability $\widehat{\lambda}_i$ is approximately 0.01.

Table 4.2 reports the ALS estimates for the different economic areas analyzed. Since the latent ES is a volatility-related process, the estimates of the ES are strongly persistent, with the autoregressive coefficient $\beta_1 = \gamma_1$ ranging from 0.69 (UK) to nearly 0.90 (PE). Similarly, absolute-valued returns, the most common proxy of volatility in practice, have a strong influence on ES.[7] On average, the value of the optimal expectile θ is 0.002, which as expected, is smaller than the target quantile, $\lambda = 0.01$. Table 4.2 also reports the p-values of several test statistics which are routinely implemented to backtest VaR-type forecasts. Since expectiles can be used to estimate VaR, as discussed previously, we can analyze if the resultant estimates provide a reasonable fitting to the data using backtesting procedures on the in-sample estimates $\widehat{m}_t(\theta)$, $t = 1, ..., T$. More specifically, we implement the unconditional coverage test by Kupiec (1995) and the conditional coverage test by Christoffersen (1998). The Kupiec test requires the empirical coverage $\widehat{\lambda}$ to be close enough to the nominal $\lambda = 0.01$. Since the optimal value of θ is chosen under the condition that $\widehat{\lambda}$ must match λ, correct conditional coverage is trivially ensured. The conditional tests by Christoffersen (1998) address simultaneously the hypotheses of correct unconditional coverage and first-order independence in the sequence of VaR exceptions. Table 4.2 shows massive p-values

[6] We randomly generate 1000 parameter vectors in order to evaluate the ALS loss-function. The ten vectors that produced the lowest values were then used as initial values in a Quasi-Newton algorithm. The estimates from the vector producing the lowest value in the loss-function is to be chosen as the final parameter vector.

[7] Note that the estimates of β_2 in the expectile-related equation (and, hence, γ_2 in the ES-related equation) are negative, reflecting that higher levels of volatility give rise to a greater ES. While it is costumary to report both VaR in ES in absolute levels (as it is understood that they refer to losses), we respect the negative sign that characterizes both downside-risk measures according to the definitions in Section 4.2.

associated to both test statistics. The overall evidence suggests that expectiles do not generate unreliable estimates for downside risk modelling; see also Taylor (2008a). [8]

Table 4.2: Expected Shortfall processes parameters estimation from the expectile-based SAV model in equations (4.5) and (4.6) for the set of analyzed regions

Region	β_{i0}	β_{i1}	β_{i2}	γ_{i2}	θ_i	$\hat{\lambda}_i$	pv_{TUC}	pv_{TI}	pv_{TCC}
US	-0.0010	0.8645	-0.3804	-0.4867	0.0028	0.0100	0.9947	0.3934	0.6948
BR	-0.0033	0.7952	-0.4080	-0.4809	0.0018	0.0100	0.9947	0.4001	0.6930
PE	-0.0009	0.8975	-0.2561	-0.3153	0.0023	0.0100	0.9947	0.3934	0.6948
CE	-0.0017	0.8507	-0.3757	-0.4304	0.0014	0.0100	0.9947	0.3757	0.6754
UK	-0.0034	0.6900	-0.8902	-1.0932	0.0023	0.0100	0.9947	0.3646	0.6545
SC	-0.0010	0.8874	-0.2897	-0.3557	0.0023	0.0100	0.9947	0.3934	0.6948
EM	-0.0022	0.8043	-0.4165	-0.5337	0.0028	0.0100	0.9947	0.3934	0.6948
GB	-0.0008	0.8815	-0.2849	-0.3487	0.0022	0.0100	0.9947	0.4001	0.6930

This table presents the ALS ES parameter estimation from the expectile-based SAV-model in the entire set of regions considered for equations (4.5) and (4.6) and the main backtesting tests. The last three columns present the p-value for TUC, TI and TCC that denote the results for Unconditional Coverage, Independence and Conditional Coverage test. ES are estimated from daily demeaned returns of bank indices.

Table 4.3 reports the usual descriptive statistics for the estimates of the expectile-based ES processes as well as the sample correlation between these series. The daily average ranges from -3.84%, for the emerging market index EM, to -6.24%, in UK, the country with the lowest daily return in the sample. These series show a considerable degree of dispersion, with minimum values that, for instance, reached -38.57% in the UK in March 2009. The analysis on sample correlations shows that extreme expected losses in the banking industry are largely correlated across different countries and economic areas, with correlations ranging from 51% (for the pair PE and BR) to 91% (for the pair PE and CE). This evidence suggests a considerable degree of commonality and the existence of global trends or common factors that propitiate systemic risk in the banking industry.[9]

Finally, Figure 4.1 shows the time-series of (demeaned) returns and the expectile-based estimates of the ES for each economic area in the sample. As expected, ES exhibit persistent time-varying dynamics characterized by massive bursts of volatility which are directly related to the events that characterized a backdrop of extreme volatility associated to the episodes of crises in the sample.

[8] We obtain similar conclusions using alternative ES models such asymmetric expectile-based model and different parametric specifications based on GARCH model volatility estimates.

[9] Several papers have exploited commonality to characterize systemic risk. For instance, Rodríguez-Moreno and Peña (2013), who use the first principal component in CDS spreads to measure systemic risk.

Table 4.3: Descriptive statistics and correlations for the estimates of the expectile-based Expected Shortfall processes from equation (4.6) for the set of analyzed regions

Panel A.- ES Descriptives Statistics							
Region	Mean	Median	Std.	Min.	Max.	Skew.	Kurt.
US	-0.0537	-0.0423	0.0377	-0.2563	-0.0155	-2.5469	10.5655
BR	-0.0462	-0.0429	0.0159	-0.1931	-0.0250	-3.6073	23.3516
PE	-0.0517	-0.0439	0.0245	-0.1804	-0.0198	-1.4161	5.2391
CE	-0.0544	-0.0455	0.0279	-0.1997	-0.0211	-1.8280	6.8485
UK	-0.0624	-0.0520	0.0382	-0.3857	-0.0178	-2.8131	14.9801
SC	-0.0533	-0.0440	0.0282	-0.1972	-0.0219	-2.2824	8.9210
EM	-0.0384	-0.0344	0.0151	-0.1802	-0.0197	-3.5055	22.7557
GB	-0.0337	-0.0296	0.0163	-0.1353	-0.0161	-2.4042	14.9801

Panel B.- ES Correlations								
Region	US	BR	PE	CE	UK	SC	EM	GB
US	1.00							
BR	0.65	1.00						
PE	0.66	0.52	1.00					
CE	0.77	0.64	0.91	1.00				
UK	0.82	0.65	0.71	0.82	1.00			
SC	0.85	0.67	0.84	0.91	0.83	1.00		
EM	0.70	0.87	0.62	0.72	0.71	0.76	1.00	
GB	0.91	0.77	0.80	0.90	0.86	0.93	0.83	1.00

Panel A presents the main descriptive statistics (mean, median, standard deviation, maximum, minimum, skewness and kurtosis) of the Expected Shortfall processes at the shortfall probability λ=0.01 for the daily demeaned returns banks portfolios corresponding to the whole set of regions considered. Panel B shows the cross correlations between the Expected Shortfall estimations.

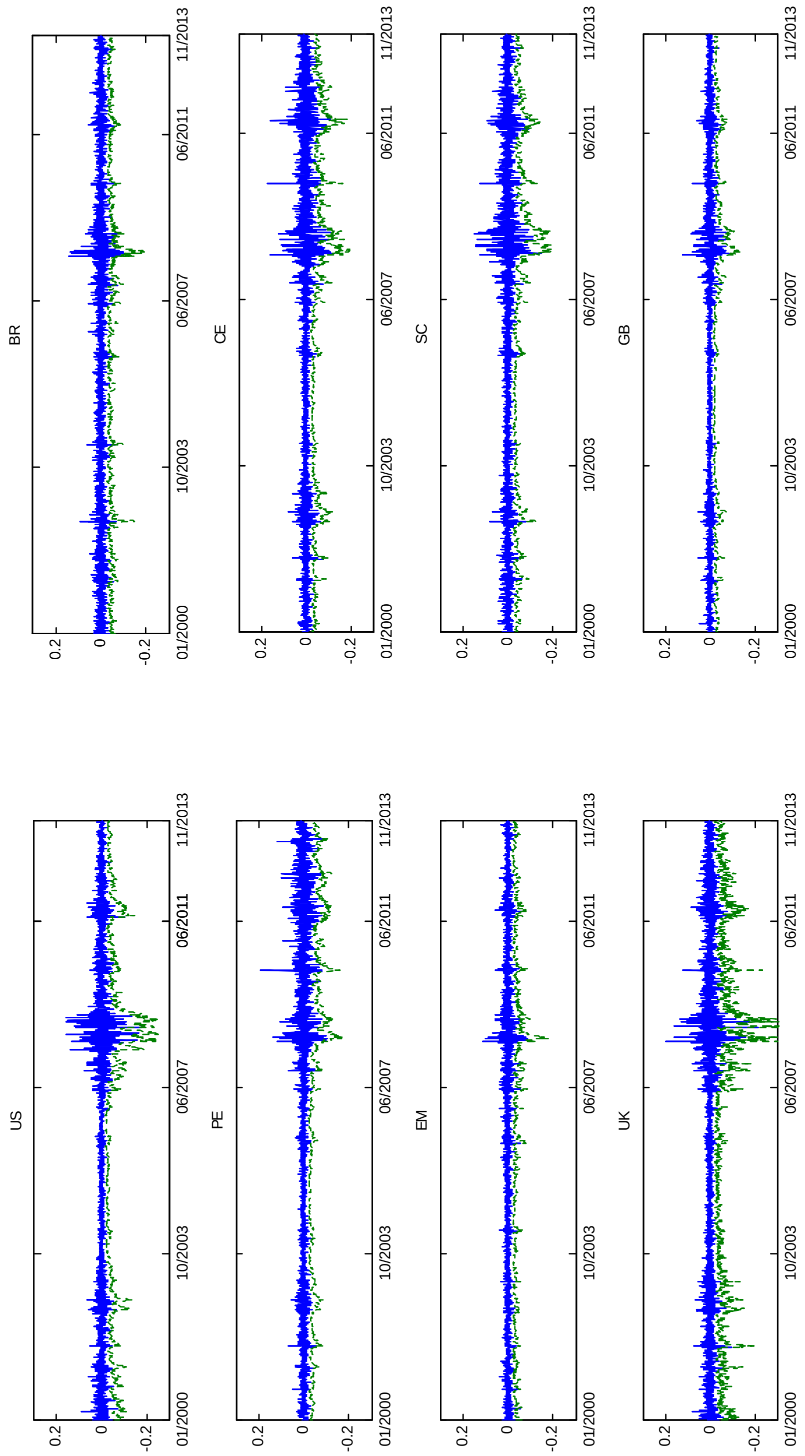


Figure 4.1: Time series for daily demeaned returns (solid blue line) and Expected Shortfall processes from expectile based model (dotted green line) in (4.6)

4.5 Risk spillovers in the global banking industry: 2SQR estimation

Given the expectile-based estimates, we now discuss the main results from 2SQR estimation. In the implementation of this methodology, we follow Adams *et al.* (2014) and estimate equation system (4.8), controlling for variables that may systematically affect the left-hand side variables. Because the banking industry is vulnerable to global trends, as discussed previously, we use the ES of the global banking index GB to capture the exposure of banks in domestic areas to this class of shocks. This ensures that the spillover coefficients $\delta_{i|s}$ that relates bank losses in two economic areas can be interpreted in a causal way, as they characterize vis-à-vis the cross-border transmission of downside risk once global-related effects are controlled for.[10] Furthermore, the inclusion of a global variables allows us to circumvent potential concerns related to neglected variables, for instance, associated to economic areas or individual countries which are not explicitly acknowledged in our analysis. The potential influence of all these areas is briefly resumed in the global index.

In addition, we consider two sets of economic regions. The first one focuses on tail interdependences in the US, peripheral and non-peripheral EMU countries, and emerging markets, namely, $\mathscr{S}_B = \{US, CE, PE, EM\}$. While this baseline set includes a reduced number of economic areas, these are of major global economic relevance and have been subject to considerable financial stress. This analysis allows us to present a detailed analysis, focused on the main interactions of this limited set. This discussion shall be completed later by considering an extended set which includes all the economic regions considered in this chapter, $\mathscr{S}_E = \{\mathscr{S}_B, UK, SC, BR\}$. This analysis not only provides a more complete picture, but also allows us to address whether conclusions are generally sensitive to the omission of potentially economic regions.

4.5.1 Basic equation system

4.5.1.1 Main results

Table 4.4 reports the parameter estimates from equation system (4.8) given the set of countries $\mathscr{S}_B = \{US, CE, PE, EM\}$, the shortfall probability $\lambda = 0.01$, and the representative quantiles $\tau \in \{0.15, 0.50, 0.85\}$ that characterize the underlying economic conditions in the local industry that receives the spillover. In this system, we allow the global banking index GB to have feedback effects with the areas in $\mathscr{S}_B$ by modelling in the same way, i.e., the full system is estimated with 5 equations. Our main interest is in the coefficients $\delta_{i|s}(\tau)$ and $\xi_i(\tau)$ in these equations. The former capture the contemporaneous response in the ES of the banking system in area i against a one percent

[10] In the literature of financial contagion, it is usual to distinguish between shock transmission through common channels, which affect multiple countries at the same time (e.g., through blanket withdrawals by common lenders), or through country-specific channels, which depend on variables that characterize country-specific financial and trade linkages. Our modelling approach implicitly captures both channels.

change in the ES of the banking system in area s. Similarly, the latter capture the exposure of the domestic banking system to systematic shocks in the global financial system. Statistical significance at the usual confidence levels is determined on the basis of maximum entropy bootstrap of Vinod and López-de-Lacalle (2009).

The estimates of $\xi_i(\tau)$ are positive and significant during normal periods ($\tau = 0.50$). This result shows that the conditional median of expected losses in the banking industry is driven by a global component, which essentially agrees with the correlation analysis discussed previously (see Table 4.3). For instance, the parameter estimates $\widehat{\xi}_{PE}$ and $\widehat{\xi}_{CE}$ in EMU areas show that, during normal market periods, a one percent shock in the ES in the global system will increase the average ES of banks in PE and CE by 0.036% and 0.017%, respectively. Clearly, the exposure to global shocks under normal market conditions tends to be smaller for economies with better macroeconomic fundamental (US and CE), while economies which traditionally have had greater inflation ratios and higher unemployment rates (PE and EM) are more vulnerable to systemic shocks.

The picture that emerges under the two extreme scenarios in the tails is different. During tranquil periods ($\tau = 0.85$), the estimates of the slope ξ are not significant in any of the areas except in the US.[11] Hence, the small bank losses that typically occur during calm periods tend to obey idiosyncratic patterns which, in general, are not related to other areas. On the other hand, during periods of financial distress ($\tau = 0.15$), the local vulnerability to global systematic shocks largely increases and becomes highly significant in all the areas. Note, for intance, that the relative ratio $\widehat{\xi}\,(0.15)\,/\widehat{\xi}\,(0.5)$ is 4.15 on average, showing a sizeable increment in the overall sensitivity. This ratio is particularly large (7.46) in non-peripheral EMU countries. According to Table 4.4, banks in the Eurozone are more vulnerable to global shocks under a stressed scenario than banks in other areas. This general pattern is fully evident in Figure 4.2, which shows the shapes of the estimated coefficient functions $\widehat{\xi}_i(\tau)$, $i \in \mathscr{S}_B$, as a function of the quantiles $\tau \in [0.10, 0.90]$. Clearly, banks in both peripheral and core EMU exhibit the largest vulnerabilities to global shocks under adverse market circumstances. The lack of a common regulatory setting and a banking supervisory system, as well as the absence of effective instruments to handle the consequences of a systemic crisis (e.g., the collapse of large-scale banks), have been pointed out as major weaknesses of the European financial industry. It was not until June 2012 when EU authorities committed to making decisive steps towards creating an effective Banking Union, adopting measures that, among others, will lead to the implementation of a single supervisory mechanism and a common bank resolution program.

The estimates of the autoregressive coefficient ϕ_i lie in the neighborhood of unit. This is expected because, as shown in the previous section (see Table 4.2), ES is a persistent process. Consistent with the evidence reported by Adams *et al.* (2014), these estimates are strictly smaller than unit during tranquil and normal periods, characterizing mean-reverting paths, and tend to be slightly greater than one during periods of distress, suggesting non-linear or explossive patterns.

[11]The coefficient remains positive and significant at the 95% confidence level. In contrast to other countries, the US shows significant links to the global system even during calm periods. This evidence is probably related to the importance and relative weight of the US banking system in the global financial system.

Table 4.4: Estimation of basic spillover system from expression (4.8) using the Expected Shortfall from expectile-based SAV model in (4.6) as a downside risk measure

	α_i	$\delta_{i\|s}$				ξ_i	ϕ_i
		US	PE	CE	EM	GB	
				τ=0.15 (Volatile)			
US	0.0013^b		0.0177^a	0.0613^a	0.0651^a	0.0475^a	1.0546^a
PE	0.0003	0.0469^a		0.0307^a	0.0323^a	0.1196^a	1.0469^a
CE	-0.0000	0.0722^a	0.0515^a		0.0233^b	0.1269^a	1.0354^a
EM	-0.0017^a	0.0430^a	0.0109^b	0.0397^a		0.0703^a	1.0161^a
GB	-0.0001	0.0415^a	-0.0006	0.0379^a	0.0286^a		0.9113^a
				τ=0.50 (Normal)			
US	0.0001		-0.0007	0.0113^a	0.0293^a	0.0185^b	0.9570^a
PE	-0.0010^a	0.0045^b		0.0247^a	0.0084^b	0.0363^a	0.9485^a
CE	-0.0007^a	0.0107^a	0.0264^a		0.0168^a	0.0170^b	0.9282^a
EM	-0.0024^a	0.0165^a	0.0094^a	0.0225^a		0.0214^a	0.8897^a
GB	-0.0005^a	0.0127^a	0.0065^a	0.0204^a	0.0236^a		0.8982^a
				τ=0.85 (Tranquil)			
US	-0.0008^a		0.0007	0.0098^b	0.0133^b	0.0369^b	0.8986^a
PE	-0.0011^a	0.0010		0.0168^a	-0.0005	-0.0052	0.9011^a
CE	-0.0015^a	0.0028	-0.0005		0.0155^b	-0.0083	0.8761^a
EM	-0.0024^a	0.0036^b	0.0003	0.0012		0.0001	0.8368^a
GB	-0.0009^a	0.0029^a	0.0042^c	0.0066^b	0.0046^c		0.8904^a

Spillover basic system coefficients estimation from (4.8) using the expectile-based SAV model in (4.6). The first column shows the constant estimation α for "i" region. The equations of each "i" region are in rows and the next four columns are the corresponding spillover coefficients $\delta_{i|s}$ (tail spillover in "i" region originated in "s" region). The last two columns present the results of the paramter estimates for control variable z_t and ES lag parameter ϕ for "i" region of the system respectively. The significances are detailed in each coefficient with the superscript text, a for 1%, b for 5% and c for 10%.

Although explosive patterns are often related to model misspecification, in our view this evidence is not particularly surprising in the current context. The dynamics of the 1% ES process during the more volatile days that characterize lower quantiles are distinctively driven by the largest outliers in the sample. An autoregressive coefficient equal to or greater than one is the only way in which an autoregressive process can accommodate the non-linear patterns which are usually associated with large volatility bursts that cause extreme market movements.

We now turn our attention to the coefficients $\delta_{i|s}$ that characterize cross-border tail contagion between different economic areas. Consistent with the hypothesis that the conditional tails of financial returns are prone to commove, the estimates $\widehat{\delta}_{i|s}$ are mostly positive and highly significant, particularly, in the excited state. Furthermore, and with regard to global shocks, the size of cross-country spillovers are characterized by state-dependencies that lead to a great deal of variability as a function of τ. In particular, cross-country spillovers are greater during periods of distress, but tend to weaken and eventually vanish during calm periods. This general pattern is fully evident in Figure 4.3, which shows the shapes of the estimated coefficient functions $\widehat{\delta}_{i|s}(\tau)$ for $\tau \in [0.10, 0.90]$. This figure and the estimates of Table 4.4 make clear that the severity of financial contagions under adverse conditions can be largely underestimated under normal market circumstances. Consequently, and as noted in Adams *et al.* (2014), standard analyses that merely focus on the conditional mean or the median analysis may lead to potentially misleading conclusions.

It is interesting to discuss the size of cross-border spillovers in the different banking systems as a response to a shock in a certain economic area, i.e., analyzing the coefficients reported by columns (second to sixth) in Table 4.4. For ease of exposition, we comment on the results in the most relevant context characterized by stressed conditions $(\tau = 0.15)$. Under these conditions, all the regions – including the global financial sector– become particularly sensitive to shocks in the US banking system. In particular, during periods of local stress, a one percent increase in the ES of US banks *directly* increases the local ES by 0.072% (CE), 0.043% (PE), and 0.041% (EM). US banks are the main contributors to the ES of the global financial system under stressed conditions, noting that a one percent increment in the expected losses of US bank increases the ES of the global financial system by 0.041%. The idiosyncratic shocks originated in a country are further amplified *indirectly* through the feedback effects caused by the network of cross-border exposures. For instance, every percentage point increase in the ES of the global system caused by the shock in the US is further transmitted into the local banking areas (including the US) with an intensity which ranges from 0.070% in emerging markets, to 0.127% in the CE.

Consequently, and according to the 2SQR estimates, the US banking system is the most important source of financial contagion in the sample. Idiosyncratic shocks originated in this country can affect all the other banking systems (particularly, those in European countries) which are under stressed conditions. The main reason for the global systemic importance of this country is that, when considering the international network of global cross-border exposures, the US banking system has a central and predominant position, since the remaining countries typically hold large portions of US-issued financial assets, particularly, European countries. For instance, according to the statistics elaborated by Degryse *et al.* (2010) on annual data from Bank for International Settlements (BIS) Consolidated Banking statistics on reporting countries in the period 1996-2006, the bank credits to the US represent, on average, 25%, 28%, and 30% of the total foreign credits held by Germany, France, and Netherlands on reporting countries, respectively. The same ratio ranges from 10% (Ireland) to 16% (Italy) in the PE area, showing a smaller exposition to the US. European banks kept large holdings of illiquid US dollar assets which were financed with short-term wholesale fundings and heavy reliance on cross-currency swaps; see McGuire and Von Peter (2009). When the market value of these claims collapsed as a consequence of the subprime crisis, European banks suffered massive losses, which were further amplified when the interbank and swap markets became impaired in 2008; see Acharya and Schnabl (2010). The estimates in our analysis successfully capture the sensitivity of EMU banks to the US and, furthermore, identify a greater sensitivity in the core EMU area, characterized by a greater reliance on US lending.

The analysis of the spillover coefficients related to the PE banking system shows that the shocks originated in this area –mainly associated to the European sovereign debt crisis– essentially had a more local nature than those originated in the early stages of US subprime crisis. The system with the largest vulnerability to shocks in the PE area is the one formed by the remaining banks in the EMU area. The main economies in CE keep large holdings of debt issued by European peripheral countries. Note, in Figure 3, that the exposure of CE to PE is highly significant for a large range of percentiles τ but, once more, the interdependence seems stronger in the low quantiles that characterized stressed conditions. In particular, for $\tau = 0.15$, the average response of expected losses of CE banks against a one percent shock in the ES of PE is 0.051%. In contrast, banks in the US and emerging-market economies exhibit weaker exposures to this area. For instance, the spillover coefficient of US on PE is 0.017. Although this coefficient is statistically significant, it seems of little economic relevance. In a similar vein, the exposure of the global banking system to the PE area is not significant. This evidence suggests that idiosyncratic shocks originating as a consequence of the European sovereign debt crisis in peripheral Europe did not affect the remaining banking systems systematically.

On the other hand, the systemic exposures of international banks to banks in the core EMU area are much more important and largely significant in all cases. Among the different areas considered, the US banking sector, with a tail spillover coefficient of 0.061, is the most vulnerable country to shocks originating in the CE. This sensitivity is nearly twice as big as that in the remaining areas. The reason underlying the vulnerability of US banks to CE banks relative to PE banks can be related to the existence of strong bilateral borrowing activities between these areas. According to Degryse *et al.* (2010), the aggregate claims on the reporting countries in the CE area (Austria, Belgium, Finland, France, Germany and Netherlands) represent around 34% of the total foreign claims held by US. Among these countries, Germany is the largest borrower, representing 17% of the foreign bank credits issued by the US. In contrast, Italy, Portugal and Spain together represent 6% of foreign claims in the US system. Note that although the *direct* exposure of US to PE is relatively moderate (the estimated spillover coefficient is 0.017), as discussed previously, the network of cross-border interconnections within the EMU defines a powerful *indirect* channel of contagion through the CE such that idiosyncratic shocks originated in peripheral EMU countries could spread to CE and, from here, to other economic areas, particularly, the US.

Finally, the 2SQR estimates reveal that, under adverse market conditions, the banking sectors in the US and the Eurozone are sensitive to shocks in emerging-market economies. Over the last decades, emerging-market economies have evolved from being peripheral players to become systemically important trade and financial centers (IMF, 2011a). Financial linkages between advanced and emerging economies are now stronger and as a result advanced economies are more exposed to the latter group. In the years preceding the global recession, the bigger banks of these areas increased their participation in emerging markets through local affiliates, which resulted in increased networks of bilateral exposures; see Tressel (2010). Financial exposures to emerging markets are mainly concentrated in foreign bank claims (IMF, 2014). According to our analysis, the exposure to emerging-market risk spillovers varies in importance across the three different regions analyzed, with the US being the banking sector with the largest vulnerability. The size of the US spillover coefficient is 0.065, which nearly doubles the size of the two EMU countries.

The relative sensitivity of the US economy to emerging-country economies poses a serious threat that has been recently outlined by an International Monetary Fund report. This report estimates that a current drop of one percentage point in emerging-market GDP could hit US GDP by around a fifth of a percentage point; see IMF (2014). This estimate is, nevertheless, conservative, as it does not account for direct financial spillovers through the financial sector. As their own report remarks, if risk premiums react further to the growth shock –due to balance-sheet exposures of financial intermediaries– financial channels would come into play and the size of the spillover in the real economy could be larger. Indeed, the analysis in this chapter reveals the existence of financial channels that can introduce contagion in advanced economies from shocks in emerging economies under adverse market conditions.

Figure 4.2: Estimated coefficients functions $\xi_i(\tau)$ from system (4.8) for a range value of quantiles $\tau \in [0.1, 0.9]$. The graph shows the influence of the global index on the remaining areas

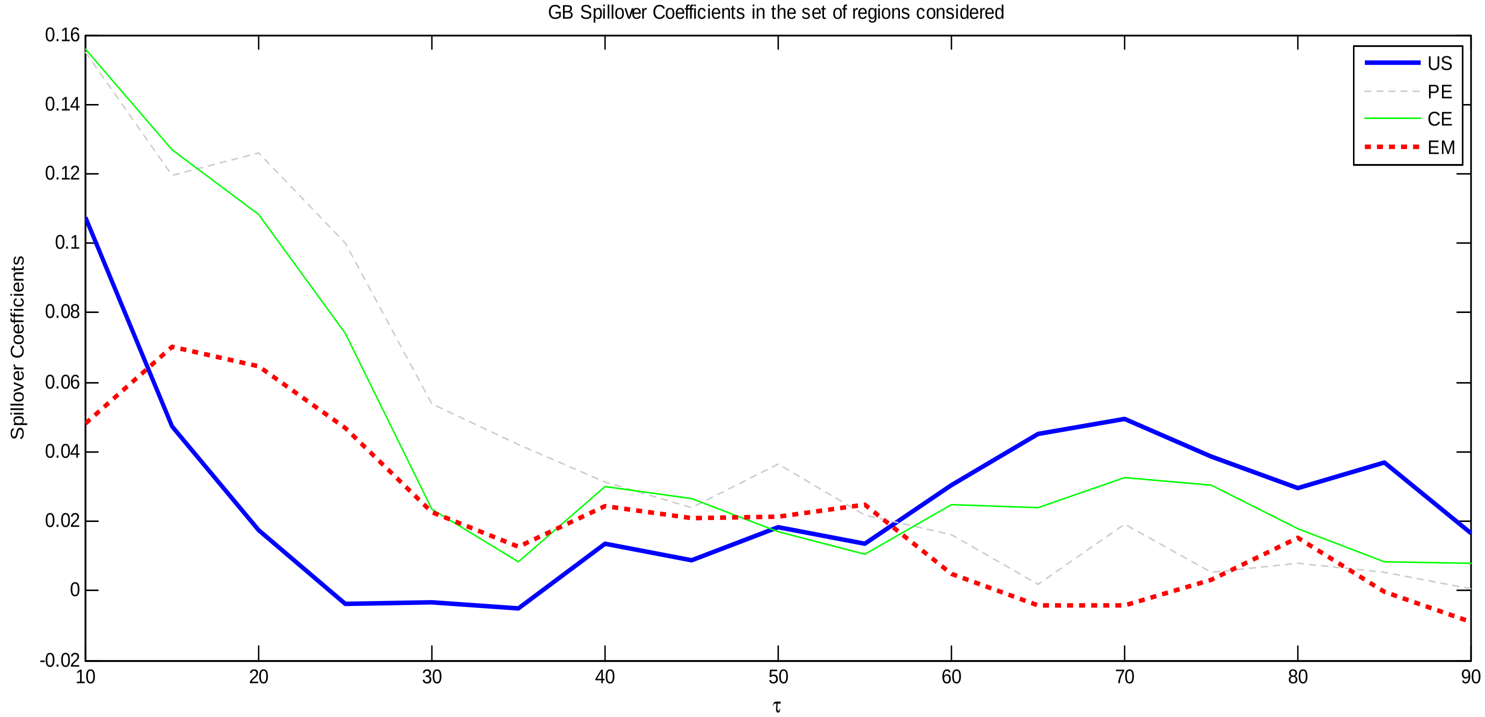
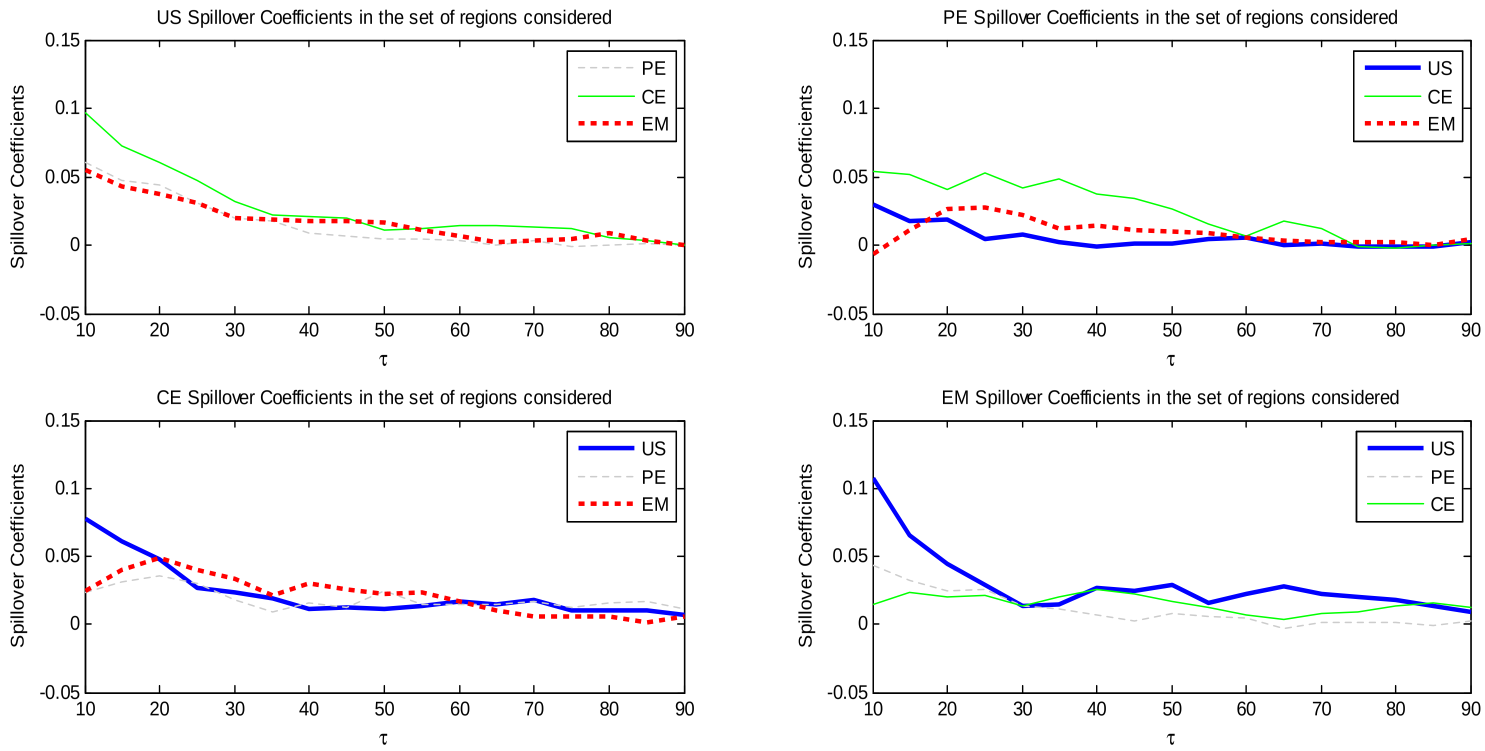


Figure 4.3: Estimated coefficients functions $\delta_{i|s}(\tau)$ from system (4.8) for a range value of quantiles $\tau \in [0.1,0.9]$. Left-upper graph shows the influence of the US on the remaining areas; right-upper graph presents the influence of PE to the other regions; left-lower graph depicts the sensibility of the remaining areas to CE. Finally, right-lower graph shows the influence of EM to the other regions



4.5.1.2 Expected duration of risk spillovers

Given the estimates of the equation system (4.8), we can characterize the expected duration of a shock through the Impulse Response Function (IRF) analysis. We adopt the same identification strategy as Adams *et al.* (2014), orthogonalizing IRF using the standard Cholesky decomposition, and ordering the shock transmitting variable last, since there is no theoretical guidance for a priori ordering. Note that this implies that a shock on the ES of certain region at time t will only affect this region at that time, spreading to the remaining areas in the following periods. Although this approach may lead to conservative IRF (which, consequently, can be regarded as the smallest estimated response given a shock), the main benefit is that it is not necessary to impose a potentially ad-hoc ordering because all economies are treated equally; see Adams *et al.* (2014) for details. As usual in this literature, we assume a unit shock of one standard deviation.

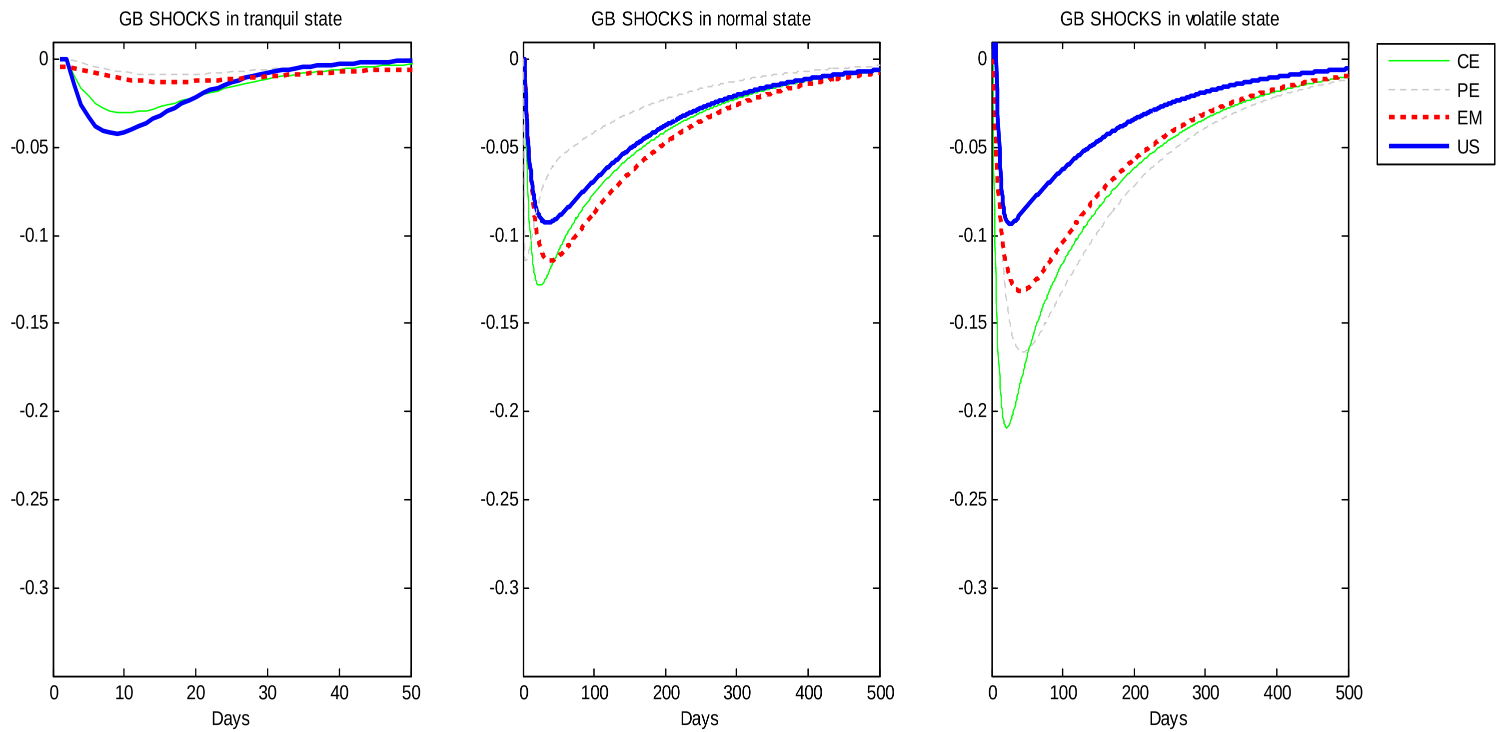
Figure 4.4 depicts the time-profile of the IRFs, characterizing the reaction of the domestic banking sector in each economic region in $\mathscr{S}_B$ against a unit shock in the ES of the global financial system. We consider tranquil, normal, and volatile market conditions. In this context, the size the immediate response depends on the spillover coefficients $\xi_i(\tau)$, whereas the persistence that characterizes the IRF depends on the size of these coefficients and the autoregressive coefficients $\phi_i(\tau)$. As expected from the analysis reported in the previous section, the IRF characterize heterogenous responses across the economic regimes analyzed. In particular, during tranquil periods, a systematic shock in the global financial industry tends to cause minor or no significant impact in the domestic areas, being quickly absorbed by the local systems. Under normal market conditions, however, systematic shocks trigger a more pronounced response in the local areas which, furthermore, tend to last over a considerably larger period of time. On average, a one-standard-deviation shock in the global system increases the domestic ES in absolute terms in an amount which ranges from 9.27% (US) to 12.81% (CE) of the size of the shock. The half-life of the IRF, defined as the number of periods required for the IRF to dissipate the response to a unit shock by half, ranges from 45 days (PE) to 130 days (EM). Nevertheless, the IRFs are strongly persistent, and it takes around 400 days to dissipate completely the effect of the shock.[12] While the shock seems to cause a greater impact on CE, the overall response under normal circumstances is very similar in all the areas analyzed.

In a stressed scenario, the overall reaction against systematic shocks in the global banking industry is more pronounced. Furthermore, the differences across countries are now much more evident. In particular, the most vulnerable area to systematic shocks is the Eurozone. The peaks of the IRFs in CE and PE lead to spillovers of about 20.91% and 16.64% of the size of the global shock. These represent substantial increments in the size of the spillover with respect to the normal

[12] We are not aware of any other paper characterizing the IRF of the expected shortfall process. However, previous literature has characterized IRF to address volatility spillovers in different markets. The papers dealing with contagion in financial and commodity market show strongly persistent IRFs in which it takes considerable time (between two and four years of trading days) for volatility to revert completely after a large shock; see, for instance, Panopoulou and Pantelidis (2009) and Jin, Lin and Tamvakis (2012).

scenario, particularly, in the CE area, although we stress that estimates should be regarded as potentially conservative in our approach. Interestingly, while the immediate response to a global shock is greater in CE, the IRF of PE decays at a slower rate, suggesting that the effects of a systematic shock in that area tend to remain significant over an extended period. Indeed, the half-life in the CE and PE areas is 87 and 133 days, respectively. On the other hand, systematic shocks cause a more moderate response in emerging-market economies, particularly, in the US, for which the peak of the IRF of US is located at 9.32% the size of the unit shock. Clearly, the IRF of the US is dominated by the remaining IRFs, suggesting that, broadly speaking, the US banking system has a stronger resilience to global shocks. This empirical evidence essentially agrees with the simulation-based results shown in Degryse *et al.* (2010). This chapter provides further evidence using a formal econometric approach.

Figure 4.4: Impulse response functions of the domestic banking sector in each economic region against Global Banking shocks for tranquil, normal and volatile state of the economy from basic system (4.8) estimation



Figures 4.5 to 4.7 show the IRFs that characterize the response of banks in each economic region in $\mathscr{S}_B$ against an (idiosyncratic) unit shock in each of the remaining areas under the three economic scenarios analyzed. In the stressed scenario, the long-term persistence of a shock would be characterized by explosive patterns (see Table 4.4), implying that ES becomes more and more negative in the long-term. In practice, however, the extreme outliers that give rise to non-linearities and bursts of volatility in low quantiles only occur during very short periods of time. Consequently, we adopt the same approach as Adams *et al.* (2014), and assume that, although a shock occurs under stressed conditions (which characterize the size of the spillovers at the time of the shock), long-term persistence is better characterized by the estimates under the a normal state. We, therefore, assume in the characterization of the IRF that the market returns to normal state coefficients after the day of the shock.

The main picture that emerges under country-specific idiosyncratic shocks is completely similar to that discussed under systematic shocks, showing large differences in both the intensity and the duration of contagion across the different economic scenarios. In particular, foreign shocks trigger a larger cross-country response in the expected losses of local banks in a stressed scenario in the domestic economy. For ease of exposition, we briefly discuss the main results for this scenario, as it poses the most relevant case. The largest response against a country-specific idiosyncratic shock is triggered by the US, which causes the ES of CE banks to increase in absolute terms about 20.9% the size of the standard shock. The half-life of the spillover in this area is 93 days. Nevertheless, the IRF exhibits a considerable persistence characterized by a low-decay to zero, and it takes over 500 days to completely remove the effects of the shock. In addition, the CE banking area is very sensitive to idosyncratic shocks originating in the PE area. A unit shock in peripheral EMU countries leads the ES of banks in the remaining EMU countries to increase the size of this shock by about 14.75% as a consequence of cross-border contagion. Persistence, as measured by the half-life, is 107 days. Shocks initiated in the PE area trigger a smaller response in the US (11.78%) with a shorter half-life (97 days). According to these estimates, the US is more sensitive to the other regions, since shocks in the CE and EM area increase the ES in the US banking system in about 15.2% and 14.5% the size of this shock, respectively, with half-lives of 95 and 109 days, respectively.

Figure 4.5: Impulse response functions of banks in each economic region against shocks in each area for basic system (4.8) from volatile state of economy

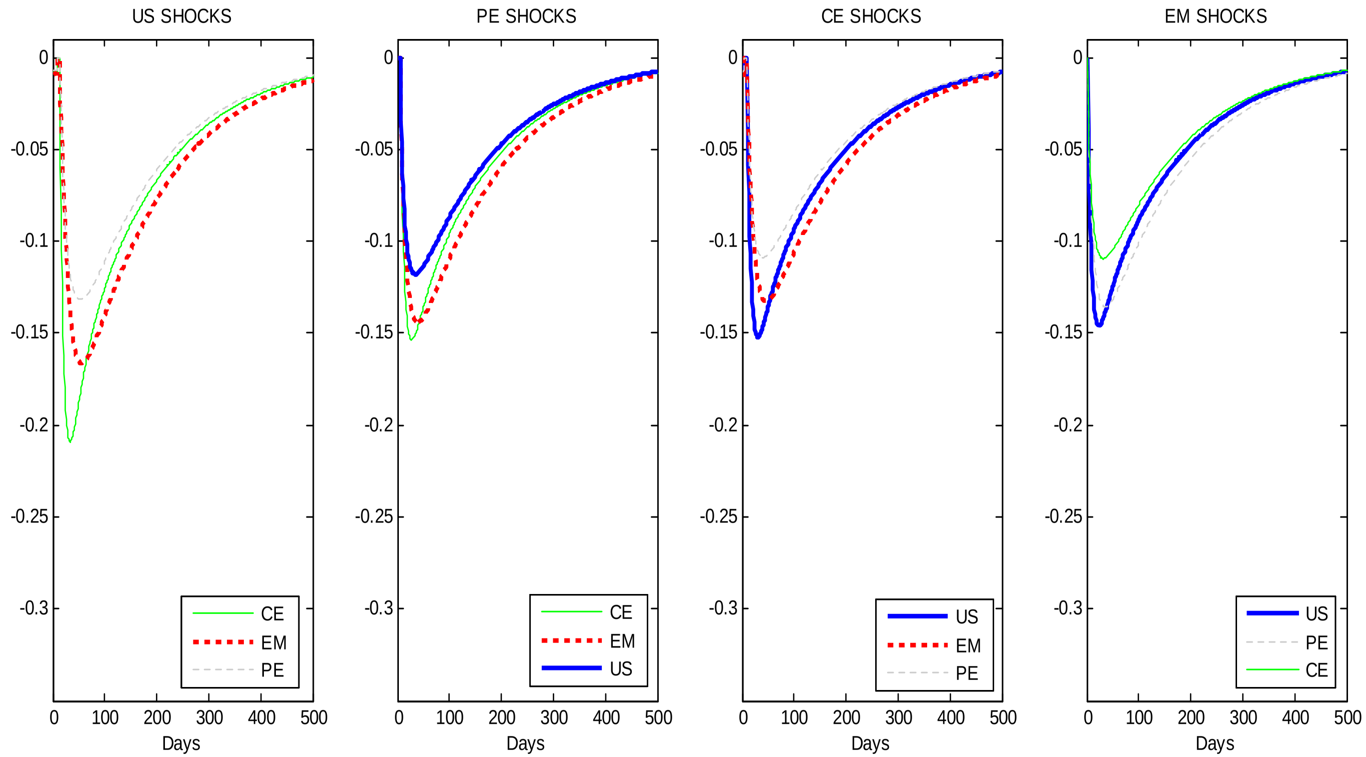


Figure 4.6: Impulse response functions of banks in each economic region against shocks in each area for basic system (4.8) from normal state of economy

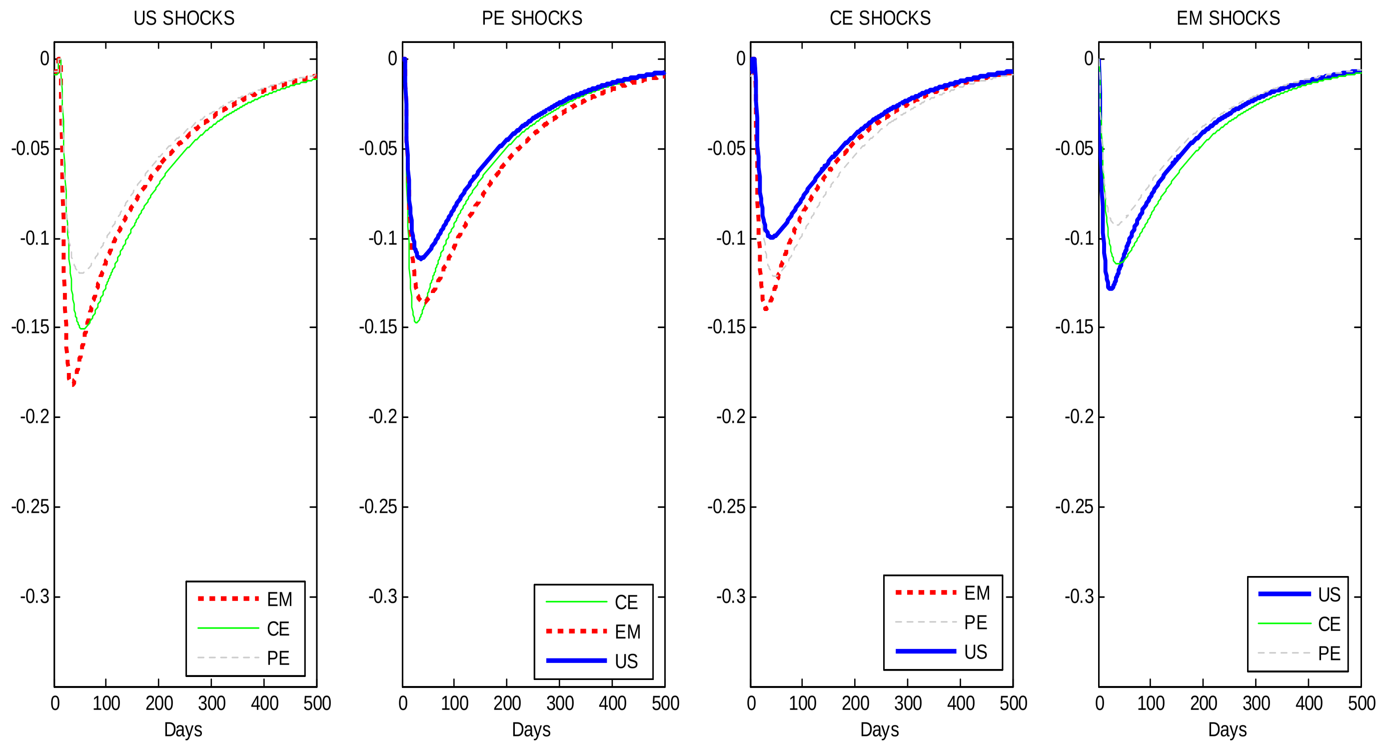
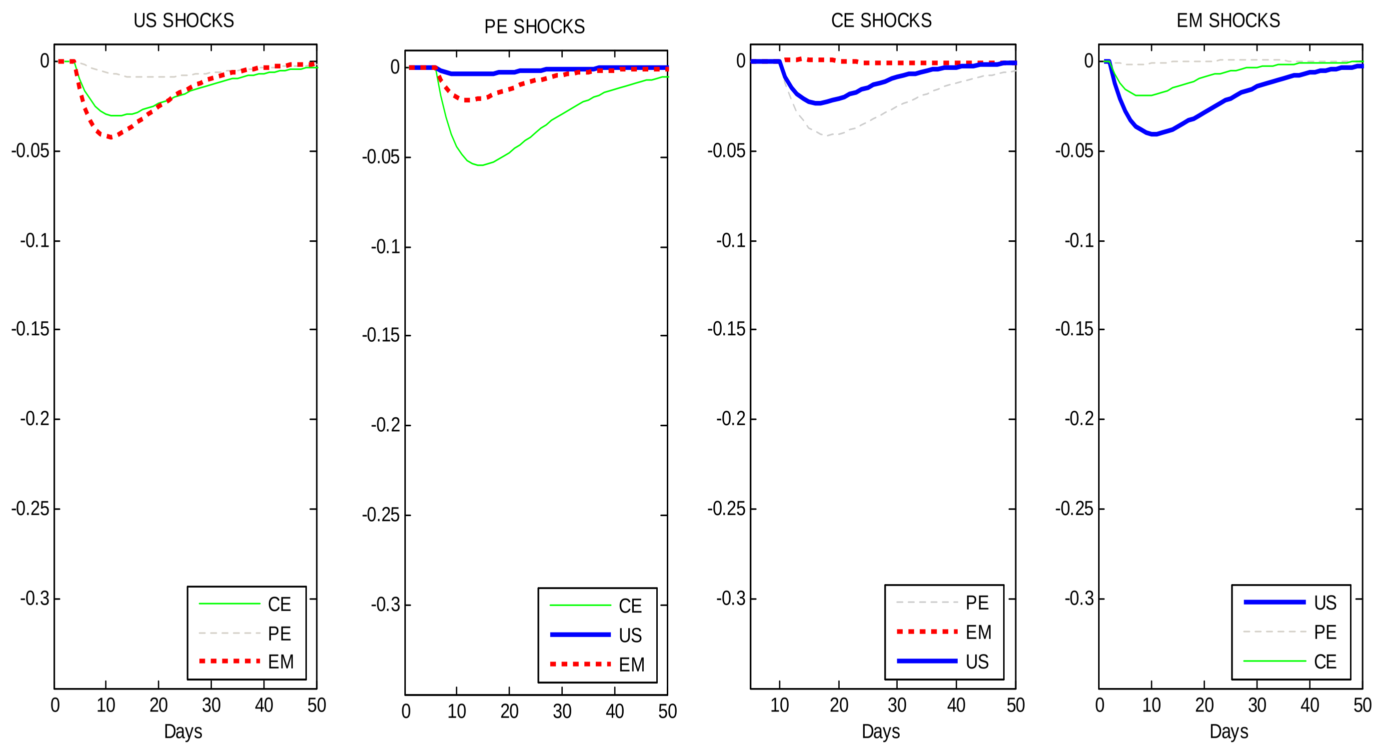


Figure 4.7: Impulse response functions of banks in each economic region against shocks in each area for basic system (4.8) from tranquil state of economy



4.5.2 Extended equation system

In this section, we discuss the main results from the analysis based on an extended set of economic areas. Together with the areas in $\mathscr{S}_B$, we consider the banking sectors in the UK, Scandinavian countries, and the BRICs subset of emerging-market economies. This analysis offers a more complete picture and, furthemore, offers us insight into the robustness of the overall conclusions to omitted variables. As we discuss below, adding new representative countries (UK) or new economic regions in both advanced and emerging areas (BR and SC) does not lead to any significant change in the main conclusions. From a robustness perspective, this result is important because it shows that the global index is able to control for the effects of omitted areas in the analysis.

Parameter estimates from the 2SQR estimation of the extended equation system and bootstrapped significance through the maximum-entropy algorithm are presented in Table 4.5. The overall analysis of the parameter estimates leads to the same conclusions discussed previously. Cross-country exposures largely increase and become highly significant in both economic and statistical terms during periods of distress. Financial vulnerabilities show a considerable degree of heterogeneity across the different areas involved, which can be related to the network of bilateral exposures that characterize international diversification in these areas. Since none of the main conclusions discussed previously change, we discuss directly the evidence related to the new areas included in the analysis, focusing particularly on the UK.

While all the economic areas exhibit significant exposures to US shocks in stressed conditions, the most vulnerable financial system to idiosyncratic shocks originating in this area is the UK. According to the 2SQR estimates, a one percent change in the expected losses of US increases expected losses in UK banks by 0.324 percentage points. While it is a well-known fact that the US and UK stock markets show strong similarities (Shiller, 1989), the ultimate reason for this remarked sensitivity in the banking-industry may be related to the fact that US-issued claims account for the largest portion of total foreign holdings within the UK banking system. According to Degryse *et al.* (2010), US claims represent, on average, about 52% of the total foreign claims held by the UK over BIS reporting countries. More generally, since large-scale banks in the UK have engaged actively in international diversification since late 1990, the British system shows large relative vulnerabilities to any of the remaining areas, particularly, the CE. The vulnerability to this area is characterized by a contemporaneous spillover coefficient of 0.119. Not surprisingly, therefore, the UK financial system turns out to be the most vulnerable area to global shocks in the sample, exhibiting a global spillover coefficient ξ of 0.224. Note that the size of this coefficient nearly doubles the size of the estimated coefficients in the European regions. Finally, regarding the vulnerability of other economic areas to shocks originating in the UK financial system, the US exhibits the largest tail spillover coefficient (0.054). This is not surprising, in the light that the UK represents about 30% of US-held foreign liabilities in other advanced economies (Degryse *et al.,* 2010). Once more, this result underlines the importance of cross-border diversification in defining the strength of financial contagion across international areas.

Table 4.5: Estimation of extended spillover system from expression (4.8) using Expected Shortfall from expectile-based SAV model in (4.6) as a downside risk measure. See details in Table 4.4

	α_i	$\delta_{i\|s}$							ξ_i	ϕ_i
		US	BR	PE	CE	UK	SC	EM	GL	
τ=0.15 (Volatile)										
US	0.0013^c		0.0175^c	0.0273^a	0.0357^a	0.0544^a	0.0380^a	0.0671^a	0.0998^a	1.0369^a
BR	-0.0041^a	0.0288^a		0.0369^a	0.0274^b	0.0185^a	0.0092^b	0.0056^a	0.0113	0.9431^a
PE	0.0005	0.0440^a	0.0132^c		0.0367^a	-0.0012	0.0048	0.0242^b	0.1257^a	1.0417^a
CE	0.0000	0.0746^a	-0.0013	0.0524^a		0.0067^c	0.0017	0.0262^b	0.1221^a	1.0344^a
UK	-0.0004	0.3240^a	0.0636^a	0.0433^a	0.1199^a		0.0748^b	0.0331^b	0.2245^a	0.7600^a
SC	0.0001	0.0532^a	0.0132^a	0.0015	0.0596^a	-0.0060		0.0594^a	0.0821^a	0.9881^a
EM	-0.0025^a	0.0425^a	0.0311^a	0.0243^a	0.0290^a	-0.0057	0.0426^a		0.0745^a	1.0186^a
GB	0.0003	0.0443^a	0.0175^b	0.0027	0.0337^a	0.0125^a	0.0168^a	0.0217^a		0.9003^a
τ=0.50 (Normal)										
US	0.0001		0.0187^a	-0.0005	0.0119^b	0.0110^b	-0.0033	0.0110^b	0.0370^a	0.9560^a
BR	-0.0034^a	0.0031		0.0168^a	0.0186^a	0.0004	0.0078^a	0.0170^a	0.0095	0.8618^a
PE	-0.0009^a	0.0052^b	0.0052^a		0.0135^a	0.0042^c	0.0175^a	0.0027	0.0396^a	0.9501^a
CE	-0.0004^a	0.0112^a	0.0229^a	0.0297^a		0.0039	0.0080^a	0.0005	0.0344^b	0.9218^a
UK	-0.0013^a	0.0948^a	0.0272^a	0.0235^a	0.0502^a		0.0310^a	0.0498^a	0.0519^c	0.7371^a
SC	-0.0009^a	0.0139^a	0.0197^a	0.0056	0.0028	0.0117^a		0.0171^a	-0.0033	0.9371^a
EM	-0.0025^a	0.0148^a	0.0058^b	0.0128^a	0.0216^a	-0.0028	0.0149^a		0.0280^a	0.8913^a
GB	-0.0003^a	0.0100^a	0.0098^a	0.0057^a	0.0164^a	0.0053^a	0.0064^a	0.0164^a		0.8870^a
τ=0.85 (Tranquil)										
US	-0.0007^a		0.0071	-0.0004	0.0033	0.0091^b	0.0122^b	0.0041	0.0458^a	0.8936^a
BR	-0.0040^a	0.0067^b		0.0046^c	0.0094^b	0.0001	-0.0038	-0.0001	-0.0117	0.8163^a
PE	-0.0010^a	0.0015	0.0014		0.0166^a	-0.0002	-0.0007	-0.0017	-0.0053	0.9017^a
CE	-0.0015^a	0.0053^c	0.0067	0.0023		-0.0011	-0.0113	0.0131^c	-0.0057	0.8788^a
UK	-0.0027^a	0.0271^a	0.0240^b	0.0109^c	0.0050		-0.0078	0.0326^b	0.0348^b	0.7153^a
SC	-0.0015^a	0.0075^b	0.0095^a	-0.0044	0.0085^b	0.0052^b		0.0007^b	0.0192^a	0.9026^a
EM	-0.0024^a	0.0052^b	0.0011	-0.0010	0.0035	-0.0020^c	0.0020^c		-0.0058	0.8368^a
GB	-0.0009^a	0.0029^a	0.0033	-0.0026	0.0049^b	0.0033^b	-0.0016	0.0020		0.8863^a

4.6 Concluding Remarks

We investigate size, direction and persistence of tail risk spillover in the banking sector for international regions by applying the state dependent system developed in Adams *et al.* (2014). The main evidence states that cross-country exposures largely increase and become highly significant in both economic and statistical terms during periods of distress. Financial vulnerabilities show a considerable degree of heterogeneity across the different areas involved, which can be related to the network of bilateral exposures that characterize international diversification in these areas. We obtain strong spillover effects from the US market to the rest of the regions considered, specially to Core Europe and UK. This result implies that downside movements in values of banks index returns caused increase in the contagion from US market to Europe due to the strong bilateral borrowing activities between these areas.

The impulse response analysis shows large differences in both the intensity and the duration of contagion across the different economic scenarios. In particular, foreign shocks trigger a larger cross-country response in the expected losses of local banks in a stressed scenario in the domestic economy. The largest response against a country-specific idiosyncratic shock is triggered by the US. The most vulnerable area to systematic shocks is Europe in stressed scenario and US banking system has stronger resilience to global shocks. The empirical results show that not only does a volatility spillover exist but there is also an important spillover effects in bank returns distribution tails that still remain an unexplored area in spillover research.

The results of this chapter are of particular interest for both policy makers and investors. The latter can improve their hedging and portfolio diversification strategies exploiting the knowledge regarding the way the financial markets influence one another. For policy makers an understanding of financial contagion would clearly be beneficial, providing them useful information about the formulation of possible decoupling strategies to insulate the economy from contagious effects and thus avoiding future spreading of crises and preserving the stability of the financial system.

Chapter 5

Conclusiones

En este capítulo se enumeran las principales conclusiones derivadas de los tres artículos que componen la tesis resumiendo así los principales resultados obtenidos.

En el Capítulo 2 se analiza la predictibilidad de la cola de la distribución condicional de los rendimientos de diferentes carteras de mercado representativas de Estados Unidos utilizando información más allá del propio rendimiento. El uso del modelo CAViaR para modelizar el Valor en Riesgo (VeR) nos permite analizar el efecto de variables diferentes al rendimiento relacionadas con liquidez a través de regresiones predictivas y *backtesting* dentro y fuera de muestra. Esta metodología nos permite estudiar la habilidad predictiva de una serie de modelos extendidos para el cálculo de *downside risk* con diferentes variables comparándolos con modelos que solo usan la información de los rendimientos.

La evidencia empírica mostrada sugiere que la medida de VeR puede ser mejorada usando variables de liquidez y volumen de forma que se puedan incorporar informaciones diferentes a las del rendimiento para obtener mejores predicciones. Los modelos construidos bajo esta idea cumplen con las reglas de SEC y mejorarían las metodologías de VeR existentes. Los resultados muestran como variables relacionadas con volumen son buenas predictoras para carteras diversificadas como la cartera de mercado de pequeña capitalización mientras que las variables de liquidez parecen predecir mejor la cola de las carteras ponderadas por valor. Se extienden pues los modelos CAViaR propuestos por Engle y Manganelli (2004) y se complementan resultados previos de la literatura.

El análisis también está relacionado con la literatura de microestructura de mercado en cuanto a la relación entre variables de mercado y movimientos en los precios. La principal hipótesis se centra en que la liquidez y las condiciones de negociación pueden ayudar a predecir movimientos en la cola de las distribuciones. Se podría ampliar el estudio usando datos intradiarios y diseñar así controles de riesgo más eficientes basados en las predicciones intradiarias. De esta forma, mientras que la literatura se centra en modelos de volatilidad estándar, la evidencia mostrada en este capítulo sugiere que los modelos basados en regresión de cuantiles pueden ofrecer un mejor desempeño.

Una de las extensiones naturales del trabajo de este capítulo sería analizar el máximo horizonte al que se puede explotar la información condicional para predicciones de *downside risk*. Tal y como argumentan Christoffersen y Diebold (2000), el riesgo depende del horizonte considerado, de manera que se pueden considerar la relevancia de utilizar diferentes horizontes para predicción de VeR. Sin embargo, no encontramos apenas en la literatura análisis sobre la habilidad de predicción del VaR para diferentes horizontes.

De la misma forma, sería interesante para futuras investigaciones, modelizar también otras medidas de *downside risk*, como por ejemplo el *Expected Shortfall* con modelos autorregresivos similares al CAViaR que estimen la media condicional. A este respecto, Taylor (2008a) propone diferentes modelos para estimar esta medida con modelos autoregresivos usando expectiles. A la vista de la evidencia mostrada en este capítulos, sería interesante poder extender estas nuevas medidas de riesgo con variables de liquidez y volumen con el fin de mejorar su desempeño en la predicción de riesgo.

En el Capítulo 3 se analizan las fuentes de las discrepancias entre los precios observados y teóricos a partir de diferentes modelos de valoración en el mercado soberano de CDS de países del G20. El objetivo es analizar si los errores de valoración contienen información relevante acerca del mercado de CDS. La metodología se basa en la medición de la volatilidad de los errores a través de una medida llamada *Noise* que capta la dispersión entre el precio observado y teórico. En concreto, mediante una simple transformación de la distancia euclídea, obtenemos una medida de *distress* de mercado similar a la utilizada por Hu *et al.* (2013) para el mercado de bonos soberanos de Estados Unidos. Los resultados muestran que los errores de valoración pueden estar relacionados con deficiencias en los modelos, así como también, por la existencia de fricciones en el mercado. La principal evidencia muestra que, tanto el modelo de Pan y Singleton (2008) como el semi-paramétrico de Nelson y Siegel (1987) y una estimación simple de la curva de la probabilidad de insolvencia, dan lugar a errores altos en momentos de *distress*.

Mediante la metodología de datos de panel, obtenemos que los errores de valoración están relacionados con la iliquidez o la volatilidad del mercado (variables como *bid ask spread,* volumen neto negociado, *default* de mercado o volatilidad de acciones de mercado) y tienden a ser más elevados cuando las condiciones de mercado son más inestables. Esta evidencia apoya la tesis de la medida de *Noise* de Hu *et al.* (2013) como medida de *distress* y liquidez del mercado la cual aumenta conforme el capital de arbitraje disminuye causando discrepancias entre los precios observados y teóricos. Este resultado es importante para los inversores con propósitos de cobertura o especulativos ya que las decisiones basadas en modelos de un solo factor pueden subestimar el riesgo en estos mercados. También es importante para reguladores y supervisores para anticipar posibles crisis financieras a través de las expectativas del mercado de CDS. Los spread de CDS contienen información sobre expectativas del mercado más allá de las condiciones de crédito. De esta forma, la severidad de las condiciones de mercado puede ser sobreestimada en momentos de distress ya que los precios de transacciones no se corresponden con los teóricos sobre todo en momentos de crisis. La ausencia de capital de arbitraje y otras ineficiencias asociadas con periodos volátiles podrían llevar a incrementos en el riesgo de iliquidez que se pueden traducir en errores de valoración más altos.

Finalmente, en el Capítulo 4, se investigan los efectos de contagio en las colas de la distribución condicional de rendimientos de diferentes índices bancarios internacionales utilizando la metodología basada en regresión de cuantiles propuesta por Adams *et al.* (2014). Esta metodología llamada *State Dependent State* (SDS), nos permite analizar los efectos de contagio dependiendo del estado de la economía al calcular cuantiles sobre medidas de *downside risk* como el *Expected Shortfall* en lugar de analizar el contagio a partir de la media o la volatilidad de los rendimientos. Se obtiene que los contagios en las colas de las distribuciones son más elevados y más significativos en momentos volátiles y de gran inestabilidad financiera. La región que lidera los contagios al resto de las regiones es Estados Unidos sobre todo hacia Reino Unido y Europa central, si bien se muestra evidencia de contagios bidireccionales entre todas las regiones consideradas en periodos de inestabilidad en el mercado, siendo US la región con mayor resistencia ante shocks en el resto de regiones.

A la vista de la evidencia mostrada en el Capítulo 4, no solo existe contagio en volatilidades sino que también existe contagio en las colas de la distribución de los rendimientos bancarios en momentos de inestabilidad financiera. Los resultados son particularmente interesantes tanto para inversores como para los responsables de política monetaria ya que, los primeros, pueden aprovechar este resultados en sus estrategias de diversificación y cobertura y los segundos pueden establecer estrategias de desacople para poder aislar a las economías de los efectos de contagio y poder evitar así las consecuencias de crisis futuras y preservar la estabilidad financiera del sistema. En futuras investigaciones sería interesante aplicar esta metodología a otros mercados y utilizar otras medidas de *downside risk* alternativas que capten el riesgo financiero de manera más eficiente.

En conclusión, los tres capítulos de esta tesis pretenden dar respuesta a nuevas necesidades en las áreas de modelización de *downside risk*, errores de valoración y contagio financiero puestas de manifiesto a partir de diferentes episodios de crisis financiera. En primer lugar, variables relacionadas con la liquidez y la actividad negociadora, nos pueden ayudar a mejorar la capacidad predictiva de los modelos de riesgo existentes en el mercado de acciones en momentos de inestabilidad financiera. En segundo lugar, se muestra evidencia de que la liquidez en el mercado de crédito tiene poder explicativo y predictivo sobre los errores de modelos de valoración y podría ser clave en el proceso de formación de precios de este nuevo producto derivado surgido durante la reciente crisis financiera. En tercer y último lugar, las medidas de contagio financiero en las colas de la distribución de los rendimientos bancarios son sensibles al estado de la economía en cuanto a tamaño, persistencia y dirección, resultado que nos ayuda a entender mejor las conexiones en el sector bancario de diferentes regiones internacionales y poder de esta forma protegerlas frente a futuras crisis.[1]

[1]Las conclusiones se presentan en castellano para cumplir con los requerimientos normativos de la Universidad de Castilla la Mancha. No obstante, al final de cada capítulo, se resumen en inglés las principales conclusiones.

Appendix A

Alternative VaR Models

In Section 2.4.2 we compare the relative performance of several CAViaR models with respect to standard alternative VaR models which are based solely on returns, including the EWMA, GARCH and EVT methods. The common setting in these parametric models assumes that returns obey dynamics given by

$$r_t = \sigma_t \eta_t, \quad \eta_t | \mathscr{F}_{t-1} \sim iid(0,1) \tag{A.1}$$

where σ_t denotes the conditional volatility of the process. We briefly discuss the main settings of these approaches in the sequel.

A. VaR EWMA

RiskMetrics popularized the EWMA procedure as an easy way to model the volatility process. The latent volatility dynamics are assumed to obey the recursive dynamics:

$$\sigma_t^2 = \varphi \ \sigma_{t-1}^2 + (1-\varphi) r_{t-1}^2, \ \ t = 1, ..., T \tag{A.2}$$

with the initial condition $\sigma_0^2 = r_0^2 = E\left(r_t^2\right)$. The smoothing parameter $0 < \varphi < 1$ can be estimated, although RiskMetrics advises the setting $\varphi = 0.95$ for data recorded on a daily basis. Then, the one-day ahead forecast given $\mathscr{F}_T$ is simply $\widehat{\sigma}_{T+1|T}^2 = \varphi \ \sigma_T^2 + (1-\varphi) r_T^2$.

RiskMetrics assumes the particularly strong assumption that the innovations η_t are conditionally normal distributed. The one-period ahead VaR forecast is then given by $-\mathscr{Z}_\lambda \widehat{\sigma}_{T+1|T}$, with $\mathscr{Z}_\lambda$ denoting the λ-quantile of the standard normal distribution. To ensure robustness against Gaussian departures, we proceed in a slightly different way. Let $\widehat{\eta}_t = r_t / \widehat{\sigma}_t$ be the estimated innovations given the EWMA estimates, and let $Q_{\widehat{\eta}_t}(\lambda)$ be the unconditional λ-quantile of the empirical distribution of $\widehat{\eta}_t$. Then, a more robust VaR forecast that does not rely upon distributional assumption is given by:

$$VaR_{\lambda,t+1} = -Q_{\widehat{\eta}_t}(\lambda) \widehat{\sigma}_{T+1|T} \tag{A.3}$$

noting that, as long as the model is correctly specified, $Q_{\widehat{\eta}_t}(\lambda)$ is a consistent estimator of $Q_{\eta_t}(\lambda)$.

B. VaR GARCH

The simplest GARCH (1,1) model is the most popular approach to model and forecast market risk in practice due to its impressive performance and statistical properties (Hansen and Lunde, 2005). The standard GARCH(1,1) model assumes that daily returns obey dynamics given by:

$$\begin{aligned} r_t &= \sigma_t \eta_t, \quad \eta_t | \mathscr{F}_{t-1} \sim iid\mathscr{N}(0,1) \\ \sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \end{aligned} \tag{A.4}$$

with $\omega > 0$, α, $\beta \geq 0$ ensuring that the $\left\{\sigma_t^2\right\}$ process is well-defined. Although daily returns are known to be non-normally distributed, the Gaussian assumption is particularly convenient because it ensures parameter consistency under certain regularity conditions even in the absence of normality. Parameters can thus be estimated by (quasi) maximum likelihood estimation, yielding a consistent estimate of the conditional variance process. The day-ahead forecast is then computed as:

$$\widehat{\sigma}_{T+1|T}^2 = \widehat{\omega} + \widehat{\alpha} r_T^2 + \widehat{\beta}\ \widehat{\sigma}_T^2 \tag{A.5}$$

given the resultant estimates. Then, paralleling the EWMA approach, given the GARCH estimates $\widehat{\sigma}_t$ and the resultant standardized innovations, $\widehat{\eta}_t = r_t / \widehat{\sigma}_t$, the robust day-ahead GARCH forecast is determined as:

$$VaR_{\lambda,T+1} = -Q_{\widehat{\eta}_t}(\lambda)\widehat{\sigma}_{T+1|T}. \tag{A.6}$$

given $(A.5)$ and the corresponding GARCH estimates $\widehat{\eta}_t$ and $Q_{\widehat{\eta}_t}(\lambda)$.

C. VaR Extreme Value Theory

This method can be seen as a parametric refinement of the previous approaches. Essentially, the procedure requires the characterization of the tail behavior of the set of i.i.d. innovations η_t in the return process. To circumvent the problem that η_t is not observable directly, the estimated residuals $\widehat{\eta}_t = r_t / \widehat{\sigma}_t$ can be used instead, with $\widehat{\sigma}_t$ determined according to some volatility model. Since GARCH estimates tend to outperform any other procedure, we estimate the empirical process $\widehat{\eta}_t$ on the basis of the GARCH(1,1) model.

The rest of the procedure is described as follows. Given the series $-\widehat{\eta}_t$, the total sample period is divided into, say, $B = 740$ blocks of length $l = 5$ observations to record the maximum value of each block (*i.e.,* the maximum loss in the period), say m_b, $b = 1,...,B$, in a time-series process. The Extreme Value Theory suggests fitting the Generalized Extreme Value distribution (GEV, also known as Fisher–Tippett distribution) to this series. The GEV arises as the limit distribution of properly normalized maxima of a sequence of i.i.d. random variables, and is characterized by the density function

$$f(z;\rho_1,\rho_2,\rho_3) = \left[\frac{1}{\rho_2}[1+\rho_3 z]\right]^{-1-1/\rho_3} \exp\left\{-[1+\rho_3 z]^{-1/\rho_3}\right\} \tag{A.7}$$

if $z > -1$, where $z = (m_b - \rho_1)/\rho_2$ denotes the standardized variable. The (unknown) parameters that characterize the shape (ρ_1), scale (ρ_2) and location (ρ_3) of the distribution can then be estimated consistently by different methods, such as maximum-likelihood. The importance of this approach is that by inverting this distribution (with the unknown parameters replaced by their consistent estimates), we can go from the asymptotic GEV distribution of maxima to the distribution of the observations themselves and obtain a closed-form expression for the unconditional VaR of $\widehat{\eta}_t$ given λ, namely,

$$Q_{\widehat{\eta}_t}(\lambda) = \widehat{\rho}_3 - \frac{\widehat{\rho}_2}{\widehat{\rho}_1}\left[1 - \left\{-\log\left(1 - \frac{1}{\lambda l}\right)\right\}^{-\widehat{\rho}_1}\right] \tag{A.8}$$

Finally, as in the EWMA and GARCH approaches, we generate the one-day ahead VaR forecast as

$$VaR_{\lambda,T+1} = -Q_{\widehat{\eta}_t}(\lambda)\widehat{\sigma}_{T+1|T} \tag{A.9}$$

with $\widehat{\sigma}_{T+1|T}$ determined from (A.5).

Appendix B

Bank Index details

In Section 4.3 we describe the dataset formed by international banking portfolios. This appendix contains several tables that report the banks and countries that form the representative indices of the local banking-industry in different economic regions such as the US, BRICs, Peripheral EMU, Core EMU, Scandinavia, the UK, Emerging Markets and the Global Banking index. This information is available in Datastream for the DS Banks Index construction of each region. We report the banks and countries for specific regional and country indices. In order to save space, we report the main areas and number of banks in emerging and global indices. Complete lists are available upon request.

Therefore, the following tables provide a list with the banks and countries or areas included in every index.

Table B.1: United States Index.

Table B.2: BRICS Index.

Table B.3: Peripheral EMU Index.

Table B.4: Core EMU Index.

Table B.5: United Kingdom Index.

Table B.6: Scandinavia Index.

Table B.7: Emerging Markets Index.

Table B.8: Global Banking Index

Table B.1: Banks included in the United States Index

Bank	**Country**
Bank of America	US
Bankunited	US
BB&T	US
Bok Financial	US
Citigroup	US
City National	US
Comerica	US
Commerce Bancshares	US
Credicorp	US
Cullen Frost Bankers	US
East West Bancorp	US
Fifth Third Bancorp	US
First Niagara Financial Group	US
First Republic Bank	US
Firstmerit	US
Hudson City Bancorp	US
Huntington Bancshares	US
JP Morgan Chase and Company	US
Keycorp	US
M&T Bank	US
New York Community Bancorp	US
Peoples United Financial	US
PNC Financial Services Group	US
Prosperity Bancshares	US
Regions Financial New	US
Signature Bank	US
Suntrust Banks	US
SVB Financial Group	US
Synovus Financial	US
TFS Financial	US
United States Bancorp	US
Wells Fargo and Company	US
Zions Bancorporation	US

Table B.2: Banks and countries included in the BRICs Index

Bank	Country
Banco Brasil On	Brazil
Bradesco On	Brazil
Bradesco PN	Brazil
Itauunibanco On	Brazil
Itauunibanco PN	Brazil
Santander Bearer On	Brazil
Santander Bearer PN	Brazil
Agricultural Bank of China 'H'	China
Bank of China 'H'	China
Bank of Communications 'H'	China
China Citic Bank 'H'	China
China Construction Bank 'H'	China
China Everbright Bank 'H'	China
China Merchants Bank 'H'	China
China Minsheng Banking 'H'	China
Industrial and Commercial Bank of China 'H'	China
Allahabad Bank	India
Axis Bank	India
Bank of Baroda	India
Bank of India	India
Canara Bank	India
Central Bank of India	India
Corporation Bank	India
Federal Bank	India
HDFC Bank	India
I N G Vysya Bank	India
Icici Bank	India
Idbi Bank	India
Indian Bank	India
Indian Overseas Bank	India
Indusind Bank	India
Jammu and Kashmir Bank	India
Oriental Bank of Commerce	India
Punjab National Bank	India
State Bank of India	India
Syndicate Bank	India
UCO Bank	India
Union Bank of India	India
Yes Bank	India
Moscow Municipal Bank Moscow	Russian Federation
Mosobl Bank	Russian Federation
Rosbank	Russian Federation
Sberbank of Russia	Russian Federation
Sberbank Russia Preference	Russian Federation
VTB Bank	Russian Federation

Table B.3: Banks and countries included in the Peripheral EMU Index

Bank	Country
Alpha Bank	Greece
Attica Bank	Greece
Bank of Greece	Greece
Bank of Piraeus	Greece
Eurobank Ergasias	Greece
General Bank of Greece	Greece
National Bank of Greece	Greece
Bank of Ireland	Ireland
Banca Carige	Italy
Banca Finnat Euramerica	Italy
Banca Monte dei Paschi	Italy
Banca Piccolo Credito Valtell	Italy
Banca Popolare di Milano	Italy
Banca Popolare di Sondrio	Italy
Banca Popolare Emilia Romagna	Italy
Banca Popolare Etruria Lazio	Italy
Banca Profilo	Italy
Banco di Desio E Della Brianza	Italy
Banco Popolare	Italy
Credito Bergamasco	Italy
Credito Emiliano	Italy
Intesa Sanpaolo	Italy
Intesa Sanpaolo RSP	Italy
Mediobanca Banca di Credito Financial	Italy
Unicredit	Italy
Unione di Banche Italian	Italy
Banco BPI	Portugal
Banco Comercial Portugues 'R'	Portugal
Banco Espirito Santo	Portugal
Banif	Portugal
Montepio	Portugal
Banco Bilbao Vizcaya Argentaria	Spain
Banco de Sabadell	Spain
Banco Intercontinental Espanol 'R'	Spain
Banco Popular Espanol	Spain
Banco Santander	Spain
Bankia	Spain
Caixabank	Spain
Liberbank	Spain

Table B.4: Banks and countries included in the Core EMU Index

Bank	**Country**
Bank FUR Tirol und Vorarlberg	Austria
Banks Bank	Austria
Erste Group Bank	Austria
Oberbank	Austria
Oberbank Preference	Austria
Raiffeisen Bank International	Austria
Banque Nationale de Belgique	Belgium
KBC Ancora	Belgium
KBC Group	Belgium
Hellenic Bank	Cyprus
USB Bank	Cyprus
Aktia 'A'	Finland
Pohjola Pankki A	Finland
Banque Nationale de Paris Paribas	France
CIC 'A'	France
Crcam Nord de France CCI	France
Credit Agricole	France
Credit Agricole Brie Picardie	France
Credit Agricole Ile de France	France
Credit Foncier de Monaco	France
Natixis	France
Societe Generale	France
Commerzbank	Germany
Deutsche Bank	Germany
Deutsche Postbank	Germany
IKB Deutsche Industriebank	Germany
Oldenburgische Landesbank	Germany
Umweltbank	Germany
Espirito Santo Financial Group	Luxembourg
Espirito Santo Financial Group Registered	Luxembourg
Bank of Valletta	Malta
Fimbank	Malta
HSBC Bank Malta	Malta
Lombard Bank	Malta
American Hypobank	Netherlands
Van Lanschot	Netherlands
Abanka Vipa	Slovenia
Nova Kreditna Banka Maribor	Slovenia
Probanka Prednostne Preference	Slovenia

Table B.5: Banks included in the United Kingdom Index

Bank	**Country**
Bank of Georgia Holdings	UK
Barclays	UK
HSBC Holdings (Ordinary $0.50)	UK
Lloyds Banking Group	UK
Standard Chartered	UK
Royal Bank of Scotland Group	UK

Table B.6: Banks and countries included in the Scandinavian Index

Bank	**Country**
Danske Bank	Denmark
Jyske Bank	Denmark
Ringkjobing Landbobank	Denmark
Spar Nord Bank	Denmark
Sydbank	Denmark
Aktia 'A'	Finland
Pohjola Pankki A	Finland
DNB	Norway
Sparebank 1 Series Bank	Norway
Sparebank 1 SMN	Norway
Nordea Bank	Sweden
SEB 'A'	Sweden
Svenska Handelsbanken 'A'	Sweden
Swedbank 'A'	Sweden

Table B.7: Number of banks and areas included in the Emerging Markets Index

Number of Banks	Area
33	Africa
118	Asia
45	BRICs
41	Europe
51	Latin America

This table reports the main areas in the emerging markets index and the corresponding number of banks. Africa is formed by Egypt, Morocco, Nigeria and South Africa; Asia contains Bahrain, Dubai, Indonesia, Jordan, Kuwait, Malasya, Oman, Pakistan, Philippines, Qatar, Sri Lanka, Taiwan and Thailand; Europe is formed by Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovenia and Turkey. Finally, Latin America is composed of Argentina, Chile, Colombia, Mejico, Peru and Venezuela.

Table B.8: Number of banks and areas included in the Global Banking Index

Number of Banks	Area
33	Africa
213	Asia
6	Australia
45	BRICs
8	Canada
38	Core EMU
51	Latin America
39	Peripheral EMU
57	Rest of Europe
14	Scandinavia
6	United kingdom
33	United States

This table reports the main areas in the global banking index and the corresponding number of banks. Africa is formed by Egypt, Morocco, Nigeria and South Africa; Asia covers Abu Dabi, Bahrain, Dubai, Dubai, Hong Kong, Indonesia, Israel, Japan, Jordan, Kuwait, Malasya, Oman, Pakistan, Philippines, Qatar, Singapur, South Korea, Sri Lanka, Taiwan and Thailand; Latin America is comprised of Argentina, Chile, Colombia, Mejico, Peru and Venezuela. Finally, rest of Europe is made up of Bulgaria, Croatia, Czech Republic, Hungary, Poland, Romania, Slovenia Switzerland and Turkey.

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