Market Frictions and the Pricing of Credit Default Swaps

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Abstract

This paper studies the informational content of 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 time of distress, and this 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.

Key Words: Credit default swaps, noise measure, illiquidity, capital arbitrage.

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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 phenomenom, 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 emphasisis on the term-structure of fixed-income securities. Hu et al. (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 et al. (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 paper, 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 undegone tremendous growth over recent years, now accounting for more than two thirds of all outstanding credit derivatives (Goldstein et al. 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 paper 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 illiquidility 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 paper 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 substantially increase during periods of financial distress such as Lehman's collapse in September 2008, or the Greek bailout in March 2010. Further-

[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 et al. (2005), Berndt et al. (2005), Pan and Singleton (2008) and Longstaff et al., 2011).

more, 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 paper 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 et al. (2005), Chen et al. (2008), Pan and Singleton (2008), Tang and Yan (2008), Bühler and Trapp (2009), Lin et al. (2009), Bongaerts et al. (2011), Nashikkar et al. (2011), Arakelyan et al. (2013), and Corò et al. (2013); see also Xing et al. (2007), Bao et al. (2011), Lin et al. (2011), and Acharya et al. (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 et al. (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, Corò 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 paper 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 paper 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 et al. (2011) characterize arbitrage opportunities from a non-arbitrage pricing model under a CIR specification, showing how to implement profitable strategies in this context; see also Duffie (1999). Our paper 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 et al. (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 et al. (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 our paper completely agree with the evidence reported in these studies, suggesting that pricing errors in derivative contracts are generally sensitive to market-wide illiquidity. Finally, our paper 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 correlates 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 paper is organized as follows. Section 2 introduces the noise or pricing discrepancy measure and discusses its suitability for the CDS market. Section 3 presents the dataset employed in this paper and explores its main statistical features. Section 4 presents the econometric framework and discusses the main results that characterize the noise measure. Section 5 analyzes the determinants of pricing errors, considering a broad set of market-wide indicators. Section 6 conducts several robustness checks. Finally, Section 7 summarizes and concludes.

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 paper. 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 paper.

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 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

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

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,

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

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

$$f_t^{m_0}(\lambda_t^{\mathbb{Q}}) + n_{1t} f_t^{m_1}(\lambda_t^{\mathbb{Q}}) + n_{2t} f_t^{m_2}(\lambda_t^{\mathbb{Q}}) \approx f_s^{m_0-\Delta t}(\lambda_s^{\mathbb{Q}}) + n_{1t} f_s^{m_1-\Delta t}(\lambda_s^{\mathbb{Q}}) + n_{2t} f_s^{m_2-\Delta t}(\lambda_s^{\mathbb{Q}}), \tag{3}$$

where the portfolio weights n_{1t} and n_{2t} are explicitly chosen to form the market neutral portfolio. On average,

[2] The default probability of the reference entity is the underlying 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.

the theoretical value of portfolio (3) must equal the market price of the portfolio, from which the following relation emerges:

$$\begin{aligned} & \left(f_t^{m_0}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_0)\right) + n_{1t}\left(f_t^{m_1}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_1)\right) + n_{2t}\left(f_t^{m_2}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_2)\right) \\ \approx \quad & \varepsilon_t^{m_0} + n_{1t}\varepsilon_t^{m_1} + n_{2t}\varepsilon_t^{m_2}, \end{aligned} \tag{4}$$

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 (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).

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

[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.

and market prices, as theoretically discussed by Duffie et al. (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$\times$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,

$$\delta_t = \sqrt{\sum_{i=1}^{N} \left(CDS_t\left(m_i\right) - CDS_t^*\left(m_i\right)\right)^2} \tag{5}$$

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 paper 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 (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 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] 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

[4]This measure has been used subsequently in a number of applied studies; see, for instance, Filipovic and Trolle (2013).

shortage of arbitrage capital. This is the central hypothesis analyzed in this paper.

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 6.2.

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 paper 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, UK and 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, UK, and US) is available on a shorter period and includes a smaller number of observations, 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 infor-

[5] Chen et al. (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.

[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 et al. (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.

mation 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.

3.1 Descriptive analysis

3.1.1 CDS spreads

Figure 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, UK, and US. A second group is characterized by Emerging Economies (henceforth EE) and is formed by the remaining countries in the sample.

[FIGURE 1 ABOUT HERE]

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 a 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 exhibits a mean-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 raised 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 1 ABOUT HERE]

Table 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.

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 paper, 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 2 ABOUT HERE]

Figure 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 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.

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 paper is that mispricing in CDS markets can be related to illiquidity, Tables 2 and 3 report descriptive statistics on trading activity and liquidity based on these variables.

[TABLE 2 ABOUT HERE]

Table 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 5.

[TABLE 3 ABOUT HERE]

Table 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 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.

4 Estimating the noise measure

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:

$$\frac{1}{4}CDS_t(m)\sum_{i=1}^{4m}E_t^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+\frac{i}{4}}(r_s+\lambda_s^{\mathbb{Q}})ds\right)\right]=(1-\mathbb{R}^{\mathbb{Q}})\int_t^{t+m}E_t^{\mathbb{Q}}\left[\lambda_u^{\mathbb{Q}}\exp\left(-\int_t^{u}(r_s+\lambda_s^{\mathbb{Q}})ds\right)\right]du, \tag{6}$$

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 (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

$$d\ln\lambda_t^{\mathbb{Q}}=\kappa^{\mathbb{P}}\left(\theta^{\mathbb{P}}-\ln\lambda_t^{\mathbb{Q}}\right)dt+\sigma^{\mathbb{Q}}dW_t^{\mathbb{P}}, \tag{7}$$

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 (7) under the risk-neutral measure $\mathbb{Q}$,

$$d\ln\lambda_t^{\mathbb{Q}}=\kappa^{\mathbb{Q}}\left(\theta^{\mathbb{Q}}-\ln\lambda_t^{\mathbb{Q}}\right)dt+\sigma^{\mathbb{Q}}dW_t^{\mathbb{Q}}, \tag{8}$$

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 (8) ensures the positiveness of risk-neutral default intensity. However, the expectations in CDS formula (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 (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 (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 (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

$$f^{\mathbb{P}}(\varepsilon_{m,t}|\psi, \mathscr{F}_{t-1}) = \phi^{\mathbb{P}}(\varepsilon_{m,t}|\sigma_M, \mathscr{F}_{t-1}) \times \phi^{\mathbb{P}}(\ln \lambda_t^{\mathbb{Q}}|\psi^{\mathbb{P}}, \sigma^{\mathbb{Q}}, \mathscr{F}_{t-1}) \times \left| \frac{\partial CDS^{\mathbb{Q}}(\lambda^{\mathbb{Q}}|\psi^{\mathbb{Q}}, \mathscr{F}_{t-1})}{\partial \lambda_t^{\mathbb{Q}}} \right|^{-1} \tag{9}$$

where $\phi^{\mathbb{P}}(\cdot)$ denotes the probability density function of the Normal distribution, $\lambda_t^{\mathbb{Q}}$ as given by expression (7), and $CDS^{\mathbb{Q}}(\cdot)$ in formula (6).

[TABLE 4 ABOUT HERE]

Table 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

[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 6 we shall consider alternative specifications that do not impose assumptions on the distribution of pricing errors.

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 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).

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 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.

[FIGURE 3 ABOUT HERE]

Table 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.

[TABLE 5 ABOUT HERE]

Since, as discussed previously, short-term maturities exhibit larger idiosyncratic patterns, an important question refers to 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 (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 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 suggests 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.

[TABLE 6 ABOUT HERE]

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 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

[9] Australia, China and 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.

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.

[FIGURE 4 ABOUT HERE]

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 et al. (2012) and Rapach et al., 2013). Nevertheless, we stress that a more detailed analysis, builing 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 7 ABOUT HERE]

Table 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%.

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.

5 Determinants of pricing errors in CDS markets

The main objective of this paper 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.

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 et al., 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, which furthermore leads 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 as 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.

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), and Pires et al. (2013) use a similar approach to identify the main determinants of CDS spreads, rather than CDS spread pricing errors; see also Peltonen et al. (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,

$$\begin{aligned}\ln noise_{CDS,it} &= \alpha + \phi \ln Bidask_{it} + \beta_1 \ln Contracts_{it} + \beta_2 \ln Netvol_{it} \\ &+ \beta_3 Marketvolatility_{it} + \beta_4 Default_t + \eta_i + \varepsilon_{it} \end{aligned} \tag{10}$$

or, using a more convenient notation,

$$\ln noise_{CDS,it} = \alpha + \phi \ln Bidask_{it} + X_{it}'\beta + \eta_i + \varepsilon_{it}, \tag{11}$$

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 (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 (11) in which persistent variables are plugged in differences, namely,

$$\ln noise_{CDS,it} = \alpha^* + \phi^* \ln Bidask_{it} + \Delta X_t' \beta^* + \eta_i + u_{it} \tag{12}$$

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 (11) and (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 et al. (2010), Cameron et al. (2011) and Thompson (2011). Furthermore, this methodology seems particularly useful in the empirical context of this paper, 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 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

[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.

variable. To this end, we regress $\ln noise_{CDS,it}$ on lagged values of all the right-hand side variables in equations (11) and (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 introduce significant biases. Consequently, and paralleling equations (11) and (12), we consider the following predictive specifications

$$\ln noise_{CDS,it} = \alpha_l + \phi_l \ln Bidask_{it-1} + X'_{it-1}\beta_l + \eta_i + v_{it} \tag{13}$$

and

$$\ln noise_{CDS,it} = \alpha_l^* + \phi_l^* \ln Bidask_{it-1} + \Delta X'_{t-1}\beta_l^* + \eta_i + w_{it} \tag{14}$$

with $\theta_l = \left(\alpha_l, \delta_l, \beta_l'\right)'$ and $\theta_l^* = \left(\alpha_l^*, \delta_l^*, \beta_l^{*\prime}\right)'$ 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 (13) and (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.

5.3 Main results

Table 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 (11) to (14). Let us first discuss the results for Model I and its predictive variation, corresponding to equation (11) and (13), respectively. These are reported in the bottom 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 sheer 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.

[TABLE 8 ABOUT HERE]

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 (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 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.

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, distinctively 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.

6 Robustness checks

This sections shows the results from different robustness checks grouped into two main categories. On the one hand, we discuss the general suitability of the model specification against different 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.

6.1 Model specification

A) Differences between advanced and emerging economies

Paralleling the analysis in the main section, Table 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.

[TABLE 9 ABOUT HERE]

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 (2012).

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.

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,

$$\lambda_t^{\mathbb{Q}}(m_\tau) = l_t + s_t m_\tau + c_t m_\tau^2, \tag{15}$$

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,

$$\lambda_t^{\mathbb{Q}}(m_\tau) = \xi_{1t} + \xi_{2t}\frac{1-e^{-\gamma_t m_\tau}}{\gamma_t m_\tau} + \xi_{3t}\frac{1-e^{-\gamma_t m_\tau}}{\gamma_t m_\tau} - \exp\left(-\gamma_t m_\tau\right), \tag{16}$$

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 et al. (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 (6), we can use the following discretized version of this formula for computing the spreads under both the QIF and NS approaches,

$$\frac{1}{4}\sum_{j=1}^{4m} e^{-\frac{j}{4}\left(r_t+\lambda_t^{\mathbb{Q}}(j)\right)} CDS_t(m) = (1-\mathbb{R}^{\mathbb{Q}})\sum_{j=1}^{4m} e^{-\frac{j}{4}r_t}\left[e^{-\frac{(j-1)}{4}\lambda_t^{\mathbb{Q}}(j)} - e^{-\frac{j}{4}\lambda_t^{\mathbb{Q}}(j)}\right], \tag{17}$$

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 5 ABOUT HERE]

Figure 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 paper. 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.

[TABLE 10 ABOUT HERE]

Table 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 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 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.

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 sheer 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 paper 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 paper 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 overall 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 paper. 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.

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Table 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.

Table 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: 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.

Table 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.

Table 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

Table 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.

Table 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.

Table 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. 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.

Table 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

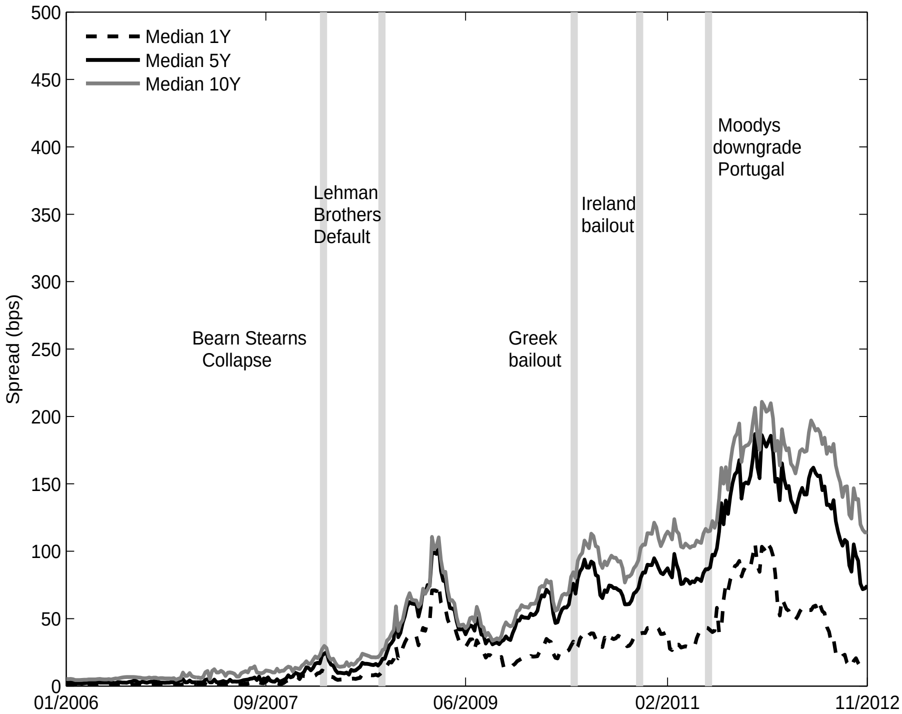
Panel data estimates for noise measure using different standard estimation methods considering two groups of countries and variables in differences. The mispricing errors have been computed using the Pan and Singleton (2008) model. Panel A shows the results for Emerging economies (EE) and Panel B for 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.

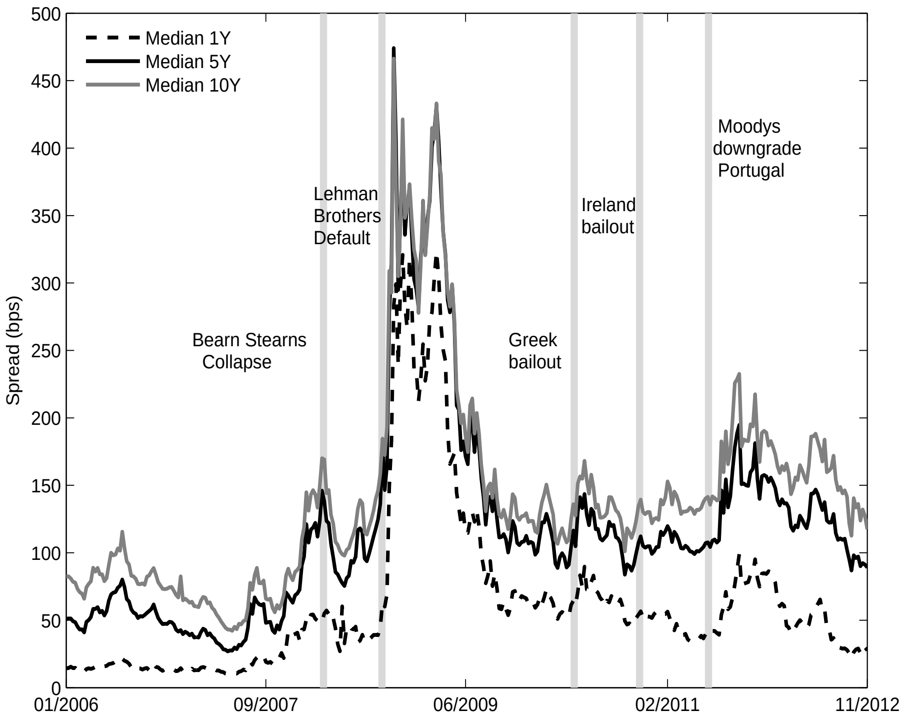
Table 10: Panel-data estimates of noise determinants for alternative pricing models

	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.

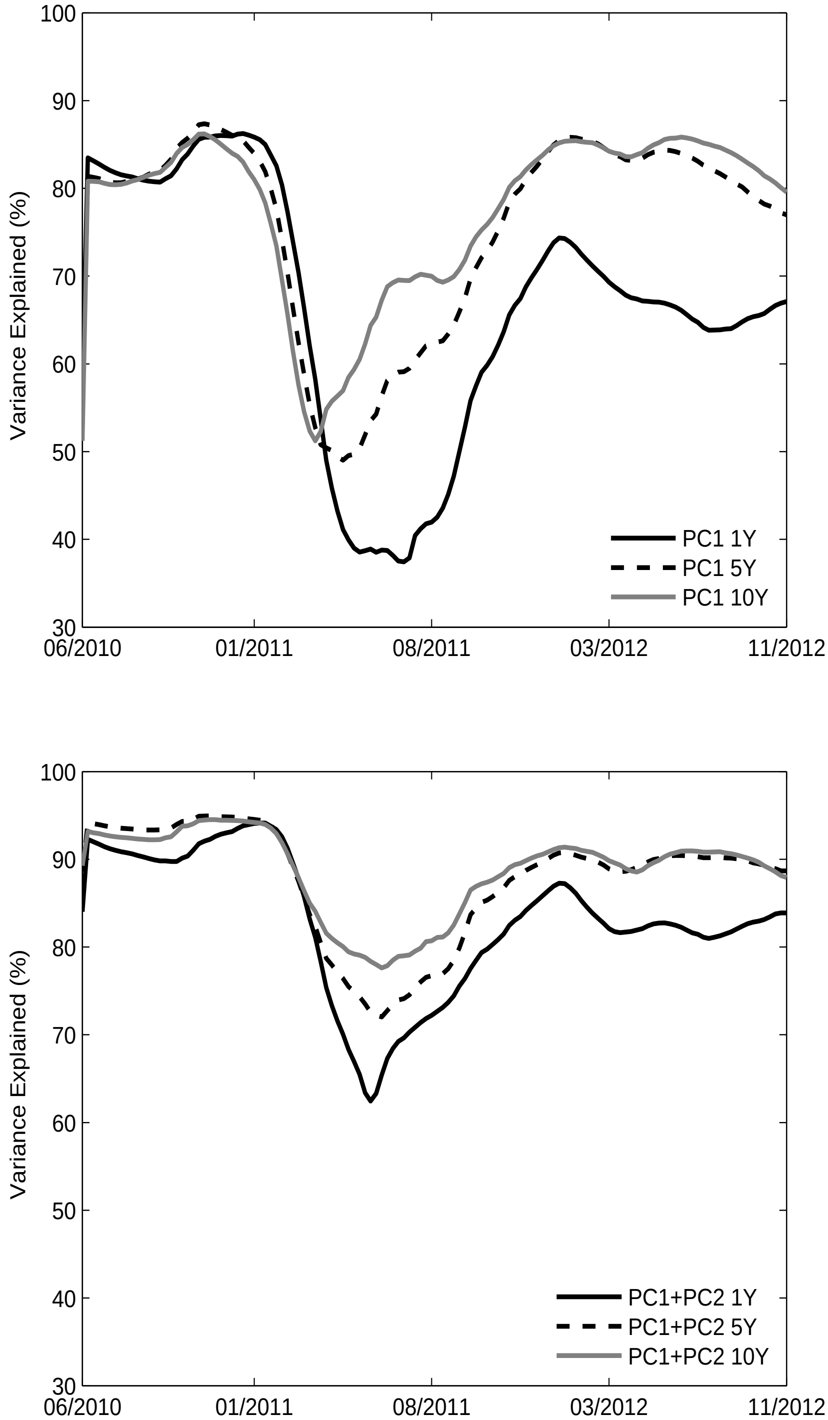
Figure 1: Cross-sectional median of sovereign CDS for different maturities





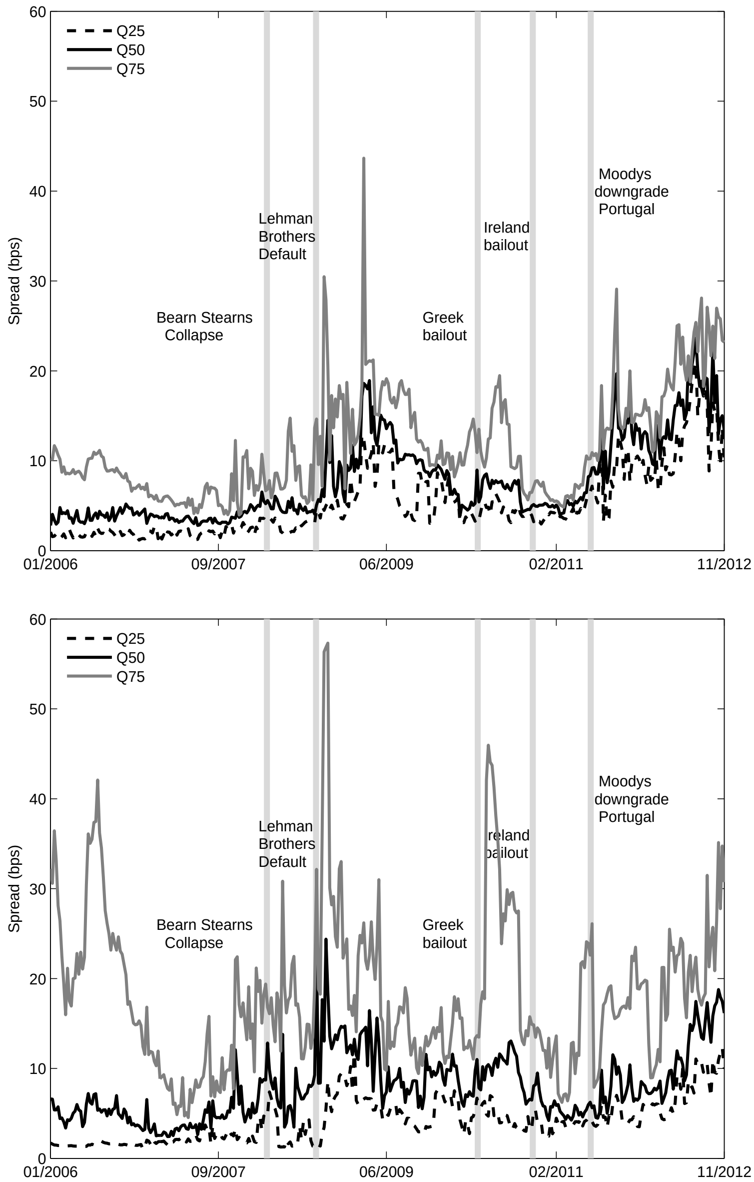
Cross-sectional medians of sovereign CDS spreads of different maturities for advanced (upper graph) and emerging (lower graph) economies. Advanced economies are Australia, France, Germany, Italy, Japan, Spain, the UK and the US. The maturities of CDS contracts are 1-, 5- and 10-year, respectively. Vertical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

Figure 2: Evolution of principal components over time



Evolution of the aggregated explained variance of three first principal components using a rolling window scheme. Each window contains 100 observations.

Figure 3: The noise measure



This Figure displays the evolution of different percentiles of the noise measure using Pan and Singleton (2008) 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.

Figure 4: Loading coefficients for principal components of the noise measure

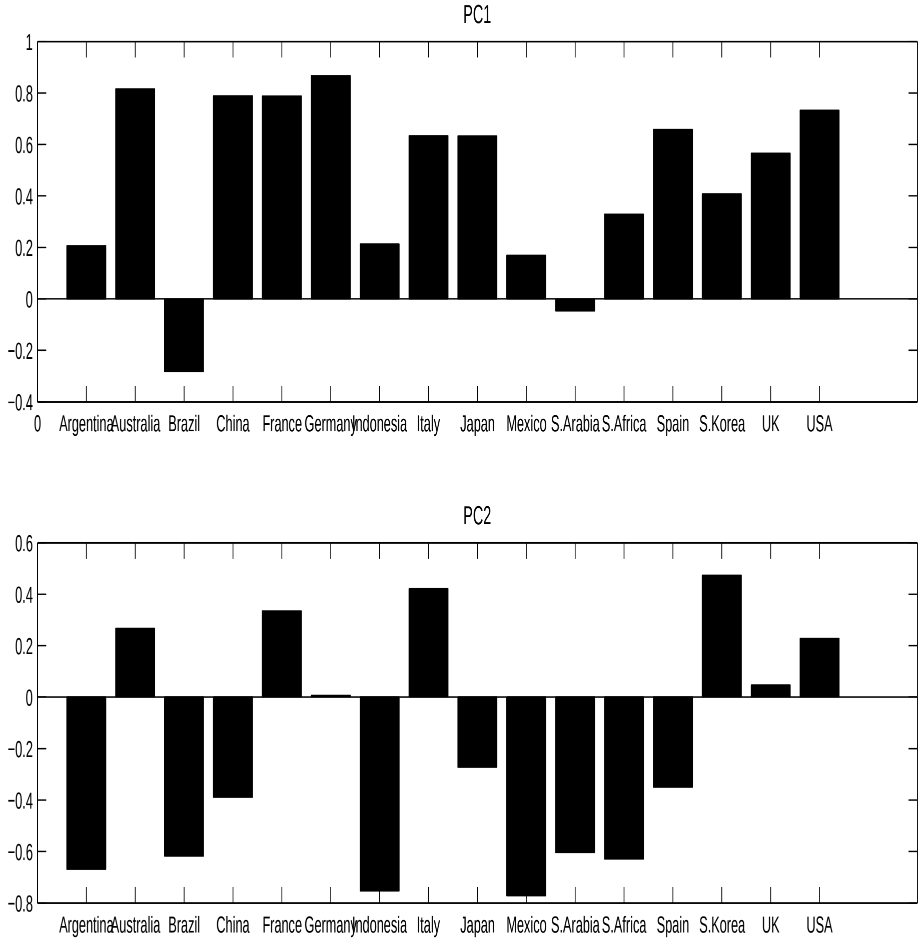
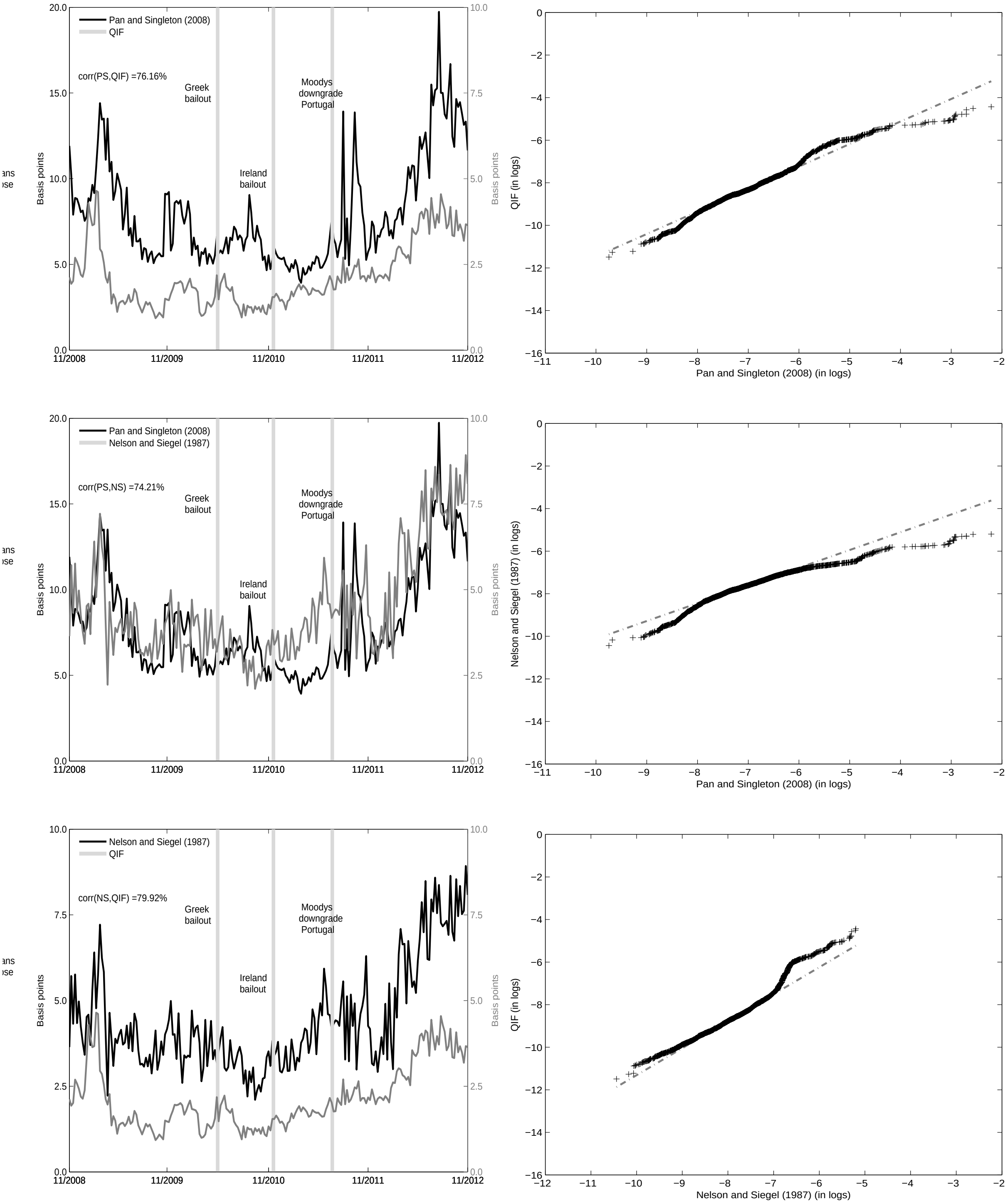


Figure 5: Cross-sectional median of sovereign CDS and qq-plots for different models



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 against the quadratic intensity model (QIF). The second row contains the Pan and Singleton (2008) model against the Nelson and Siegel (1987) model. The third row depicts the QIF model against the Nelson and Siegel (1987) model.