The surface of implied firm's asset volatility

First version: March 2016
This version: September 2017

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Abstract

This paper analyzes the surface of CDS implied firm's asset volatility at the aggregate market level, using a sample of European investment-grade firms during the 2007-2014 period. The term structure of asset implied volatilities is backed-out from the term structure of CDS spreads, while the moneyness dimension is proxied by the ratio of the default barrier to asset value. We find both a downward sloping term structure and a negative skew. Principal component analysis on the entire volatility surface shows that the first four components interpreted as a level, a term structure, a skew and a moneyness-related curvature mode capture 86% of the daily variation in asset implied volatility. We also find that the term structure slope is related to market and funding illiquidity, investors' risk aversion, informational frictions, demand/supply factors and momentum.

Keywords: Firm's asset implied volatility, Volatility surface, CDS spreads
JEL: G12, G13, G32

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We thank Santiago Forte, Fernando Muñoz Sánchez, Zoltán Schepp and Antonio Vaello Sebastiá, as well as conference participants at the IFABS Conference 2016, Barcelona, Spain, the Finance Forum 2016, Madrid, Spain and the World Finance Conference 2017, Sardinia, Italy for valuable comments and suggestions. Financial support from the Spanish Ministry of Economics and Competitiveness through Project ECO2013-48496-C4-4-R is gratefully acknowledged. This work was developed while Lidija Lovreta was Visiting Professor at Universitat Autònoma de Barcelona.

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1. Introduction

Equity implied volatility has been thoroughly studied in the literature (Heynen et al., 1994; Avellaneda and Zhu., 1997; Peña et al., 1999; Fengler et al., 2002, among others). In particular, it is common to plot implied volatilities against the option's strike price and against time to maturity, which results in a volatility surface. Although the Black-Scholes model predicts a flat profile for the implied volatility surface (i.e., all options on the same underlying should provide the same implied volatility), empirical studies have found that implied volatilities from stock options exhibit both smiles/smirks and term structure. Moreover, the level of implied volatilities is found to change over time, changing the shape of the implied volatility surface (Cont and da Fonseca, 2002; Andersen et al., 2015). On the contrary, despite the fact that the volatility of the underlying firm's assets is one of the key determinants of default probabilities and therefore, of the price of credit sensitive instruments, surprisingly little is known about the behavior of this key parameter. In particular, Choi and Richardson (2016) argue that more emphasis in research should be put on understanding the cross-sectional and time-series behavior of unlevered firm's asset volatility. In this paper, we contribute to the scarce existing literature on firm's asset volatility by studying the dynamics of the market-wide Credit Default Swap (henceforth CDS) implied asset volatility as a function of time to maturity and moneyness.

The main difficulty inherent in the examination of firm's asset volatility is the latent nature of the underlying value of the firm's assets. In order to overcome this problem several approaches have been considered: to proxy firm's asset volatility with some measure of equity volatility (either historical or implied), to deleverage equity volatility (either historical or implied), or to estimate firm's asset volatility using historical equity and bond returns as well as their covariance.[1] These approaches however, carry several drawbacks. First, using only equity volatility overlooks an important theoretical relation in which equity volatility is not only a function of asset volatility, but also a function of leverage. Empirical evidence suggests that asset volatility and leverage tend to be negatively related, that equity volatility positively depends on leverage, and that equity and asset volatility have different time-series properties due to leverage (Choi and Richardson, 2016).

[1] See for example: Collin-Dufresne et al. (2001), Alexander and Kaeck (2008), Correia et al. (2013), Schaefer and Strebulaev (2008), and Choi and Richardson (2016).

Second, deleveraging implied equity volatility could only be done by using current leverage (not the expected future leverage), and only for the short end of the maturity space (equity options are normally traded for maturities lower than 1 year). In credit risk management, however, medium and long maturities are equally important. In fact, one of the key inputs in the structural models of default is precisely the long-run estimate of the firm's asset volatility. Finally, some of the methods rely on historical volatility, while when estimating asset volatility for pricing purposes one has to bear in mind the fact that the theoretical value of credit sensitive instruments depends on the expected (forward-looking) volatility over its lifetime.

The theoretical analogy of corporate securities with stock options allows us to see that CDS contracts embed a short position in out-of-the money puts, with the firm's asset value as the underlying state variable. Therefore, we can borrow the basic idea from the literature on stock options and use structural models of default to back-out the volatility of the firm's assets from observable CDS spreads. Such an approach is interesting for several reasons. First, it allows us to study the volatility of the underlying state variable that reflects the whole capital structure of the firm. Second, in this way we obtain a forward-looking asset volatility measure, as opposed to historical-based measures studied so far in the literature (e.g.,Choi and Richardson, 2016).[2] Third, this approach allows us to investigate differences in market participants' perceptions of uncertainty over longer time horizons, up to 10 years. This contrasts with the relatively short maturities of stock options commonly explored in equity implied volatilities (up to 1 year). Finally, equity implied volatility is typically obtained from stock options traded in organized markets, whereas CDS contracts are traded in opaque over-the-counter (OTC) markets. Therefore, we could expect that peculiarities of the CDS market affect the shape of the implied asset volatility surface.

In this paper, we consider a sample of non-financial investment-grade companies that belonged to the iTraxx European index during the 2007-2014 period. The term structure of implied firm's asset return volatilities is backed-out from the whole term structure of CDS spreads (1 to 10-year maturity). The moneyness dimension in the equity implied volatility literature is given by the strike price or the delta. For asset implied volatility, we proxy

[2] Choi and Richardson (2016) compute asset volatility on the basis of historical equity, bond and loan returns.

moneyness by the ratio of the default threshold to the asset value (a measure of how close the option is to being exercised).

We obtain several novel results. First, principal component analysis (henceforth PCA) for the term structure of asset implied volatilities shows that the first three principal components interpreted as the level, shift and curvature components are enough to explain most of the variation in daily changes of asset implied volatilities (more than 99%). As for the moneyness dimension, we perform PCA separately for each of the 7 maturities available. Similarly to the PCA on the maturity dimension, we find that the first three principal components correspond to a level, shift and curvature mode. Together, these three components explain between 86% of the smirk variation, for 1-year maturity, and 90% for 10-year maturity, with an explanatory power increasing with maturity. Finally, PCA on the entire surface shows that the first four principal components explain 86% of the surface variation and they can be interpreted as a level mode, a term structure mode, a skew mode, and a moneyness-related curvature mode.

Second, we find a downward sloping term structure of asset implied volatilities, irrespective of the time period, even when the term structure of CDS spreads inverts. Moreover, the term structure gets steeper during crises and flatter in tranquil periods. This is in contrast with the typical equity implied volatility curve which is usually found to be upward sloping (Alexander, 2008) because of the natural uncertainty associated with longer time horizons (the market perceives much less risk for the short-term).[3] With respect to moneyness, we find a negative skew, in line with evidence on equity implied volatility. The skew gets steeper during crises and is flatter for longer-term maturities.

Third, to understand the nature of the information embedded in the asset volatility term structure, we study variables potentially associated with the term structure slope. We find that the downward sloping term structure is associated to more insider trading occurring on CDS contracts with short maturities, and more demand for credit protection on the short term due to risk aversion, especially during crises. Overall, our results indicate that the information in the volatility term structure is related to market and funding illiquidity, investors' risk aversion, informational frictions, demand/supply

[3] Nevertheless, downward sloping and flat term structures have also been detected especially in times of crisis (Andersen et al., 2015; Cont and da Fonseca, 2002).

factors, and momentum.

Finally, we have estimated asset implied volatility using the structural model of Forte (2011) and the estimation procedure proposed by Forte and Lovreta (2012). To verify the robustness of our findings to different modeling and estimation procedure assumptions, we perform a variety of robustness checks. The results confirm the robustness of our findings.

The rest of the paper is organized as follows. Section 2 summarizes the estimation of the firm's asset value and asset implied volatility. Section 3 offers a full description of our data set. Section 4 provides our empirical results on the surface of the asset implied volatility, the factors associated with the term structure slope and robustness checks for different model and estimation specifications. Finally, Section 5 concludes.

2. Implied firm's asset volatility

Market participants track on regularly bases implied equity volatilities from stock options. However, in the case of stock options, the implied equity volatility is the only unobservable variable out of the five needed to price an option. The stock price, strike price, time to maturity and interest rate could be obtained from market data. To back-out implied asset volatilities from CDS spreads, however, we need to cope with one additional problem: the underlying firm's asset value is not observable. To overcome this problem we need to define not only a structural model at hand together with the default barrier specification, but also an appropriate estimation procedure. We proceed in two steps. First, we use a structural credit risk model to assess the firm's asset value using only information on the market capitalization, 1-10 year swap rates, and a sub-set of accounting items: short and long-term liabilities, interest expenses and cash dividends. In the second step, we determine the implied firm's asset volatility from CDS spreads.

2.1. Estimation of firm's asset value

The structural model in our baseline case is the one suggested by Forte (2011). This model represents the debt structure as the sum of an arbitrary number of coupon bonds, each with its own principal, coupon, and maturity; therefore, the model is flexible enough to accommodate any possible debt profile. The market value of total assets at any time t, V_t, is assumed to evolve according to the continuous diffusion process:

$$dV_t = (\mu - \delta)V_t dt + \sigma V_t dz, \quad (1)$$

where μ is the expected rate of return on the asset value, δ is the fraction of the asset value paid out to investors, σ is the asset return volatility, and z is a standard Brownian motion. Default occurs whenever V_t reaches a specific critical point V_b, defined as a fraction β of the nominal value of total debt P:

$$V_b = \beta P. \quad (2)$$

The value of an individual bond d_n, with maturity τ_n, principal p_n, and constant coupon flow c_n, is given by:

$$d_n(V_t, \tau_n) = \frac{c_n}{r} + \mathrm{e}^{-r\tau_n}\left[p_n - \frac{c_n}{r}\right][1 - F_t(\tau_n)] + \left[(1-\alpha)\beta p_n - \frac{c_n}{r}\right] G_t(\tau_n), \quad (3)$$

for $n = \{1, ..., N\}$, where r is the risk-free rate, α represents bankruptcy costs, and the expressions for $F_t(\tau_n)$ and $G_t(\tau_n)$ are given in the Appendix A.

The total debt value is then represented by the sum of all outstanding bonds:

$$D(V_t) = \sum_{n=1}^{N} d_n(V_t, \tau_n), \quad (4)$$

and the equity value is given by:

$$S_t = g(V_t) = V_t - D(V_t|\alpha = 0), \quad (5)$$

where $D(V_t|\alpha = 0)$ is the market value of total debt when bankruptcy costs equal zero (see Forte, 2011).

To resemble the true debt structure as much as possible, we assume that at each instant t the company has ten bonds - one with a maturity of one year and principal equal to the short-term liabilities and nine with maturity ranging from two to ten years, each with principal equal to 1/9 of the long-term liabilities. The coupon of each bond is determined as 1/10 of the total interest expenses. The total principal is defined as the sum of the short-term liabilities (STL) and long-term liabilities (LTL). Daily data on the principal value of debt, as well as daily data on interest expenses is determined using linear interpolation between yearly data. The equity value is proxied with the market capitalization. The payout rate δ is computed as the average annualized payment of interest expenses and cash dividends divided by the value of the firm proxied by the sum of the market value of equity and the book value of total liabilities.

For the assessment of hidden parameters in the structural credit risk model we start from the Maximization Maximization (MM) algorithm proposed by Forte and Lovreta (2012). This procedure assumes that the company determines the default policy in the best interest of the equity holders. It is practically implemented in two maximization steps. Step 1 updates the value, volatility, and expected return on the firm's assets by maximizing the log-likelihood function for the time series of equity prices. Step 2 updates the default barrier by maximizing the average equity holders' participation in the firm's asset value. The algorithm is successively repeated until convergence is achieved. Forte and Lovreta (2012) demonstrate that theoretical credit spreads based on this estimation procedure offer the lowest CDS pricing errors when compared to other, traditional default barrier specifications: the smooth-pasting condition value, maximum likelihood estimate, KMV's default point, and nominal debt.

The log-likelihood function for the time series of equity prices in the first step of the MM algorithm requires that the default barrier is constant along the sample period. For the time period of 7 years considered in this study this would not be a reasonable assumption. We replace the first step with the common recursive procedure of estimating the constant volatility parameter which is based on the following algorithm for an assumed value of the default barrier parameter β:[4]

1. Proposing an initial value for σ, σ_0;
2. Estimating V_t series using the information on the stock market capitalization S_t, so that (5) holds for all t;
3. Estimating new volatility σ_1 from the obtained V_t series;
4. End of the process if $\sigma_1 = \sigma_0$. Otherwise, σ_1 is proposed at step 1.

The process is repeated until convergence is achieved. In the second step, for the asset value series V_t and volatility σ_1 obtained in the first step, we verify as in Forte and Lovreta (2012) whether the initially assumed default barrier parameter β maximizes the average equity holders' participation in

[4] The same modification is used in Forte and Lovreta (2016).

the firm's asset value. Finally, β is updated and the whole two-step algorithm is repeated until convergence.

2.2. Estimation of firm's asset implied volatility

Having estimated the series of firm's asset value, we now obtain asset implied volatilities by matching the theoretical credit spread to our time-series of observable CDS spreads. The theoretical credit spread at time t is determined as the premium from issuing at par value a hypothetical bond with the same maturity as the corresponding CDS contract. This bond is assumed to pay a coupon $c_t\ (\tau, p)$, so that the following equation holds:

$$d(V_t, \tau|p) = p. \tag{6}$$

Accordingly, the bond yield is:

$$y_t(\tau) = \frac{c_t(\tau, p)}{p}, \tag{7}$$

and consequently the theoretical credit spread is determined as the difference between the yield of this hypothetical bond and the corresponding risk-free rate:

$$CDS_t = h(V_t, \beta, \sigma) = y_t(\tau) - r_t. \tag{8}$$

The firm's asset implied volatility is therefore given by:

$$\sigma_t^{imp} = h^{-1}(CDS_t|V_t, \beta)$$

The estimation of asset implied volatility requires that we define a value for the bankruptcy costs parameter α which impacts the debt value by affecting the recovery rate $(1 - \alpha)\beta$. To facilitate comparisons with previous studies we follow the common market practice for CDS spreads valuation of assuming a recovery rate of 40%. A recovery rate of 40% is also used in Forte and Lovreta (2012), Correia et al. (2013), and Ericsson et al. (2015), among others, and is consistent with the average Moody's (2015) historical recovery rate on senior unsecured bonds, 37.4% during the 1982-2014 period.

3. Data

In this paper we use a sample of non-financial companies that belong to the iTraxx Europe index, which we track during the December 2007 - December 2014 period. The iTraxx Europe index comprises the most liquid 125 CDS referencing European investment-grade companies. We consider Euro-denominated CDS contracts on senior unsecured debt for maturities of 1, 2, 3, 4, 5, 7 and 10 years. Daily data on CDS spreads, market capitalization and 1-10 year swap rates, as well as yearly data on current liabilities, total liabilities, interest expenses and cash dividends are downloaded from Datastream. We exclude companies in the banking and financial sector due their different capital structure, private companies, and companies for which we lack data on either market capitalization or CDS spreads for the overall sample period. Additionally, we exclude all companies involved in corporate operations that resulted in significant modification of their capital structure. The final sample includes 55 actively traded firms which are tracked during the entire 2007-2014 period.[5] The complete list of companies considered is provided in Table B.1 (see Appendix B). The average company in the sample has a market capitalization of €23.7 billion, leverage of 0.53, and a historical equity volatility of 29.6%.[6]

The main descriptive statistics for a sample of CDS spreads that we use to derive the time-series of asset implied volatilities are presented in Table 1. The term structure of CDS spreads averaged over the entire sample period is upward sloping, with spreads ranging from 82 basis points (bp hereafter) for 1-year maturity contracts to 166 bp for 10-year maturity contracts. The standard deviation, skewness and kurtosis decrease with maturity. This implies that for longer maturities the distribution of CDS spreads becomes less asymmetric and has thinner tails, having less probability of observing extreme values. In Figure 1 we plot the time-series evolution of the cross-sectional mean of firm-specific CDS spreads across different maturities. We notice that although the term structure is in general upward sloping, during the crisis it gets inverted. Specifically, the term structure of CDS spreads exhibits a decreasing slope only during the period that spans from November

[5]In this way we avoid the possibility of obtaining spurious results due to changes in the sample composition over time.

[6]Leverage is calculated as the ratio of the book value of total liabilities to the sum of the market value of equity and the book value of total liabilities.

2008 to June 2009. The inversion of the term structure during crisis periods has already been documented in the literature (see Pan and Singleton, 2008).

[Table 1 about here.]

[Figure 1 about here.]

The analysis could also be done considering the bond market. However, we refrain from this approach for a couple of reasons. First, the CDS market is more liquid than the bond market, and CDS contracts are typically traded on standardized terms, have a fixed maturity structure, and are not affected by callability. As a result, the CDS market tends to be less influenced by non-default factors such as taxes, illiquidity, and market microstructure effects, documented to substantially affect bond prices (Longstaff et al., 2005; Ericsson and Renault, 2006). Second, a number of studies have undoubtedly shown that CDS spreads reflect changes in credit risk more accurately and quickly than corporate bond yield spreads (Blanco et al., 2005; Forte and Peña, 2009; Norden and Weber, 2009). As a result, CDS spreads are used as a preferred market benchmark for credit risk (Blanco et al., 2005; Longstaff et al., 2005).

4. Empirical Results

4.1. Preliminary analysis

In the literature on *equity* implied volatility it is quite common to study the dynamics of the market-wide volatility rather than to focus on the firm-specific one (Skiadopoulos et al., 2000; Cont and da Fonseca, 2002; Fengler et al., 2002; Andersen et al., 2015, among others). That is, equity implied volatilities are usually extracted from option prices having as an underlying a market index such as S&P500 or FTSE100. However, a similar analysis for the *asset* implied volatility is not that straightforward: not only is the underlying index unobservable, but also the associated capital structure and its dynamics over time, needed to convert CDS prices into implied volatilities. To assess the market-wide asset volatility we take an alternative approach and first analyze the systematic variation in firm-level implied volatility for our sample of 55 firms. We perform PCA on daily changes in firm-level implied volatilities, separately for each maturity from 1 to 10 years. Table 2 shows the explanatory power of the first principal component across maturities. Interestingly, we can see that the explanatory power increases with maturity, ranging from 24% of the variation for 1-year maturity to 34% of the variation for 10-year maturity. Secondly, we show that this systematic variation is well captured by changes in the cross-sectional mean of firm-level volatilities. The last column of Table 2 shows that the two variables are almost perfectly correlated. This implies that by taking the changes in the mean implied volatility for the whole sample of firms, we are actually capturing the first principal component that drives the variation of individual firm-level volatility. Accordingly, in the subsequent analysis we use the mean implied volatility as a measure of asset volatility at the index level.

[Table 2 about here.]

Table 3 presents the descriptive statistics of the market-wide asset implied volatility over different maturities. The mean ranges from 0.263 for 1-year maturity to 0.168 for 10-year maturity, showing a clearly decreasing pattern. The median asset implied volatility is very close to the mean for all maturities. The shortest and longest maturity implied volatilities are more volatile than medium maturity volatilities. A possible explanation for this could be the fact that extreme maturities CDSs are traded less often as compared to medium maturity CDSs. Indeed, according to Blanco et al. (2005), Alexander and Kaeck (2008), and Pan and Singleton (2008), the 5-year maturity "is by far the most liquid maturity in the CDS market". Moreover, Arakelyan et al. (2013) analyze the illiquidity of the CDS market and find that the shortest maturity CDSs are relatively highly illiquid contracts, with 5-year maturity contracts being the most liquid in general. They document an asymmetric U-shaped pattern for the slope of the term structure of bid-ask illiquidity for CDS spreads. Regarding skewness and kurtosis, as in the case of the CDS spreads, we observe that they are both decreasing in maturity. Therefore, the distribution becomes less asymmetric and has thinner tails for longer maturities.

[Table 3 about here.]

Finally, in the last two columns of Table 3, we estimate the fractional degree of persistence, d, using two commonly applied semi-parametric approaches: the Geweke and Porter-Hudak (1983), and the exact local Whittle estimator (ELW) of Shimotsu and Phillips (2005), here labeled as GPH and ELW, respectively. The GPH statistics is estimated using differenced data and the bandwidth parameter m is set in both cases to $T^{0.5}$, where T is the number of observations. The results show that the parameter d lies in the non-stationary region for all implied volatility series, that is, across all maturities, and that mean-reversion tends to disappear with maturity. To be specific, the GPH (ELW) degree of persistence rises from 0.8 (0.9) for 1-year maturity, to 1.1 (0.97) for 10-year maturity. This is in line with the findings on equity implied volatility where long-term volatilities are usually less volatile and more persistent as compared to short-term volatilities (Alexander, 2008; Guo et al., 2014). Although the order of integration is in general lower than 1 implying that a shock in the process eventually dies in the long-run, statistically, the unit root null cannot be rejected in any of the series when judged by the standard errors of the estimates.[7]

The evolution of the mean asset volatility over the whole period analyzed, and for the seven different maturities is plotted in Figure 2. First of all, we notice that there exists a high correlation among implied volatilities for all maturities. This will allow us to use principal component analysis to find the uncorrelated sources of risk which drive the evolution of asset implied volatilities. Secondly, we can observe that the asset implied volatilities for shorter maturities are higher than those for longer maturities. Fixing a date and looking across maturities we note that we have a downward sloping term structure for asset implied volatility.[8] This slope is steeper for short-term maturities and quite smooth for longer-term maturities. On the other hand, if we study the evolution across time, we observe higher implied volatilities for all maturities at the beginning of our chosen period (during the financial crisis), with lower values towards the end of the period analyzed.

[Figure 2 about here.]

4.2. Principal component analysis

Having defined the proxy for volatility at the index level, in this section we apply PCA to daily changes in asset implied volatility.[9] We use changes

[7] The standard error of the GPH estimates of d is 0.114 and are calculated using the asymptotic variance $(\pi^2/6)$. The asymptotic standard error of the ELW estimates is $(4m)^{1/2}$ and equals 0.077.

[8] We verified that the term structure of asset implied volatility is downward sloping for every single day in our sample that covers the period 2007-2014.

[9] We have also performed an analysis for weekly and monthly data and obtained similar results as reported in the online appendix.

in implied volatilities rather than levels given that our preliminary analysis shows that asset implied volatility lies in the non-stationary region. Moreover, this is in line with the literature on equity implied volatilities which has mainly applied PCA to daily changes in equity implied volatility. We proceed as follows: we first apply PCA on the maturity dimension, analyzing the term structure of asset implied volatilities. We then perform PCA on the second dimension, moneyness, proxied by the ratio of the default barrier to asset value. Finally, we apply PCA on the entire implied volatility surface, analyzing both dimensions simultaneously.

4.2.1. PCA on maturity

The correlation matrix for the changes in mean asset implied volatilities is shown in Table 4. We can see that correlations are highest for adjacent maturities and decrease as the maturity difference between the volatilities increases. At the same time, the 1-year implied volatility has a lower correlation with the other rates. The results of the PCA performed on the correlation matrix are shown in Table 5.[10]

[Table 4 about here.]

The largest eigenvalue is 6.4031, thus the proportion of the total variation that it explains is of 91.47%, given that the total variation is given by the trace of the matrix, equal to 7. The second largest eigenvalue, 0.4915, explains a further 7.02%, and the third largest eigenvalue, 0.0484, explains another 0.69% of the total variation. Taken together, the first three largest eigenvalues explain 99.19% of the total variation in the changes of asset implied volatility. Panel a) of Figure 3 shows that the eigenvalues indeed decay quickly and that with only three eigenvalues we can account for most of this variation.[11]

[10] We obtain similar results for the PCA performed on the covariance matrix (see the online appendix).

[11] To be consistent with the previous literature on equity implied volatility and interest rates, we discuss the first three principal components which are usually identified as the level, slope and curvature components, respectively. Nevertheless, we have also applied several criteria such as the Gutman-Kaiser criterion (also known as the mean eigenvalue rule of thumb), Velicer's MAP criterion, Catell's Scree test, Horn's Parallel Analysis, and the proportion of variance explained rule of thumb. The majority of these criteria indicates that two principal components should be retained.

[Table 5 about here.]

Panel b) of Figure 3 plots the first three eigenvectors corresponding to the three largest eigenvalues. The fact that the correlations are quite high is reflected in the similarity of the weights on the first principal component, except for the 1-year maturity which has a lower correlation with the rest of the system. All of the components of the first eigenvector are positive. Thus a positive shock in the first principal component (an upward shift) induces a roughly parallel shift in the term structure of the implied volatility, resulting in a global increase of all the implied volatilities. Therefore, the first principal component can be interpreted as a "level" or a "trend" component of the implied volatility term structure. For the overall sample period, 91.47% of the total variation in the term structure can be attributed to (roughly) parallel shifts.

[Figure 3 about here.]

The factor weights on the second principal component change sign, decreasing monotonically from 0.60 for the 1-year maturity to -0.56 for the 10-year maturity. Therefore, a positive shock in the second principal component leads to a change in the slope of the term structure of implied volatilities, with short maturities moving up and long ones moving down. We thus interpret the second principal component as a "slope" or "tilt" component which explains 7.02% of the total variation.

The third eigenvector has a positive weight for the shortest maturity, with decreasing and negative weights for the medium-term volatilities, and positive and increasing weights for the longer maturities. Thus, the third principal component is interpreted as a "convexity" component, influencing the convexity of the term structure. For our sample period 0.69% of the total variation is due to changes in convexity.

To better understand the evolution of asset implied volatility during tranquil and volatile periods, we perform dynamic PCA using a rolling window of 252 days. The evolution of the explanatory power of the first principal component is plotted in Figure 4 (left axis). In 2008-2009 the proportion of the variation in daily changes of asset implied volatilities explained by the first principal component alone peaks to more than 94%, showing a high systematic risk.[12] Another period characterized by high volatility and elevated systematic risk is 2011-2012, when the first principal component has an explanatory power above 92%. This period was marked by a volatility spike following the US Treasury bonds downgrade from their AAA rating, and the fears of contagion in the European sovereign debt crisis. Nevertheless, in the more tranquil periods the first principal component explains at least 81.6% of the variation in daily changes of asset implied volatility.

[Figure 4 about here.]

We also analyze the correlation between the movements in asset implied volatilities and the underlying asset returns using the same rolling window. The time evolution of the correlation between the first principal component and the underlying asset returns is shown in Figure 4 (right axis). We observe a strong positive correlation between the underlying asset returns and the first principal component of implied volatilities. This correlation varies from around 35% in tranquil periods to almost 80% in highly volatile periods. Our findings contrast with the empirical evidence on the correlation between stock returns and *equity* implied volatility. Indeed, several studies on the *equity* implied volatility find evidence of the so-called leverage effect: the negative correlation of *equity* implied volatility and asset returns (see for example Cont and da Fonseca, 2002 and Choi and Richardson, 2016, among others).[13] Nevertheless, our results are not surprising given that asset volatility and leverage tend to be negatively related, while equity volatility positively depends on leverage (Choi and Richardson, 2016).

Finally, we plot in Figure 5 the evolution of the empirical term structure slope of asset volatility (right axis), computed as the difference between asset implied volatility for 10-year maturity and asset implied volatility for 1-year maturity. We find a very strong correlation of -0.97 between the second principal component and changes in the empirical term structure slope, further confirming that PC2 is indeed a slope factor.[14] We can observe that the term

[12]Note that the first point on the graph corresponds to an estimation period from December 14, 2007 to December 1, 2008, given our rolling window of 252 days.

[13]A large sudden fall in the stock price increases the debt to equity ratio and the firm's leverage increases. Thus equity volatility tends to increase following a large sudden fall in the stock price.

[14]The negative sign is simply due to the fact that the principal component estimator allows us to identify factors up to a change of sign (see Bai and Ng, 2002).

structure of asset implied volatilities is downward sloping every single day in our sample period (negative slope), and that during the financial crisis the term structure becomes steeper. To shed more light on this result, we also plot in Figure 5 (left axis) the slope of the term structure of CDS spreads (computed as the difference between 10-year maturity and 1-year maturity CDS spreads) for our portfolio of 55 firms. We note that the term structure of CDS spreads is in general upward sloping (positive slope), although it gets inverted during the period November 2008 - June 2009.

[Figure 5 about here.]

4.2.2. PCA on moneyness

In the literature on equity implied volatility, moneyness is proxied either by the relative position of the stock price with respect to the strike price or by the delta. In our case, for *asset* implied volatility, moneyness is proxied by V_b/V_t, the ratio between the default barrier and the firm's asset value. However, unlike stock options where option prices with different strikes and maturities on the same underlying are available at a given moment, for asset implied volatility we observe CDS prices for different maturities, but for a single ratio of the default barrier to asset value for a certain company at a given moment in time. To overcome this difficulty, we group firms into moneyness bins (buckets), forming sub-groups or sub-indices for different ranges of the ratio of the default barrier to asset value.[15] We fix the intervals as follows: < 0.3, $[0.3, 0.4)$, $[0.4, 0.5)$, $[0.5, 0.6)$, $[0.6, 0.7)$, > 0.7.[16] The dynamics of the moneyness smirks are analyzed by applying PCA separately to each maturity level from 1 to 10 years.

We now define our measure for market-wide volatility for each moneyness bin. Similarly to the approach taken before, we proxy the market-wide implied volatility by the mean of firm-level implied volatilities across all firms belonging to a given moneyness bin. Table 6 shows the correlation between

[15] Skiadopoulos et al. (2000) analyze implied equity volatility for different maturity buckets.

[16] The moneyness bins were chosen to guarantee a minimum of two observations for each range. A slightly different division of the form $[0.35-0.45)$ would not affect our results (see the online appendix). Given that volatility changes daily, there is the possibility that firms change bins over time. This rarely happens in the sample, since in general all volatilities tend to move in tandem, and an increase in the volatility of the first bin is accompanied by an increase in the volatility of the rest of the bins.

changes in the mean implied volatility across firms in a given bin and the first principal component of a PCA performed on changes in individual firm-level volatilities (the analysis is carried out separately for each bin). We can observe that indeed the two variables are very strongly correlated.

[Table 6 about here.]

For the moneyness dimension, a further issue with respect to the maturity dimension is that we are considering the implied volatility for different sub-indices (composed of firms belonging to the same moneyness bin) rather than the implied volatility for the entire index (consisting of the entire sample of 55 firms). This is why we verify (for every maturity level) that the changes in the mean volatility for the different sub-indices are strongly correlated with the changes in the mean volatility for the index level, as shown in Table 7.

[Table 7 about here.]

We perform PCA on the moneyness dimension separately for each maturity from 1 to 10 years. Table 8 presents the cumulative explanatory power of the first three principal components. The first principal component explains between 69% and 77% of the variation in implied asset volatilities, depending on maturity. The second component explains between 8% and 10% of the variation, and the third one between 5% and 7%. In total, the first three principal components explain 86% of the variation in asset implied volatility for 1-year maturity. The explanatory power of the first three principal components is increasing with maturity, reaching a total of 90% of the variation for the 10-year maturity.[17]

[Table 8 about here.]

Figure 6 plots the first three eigenvectors corresponding to the largest three eigenvalues, for all available maturities ranging from 1 year (panel a) to 10 years (panel g). The figure shows that, for every maturity, the first PC represents a near parallel shift. Therefore, an upward shift in the

[17]As for the PCA on maturity, most of the previously mentioned criteria for the number of components, indicate that the first two principal components should be retained. However, we report the first three to facilitate comparisons with the literature on equity volatility.

first principal component would lead to a near parallel shift in the smirk of the implied volatility. We can thus interpret it as a "level" component. Furthermore, the factor loadings are very similar across all maturities.

The factor weights on the second principal component change sign, increasing from around -0.4 for the lowest moneyness bin to around 0.8 for the highest moneyness bin. The second component corresponds then to a change in the slope of the asset volatility smirk, with volatilities corresponding to low moneyness bins moving down and those corresponding to high ones moving up. As before, the factor loadings for the second PC are very similar across all maturities. Similar to the maturity dimension, we obtain that this second principal component is highly correlated with changes in the empirical slope of the moneyness smirk (defined as the difference in the implied volatility of firms in the highest moneyness bin and that of firms in the lowest moneyness bin). Table 9 shows these correlations across all maturities.

[Table 9 about here.]

The third eigenvector however differs across maturities. For very short or very long maturities, i.e., 1 and 10 years, it has a positive weight for the smallest moneyness, with decreasing and negative weights for the medium levels of moneyness, and positive and increasing weights for the highest moneyness bin. On the contrary, for intermediate maturities ranging from 2 to 7 years, we have quite the opposite behavior: a negative weight for the first moneyness bin, with increasing and positive weights for medium bins, and negative and decreasing weights for the highest moneyness bins. Thus, the third principal component is interpreted as a "convexity" component irrespective of maturity. Nevertheless, the influence that the third PC has on the convexity of the volatility smirk differs for very short/long maturities and for intermediate maturities.

[Figure 6 about here.]

4.2.3. PCA on the asset implied volatility surface

We now analyze the dynamics of the entire volatility surface. Figure 7 plots the asset implied volatility surface as a function of moneyness and maturity. We can see that asset implied volatility decreases both across the moneyness bins and across maturity. Since more indebted firms are more likely to be in a high moneyness bin, the negative skew obtained could be explained by the negative relationship between asset volatility and leverage. As Choi and Richardson (2016) suggest, firm's asset volatility decreases with leverage (and thus with moneyness) since firms with lower asset volatility can probably better exploit the tax advantage of debt while maintaining a relatively low cost of financial distress.

The shape of the asset implied volatility surface could also be related to the tendency of borrowing-constrained investors to overweight riskier assets which ultimately leads to a low-risk anomaly evidenced across a broad range of asset classes including corporate bonds (Ilmanen et al., 2004; Kozhemiakin, 2007; Frazzini and Pedersen, 2014; Houweling and Van Zundert, 2017).[18] If investors seeking to get exposure to credit risk perceive the CDS market as an alternative to the bond market, the tendency to overweight riskier assets would translate into higher selling pressure for CDS contracts at longer maturities and for lower-rated issuers (which are more likely to be in high moneyness bins). Alternatively, the shape of the asset implied volatility surface could be related to investors' preference for lottery-like assets (Boyer and Vorkink, 2014; Bali et al., 2016). In particular, Boyer and Vorkink (2014) find that options trading out-of-the money offer substantially more skewness (a proxy for lottery-like characteristics) than in-the-money options, especially as maturity decreases. This would in contrast, translate into higher buying pressure for CDS contracts at shorter maturities and for lower moneyness bins (which are deeper out-of-the-money). However, both effects would produce a downward sloping term structure and moneyness smirk, in line with our shape of the asset volatility surface.

Comparing to the findings on equity volatility, a similar negative skew is found for equity implied volatility (Cont and da Fonseca, 2002; Andersen et al., 2015). However, a downward sloping term structure of equity implied volatility is not common, especially during tranquil periods. We will address this issue in more detail at the end of this section and in Section 4.3.

[Figure 7 about here.]

We next pool together the maturity levels and perform PCA on the entire data set. The results of the PCA on the volatility surface are presented in Figure 8 and Table 10. The factor loadings of the first principal component

[18] These studies show that short-dated and/or high-rated bonds earn higher risk-adjusted returns.

(panel a) of Figure 8) show an almost parallel shift in the entire volatility surface. The first factor explains 68% of the surface variation (see Table 10). The factor loadings of the second principal component indicate that this is a skew factor, with volatilities in low moneyness bins moving in the opposite direction from those in higher moneyness bins, with little variation across maturity. This factor explains 7.69% of the surface variation. Panel c) of Figure 8 plots the factor loadings for the third principal component which appears to be a term mode, with short term volatilities moving in the opposite direction from longer term ones. Finally, the fourth factor plotted in panel d) appears to be a curvature mode related to moneyness.[19] Together, the first four principal components explain 85.85% of the surface variation.[20]

[Table 10 about here.]

[Figure 8 about here.]

Finally, we look at the dynamics of the asset implied volatility surface. Given that the second principal components for both the maturity and moneyness analyses are highly correlated with changes in the empirical term structure and moneyness smirk slopes, respectively, we will use the latter ones to study the evolution of the surface across time. Panel a) of Figure 9 shows the evolution of the term structure slope for different moneyness bins. We observe that for all moneyness bins except the last one, the term structure is downward sloping during the whole sample period. For the highest moneyness bin (firms with asset value closer to default barrier, thus the put option is near the money) the term structure is sometimes slightly upward sloping. This is closer to the term slope behavior observed in the equity options market as previously discussed. Moreover, we can see that in general during the financial crisis of 2008-2009 the term structure became more steeply negative. Since our sample consists of investment-grade companies,

[19] In the literature on equity implied volatility surfaces the first principal component is found to be a level mode. According to some studies the second and third one correspond to a term structure and to a skew mode, respectively (see Derman and Kamal, 1997). According to other studies however, the second mode is found to be a skew mode, and the third one another skew-related curvature mode (see Cont and da Fonseca, 2002).

[20] The majority of the criteria applied show that the first six principal components should be retained. The fifth and sixth eigenvectors reported in the online appendix have the shape of a quartic and a quintic polynomial, respectively.

at the index level the options considered are deep out-of-the money with an average moneyness of 0.488. The previous findings for the highest moneyness bin seem to indicate that opposite results might be obtained for high yield firms.

In panel b) of the same figure we observe that the moneyness slope is always negative during the sample period and this holds for all maturities. The shorter the maturity the steeper the moneyness smirk. This is in line with evidence on equity implied volatility by Peña et al. (1999) who find that equity implied volatility with shorter term maturity have steeper moneyness slopes. Furthermore, during the financial crisis of 2008-2010, we observe that the moneyness smirk of asset implied volatility becomes much steeper. This is consistent with the evidence of Han (2008) who finds that the index option volatility smile is steeper when market sentiment becomes more bearish.

In the remainder of this section, given that our result of a downward sloping term structure contrasts with a typically upward sloping one found for equity volatility, we would like to further analyze this issue. As mentioned in the introduction, one of the approaches used in the literature to estimate implied asset volatility is simply deleveraging equity volatility implied from equity options data. One could then wonder if similar term structures would be obtained for asset volatility implied from equity options data compared to credit markets data. To shed some light on this issue, we note that theoretically equity volatility is a function of asset volatility and the leverage component.[21] Therefore, implied equity volatility in addition to information about expected future asset volatility possibly contains information about expected future leverage. In contrast, in empirical applications, when the equity implied volatility is deleveraged in order to calculate asset volatility, this is done by assuming current leverage, not the expected future leverage. This means that equity volatility implied from stock options would be simply divided by the current leverage component which is the same across the maturity structure on the same day. Given that the leverage multiplier has a positive value, such a calculation would lead to the same term structure (upward or downward sloping) for asset volatility, as the one of equity volatility. Abstracting from the leverage effect, the direct comparison of the term

[21] This relation could be represented as in Choi and Richardson (2016): $\sigma_E = (V/E * \partial E/\partial V)\sigma_V$, where V is the market value of firm's assets, E is the market value of equity and the term within the brackets represents the leverage component (or leverage multiplier) in which the derivative depends on the structural model at hand.

structures implied from the two markets is unfortunately not straightforward and poses two additional major problems: a maturity and moneyness mismatch. Indeed, most papers on equity implied volatility consider very short maturities of up to 1 year in general, and many focus exclusively on at-the-money options (Heynen et al., 1994; Avellaneda and Zhu., 1997, among others). This contrasts with the CDS market which is a natural environment precisely for the opposite, long dated OTM options. For a proper comparison, one would need to analyze the term structure of asset volatility implied from deep out-of-the-money put options with longer maturities. Therefore, strictly speaking, our results are not directly comparable to the existing evidence from the equity implied volatility literature.

[Figure 9 about here.]

4.3. Determinants of the empirical term structure slope

In this section we extend the previous analysis by examining a set of variables potentially associated with the term structure slope of asset implied volatilities. Our interest in this issue is motivated by several reasons. First, our finding of the downward sloping term structure of asset implied volatilities contrasts with the commonly reported upward sloping term structure of equity volatilities implied from stock options. Second, the equity implied volatility literature shows that the surface of equity implied volatilities is affected by a number of factors which are primarily related to different aspects of liquidity and to characteristics of the underlying stock returns (Peña et al., 1999; Amin et al., 2004; Bollen and Whaley, 2004; Chou et al., 2011; Deuskar et al., 2011, among others). Third, Ericsson and Renault (2006) find supporting evidence for the downward-sloping term structure of liquidity spread in the corporate bond yield spreads. That is, these authors find that illiquidity represents a substantial part of the credit spread for short maturities while the illiquidity component is much smaller for long-term maturities. Fourth, if present in the CDS market, the tendency of borrowing-constrained investors to overweight riskier assets (Frazzini and Pedersen, 2014) and/or the investors' preference for lottery-like assets (Boyer and Vorkink, 2014; Bali et al., 2016) could result in excess supply of long-term CDS contracts and/or excess demand for short-term CDS contracts, respectively. Finally, Pan and Singleton (2008) study the term structure of sovereign CDS spreads and report higher mispricing at shorter maturities, probably related to liquidity and demand/supply factors.

Taking all pieces together, these findings suggest that larger asset volatilities are needed in order to match observed CDS spreads for shorter maturities (and vice versa) resulting in a downward sloping term structure. Since mispricing seems to be less severe at the long end of the maturity spectrum, this could further explain a steeper downward slope at the short-end and relatively flat term structure on the long-end.[22] These findings also point to the possible existence of factors associated with the term-structure slope of asset implied volatilities especially in the context of the highly concentrated CDS OTC market in which participants are mainly insiders. In line with the existing literature on equity implied volatility and our own findings, we consider variables related to the market and funding illiquidity of the CDS market, as well as variables related to the underlying firm's asset returns and investor's risk aversion. A detailed description follows:

Momentum (MOM). Amin et al. (2004) argue that momentum can change investor's risk aversion and their perception of the distribution of the underlying asset return and therefore affect the supply and demand for options. For example, if past returns are negative, investors expect future stock returns to be lower than average and, accordingly, create an upward pressure on put prices. Amin et al. (2004) find that equity implied volatility estimates increase with declining stock prices and that implied volatility increases are more pronounced for short-maturity options. Likewise, Peña et al. (1999) find market momentum to be a relevant factor associated with the shape of the equity volatility smile. We construct the market momentum variable on the basis of the most recent index returns, in line with Han (2008). We first form an equally-weighted index from individual firm's asset values of all companies in the sample and then construct the time-series momentum or "trend" as the cumulative excess return on the index over the previous 60 days.[23]

[22] An upward sloping term structure of CDS spreads reflects the larger default probability normally associated with longer maturities for investment-grade firms. At first sight, the natural uncertainty associated with longer horizons might lead one to expect an upward sloping term structure for asset implied volatility. In the context of our application, this would imply higher upward (downward) pressure on CDS spreads at the long-run (short-run), which would not be in line with findings across corporate bond, option and CDS markets.

[23] Alternatively, for robustness purposes, we have considered a value-weighted index (see the online appendix).

Dealer funding costs (TED). Brunnermeier and Pedersen (2009) show that the availability of the speculator's capital affects the discrepancy between prices and fundamentals. An adverse shock to speculators' funding liquidity (availability of funding) forces speculators to provide less liquidity to the markets. In the CDS market, liquidity providers are primarily the sellers of CDS contracts (Bongaerts et al., 2011), and therefore, worsening aggregate funding conditions might result in the overall decrease in the supply of credit protection. However, a contrary effect might occur through the bond market channel: when funding costs are high, investors might prefer selling CDS contracts to buying bonds, and ultimately increase the supply of credit protection. We proxy the availability of the speculator's capital with the TED spread (the spread between the 3-month LIBOR rate and the 3-month T-Bill yield), usually considered as the funding liquidity indicator.

Investors' risk appetite (RA). Investors' risk appetite or, alternatively, investors' risk aversion, affects investors' hedging-related demand for credit protection as well as their willingness to take on credit risk. Garleanu et al. (2009) model the demand pressure effect on option prices and find that the impact of demand pressure increases with dealers' risk-aversion. In addition, these authors find empirical support for the hypothesis that the market-makers' risk aversion plays an important role in pricing options and that this effect is stronger when their risk aversion is higher. We proxy shifts in the global investors' risk appetite with the difference between the yield of the iBoxx index of BBB and the yield of the iBoxx index of AAA European corporate bonds. A widening of the spread between BBB and AAA yield signals decreasing risk appetite (i.e., increasing risk aversion) and shifts of investors preferences towards safer assets.

Relative bid-ask spread slope (RBAS). The bid-ask spread is the most common proxy for market liquidity used by numerous studies in the equity options literature. Peña et al. (1999) and Chou et al. (2011) find that option bid-ask spread seem to be a key determinant of the curvature of the equity volatility smile. Deuskar et al. (2011) show that in the OTC derivative markets illiquidity has an opposite effect to that found in markets for assets in positive net supply (equities and bonds). That is, in the OTC derivative markets illiquid options (high bid-ask spread) trade at higher prices than liquid options (low bid-ask spread). To capture the effect of market illiquidity on the term-structure slope of asset implied volatilities, we define the RBAS variable as the difference between the relative bid-ask spread of the 10-year and 3-year CDS iTraxx index.[24] The relative bid-ask spread is calculated as the ratio of the difference between bid and ask quotes to the mid-quote. We additionally control for the general market level of liquidity with the relative bid-ask of the most liquid 5-year CDS iTraxx index.

Adverse shocks slope (ADS). Han and Zhou (2014) show that information asymmetry affects yield spreads for both long-term and short-term bonds, and that the effect is much stronger for the short-term sample. Yu (2005) studies the effect of perceived accounting transparency on the term structure of credit spreads and finds that the transparency spread is especially large for short-term bonds. Finally, Acharya and Johnson (2007) show that insider trading in the CDS market is asymmetric consisting mainly of bad news (i.e., severe negative shocks). We proxy informational frictions with large positive jumps in the CDS prices. Following Acharya and Johnson (2007) we define an adverse shock as a daily increase in the CDS spread level of 50 bp or more. To capture the term structure effect we further calculate the slope variable, ADS, as the difference between the frequency of adverse shocks of the 10-year and 1-year contracts for a cross-section of 55 companies. We additionally control for the general market level of extreme upward jumps in the CDS spreads with the average frequency of adverse shocks across the whole term structure.

Buying pressure slope (BPS). Bollen and Whaley (2004) show that net buying pressure, defined as the difference between the number of buyer-motivated and seller-motivated contracts, significantly affects the shape of the implied volatility function for S&P 500 index options and that the effect is especially pronounced for index puts. Since we do not have transaction data we take an alternative approach and approximate buying pressure as the difference between the mid and efficient price.[25] We use the idea that bid and ask quotes are not necessarily symmetric around the efficient price and, the higher the demand pressure, the closer the efficient price will be to the bid quote. We determine the efficient price from bid and ask quotes using the Gonzalo and Granger (1995) permanent-transitory decomposition under the

[24] The iTraxx index for 1-year maturity contracts is not available.

[25] Note that we have used the mid quote as the hypothetical transaction price when deriving implied volatilities.

long-run equilibrium VECM framework. To capture the slope effect, we further define the BPS variable as the difference between the relative demand pressure of the 10-year and 3-year iTraxx index contracts.[26] We control for the aggregate market demand pressure with the relative demand pressure of the 5-year iTraxx index contracts.

We formally test for the presence of unit roots in the empirical term structure slope series using the Augmented Dickey-Fuller (ADF) test. We fail to reject the null hypothesis of the presence of unit-roots for the entire term structure slope as well as for the long-end of the term structure. For the short-end, we can reject the null hypothesis only at the 10% significance level. In contrast, the null hypothesis of non-stationarity for the first differences in the empirical slope series is rejected at 1% significance level in all of the cases (see the online appendix). Test statistics for the ADF test for the level of the series are reported in Panel A of Table 11 (the results on the first differences are reported in the online appendix). Descriptive statistics of the above-mentioned variables are provided in Panel B of Table 11.

[Table 11 about here.]

We specify the regression model as follows:

$$\begin{aligned} \Delta Slope_t &= \beta_0 + \beta_1 MOM_t + \beta_2 \Delta TED_t + \beta_4 \Delta RBAS_t + \beta_5 ADS_t \\ &\quad + \beta_6 BPS_t + \beta_7 \Delta Slope_{t-1} + Controls_t + \epsilon_t \end{aligned} \tag{9}$$

were $Slope_t$ refers to the empirical term structure slope, that is, the difference between the 10-year and 1-year maturity implied volatilities and Δ denotes the first difference operator. We consider slope changes rather than levels given the results of the ADF test and also include as a regressor the one-period lag of the dependent variable. The results of the OLS time-series regression with Newey-West standard errors are presented in Table 12. We report results for the entire term structure slope as well as results for the short-end (5-year minus 1-year implied volatility) and long-end (10-year minus 5-year implied volatility) of the term structure. To differentiate between

[26] We define the relative demand pressure as the difference between the mid-quote and the efficient price scaled by the mid-quote.

effects in crisis and non-crisis periods we determine endogenously the timing of the structural break using the Quandt-Andrews test with 15% trimming. The endogenously estimated break date falls on the 5th of February 2009, a date which we use to divide the sample into crisis and post-crisis periods.

[Table 12 about here.]

We can notice first that momentum is positively related to the term structure slope.[27] That is, the term structure slope is flatter in bullish markets, and steeper in bearish markets.[28] If we additionally consider the results from Figure 5 that the term structure is steeper during the crisis, we can conclude that highly volatile periods with negative momentum have steeper term structure slopes. Looking at columns two and three we see that this effect is stronger at the short-end of the curve. Moreover, the effect is higher in the crisis sub-sample (columns four and five). Intuitively, in periods with negative momentum there is an increase in the demand for credit protection, and this is particularly important for short-term maturities, as investors believe that crises eventually end.

Regarding the TED spread, we find that an increase in funding costs is associated with a flatter term structure. This could be due to two reasons. On the one hand, with higher funding costs a flight to quality might occur from the long-term CDS contracts to the short ones, since the speculators' capital deteriorates which induces them to provide liquidity in the short-term less risky securities. On the other hand, anecdotal evidence suggests that short dated CDS contracts are used by large institutional money management firms to express their views (Pan and Singleton, 2008). This evidence, combined with the fact that the primary motive for trading in this market is gambling (Crotty, 2009), could imply that in times of higher funding costs these institutions could reduce their speculation-related demand for short term maturity CDS contracts (thus focusing on their function of liquidity suppliers). Both channels would lead to a flatter term structure. Our results regarding the TED spread are also consistent with those of Frazzini and Pedersen (2014), who find a negative relation between BAB (betting against beta) returns and

[27] We simply look at the association measures between variables, we do not attempt to identify causality.

[28] We remind the reader that we have a downward sloping term structure, thus a negative slope. Therefore, an increase in the slope implies that the term structure becomes flatter.

the TED spread. As before, we obtain stronger results at the short-end of the curve, and importantly this variable is only significant during the crisis.

An increase in risk aversion is associated with a steeper term structure, is driven by the short-end of the curve, and is only significant during the crisis sub-sample. A higher risk aversion (higher default risk/premium) indicates that investors *en masse* are worried about credit events, and therefore they buy credit protection. Since this is only significant in the crisis sub-sample, the results suggest that investors worry over the near term, driving up the implied volatility curve at its short-end.

The last three explanatory variables represent the slopes in transaction costs, adverse shocks and buying pressure, all measured as the difference between the long-end (10-year maturity) and short-end of the curve (3 or 1-year maturity depending on data availability). We obtain positive coefficients for all of them. First, when there are changes in transaction costs (bid-ask spread) such that long-term contracts become more illiquid as compared to short-term ones, the term structure of asset implied volatility becomes flatter. Put differently, the more illiquid short-term contracts become relative to long-term ones, the steeper the implied volatility term structure. This is in line with the evidence of Bongaerts et al. (2011) who show that in the CDS markets it is the protection seller that earns the illiquidity premium, i.e., more illiquid contracts are more expensive. Unlike most of the variables, the relative bid-ask spread slope effect is driven by the long-end of the curve and is only significant in the post-crisis sub-sample.

Second, regarding the term structure of adverse shocks, surprisingly we find that in general it is downward sloping, despite the fact that short-term credit spreads are in general lower than long-term ones (upward sloping term structure of CDS spreads). This might indicate that there exists more informed trading at the short-end of the curve. The positive coefficient for the ADS variable indicates that a steeper term structure of adverse shocks is associated with a steeper implied volatility term structure. Third, the term structure slope of asset implied volatility is also driven by the buying pressure slope. An increase in the buying pressure at the short-end relative to the long-end of the curve pushes CDS spreads up at the short-end, leading to a steeper term structure of implied volatility. Similarly, the net demand skew was found to be positively and significantly associated with the equity implied volatility skew for S&P 500 index options (Garleanu et al., 2009). As in most cases, the results are driven by the short-end of the curve and are stronger for the crisis subsample.

4.4. Robustness checks

It could be argued, however, that the level of implied volatility is sensitive to the specific set of modeling assumptions and the estimation procedure. In particular, extracting implied volatilities from observable CDS spreads basically requires the estimates of: the firm's asset value, default barrier and recovery rate. Therefore, in order to mitigate these concerns and verify the robustness of the main findings of the paper, we conduct several robustness checks along these three dimensions, structured along five robustness sets. For each robustness check, we present the mean implied volatility across maturity, main descriptive statistics for the empirical term structure slope, correlations with our baseline specification (Table 13), as well as term structure and moneyness smirk slopes (Table 14). For the ease of comparison, Panel A of each table presents the results for our baseline framework (MM). A detailed description follows.

We first confirm that results are robust to other default barrier specifications plausible within our baseline framework. Specifically, we replicate the analysis using the smooth-pasting (SP) condition (Leland and Toft, 1996) and the principal (P) value of the debt as these are shown to provide sensible credit spread estimates in line with those observed in the CDS market (see Forte and Lovreta, 2012 for a discussion). Moreover, in that way we actually consider the lower and the upper bound for the default barrier parameter. The lower bound is defined by the smooth-pasting condition value that provides the lowest possible default barrier that guaranties nonnegative equity values. The upper bound is represented by the face value of debt. For illustrative purposes, we plot in Figure 10 the empirical term structure slope (i.e., the difference between 10-year and 1-year asset implied volatility) for the three different default barrier specifications. First, we can notice that the smooth-pasting condition value and the principal value of debt provide the upper and the lower bound, respectively, for the slope of asset implied volatility (and the level of asset implied volatility itself). Second, the empirical term structure slope is negative for all days during our sample period irrespective of the default point assumption. Finally, we can notice that the time-series evolution of our baseline term structure slope (based on the empirically optimal default boundary value) is almost mirrored for different default barrier assumptions, which further confirms the robustness of our findings. This first set of results is reported in Panel B of Table 13 and Table 14, with the corresponding notation SP and P for the two robustness checks performed.

[Figure 10 about here.]

We next verify that the results of the paper are not materially affected by the interpolation of accounting data. In this exercise, instead of data interpolation, we consider constant values per year reported in the last available annual firm's balance sheet and income statement. These results are reported in Panel C of Table 13 and Table 14, with the corresponding notation PC.

Third, in our baseline implementation we have used a fixed recovery rate of 40%. Although, this is usually considered as a market convention, we account for the possible time-series and cross-sectional differences within two robustness checks. On the one hand, to reflect the findings in the literature that recovery rates change with economic cycles (Altman et al., 2005) we rely on Moody's (2015) historical recovery rates (RR_H) for senior unsecured bonds. On the other hand, to account for the cross-sectional dimension we rely on the result of Glover (2016) who finds that the costs used ex ante by credit markets in pricing debt amount to 44.5% of the firm value in default. That is, we now fix the costs that the firm expects to incur in the case of default, α, and allow recovery rates to differ among the companies (RR_C). In both robustness tests, the firm's asset value and default barrier are estimated following the two-step procedure described in the main body of the paper. The results of these two tests are reported in Panel D of Table 13 and Table 14, with the corresponding notation RR_H and RR_C.

Fourth, we consider the possibility to treat the firm's asset value and the default barrier as "observables", and, consequently, to avoid relying on any specific structural model or estimation procedure to assess their values (Charitou et al., 2013; Bharath and Shumway, 2008). Within this robustness set we consider: a) The approach of Charitou et al. (2013), labeled as CDLT, in which firm's asset value is proxied with the sum of the market value of equity and book value of total liabilities and the default barrier is set to the level of total liabilities ($STL + 1LTL$); b) The approach of Bharath and Shumway (2008), labeled as BS, in which the firm's asset value is proxied with the sum of the market value of equity and default barrier, set as in KMV to the value of $STL + 0.5LTL$. c) For completeness, we also consider Afik et al. (2016), labeled as AAG, who suggest a default barrier of $STL + 0.1LTL$. We set the asset value as before to the sum of the market value of equity and the default barrier. This "selection" of ad hoc default boundaries are indicative of an upper (Charitou et al., 2013) and lower (Afik et al., 2016) bound for the term structure slope, respectively, when the default barriers are exogenous and predefined. The results of these three approaches are reported in Panel E of Table 13 and Table 14, with the corresponding notation CDLT, BS and AAG.[29]

Finally, in the fifth robustness set, we consider the model of Leland and Toft (1996) that includes endogenous default, taxes and arbitrary maturity of the firm's aggregate debt. Following Ericsson et al. (2015) we consider three different choices for the maturity of the firm's aggregate debt: 5, 6.76 and 10 years, to which we refer for the sake of brevity as short (LT_S), medium (LT_M) and long (LT_L). We also set the tax rate to 20%, realized costs of financial distress to 15%, and the CDS recovery rate to 40%.[30] The nominal amount of debt, the coupon paid to all the firm's debt holders, and the payout ratio are set as in our base case. It is worth noting that the average payout ratio for our sample of companies (2.76%) is very close to the average payout ratio of 2.65% reported in Ericsson et al. (2015). The firm's asset value is estimated using the two-step procedure applied in the main body of the paper with the difference that the Step 2 of the procedure is replaced by estimating the default barrier using the smooth-pasting condition value. This set of results is reported in Panel F of Table 13 and Table 14.

[Table 13 about here.]

[Table 14 about here.]

The main results of the paper are robust to all these different specifications as we can observe in Table 13 and Table 14. We can see that the term-structure is on average downward sloping. Moreover, the first three principal components obtained with the different robustness specifications are very highly correlated with those obtained with our baseline model. The same holds for the changes in the empirical term structure slope. When taking a closer look on the term structure slope across moneyness bins, we observe that for all the robustness specifications the slope is more negative for low moneyness bins (deep-out-of-the-money put options) and as we move to higher bins (the options are closer to being at-the-money), the slope gets less

[29] The default barrier, or more generally the default barrier-to-asset value ratio, could also be related to other accounting variables (see for example Dionne and Laajimi, 2012 and Li and Miu, 2010).

[30] We refer the reader to the original papers of Leland and Toft (1996) and Ericsson et al. (2015) for details.

negative or even positive in the case of the last moneyness bin, confirming our results for the baseline model. Finally, regarding the moneyness smirk slope, we note that it is negative for all maturities and we confirm our finding that the shorter the maturity the steeper the moneyness smirk. Detailed results, including the replication of Figure 3 (PCA analysis on maturity), Figure 7 (asset implied volatility surface), Figure 9 (term structure and moneyness smirk slopes), and Table 12 (determinants of the term structure slope) for all five robustness sets are provided in the online appendix.

5. Conclusions

In this paper, we analyze the surface of asset implied volatility, as a function of maturity (term structure) and as a function of moneyness (proxied by the ratio of the default barrier to asset value). We estimate the firm's asset value in the framework of a structural model of default and back-out asset implied volatility from observed CDS spreads. Our sample includes 55 non-financial investment-grade companies that belong to the iTraxx Europe index, and spans over the 2007-2014 period.

Principal component analysis on both the term structure and moneyness dimension shows that three factors (level, slope and curvature) are enough to capture most of the variation in daily changes of the asset implied volatility. In a dynamic framework, the first principal component on the term structure dimension has higher explanatory power during periods of elevated systematic risk, and lower explanatory power during tranquil periods. PCA on the entire volatility surface shows that the first principal component is a level mode that makes the entire surface move up or down, while the second principal component is a term structure mode. The third principal component corresponds to a skew mode, and the fourth one to a moneyness-related curvature mode.

Unlike the typical term structure of equity implied volatility, we find a downward sloping term structure of asset implied volatility both averaging across the whole sample period and for every single day in our sample. In times of crisis, when the term structure of CDS spreads inverts, the term structure of asset implied volatility becomes steeper. To better understand this novel finding, we have analyzed the variables potentially associated with the empirical term structure slope. Our results suggest that the downward sloping term structure of asset implied volatility is associated with market and funding illiquidity, investors' risk aversion, informational frictions, demand/supply factors, and momentum. These variables have higher explanatory power precisely in crisis periods. Regarding the moneyness dimension, in line with evidence on equity implied volatility, we find a negative skew. This skew is steeper for short-term maturities, and gets steeper during crises. Finally, less indebted firms with low moneyness exhibit steeper negative term structure slopes.

Given the important differences found in the dynamics of asset implied volatility compared to equity implied volatility, we conclude that the latter one should not be used as a proxy for asset implied volatility in pricing credit sensitive instruments. On the contrary, further research on asset implied volatility is needed to better understand its behavior and how the latter differs from the evolution of equity implied volatility. In particular, it would be interesting to know if the identified differences in the term structure of asset and equity implied volatility are due to differences in moneyness and maturity,[31] or to the different informational content of credit markets compared to options markets. An interesting avenue for future research that could shed some light on this issue would be to analyze high-yield firms, as opposed to our study that focuses on investment-grade firms. The comparison could then be done starting from equal grounds at least regarding moneyness, since in high-yield firms CDS contracts are near the money options, similar to at-the-money equity options used in the equity implied volatility literature.

Appendix A.

The expressions for $F_t(\tau_n)$ and $G_t(\tau_n)$ are as follows:

$$F_t(\tau_n) = \Phi\left[h_{1t}(\tau_n)\right] + \left(\frac{V_t}{V_b}\right)^{-2a} \Phi\left[h_{2t}(\tau_n)\right];$$

$$G_t(\tau_n) = \left(\frac{V_t}{V_b}\right)^{-a+z} \Phi\left[q_{1t}(\tau_n)\right] + \left(\frac{V_t}{V_b}\right)^{-a-z} \Phi\left[q_{2t}(\tau_n)\right];$$

where

[31] As previously mentioned, the moneyness and maturity mismatch impede a direct comparison of the two.

$$q_{1t} = \frac{-b_t - z\sigma^2\tau_n}{\sigma\sqrt{\tau_n}}; \quad q_{2t} = \frac{-b_t + z\sigma^2\tau_n}{\sigma\sqrt{\tau_n}};$$
$$h_{1t} = \frac{-b_t - a\sigma^2\tau_n}{\sigma\sqrt{\tau_n}}; \quad h_{2t} = \frac{-b_t + a\sigma^2\tau_n}{\sigma\sqrt{\tau_n}};$$

$$a = \frac{r - \delta - \frac{\sigma^2}{2}}{\sigma^2}; \quad b_t = \log\left(\frac{V_t}{V_b}\right); \quad z = \frac{\sqrt{\left(a\sigma^2\right)^2 + 2r\sigma^2}}{\sigma^2}.$$

Appendix B.

Table B.1: The 55 companies included in our sample

AB Volvo	EDP Energias de Portugal SA
Bayerische Motoren Werke AG	Iberdrola SA
Compagnie Generale des E. Michelin SCA	Repsol SA
Continental AG	RWE AG
Daimler AG	Technip
Peugeot SA	Akzo Nobel NV
Renault SA	Anglo American PLC
Valeo SA	BAE Systems PLC
Deutsche Lufthansa AG	Bayer AG
Kingfisher PLC	Compagnie de Saint Gobain SA
Koninklijke Philips NV	Investor AB
LVMH Moet Hennessy Louis Vuitton SE	Lafarge SA
Marks and Spencer Group PLC	Linde AG
Kering SA	Rolls-Royce Holdings PLC
Sodexo SA	Siemens AG
British American Tobacco PLC	Stora Enso OYJ
Carrefour SA	UPM Kymmene OYJ
Casino Guichard Perrachon SA	BT Group PLC
Diageo PLC	Deutsche Telekom AG
Danone SA	Orange SA
Henkel & Co KGaA AG	Hellenic Telec. Organization SA
Imperial Tobacco Group PLC	Koninklijke KPN NV
J Sainsbury PLC	Pearson PLC
Metro AG	STMicroelectronics NV
Tesco PLC	Telefonica SA
Unilever NV	Wolters Kluwer NV
BP PLC	WPP PLC
E.ON SE	

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Figures

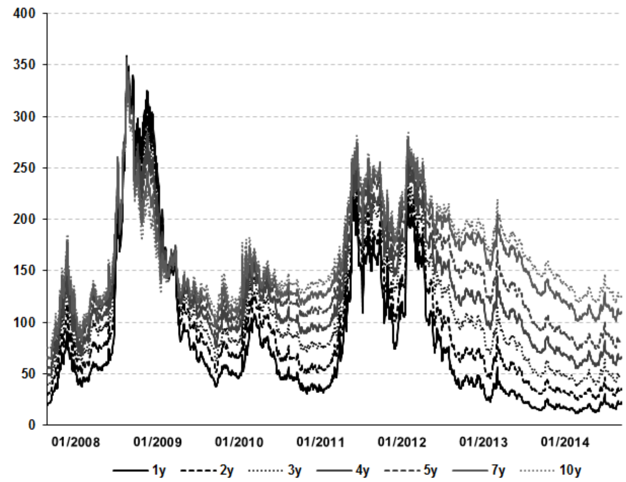


Figure 1: The term structure of CDS spreads. The graph depicts the average CDS spreads in basis points for the sample of 55 firms, for different maturities ranging from 1 to 10 years, during the entire sample period.

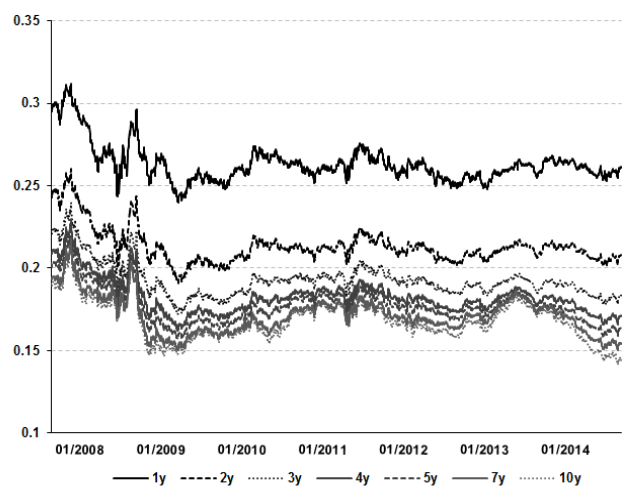
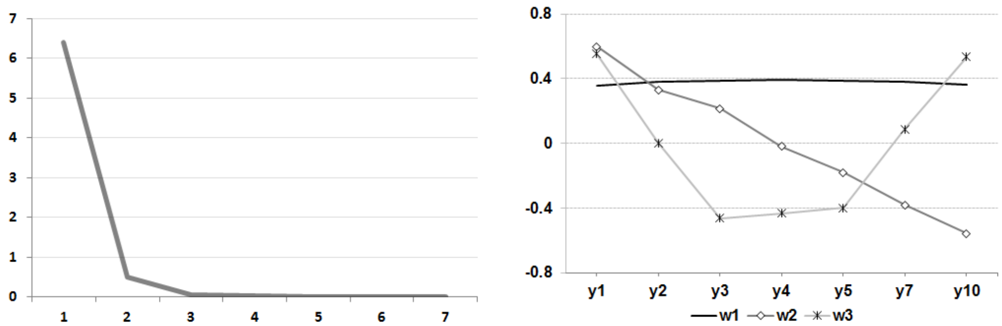


Figure 2: The term structure of asset implied volatility. The mean asset implied volatility over the 55 firms in our sample is plotted for each maturity ranging from 1 to 10 years, during the whole sample period.



a) Sorted eigenvalues

b) First three eigenvectors

Figure 3: Principal component analysis on maturity. Panel a) plots the sorted eigenvalues of a PCA on the maturity dimension on the correlation matrix of daily changes in asset implied volatility, as a function of their rank. Panel b) shows the first three eigenvectors corresponding to the three largest eigenvalues for the seven maturities from 1 year (y1) to 10 years (y10). The PCA corresponds to the whole sample period.

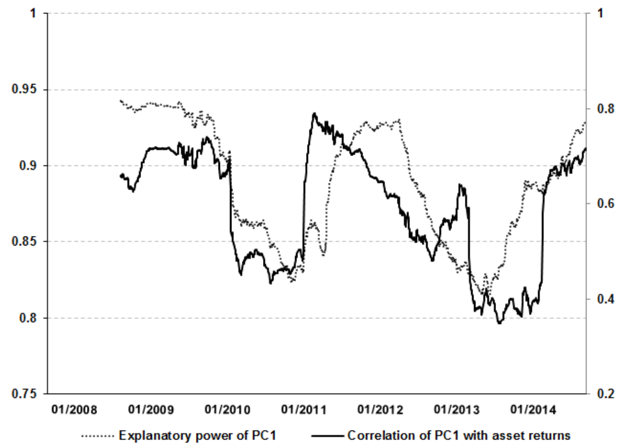


Figure 4: Principal component analysis on maturity with rolling window. We perform PCA on maturity with a rolling window of 252 days. The dotted curve represents the explanatory power of the first principal component (left-hand scale). The solid curve represents the correlation of the first principal component with asset returns (right-hand scale). Each point on the graph corresponds to a PCA taken on the previous 252 days. The first data point corresponds to a PCA over the December 14, 2007- December 1, 2008 period.

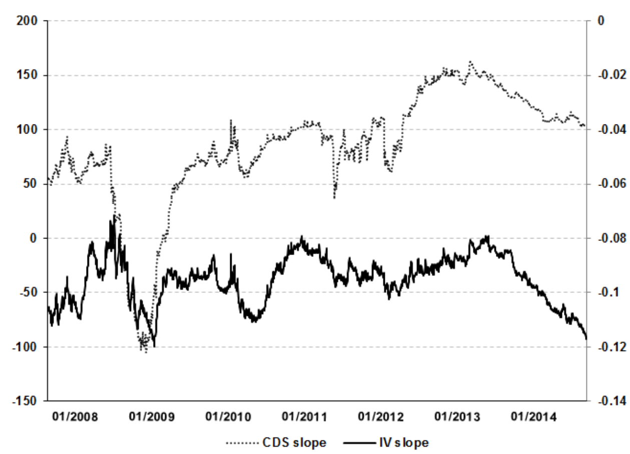
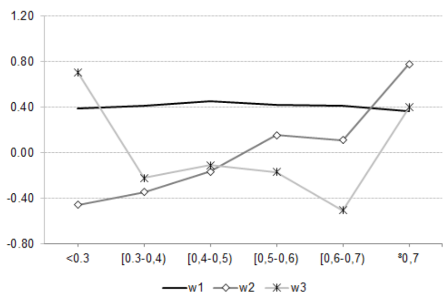
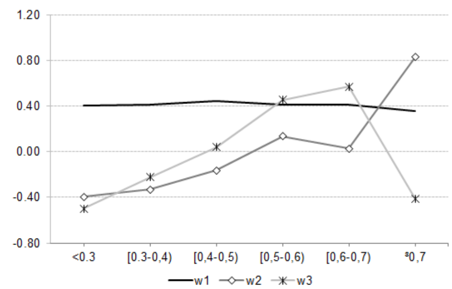


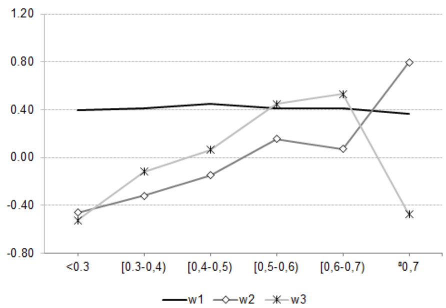
Figure 5: Empirical term structure slopes. The dotted curve represents the empirical term structure slope for CDS spreads computed as the difference between 10-year maturity and 1-year maturity CDS spreads (left-hand scale in basis points). The solid curve represents the empirical term structure slope for asset implied volatility (right-hand scale). It is calculated as the difference between 10-year and 1-year maturity asset implied volatility.



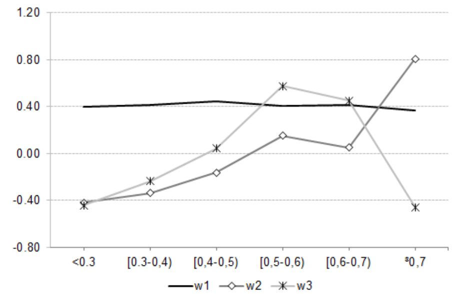
a) 1-year maturity



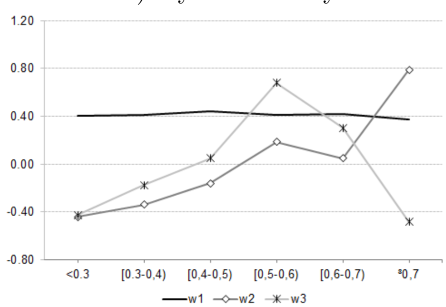
b) 2-year maturity



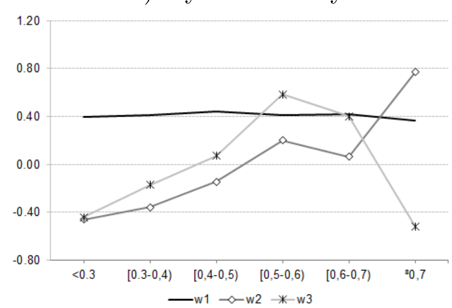
c) 3-year maturity



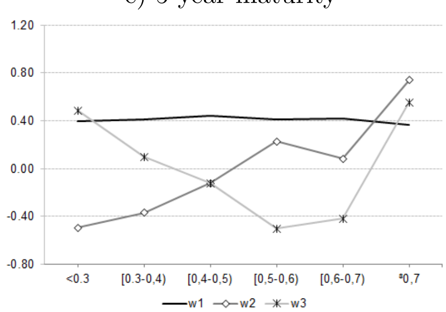
d) 4-year maturity



e) 5-year maturity



f) 7-year maturity



g) 10-year maturity

Figure 6: Principal component analysis on moneyness. PCA is performed on the moneyness dimension, separately for each maturity. We depict the first three eigenvectors corresponding to the largest eigenvalues.

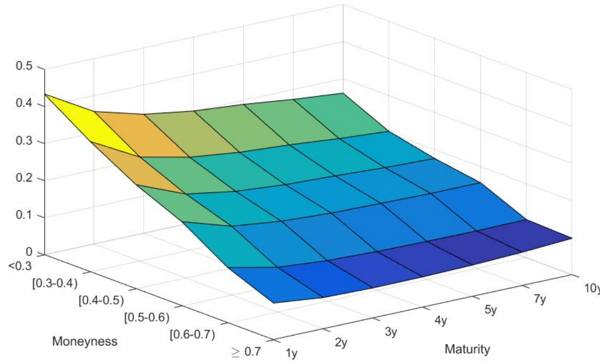
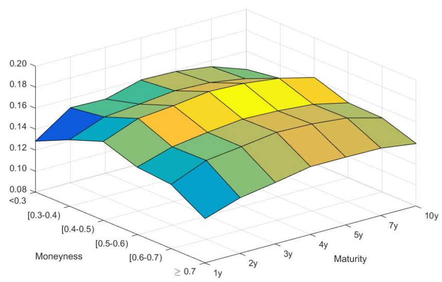
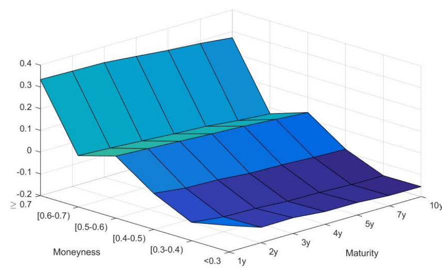


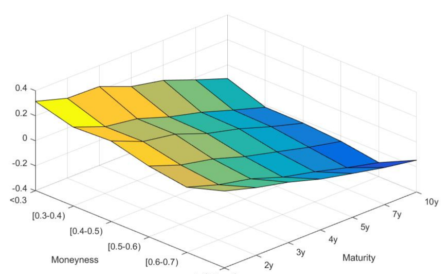
Figure 7: Asset implied volatility surface. The graph reports the volatility surface, i.e., the asset implied volatility as a function of maturity and moneyness.



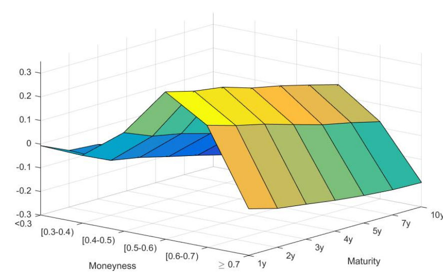
a) First principal component



b) Second principal component

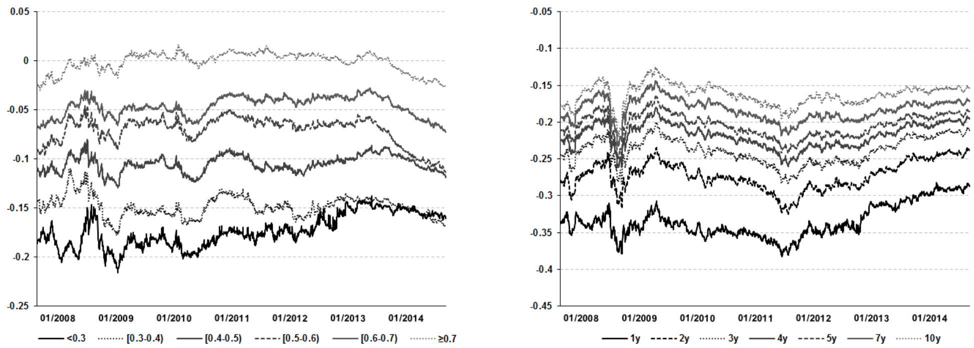


c) Third principal component



d) Fourth principal component

Figure 8: Principal component analysis on surface. PCA is performed on the surface of asset implied volatility, pooling together the moneyness bins for all maturities, for the entire sample period. The first four principal components are depicted in panels a) to d).



a) Term structure slope b) Moneyness smirk slope

Figure 9: The dynamics of the empirical term structure and moneyness smirk slopes. Panel a) plots the empirical term structure slope for the six different moneyness bins during the entire sample period. It is computed as the difference between the 10-year maturity and 1-year maturity asset implied volatility. Panel b) reports the empirical moneyness smirk slope for all maturities. This is computed as the difference between the implied volatility for the highest moneyness bin and the implied volatility for the lowest moneyness bin.

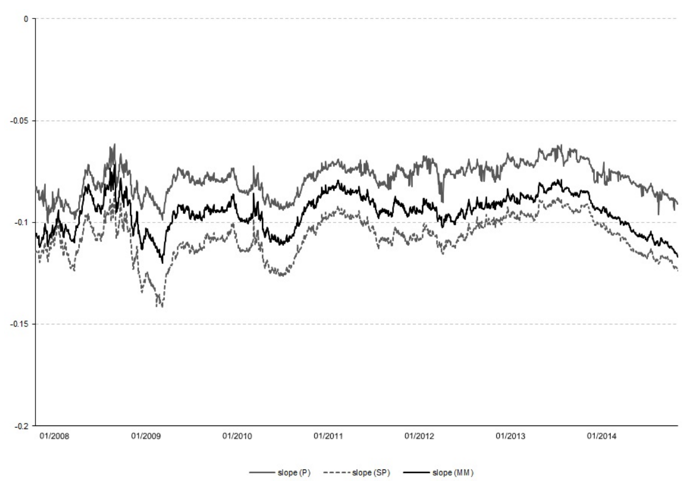


Figure 10: Empirical slope for the first robustness set. The graph depicts the time-series evolution of the empirical term structure slope (i.e., the difference between 10-year and 1-year asset implied volatility) for three different default barrier specifications: the nominal value of debt (P), the smooth-pasting condition value (SP) and the value that maximizes the average equity holders' participation in the firm's asset value (MM).

Tables

Table 1: Descriptive statistics of CDS spreads. This table reports the main descriptive statistics for CDS spreads on a cross-sectional basis: the mean, median, standard deviation, minimum, maximum, skewness and kurtosis.

Maturity	mean	median	st. dev.	min	max	skewness	kurtosis
1y	82.14	54.30	73.17	12.22	358.47	1.66	5.24
2y	99.40	74.90	67.52	24.96	354.96	1.43	4.57
3y	116.72	95.71	63.35	37.73	357.28	1.20	3.91
4y	130.79	113.41	57.59	48.12	357.11	1.09	3.70
5y	144.91	130.17	54.33	55.48	358.45	0.97	3.42
7y	158.53	143.23	48.53	64.50	348.84	0.85	3.21
10y	166.20	151.01	45.28	73.53	341.71	0.81	3.16

Table 2: Systematic variation in firm-level volatility. The proportion of variance explained by the first principal component is shown for PCA on the changes in firm-level implied asset volatilities for the sample of 55 individual firms. This analysis is performed separately for each maturity. The correlation between changes in the cross-sectional mean of firm-level volatilities and PC1 for changes in firm-level volatility is reported in the last column.

Maturity	Proportion	Correlation
1y	0.2427	0.9899
2y	0.2843	0.9897
3y	0.2982	0.9881
4y	0.3225	0.9878
5y	0.3351	0.9871
7y	0.3390	0.9863
10y	0.3433	0.9860

Table 3: Descriptive statistics of asset implied volatilities. This table reports the main descriptive statistics for asset implied volatilities on a cross-sectional basis: the mean, median, standard deviation, minimum, maximum, skewness, kurtosis and fractional degree of persistence. The fractional degree of persistence is estimated using the commonly applied semi-parametric approach of Geweke and Porter-Hudak (1983), d_{GPH}, and the exact local Whittle estimator of Shimotsu and Phillips (2005), d_{ELW}.

Maturity	mean	median	st. dev.	min	max	skew.	kurt.	d_{GPH}	d_{ELW}
1y	0.263	0.261	0.013	0.240	0.312	1.76	6.81	0.808	0.901
2y	0.213	0.212	0.011	0.191	0.260	1.72	6.65	0.912	0.902
3y	0.193	0.192	0.011	0.172	0.240	1.49	5.75	0.914	0.911
4y	0.183	0.181	0.011	0.162	0.230	1.36	5.35	0.926	0.921
5y	0.178	0.176	0.011	0.157	0.225	1.08	4.68	0.979	0.931
7y	0.171	0.171	0.011	0.150	0.218	0.71	3.83	1.078	0.953
10y	0.168	0.167	0.012	0.142	0.215	0.51	3.58	1.139	0.969

Table 4: Correlation matrix of changes in mean implied volatilities by maturity

	1y	2y	3y	4y	5y	7y	10y
1y	1.000						
2y	0.952	1.000					
3y	0.934	0.967	1.000				
4y	0.875	0.960	0.972	1.000			
5y	0.824	0.911	0.950	0.983	1.000		
7y	0.754	0.864	0.899	0.958	0.978	1.000	
10y	0.668	0.788	0.827	0.903	0.935	0.981	1.000

Table 5: PCA on maturity

Component	Eigenvalue	Proportion of variance	Cumulative proportion
PC1	6.4031	0.9147	0.9147
PC2	0.4915	0.0702	0.9849
PC3	0.0484	0.0069	0.9919

Table 6: Correlation between changes in the mean implied volatility across firms in a given moneyness bin and PC1 for individual firm-level volatilities of firms within the same bin

Maturity	< 0.3	$[0.3, 0.4)$	$[0.4, 0.5)$	$[0.5, 0.6)$	$[0.6, 0.7)$	≥ 0.7
1y	0.907	0.958	0.991	0.909	0.972	0.987
2y	0.932	0.965	0.989	0.903	0.971	0.991
3y	0.937	0.965	0.989	0.897	0.970	0.994
4y	0.936	0.966	0.989	0.904	0.970	0.995
5y	0.937	0.965	0.989	0.900	0.972	0.996
7y	0.934	0.961	0.989	0.904	0.970	0.997
10y	0.934	0.958	0.990	0.913	0.971	0.997

Table 7: Correlation between changes in the mean implied volatilities at the sub-index level (across firms belonging to a given moneyness bin) and at the index level (across all firms)

Maturity	< 0.3	$[0.3, 0.4)$	$[0.4, 0.5)$	$[0.5, 0.6)$	$[0.6, 0.7)$	≥ 0.7
1y	0.784	0.855	0.947	0.874	0.810	0.667
2y	0.839	0.871	0.954	0.879	0.835	0.690
3y	0.834	0.874	0.956	0.883	0.844	0.705
4y	0.853	0.882	0.960	0.894	0.865	0.725
5y	0.852	0.884	0.960	0.895	0.876	0.741
7y	0.848	0.881	0.960	0.897	0.879	0.740
10y	0.836	0.880	0.961	0.899	0.886	0.734

Table 8: PCA on moneyness by maturity. The cumulative explanatory power of the first three principal components is reported.

	1y	2y	3y	4y	5y	7y	10y
PC1	0.6949	0.7296	0.7363	0.7589	0.7667	0.7652	0.7628
PC2	0.7917	0.8190	0.8244	0.8414	0.8461	0.8475	0.8498
PC3	0.8625	0.8766	0.8806	0.8927	0.8961	0.8976	0.9018

Table 9: Correlations between PC2 on moneyness and changes in the empirical moneyness smirk slope. The empirical slope is computed as the difference between the mean asset implied volatility for the highest moneyness bin and the mean asset implied volatility for the lowest moneyness bin.

	1y	2y	3y	4y	5y	7y	10y
Corr	0.7241	0.6761	0.7182	0.7220	0.7461	0.7769	0.8076

Table 10: PCA on the volatility surface

Component	Eigenvalue	Proportion of variance	Cumulative proportion
PC1	28.6416	0.6819	0.6819
PC2	3.2285	0.0769	0.7588
PC3	2.2214	0.0529	0.8117
PC4	1.9643	0.0468	0.8585

Table 11: Descriptive statistics for regression variables. This table provides main descriptive statistics and summary results for the Augmented Dickey-Fuller (ADF) Test for the presence of unit roots for the empirical term structure slope (in Panel A) and the explanatory variables used in equation (10)(in Panel B). The lag-length is selected on the basis of a downward t-test, i.e., starting from the maximum number of lags (p_{max}) the number of lags is reduced until the last lag of the first difference included is significant at the 5% level. The maximum number of lags is determined according to $p_{max} = [12(T/100)^{1/4}]$, where [] denotes the integer part and T is the sample size. ADF unit root tests are performed for the three possible alternatives: without constant and trend in the series, with constant and without trend, and with constant and trend. Reported ADF test statistics correspond to the model with the lowest Schwarz Information Criterion.

Panel A:

	mean	median	st. dev.	min	max	ADF	p-value
Slope_{10y-1y}	-0.095	-0.094	0.009	-0.120	-0.072	-2.490	0.119
Slope_{5y-1y}	-0.086	-0.085	0.006	-0.103	-0.067	-2.807	0.057*
Slope_{10y-5y}	-0.010	-0.009	0.003	-0.019	-0.002	-2.201	0.208

Panel B:

	mean	median	st. dev.	min	max	ADF	p-value
MOM	-0.015	0.694	3.586	-12.312	8.573	-4.178	0.001***
TED	0.486	0.230	0.570	0.090	4.580	-2.482	0.120
RA	1.597	1.446	0.915	0.054	4.464	-1.834	0.370
RBAS	-1.468	-0.927	2.199	-17.332	5.646	-5.863	0.000***
RBAL	0.719	0.644	0.492	0.069	7.370	-1.924	0.052*
ADS	-0.158	0.000	1.061	-23.636	3.636	-5.945	0.000***
ADL	0.234	0.000	0.896	0.000	14.545	-6.113	0.000***
BPS	-1.468	-0.927	2.199	-17.332	5.646	-8.140	0.000***
BPL	0.719	0.644	0.492	0.069	7.370	-9.446	0.000***

Table 12: Determinants of the term structure slope of asset implied volatility. This table depicts the results from the regression given in (9). Standard errors are calculated as Newey-West HAC Standard Errors. t-statistics are given in parentheses. *, **, and *** denote significance at the 10%, 5% and 1% levels, respectively. For the ease of exposition, the values of independent variables are divided by 100.

Variable	Δ slope(10y-1y)	short-end Δ slope(5y-1y)	long-end Δ slope (10y-5y)	Before 05/02/2009	After 05/02/2009
constant	-0.00003	-0.00001	-0.00001	0.00067**	-0.00003
	(-0.918)	(-0.566)	(-1.289)	(2.435)	(-0.954)
MOM	0.28349***	0.19479**	0.08910**	0.83752**	0.28608***
	(2.664)	(2.394)	(2.483)	(2.338)	(2.883)
ΔTED	0.35905***	0.25116***	0.11044***	0.30223***	0.30718
	(6.136)	(6.742)	(4.214)	(4.972)	(0.868)
ΔRA	-0.12455*	-0.14394***	0.01905	-0.49768*	-0.07299
	(-1.869)	(-2.622)	(0.902)	(-1.871)	(-1.321)
ΔRBAS	0.32009**	0.16471	0.15552***	0.30672	0.26134*
	(2.008)	(1.381)	(2.915)	(0.591)	(1.745)
ADS	0.06763***	0.04765***	0.02000***	0.08672***	0.04383***
	(8.505)	(7.403)	(5.244)	(11.107)	(3.442)
BPS	0.20452**	0.14169*	0.06489	4.56909**	0.23057**
	(2.035)	(1.724)	(1.335)	(2.009)	(2.122)
ΔSLOPEt-1	-0.01368	-0.01906	-0.04914*	0.10179**	-0.09412***
	(-0.452)	(-0.612)	(-1.703)	(2.120)	(-3.054)
Adjusted R^2	0.1187	0.1033	0.0828	0.3231	0.0354
F-statistic	25.709	22.142	17.562	15.176	6.639
Prob(F-statistic)	0.000	0.000	0.000	0.000	0.000
Durbin-Watson stat	2.021	2.026	2.009	1.921	2.012

Table 13: Robustness checks: Implied asset volatility, empirical slope and correlations with the baseline specification. This table presents implied asset volatility for 1 to 10-year maturity, the main descriptive statistics for the empirical term structure slope, as well as correlations between the first three principal components and the changes in the empirical slope obtained with each robustness specification and those obtained with our baseline specification (MM). Panel A presents the results for our baseline framework (MM). Panels B-F report the results obtained for the five robustness sets as described in Section 4.4, respectively.

		Implied volatilily							Empirical slope				Correlations			
		1y	2y	3y	4y	5y	7y	10y	mean	min	max	sdev	PC1	PC2	PC3	ΔES
Panel A	MM	0.263	0.213	0.193	0.183	0.178	0.171	0.168	-0.095	-0.120	-0.072	0.009	1.000	1.000	1.000	1.000
Panel B	P	0.224	0.180	0.163	0.154	0.150	0.145	0.143	-0.081	-0.106	-0.054	0.009	0.989	0.991	0.919	0.987
	SP	0.314	0.267	0.241	0.228	0.221	0.213	0.207	-0.107	-0.142	-0.084	0.010	0.967	0.987	0.820	0.980
Panel C	PC	0.265	0.213	0.193	0.182	0.177	0.171	0.168	-0.097	-0.120	-0.072	0.008	0.941	0.983	0.918	0.959
Panel D	RR_C	0.271	0.219	0.199	0.189	0.185	0.180	0.178	-0.093	-0.119	-0.068	0.010	0.998	0.994	0.896	0.989
	RR_H	0.266	0.214	0.194	0.184	0.179	0.173	0.170	-0.096	-0.120	-0.075	0.009	0.947	0.963	0.880	0.972
Panel E	CDLT	0.218	0.175	0.158	0.150	0.146	0.141	0.139	-0.079	-0.103	-0.055	0.008	0.971	0.992	0.914	0.984
	BS	0.268	0.215	0.194	0.184	0.179	0.172	0.169	-0.099	-0.128	-0.076	0.009	0.983	0.994	0.903	0.978
	AAG	0.334	0.268	0.242	0.229	0.222	0.213	0.206	-0.128	-0.161	-0.105	0.012	0.993	0.988	0.869	0.966
Panel F	LT_S	0.268	0.216	0.195	0.185	0.180	0.174	0.170	-0.098	-0.122	-0.069	0.009	0.951	0.990	0.897	0.978
	LT_M	0.283	0.227	0.206	0.195	0.189	0.183	0.179	-0.104	-0.128	-0.076	0.009	0.946	0.990	0.889	0.978
	LT_L	0.305	0.245	0.222	0.210	0.204	0.196	0.191	-0.113	-0.138	-0.087	0.010	0.929	0.990	0.878	0.976

Table 14: Robustness checks: Term structure and moneyness smirk slopes. Panel A presents the results for our baseline specification (MM). Panels B-F report the results obtained for the five robustness sets as described in Section 4.4, respectively.

		Term structure slope						Moneyness smirk slope						
		<0.3	[0.3-0.4)	[0.4-0.5)	[0.5-0.6)	[0.6-0.7)	≥0.7	1y	2y	3y	4y	5y	7y	10y
Panel A	MM	-0.179	-0.148	-0.105	-0.071	-0.046	-0.001	-0.335	-0.273	-0.239	-0.218	-0.204	-0.183	-0.162
Panel B	P	-0.196	-0.142	-0.104	-0.077	-0.047	-0.015	-0.322	-0.247	-0.215	-0.195	-0.182	-0.161	-0.141
	SP	-0.208	-0.136	-0.112	-0.066	-0.017		-0.393	-0.303	-0.262	-0.238	-0.220	-0.193	-0.167
Panel C	PC	-0.187	-0.148	-0.105	-0.071	-0.044	0.010	-0.360	-0.279	-0.244	-0.222	-0.207	-0.185	-0.164
Panel D	RR_C	-0.188	-0.146	-0.102	-0.064	-0.042	0.006	-0.352	-0.273	-0.238	-0.217	-0.202	-0.179	-0.158
	RR_H	-0.189	-0.149	-0.105	-0.069	-0.045	0.000	-0.352	-0.274	-0.240	-0.219	-0.205	-0.184	-0.163
Panel E	CDLT	-0.184	-0.144	-0.101	-0.079	-0.049	-0.024	-0.306	-0.237	-0.208	-0.191	-0.180	-0.163	-0.146
	BS	-0.213	-0.144	-0.107	-0.075	-0.046	-0.001	-0.370	-0.284	-0.247	-0.223	-0.207	-0.182	-0.158
	AAG	-0.242	-0.139	-0.101	-0.066	-0.044	0.009	-0.521	-0.401	-0.348	-0.315	-0.292	-0.257	-0.224
Panel F	LT_S	-0.194	-0.152	-0.106	-0.084	-0.051	-0.026	-0.327	-0.255	-0.225	-0.207	-0.195	-0.177	-0.159
	LT_M	-0.203	-0.157	-0.111	-0.078	-0.051	-0.005	-0.350	-0.269	-0.234	-0.212	-0.197	-0.174	-0.152
	LT_L	-0.207	-0.142	-0.114	-0.079	-0.053	0.003	-0.346	-0.263	-0.226	-0.203	-0.186	-0.160	-0.135