

Default risk premium in credit and equity market: A new approach for structural model estimation

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31 August, 2015

ABSTRACT

We propose a novel methodological approach to estimate a corporate structural model, by using data from credit and stock market, and we reconstruct the dynamics of the market value of assets and debt, and the default boundary, for a sample of non-financial firms. We exploit our results to extract the default risk premium, which combines the risk-neutral and the real-world measure of default probability. We show that the equity and the credit market exhibit a relationship with the default risk premium which is opposite to each other, by implementing a long-short portfolio strategy based on the default risk premium, and we report a significant performance. Therefore, we argue that the 'distress puzzle', that is the counterintuitive negative relationship between default risk and stock return, can be solved, if the credit and the equity market securities are related through a default risk indicator, which combines the risk neutral and the real world default measures, and which is computed by using a structural model estimation, with only market data.

JEL classification: C4, G12, G32, G33.

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I. Introduction

In a corporate structural model, the default risk of a firm is expressed by the probability that the firm is not able to pay back the outstanding debt to the creditors, or by the probability that the value of the assets fall below a critical threshold. The default risk can be then expressed by using the real-world or the risk-neutral probability measure. The first provides information about the actual and physical risk of default, while the second reflects the conjecture of the market about such risk.

Indeed, for pricing firm's securities, both the real-world and the risk-neutral probability measures are important. The real-world measure describes the physical evolution over the time of the firm's economic fundamentals, such as the asset and the liabilities. The risk-neutral measure reflects the market evaluation of the fundamental indicators, that are also the underlying assets of the securities issued by the firm.

We estimate a corporate structural model with a non-linear Kalman filter in conjunction with maximum likelihood estimation, by using only market data. The non-linear filter reconstructs the dynamics of the market value of asset and debt, by using both the two probability measures. The real-world measure describes the dynamics of the state variable, that is the firm's economic fundamental. The risk-neutral measure, instead, maps the current value of the state onto the price of the securities issued by the firm. The maximum likelihood estimation returns the value of the model parameters. In particular, we combine information from credit and stock market, by using credit default swap (CDS) spreads and equity value¹.

We use the output of the structural estimation to compute both the real-world and the risk-neutral probability of default, for each firm. Then, we combine the two measures to extract the default risk premium, defined as the ratio between the risk-neutral and the real-world default probability. We show that the equity and the credit market exhibit a relationship with the default risk premium which is opposite to each other. We construct, in fact, a long-short portfolio strategy of equity shares and CDS, based on the one-step ahead forecast of the firm's default risk premium, and we report highly significant performance.

An expected increase in the premium, then, can be associated to an expected increase in the equity price, and to an expected downturn of the CDS spread, at the same time. This two-fold effect may occur when the drop in the actual default probability of a firm is more pronounced than in the respective risk-neutral measure. Hence, a risk-averse investor, who evaluates securities by using the real-world measure, is willing to pay more to buy a firm's stock, and to pay less to buy an insurance against the firm's default.

Otherwise, an expected increase in the premium can be associated to an expected drop in the equity price, and simultaneously to an expected increase in the CDS spread. It may happen when the increase in the risk-neutral default probability of a firm is greater than in the respective real-world measure. Hence, the firm's shareholders and the insurance's sellers, who evaluate securities by using the risk-neutral measure, are willing to sell stocks at a lower price, and to sell insurance at a higher price, respectively.

We empirically find that the first two-fold effect occur for firms with default risk premium, on

average, greater than one. The second pair of relationships, instead, is observed for those firms which report, on average, a default risk premium lower than one.

Therefore, the paper makes two contributions. First, we propose a novel methodological approach to estimate a corporate structural model, by using only market information, for a sample of non-financial firms, across different geographic regions. We generally find that the firm's market value of the leverage, defined as the ratio between debt and asset, reaches the peak around the 2008-2009 financial crisis. Also, we estimate the actual value of the default boundary for each firm in our sample, and we find that on average our sample firms have values of the default barrier around 75% of the face value of the debt. This result is substantially similar to the findings of Davydenko (2012), who estimates a default boundary around 70% of the debt value, and Wong and Choi (2009), who report a default barrier equal to 74% of the debt.

As second contribution, we bring new insight on the broad literature which links the default risk and the equity returns, and recently the CDS and the equity market. We argue that the 'distress puzzle', that is the counterintuitive negative relationship between default risk and stock return, can be solved, if the credit and the equity market securities are related through a default risk indicator, which combines the risk neutral and the real world default measures, and which is computed by using a structural model estimation, with only market data.

We think, in fact, to the market prices as the final result of the overall willingness of the investors to buy and sell, and then they incorporate the views and the forecasts of all the investors. Instead, the book data reflect a backward looking perspective, and they are released with a low frequency, at quarterly or even annual regularity. Moreover, they may be affected by management evaluations and relevant items for the firm's business may be omitted in the balance-sheet. With the aim of capturing the actual market conjectures on the firm's economic fundamentals, we overcome the drawbacks related to the book data with our pure market-based approach for the structural model estimation.

Structural models explain the credit events in terms of the firm's economic fundamentals, where the firm's asset value moves randomly through time with certain return and volatility. We use a structural model to relate the market variables to the firm's economic fundamentals, following the seminal papers of Black and Scholes (1973) and Merton (1974). We focus on a specific credit event, the firm's default. In particular, we use a first-time passage model, where the default occurs as soon as the asset value crosses from above a default barrier (Black and Cox (1976)). The boundary level of the asset value which triggers default can be fixed exogenously as in Longstaff and Schwartz (1995), or endogenously with the shareholders that optimally liquidate the firm as in Leland (1994) and Leland and Toft (1996). In the first case the barrier may represent certain covenants between creditors and debtors, where managers are committed to maintain some financial ratios above pre-specified levels in order to preserve the possibility of debt financing. An endogenous barrier is the result of an equity value maximization process implemented by the firm's shareholders.

Consistently with the previous literature, we specify a default barrier that is strictly positive but no greater than the book value of liabilities. The intuition is simple. As long as the asset value is above the default boundary, even if is below the face value of the debt, the shareholders are

willing to cover the promised payment and bear these losses in order to keep the firm operating. Otherwise, the firm defaults and the equity holders get nothing.

The first method to estimate a structural model *à la* Merton is based on a system of two equations which link the equity value and volatility to the unobservable asset value and volatility. This method, proposed by Jones, Mason, and Rosenfeld (1984), Ronn and Verna (1986), and improved and amended by Bohn and Crosbie (2003), Vassalou and Xing (2004), is known as Volatility-Restriction (VL). Duan (1994) highlights the drawbacks of this approach and constructs a transformed likelihood function to estimate the asset values from the observable equity prices.

Brockman and Turtle (2003) address the estimation of a structural model with early default risk, and they proxy the value of the asset by adding the equity value to the book value of the debt (Market Proxy). They report values of the default boundary above the nominal value of the debt. Ericsson and Reneby (2004), Li and Wong (2008), show that the maximum-likelihood approach of Duan (1994) outperforms both the VL and the market proxy methods, either in the Merton model or in the barrier-dependent structural model. Perlich and Reisz (2007) attribute the misleading results of Brockman and Turtle (2003), which would predict that the equity holders liquidate the firm when the asset value is more than enough to guarantee the final debt payment, to the overvaluation of the market value of the debt when it is replaced by the nominal face value. By using a transformed maximum-likelihood approach to estimate a barrier-dependent model, Wong and Choi (2009) report values of the barrier around 70% of the face value of the debt. As in the original Duan (1994) formulation, they use equity prices to infer the asset value, by constructing a modified likelihood function adapted to the barrier framework. Similar results are documented in Davydenko (2012), where the market value of the asset just prior to default is estimated for that firms which have market value of debt pretty entirely observable. It is the case of firms' capital structure with almost all the debt items traded on the market. Forte (2011) proposes a calibration approach to derive the asset value from the equity prices, and the default boundary level from the CDS spreads, while Forte and Lovreta (2012) implement a double-stage maximization algorithm which extracts both the asset and the barrier values from stock prices, under the assumption that the equity values incorporate the optimal level of the barrier. These two last papers estimate barrier values below the nominal debt.

Our paper nests in this literature, with several novel innovations. We estimate a barrier-dependent structural model, by using only market data. In contrast with Brockman and Turtle (2003), Perlich and Reisz (2007), Wong and Choi (2009), Forte and Lovreta (2012), we use not only equity prices but also CDS spreads. This approach allows us to infer also the debt value, instead of using the book value of the debt as input data. Moreover, differently from Forte (2011), equity value and CDS spreads enter in our estimation model simultaneously, in order to estimate at the same time the asset value dynamics and the barrier value. In particular, we propose a non-linear Kalman filter in conjunction with quasi maximum likelihood estimation. The filter reconstructs the dynamics of the unobservable variable by a set of predicting and updating equations. The model parameters are then estimated by performing a maximum likelihood algorithm.

In the second part of the paper, we focus on the dynamics of the default risk premium which

captures remarkable attention in both asset pricing and credit risk literature. The premium proxies the distance between the actual evaluation of the default risk and the evaluation reflected in the securities pricing. Accordingly, we define this premium as the ratio between the default probability under the risk-neutral and the real-world measure, which we calculate by using the estimates of the structural model. We show that the dynamics of the premium is related in an opposite fashion to the equity and the credit market securities, which is consistent with the economic intuition and the financial theory of an opposite relationship between the credit and the stock market securities dynamics.

Then, the forecast of the premium dynamics allows to exploit a significantly performing trading strategy, by constructing long-short portfolios of equity shares and CDS, based on such forecast. We can do that, as the filter generates a forecast for the state variable one-step ahead. Then, by using the model pricing equations, and the model parameters estimation, we can produce a forecast for the premium one-step ahead.

In general, the default risk premium arises from the gap between the risk-neutral default probability, extracted from the credit-based securities spreads, and the real-world measure of default, which expresses the actual probability of a credit event. Different approaches have been proposed to assess this key measure. Hull, Predescu, and White (2005) compute the ratio between the risk neutral and the real world default probability by using corporate bond spreads and historical data, while Driessen (2005) estimates a reduced-form model to derive a default risk premium, constant over time, implied by corporate bond spreads and rating agency based default probability, with a Kalman filter. He finds that the premium is statistically and economically significant. In a pioneer work on the CDS-based default risk premium, Berndt, Douglas, Duffie, Ferguson, and Schranz (2008) perform both a panel regression and a reduced form model by using 5-years CDS spreads and Moody's EDFs data, and they show that the premium is time, sector, and rating-varying. Diaz, Groba, and Serrano (2013) replicate Driessen (2005) and Berndt et al. (2008) by using a wider term structure of CDS spreads on European firms. The default risk premium has been recently studied in a structural model by Huang and Huang (2012), who calibrate different structural models with corporate bond spreads and rating agency default data. They support the conclusion that the premium decreases with the credit quality, and after the crisis periods. The closest paper is the recent work by Friewald, Wagner, and Zechner (2014), who explore the cross-sectional relation between the credit risk premium implied in the CDS spreads and the equity returns. They argue that either a positive or a negative relation, recently referred to as 'distress puzzle', between stock returns and default risk is consistent with structural models.

In contrast with the previous papers, we extract the default risk premium gathering the information conveyed simultaneously from both the credit and the equity market. We find that this premium is time-varying, and decreases as consequence of a crisis period, when the actual default risk substantially increases. For most of the firms, we find that on average the premium is greater than one, implying risk-neutral higher than real-world default probabilities. However, we report opposite results for about one quarter of our sample firms.

The rest of the paper is organized as follows. In the next section we discuss our model and the

estimation methodology. The data are described in Section 3, and Section 4 presents the empirical results on the structural model estimation. In Sections 5 we report our findings on the default risk premium, and we relate the default risk premium to the market data dynamics. Section 6 concludes and introduces further potential research directions.

II. The Model

We define the firm i as an entity fully financed with equity, with market value $E_{i,t}$ at time t , and a zero-coupon debt instrument with a face value of F_i maturing at time T . Let $V_{i,t}$ be the asset value of the i -th firm and $Z_{i,t}$ its risky zero-coupon bond value at time t . Then, the following condition holds for every time point and for every firm:

$$V_{i,t} = E_{i,t} + Z_{i,t}$$

The asset value of the i -th firm is described by a geometric Brownian motion on the filtered probability space $(\Omega, \mathcal{F}, \{\mathcal{F}_t : t \geq 0\}, \mathcal{P})$:

$$dV_{i,t} = \mu_{V_i} V_i dt + \sigma_{V_i} V_i dW_{i,t},$$

where μ_{V_i} and σ_{V_i} are the \mathcal{P} -drift and diffusion constant coefficients, $W_{i,t}$ is a standard Brownian motion under the physical probability measure \mathcal{P} .

We define the i -th firm's market value of leverage as $L_{i,t} = \ln\left(\frac{F_i}{V_{i,t}}\right)$, following an arithmetic Brownian motion,

$$dL_{i,t} = \mu_{L_i} dt - \sigma_{L_i} dW_{i,t}, \tag{1}$$

where $\mu_{L_i} = -(\mu_{V_i} - \frac{1}{2}\sigma_{V_i}^2)$ is the \mathcal{P} -leverage drift coefficient, and $\sigma_{L_i} = \sigma_{V_i}$ is the leverage diffusion component. As result of the inverse relationship between the asset and the leverage values, the minus before the diffusion component stands for the perfect and negative correlation between the Brownian motions of the asset value and the leverage dynamics.

For pricing the firm's securities, we adopt a first-time passage framework, as in Black and Cox (1976), Longstaff and Schwartz (1995), with a constant and deterministic barrier, that we assume to be below the face value of the debt. Default occurs as soon the asset value of the i -th firm crosses from above the barrier C_i at any time s , with $t \leq s \leq T$, where T is the outstanding firm's debt maturity. Therefore, the firm's equity value $E_{i,t}$ can be considered as a down-and-out European call (DOC) option, written on the firm's asset value, with maturity T . The pricing formula for the equity value in a DOC framework is rearranged in order to express the observable equity value as function of the firm's leverage.²

$$\begin{aligned}
E_{i,t} = & \frac{F_i}{e^{L_{i,t}}} \Phi(d_1) - F_i e^{-r(T-t)} \Phi(d_1 - \sigma_{L_i} \sqrt{(T-t)}) - \frac{F_i}{e^{L_{i,t}}} \exp\left((K_i + L_{i,t}) \left(\frac{2r}{\sigma_{L_i}^2} + 1\right)\right) \Phi(d_1^{C_i}) \\
& + F_i e^{-r(T-t)} \exp\left((K_i + L_{i,t}) \left(\frac{2r}{\sigma_{L_i}^2} - 1\right)\right) \Phi(d_1^{C_i} - \sigma_{L_i} \sqrt{(T-t)}), \quad (2)
\end{aligned}$$

where

$$d_1 = \frac{-L_{i,t} + (r + \frac{1}{2}\sigma_{L_i}^2)(T-t)}{\sigma_{L_i} \sqrt{(T-t)}}, \quad d_1^{C_i} = \frac{(2K_i + L_{i,t}) + (r + \frac{1}{2}\sigma_{L_i}^2)(T-t)}{\sigma_{L_i} \sqrt{(T-t)}}$$

Φ stands for the cumulative distribution function of a standard normal variable, and $K_i = \ln\left(\frac{C_i}{F_i}\right)$. The parameter K_i measures the willingness to the gamble for resurrection of the shareholders. As the default barrier is below the face value of the debt, K_i assumes only negative values. The larger is the magnitude of the absolute value of K_i , the larger is the distance between the face value of the debt F_i and the default barrier C_i , and the larger is the potential amount the shareholders are willing to take out of their pocket in order to bail out the firm's debt, and to keep the firm operating.

The firm's default risk is also priced in the credit default swaps (CDS) issued with different maturity τ_j , with j going from 1 to J , where the longest maturity τ_J matches the firm's debt maturity T . In a CDS contract, the protection buyer pays a fixed premium each period until either the default event or the contract expiration, and the protection seller is committed to buy back from the buyer the defaulted bond at its par value. Therefore, the price of the CDS, i.e. the premium (the spread) paid by the insurance buyer, is defined at the inception date of the contract in order to equate the expected value of the two contractual legs. Then, by assuming the existence of a default-free money market account appreciating at a constant continuous interest rate r , and M periodical payments occurring during one year, the CDS spread γ with time-to-maturity τ_j , priced at $t = 0$, solves the following equation:

$$\sum_{m=1}^M T \frac{\gamma}{M} \exp\left(-r \frac{m}{M}\right) \mathcal{E}_0^{\mathcal{Q}}[1_{t^* > \frac{m}{M}}] = \mathcal{E}_0^{\mathcal{Q}}[\exp(-rt^*) \alpha 1_{t^* < \tau_j}],$$

where t^* stands for the time of default, α is the amount paid by the protection seller to the protection buyer in case of default, and $\mathcal{E}_0^{\mathcal{Q}}$ indicates that the expectation is taken under the risk-neutral measure \mathcal{Q} . Therefore, $\mathcal{E}_0^{\mathcal{Q}}[1_{t^* < \tau_j}]$ is the probability that the firm defaults at any time before τ_j , that is the probability that the asset value crosses from above the barrier C_i . At t , this probability is equal to:

$$PD_{i,t}^{\mathcal{Q}}(\tau_j) = \Phi \left(\frac{K_i + L_{i,t} - (r - \frac{1}{2}\sigma_{L_i}^2)(\tau_j - t)}{\sigma_{L_i}\sqrt{(\tau_j - t)}} \right) + \exp \left((K_i + L_{i,t}) \left(\frac{2r}{\sigma_{L_i}^2} - 1 \right) \right) \Phi \left(\frac{(K_i + L_{i,t}) + (r - \frac{1}{2}\sigma_{L_i}^2)(\tau_j - t)}{\sigma_{L_i}\sqrt{(\tau_j - t)}} \right), \quad (3)$$

if $\tau_j < T$, otherwise

$$PD_{i,t}^{\mathcal{Q}}(\tau_J) = 1 - \Phi \left(\frac{-L_{i,t} + (r - \frac{1}{2}\sigma_{L_i}^2)(\tau_J - t)}{\sigma_{L_i}\sqrt{(\tau_J - t)}} \right) + \exp \left((K_i + L_{i,t}) \left(\frac{2r}{\sigma_{L_i}^2} - 1 \right) \right) \Phi \left(\frac{(2K_i + L_{i,t}) + (r - \frac{1}{2}\sigma_{L_i}^2)(\tau_J - t)}{\sigma_{L_i}\sqrt{(\tau_J - t)}} \right), \quad (4)$$

as $\tau_J = T$, and we have to consider not only the early bankruptcy risk as in the equation (3), but also the probability of the firm not being able to pay back the outstanding debt F_i at time T , even though the asset value never crossed the default boundary.

The face value of the debt, F_i , appears in the equations (2) and (4) (even not explicitly in (4), where it appears in terms of the parameter K_i), and this is consistent with the market evaluation which takes into account the information released by the company with the book data in order to form a proper assessment of the firm's value, and the firm's riskiness. Nevertheless, we define $V_{i,t}$ as the market value of the i -th firm at time t , as we obtain this estimation by using the information contained in market data.

However, we need to estimate F_i because we are mapping companies which are normally characterized by more complex debt structure, in terms of debt instruments and maturities, in very simple debt structure companies with one single zero-coupon bond issue. This simplification does not affect the definition of default risk. In fact, what only matters in terms of default risk is the threshold triggering the default. As long as the asset value is above the default boundary the shareholders are willing to cover the firm's losses, even if the asset value is not enough to meet the promised debt payment at maturity. In practice, the shareholders would buy additional shares in order to bail out the maturing debt holders, still assessing as profitable the investment in the company.

We formulate our problem in a state-space model, where the measurement equations come from (2) and (3-4), and the default probability for different time horizons can be extracted from the CDS spreads according to O'Kane and Turnbull (2003). The firm's leverage $L_{i,t}$ is unobservable, while we assume to observe $E_{i,t}$ on the equity market, and we suppose to observe the CDS spreads for four time horizons (1,3,5, and 10 years). Hence, we have five measurement equations. The noise terms associated with the CDS implied-default probability for different time to maturities τ_j are assumed to be uncorrelated, and with equal variance.

$$(I - IV) : PD_{i,t}^Q(\tau_j) = g(L_{i,t}; K_i, \sigma_{L_i}) + \epsilon_{i,t}(\tau_j), [j = 1, 3, 5, 10]$$

$$(V) : E_{i,t} = h(L_{i,t}; K_i, \sigma_{L_i}, F_i) + \varsigma_{i,t},$$

where the time to maturity is expressed in years, and $j = 10$ stands for the maturity T of the outstanding debt F_i (i.e., 10 years). The functions g and h define the non-linear relationships between the observable and the latent variable, and $\epsilon_{i,t}(\tau_a)$ is the measurement noise associated with the CDS implied-default probability equation and the time horizon j . These four measurement noises, for each firm i , are assumed to follow a multivariate normal distribution, with zero mean, and diagonal covariance matrix R_i . We assume a homoscedastic covariance matrix, which is firm-varying. $\varsigma_{i,t}$ is the measurement noise associated with the equity equation, and we assume it to be normally distributed, with zero mean and variance ω_i .

On the other side, the transition equation describes the evolution of the firm's leverage. It follows from the discretization of the stochastic process defined in (1):

$$L_{i,t+\delta t} = L_{i,t} + \mu_{L_i} \delta t + \eta_{i,t+\delta t},$$

where $\eta_{i,t+\delta t} = \sigma_{L_i}(W_{i,t} - W_{i,t+\delta t}) \sim \mathcal{N}(0, Q_i)$ is the transition error, and $Q_i = \sigma_{L_i}^2 \delta t$.

The dynamics of $L_{i,t}$, and the parameters of the model, such as the face value of the debt F_i , the parameters of the leverage \mathcal{P} -dynamics $(\mu_{L_i}, \sigma_{L_i})$, and the willingness to the gamble for resurrection K_i , are then estimated by performing a non-linear Kalman filter in conjunction with quasi-maximum likelihood estimation. For parsimony, the steps to implement the non-linear Kalman filter, and the construction of the likelihood function, are described in details in the Appendix A.

The estimation of the dynamics of the firm's asset value $V_{i,t}$, the dynamics of market value of the debt $Z_{i,t}$, and the level of the default boundary C_i , becomes straightforward, once we have obtained the estimates on the leverage dynamics, and the parameters of the model. In fact, from the definition of $L_{i,t}$, and K_i , it immediately follows that:

$$\begin{aligned} V_{i,t} &= \frac{F_i}{e^{L_{i,t}}}, \\ C_i &= e^{K_i} \times F_i, \\ Z_{i,t} &= V_{i,t} - E_{i,t}. \end{aligned} \tag{5}$$

III. Data

Our dataset consists of the market variables that we use to obtain the estimates on the market value of assets and liabilities of our sample firms. In particular, we use daily CDS spreads traded on four different maturities (1 year, and 3,5,10 years), which are the most liquid on the CDS market, and daily market capitalization (i.e., the product between the number of outstanding shares and the share price).

The CDS premia are expressed in basis point. In a CDS transaction, the premium, which the buyer of credit risk (i.e. the protection seller) receives, is expressed as an annualized percentage of the notional value of the transaction and this value is recorded as the 'market price'. The details of a CDS transaction are recorded in the CDS contract, which is usually based on a standardized agreement prepared by the International Swaps and Derivatives Association (ISDA), an association of major market participants.³

The event triggering the payment of the protection leg in a CDS contract ranges from no-restructuring to full-restructuring. As priority rule, we select, when is possible, the contracts that adopt the no-restructuring (MR) clause, as it is the standard convention after the CDS Big Bang protocol in April 2009. Otherwise, we include the contracts that adopt the modified-restructuring (MR) clause, as it was the standard convention before the protocol. As last options, we include the contracts with full-restructuring or modified-modified restructuring clause.

We take CDS data from Thomson Reuters by Datastream, which provides information on CDS spreads from December 2007. The sample firms are chosen from the reference entities listed on the Markit indexes, where the most liquid companies in terms of CDS transactions are quoted. In particular, we refer to the iTraxx indexes for Australia, Japan, and Europe. In the last index, we select only the Eurozone entities to ensure homogeneity in currency. The CDX North America - Investment Grade index is adopted for the United States sample, where we select only the US companies, for the same currency homogeneity reason.⁴

First, we keep only the reference entities with active CDS contracts before the 20th December 2007, which is the starting point of our time series. It goes from the 20th December 2007 to the 19th December 2013. The choice of this time window is driven by the so-called International Monetary Market dates.⁵

Moreover, we exclude the financial firms, which are characterized by a peculiar capital structure in terms of assets and liabilities, that would deserve a specific analysis and discussion.

Also, we control for the stale prices, where a price is defined stale when remains equal for many consecutive days. This issue may have an impact on the inversion from the CDS spreads curve to the risk-neutral default probabilities. In fact, a massive discrepancy in the number of active trading days between CDS on the same entity with different maturities may produce non-monotone default probabilities. In this case, for instance, we would have higher probability of defaulting in a time interval going from now to one year than defaulting from now to five years. As consequence, we would end up with a negative probability of defaulting in the time interval going from one to five years, i.e. negative forward default probability. Instead, the default probability for longer time horizons must be at least equal to the default probability for shorter time horizons, as the longer horizon nests the shorter.

This same finding can be a consequence of an enormous variation in the CDS spread recorded for only one or some of the four maturities. We find 5 companies to show this illogical result, and we drop out from the dataset the companies with negative forward-default probabilities for more than the 1% of the entire time series, for at least one time horizon, and we set this negative forward measure to zero for the remaining entities, in order to retrieve a monotone non-decreasing term structure of the default probability. In fact, while it is possible to have a CDS downward sloping

term structure when the company is perceived to be riskier in the short term than in the long term (similarly to a downward sloping term structure of interest rates), this curve must be not too steep.

At the end, we are left with a CDS dataset of 172 firms. The data on the daily market capitalization, for these companies, and the same time series, are downloaded from Bloomberg. Finally, we delete from our dataset 8 firms with no data on the market capitalization value, and we are left with a final dataset of 164 firms, geographically divided as follows: Australia (9), Japan (10), United States (89), Europe (56).

As proxy of the risk-free rates, we use the sovereign bonds curve constructed by Bloomberg for Unites States, Australia, and Japan. The European curve is given by an aggregation of the sovereign bonds issued by France, Germany, and Holland. Given the CDS spread, the termination date, the arbitrary assumption on the recovery rate (we follow the common approach of a recovery rate equal to 40% of the notional value), and the risk-free term structure, we can extract from the CDS spread the risk-neutral default probability for the corresponding maturity. In practice, there is only one arbitrage-free PD (for a certain debt instrument, with a certain contractual structure) that is implied by the market default swap spreads, and equates the starting value of the premium leg (protection buyer) and the protection leg (protection seller) in a CDS contract.⁶

Summary Statistics

We report in the table 1 the descriptive statistics about the CDS spreads for all the entities in our sample. The statistics for each geographic region are available upon request.

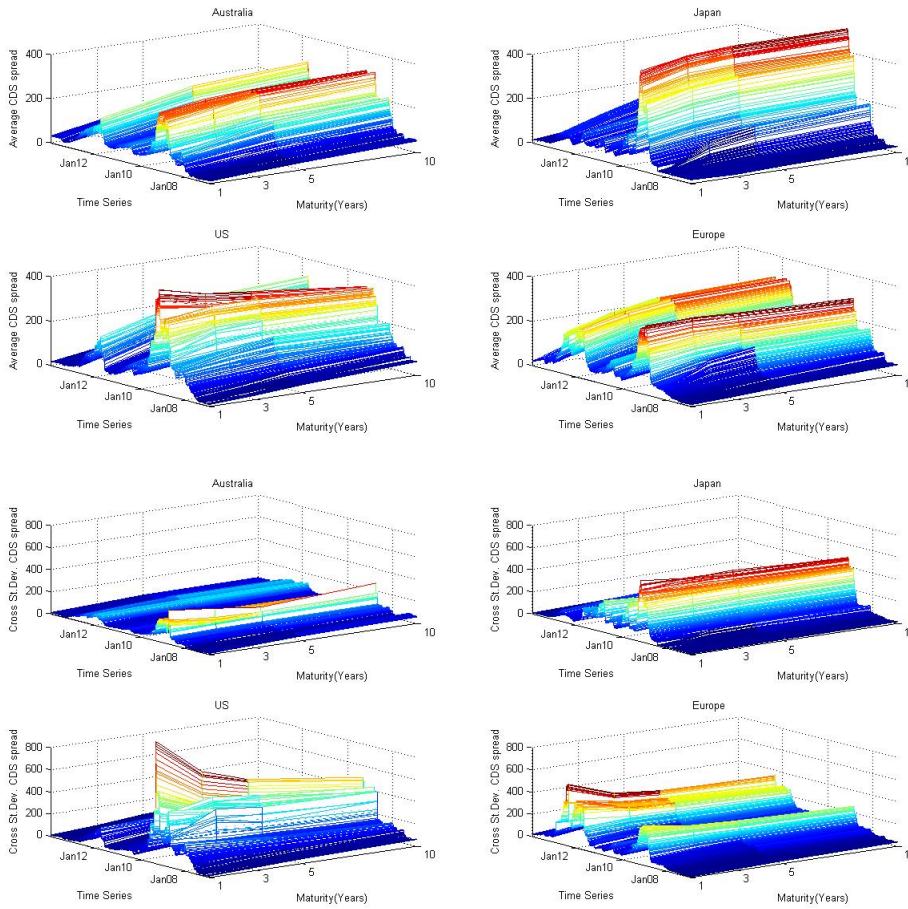
[Insert Tables 1, here]

The upper graph of figure 1 shows the term structure of the average CDS spreads for each region. The worldwide propagation of the 2008-2009 financial crisis is the main source of the peak in the CDS premia around that time interval. The difference in the CDS spreads across years is very pronounced for the shorter time horizons, and in particular for the one-year maturity, while the CDS premia paid on the longer time horizons are more stable over the entire time series. It turns out that the conjecture of the market on the default risk in the short-term dramatically rose up.

These features are homogeneous across regions. However, the larger premia paid on the US reference entities in the first part of the time window arise from the strong concentration of the financial turmoil in the US market, and the higher spreads quoted for the Eurozone companies in the last years follow from the European sovereign debt crisis starting in the 2011.

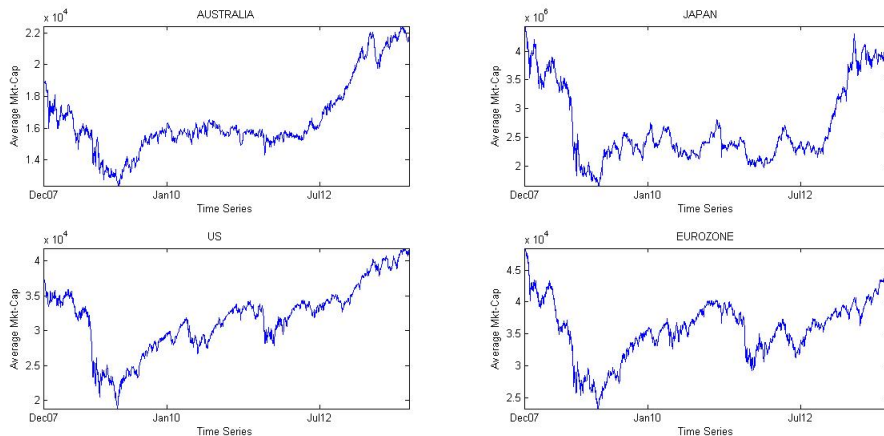
The financial crisis of 2008-2009 is also characterized by a larger cross-sectional standard deviation of the CDS spreads (figure 2, lower graph), showing an increase in the heterogeneity between the CDS premia paid on the different entities. It is evident for the US sample, and is emphasized by the same scale used in the lower part of figure 2. However, the gap across years in this dispersion measure is clearly present in each region. The combination of higher average spreads and higher heterogeneity across spreads reflects the attitude of the insurance sellers, even more emphasized

Figure 1. CDS Spreads. Regional Average and Standard Deviation



The four upper plots show the cross-sectional average of the CDS spread across the four geographic regions, along the sample time series (X -axis), and the four different maturities (Y -axis). The four lower plots show the cross-sectional standard deviation of the CDS spread across the four geographic regions, along the sample time series (X -axis), and the four different maturities (Y -axis). Both the average and the standard deviation are expressed in basis points.

Figure 2. Market Capitalization. Regional Average



The plots show the cross-sectional average of the market capitalization across the four geographic regions, along the sample time series. The firm's market capitalization is calculated as number of outstanding shares times the share price, and is expressed in millions of the local currency.

during a crisis period, to ask for a very large premium on the risky entities, and to be willing to accept a lower price on the more safe companies.

The summary statistics for the firms' market capitalization are calculated for each region as this data is expressed in millions of the local currency.

[Insert Table 2, here]

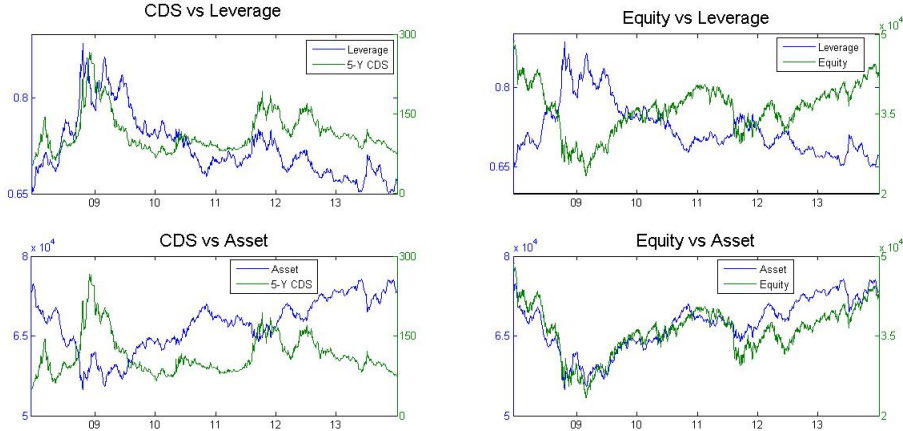
The historical pattern of the equity value generally pairs with the trend described for the CDS spreads. The market value for the shareholders drop in the core of the sub-primes distress, whilst a pretty constant increase starts at the end of 2009. Few peculiarities still appear across regions. The market capitalization swiftly grows up for the US and Eurozone firms from 2009 to 2010, then the US companies keep substantially rising up, while the Eurozone entities move around that level of equity value for the remaining part of the time series. The shift at the end of the financial crisis is not terribly noticeable for the Australian and the Japanese firms. On the other hand, these companies show a big jump during the 2013.

IV. Empirical Results

We combine the CDS spread-implied default probability and the equity value to compose the set of observable variables, which appear on the left-hand-side of the equation (I-IV), and (V), respectively. We are gathering information from credit and equity market to estimate the unobservable dynamics of the market value of the firm's leverage, and the hyperparameters of the model. We perform this estimation for each firm, one-by-one.

The estimation of the state variable dynamics $L_{i,t}$ is achieved by the iteration of the predicting and the updating equations of the non-linear Kalman filter. The hyperparameters are estimated by performing a maximum likelihood algorithm, under the assumption of normality for the measurement errors, given by the difference between the actual and the fitted value of the observable

Figure 3. Leverage and Assets - Eurozone



The first plot (CDS vs Leverage) shows the estimated mean firm's leverage against the observed mean CDS spread for the 5-years maturity, along the sample time series, for the Eurozone firms. The leverage is expressed as $e^{L_{i,t}} = \frac{F}{V_{i,t}}$, and the CDS spread in basis points. The second plot (Equity vs Leverage) shows the estimated mean firm's leverage against the observed mean Equity value, for the Eurozone firms, where the equity value is expressed in millions of Euro. The third plot (CDS vs Asset) shows the estimated mean firm's asset value ($V_{i,t}$) against the observed mean CDS spread for the 5-years maturity. The last plot (Equity vs Asset) shows the estimated mean firm's asset value against the observed mean Equity value, for the Eurozone firms.

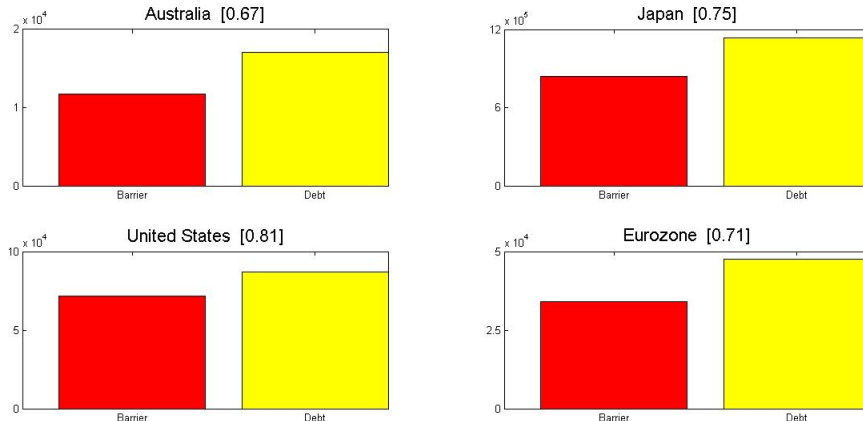
variables. The fitted value of the observable variables is computed from the equations (2) and (3-4), respectively, by using the current estimate of the state variable.

As result, we reconstruct the time series of the market value of the leverage for each firm in our sample. Then, by mean of the equation set (5), we also reconstruct the time series of the market value of the asset, and we provide a quantitative measure of the firm's outstanding debt coupled with a measure of the default boundary. Figure 3 shows the dynamics of leverage and asset value averaged across firms for the Eurozone sample. The leverage value is expressed in terms of debt-to-asset ratio. The plots for the other regions are reported in the Appendix C. We compare these dynamics against the time series of the market data, such as the equity value and the CDS spreads. In particular, we use the 5-years CDS maturity as benchmark in the following plots.

On average, the market value of the Eurozone corporate's leverage exhibits a peak around the 2009 financial crisis, when the debt counted for more than 80% of the market value of the asset. After a decreasing trend until the beginning of 2011, this ratio has grown up as consequence of the sovereign debt crisis, before starting again to decrease in the last part of the time series. The value of the asset shows indeed the opposite dynamics, with a lowest peak around the great recession, and an increasing trend in the second part of the time series, partially interrupted during the sovereign debt crisis in 2012.

We can also appreciate how the market value of the leverage has a very similar pattern to the CDS spread dynamics. It means that our estimation correctly reflects the evaluation of the credit market in terms of firm riskiness. On the other side, the leverage moves in the opposite direction with respect to the market capitalization of the firm along the entire time period. Then, our estimation of the leverage is simultaneously able to reflect also the market value of the firm as reported by the stock market. Symmetrical discussion applies to the asset value estimation, which follows an opposite trend with respect to the CDS spread, and shows a pretty overlapping dynamics

Figure 4. Debt and Barrier



The four plots show the cross-sectional average of the debt and default barrier values, across the four geographic regions. The values are expressed in millions of the local currency, and the title of each plot reports the average ratio between the default boundary value and the value of the debt.

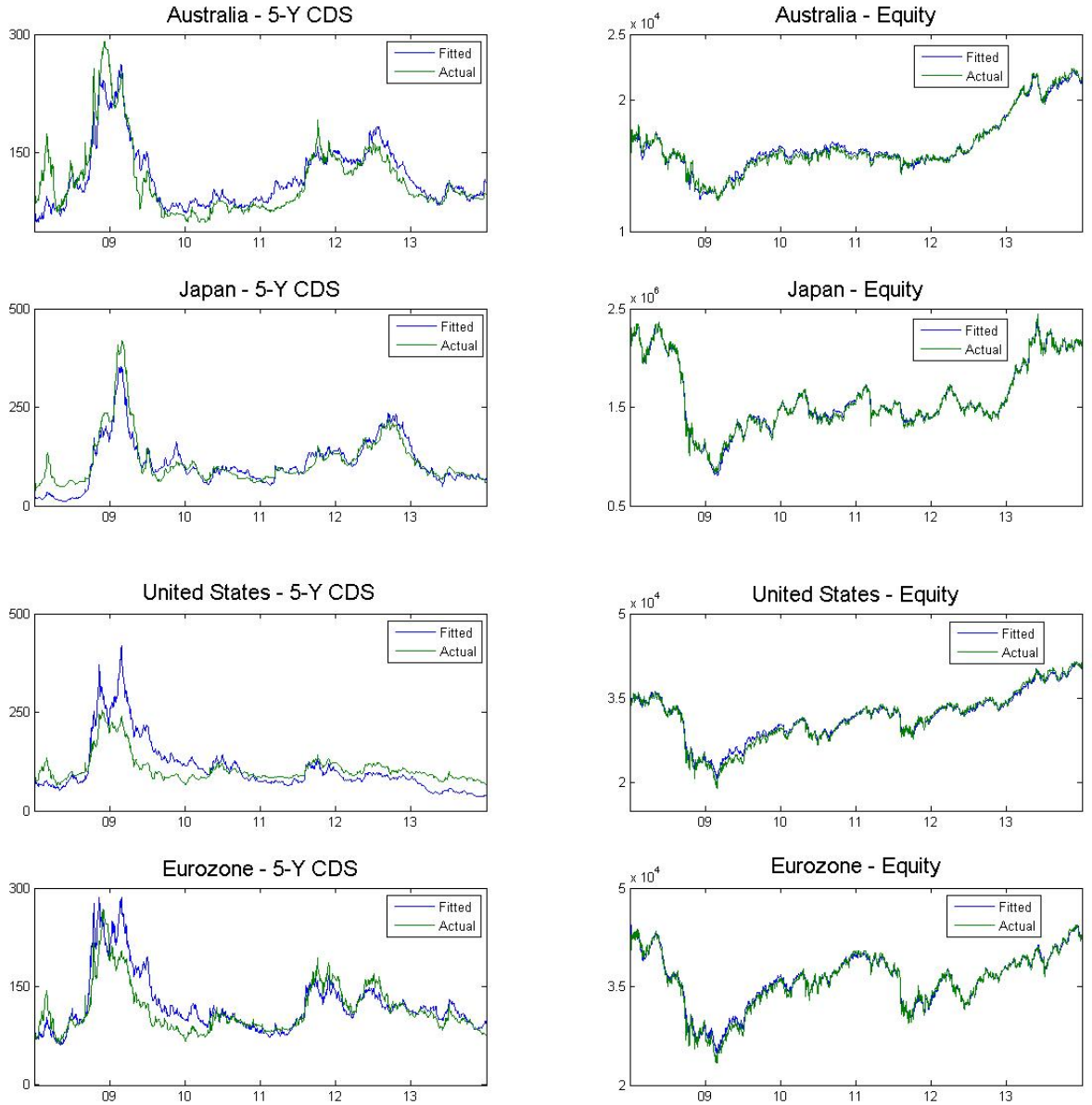
with respect to the equity value. We derive similar results for the other geographic regions in our sample. However, the downturn of the asset value (increase in the leverage) is less pronounced around the 2012 for the other regions, as the sovereign debt crisis has produced lower effective impact on the non-European firms.

A key parameter in our framework is the willingness of the shareholders to rescue the firm in case of distress to avoid default and keep the firm operating. It is measured by K_i , which proxies the distance between the default boundary and the value of the debt. By plugging in the equation set (5) the estimate of K_i , coupled with the estimation of the market value of leverage and asset, we are able to quantify default barrier and outstanding debt for each firm. Figure 4 shows the average barrier and debt for each region, and reports the ratio barrier-to-debt which immediately provides an idea of the distance between these quantities, and therefore the willingness of shareholders' bail-out.

We document similar barrier-to-debt ratios for the different geographic areas, between 67% (Australia) and 81% (United States). Intuitively, this result suggests that the Australian firms are more likely to be rescued by the shareholders with respect to the US firms. These findings are very similar to the estimates reported by Davydenko (2012), who argues that the firms on average default when the asset value drops until 70% of the debt value, and by Wong and Choi (2009), who also estimate a Black-Cox default boundary, even with a different econometrics approach, and they find this boundary to lie around 74% of the debt.

Finally, we also show our estimation model ability in fitting the real data. By using our estimates of the hyperparameters, and the reconstructed dynamics of the unobservable variables, we generate a fitted time series of equity value and CDS spreads. Figure 5 compares our fitted time series of the market data against the actual observations. We show the average fitted 5-years CDS spread and equity value against the average actual CDS spread and equity value, for each region.

Figure 5. Estimation Performance: Fitting Real Data



The plots compare the fitted dynamics of the 5-years CDS spread and Equity value, by using the structural estimation results, against the observed 5-years CDS spread and Equity value, for the average firm across regions, along the sample time series. The CDS spread is expressed in basis points, and the Equity value is expressed in millions of the local currency.

In order to statistically test our structural estimation ability in fitting real data, we construct a daily long-short portfolio strategy, over the sample time series. By using the fitted-by-model dynamics of the equity value and CDS spreads, at each day, we buy that stocks and CDS for which we forecast an increase in the price in the next day, and we sell otherwise.

Table 4 reports a highly significant performance achieved by this strategy, for all securities. As robustness, we perform a long-short portfolio strategy with randomly selected firms. At each day, we randomly split the sample in two sub-samples, and we buy the security for the firms in the first sub-sample, and we sell the security for the firms belonging to the second sub-sample. We repeat this exercise for 1000 simulations, where each simulation generates a trading strategy performance over the sample time series. Table 4 reports the maximum performance achieved across the 1000 simulations, which is not significant for none of the securities.

Therefore, we can conclude that our results have significant ability in fitting the real-data, thus allowing to generate statistically significant performance, which is not reachable with random selection of portfolios.

V. The Default Risk Premium

The premium which compensates investors for the risk of default of the security reference entity plays a prominent role in the financial analysis on credit risk and asset pricing. Previous papers have disentangled the estimation of the default risk premium with different approaches, mostly using either corporate bonds or credit default swaps to extract the risk-neutral probability of default, and the rating agency data to compute the real-world measure of default.

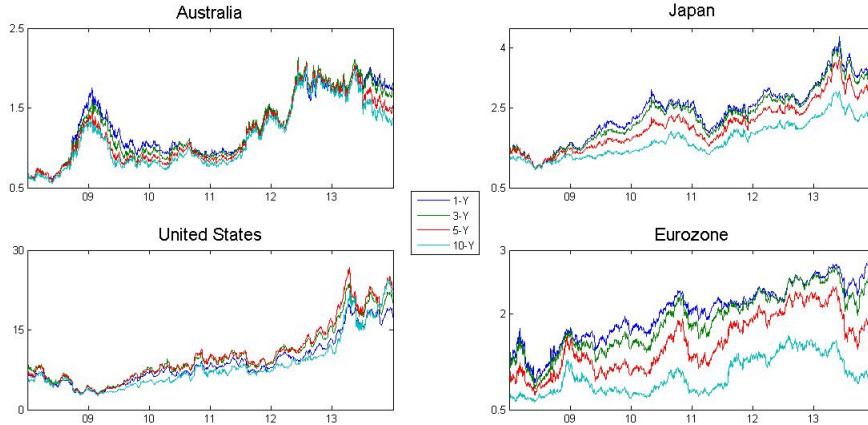
Berndt et al. (2008) report a premium roughly equal to two, discussing that the investors then price twice the expected default loss, evaluated under the actual probability measure. Instead, in case of corporate bonds, the premium describes the amount required by the investors to bear the risk related to the company's default, which indeed will affect the bond repayment. Driessen (2005) estimates that the investors multiply the actual default probability with a factor close to 6, in order to price corporate bonds.

Hence, the default risk premium proxies the distance between the actual evaluation of the default risk and the evaluation reflected in the securities pricing. We extract this measure not only from the credit market, by using CDS spreads, but also from the equity market, by including information on the firm's equity value. We calculate the default risk premium as the ratio between the risk-neutral and the real-world default probability, for each firm i , and each time horizon τ_j .

$$DRP_{i,t}(\tau_j) = \frac{PD_{i,t}^Q(\tau_j)}{PD_{i,t}(\tau_j)} \quad (6)$$

The result is a firm-specific daily term structure of the default risk premia. The risk-neutral and the real-world measures of default probability are computed by using the equation (3-4), where we plug in the estimates of the hyperparameters, and the estimated value of the unobservable variable $L_{i,t}$. What determines the difference between the two measures is the drift component of the asset value dynamics. In the equation (3-4), we keep the risk-free rate to estimate the risk-

Figure 6. Term Structure of Default Risk Premia. Median Firm



The plots show the term-structure of the estimated default risk premium, for the median firm across regions, along the sample time series. The default risk premium is expressed as ratio between the risk-neutral and the real-world default probability, which have been both calculated with a daily frequency, and for each firm, by using the structural estimation results.

neutral default probability, whilst we use the actual leverage drift coefficient, μ_{L_i} , to estimate the real-world measure of default risk. This coefficient is related to the asset drift coefficient as follows

$$\mu_{V_i} = - \left(\mu_{L_i} - \frac{1}{2} \sigma_{L_i}^2 \right),$$

where σ_{L_i} comes from the quasi-maximum likelihood estimation, and μ_{L_i} is the outcome of a matching moment approach.

In fact, after performing the quasi-maximum likelihood algorithm to obtain the estimates of the hyperparameters, then we accomplish the non-linear squares minimization for calibrating the measurement errors variances to the observed market data, and we consequently reconstruct the dynamics of the firm's market value of the leverage which is able to simultaneously fit the CDS spreads and the equity value. Finally, we compute the mean of the first differences divided by the time step. Therefore, μ_{L_i} returns a measure of the average growth of the leverage value along the entire time series. It contains information on the growing trend of the leverage coming from both the credit and the equity market. ⁷

Figure 6 shows the term structure of the default risk premia for the median firm in each regional sample. The default risk premium is substantially time varying. The variation over time of the premium is primarily due to the evolution in time of the market value of the firm's asset and leverage. In particular, it exhibits a lowest peak around the great recession, and an additional less pronounced downturn during the sovereign debt crisis. This pattern follows from a greater actual default risk during the periods of turmoil, which increases the real-world default probability.

This finding is consistent with Huang and Huang (2012), who argue that the default risk premium decreases as the credit quality declines, as the real default risk accounts more for the lower-rating firms. In terms of magnitude, we report similar but lower premia with respect to Berndt et al. (2008) and Driessen (2005), with the exception of the US sample, which exhibits default risk premia significantly larger. Such lower premia are primarily due to our sample period which spans

over both the two recent crises, when the actual default risk has substantially increased.

[Insert Table 3, here]

Moreover, the premium is generally higher for the shorter time horizon, with again the exception of the US sample for the mid-time horizons, for two possible reasons. First, we know that the structural models which do not include jumps in the asset value tend to underestimate the actual default probability for short time horizons. However, Huang and Huang (2012) argue that including jumps do not substantially affect the fraction of spread explained by credit risk, unless if the model is calibrated with rather extreme values. Second, especially for investment grade companies, Huang and Huang (2012) also document that the mean reversion of credit quality increases the credit risk for longer maturities.

We generally find that the default risk premium is greater than one, that is the risk-neutral default probability is higher than the corresponding real-world measure. However, we document the presence of a few firms with estimated actual default probability higher than the corresponding risk-neutral measure, and therefore default risk premium lower than 1.

For instance, narrowing our attention on the 10-years maturity, we find that the 32% of our sample firms (53 out of 164) is characterized by an average default risk premium lower than 1. Looking at the 5-years maturity, instead, the percentage of firms with average default risk premium lower than one drops to 26% of the sample (43 firms). Similar results are obtained for the 3-years (41 firms), and 1-year maturity (40). In the next section we explore the relation between this result and the dynamics of the market data, by implementing a trading strategy of long-short default risk premium portfolios.

A. *Long-Short Portfolio Strategy*

We start linking the default risk premium and the market data dynamics in a descriptive analysis, where we assess the sample correlation between the premium and the market variables. We calculate the average premium for each firm over the sample time series, and we rank the firms according to the average premium in ascending order. In the following graphs we show the correlation coefficient between the default risk premium and both the equity value and the 10-years CDS spread, after sorting the firms.

Figure 7 clearly highlights that the firms with average default risk premium higher than one exhibit positive correlation with the dynamics of the equity value, while the firms with average premium lower than one report opposite relationship with the equity prices. On the other hand, the low premium firms show positive correlation with the CDS-spread dynamics, as described by figure 8. Then, this correlation substantially decreases as the premium increases, even if this opposite relationship is not such strongly monotone as for the low premium firms sub-sample.

Further than graphically, table 6 supports these results statistically. The difference in the equity-DRP correlation between the high and the low risk premium firms is positive and very significant, and the difference in the CDS-DRP correlation between the high and the low risk premium firms is negative and very significant too. The bottom line is that the market variables exhibit a relationship

Figure 7. DRP and Equity Prices

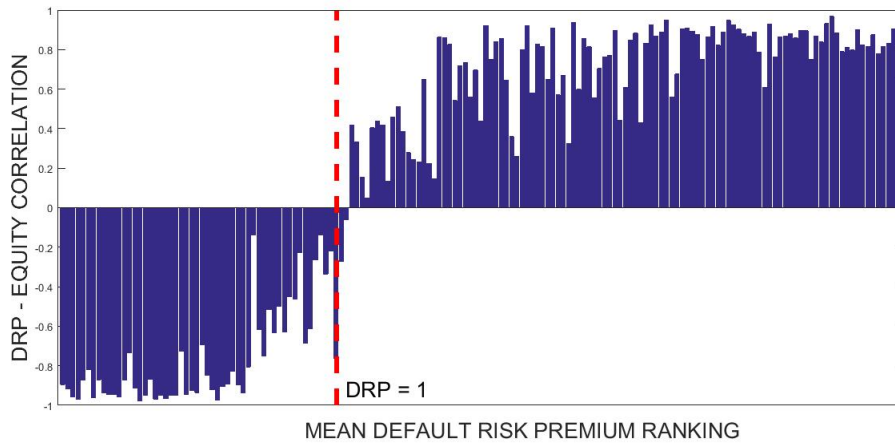


Figure 8. DRP and CDS spreads

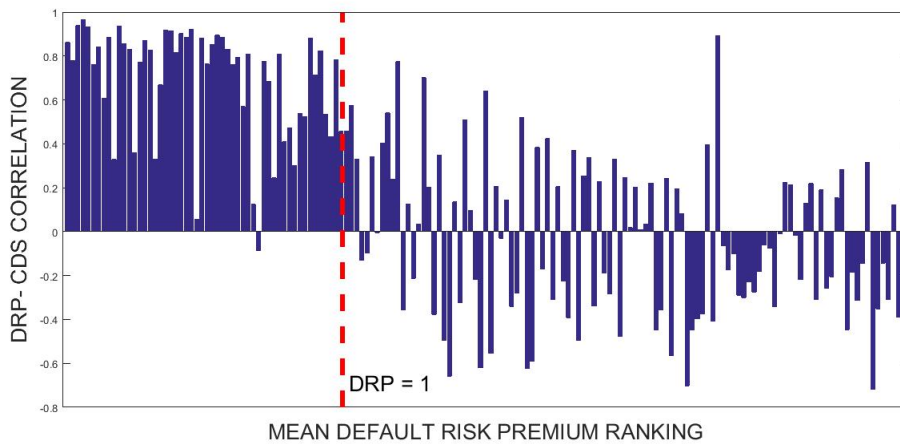


Figure 7 shows the sample correlation between the equity prices and the default risk premium, for firms ranked according to the average premium over the time series. Figure 8 shows the sample correlation between the 10-years CDS spread and the default risk premium, for firms ranked according to the average premium over the time series. In both graphs, the dotted-red line is drawn in correspondence of the first firm with average premium higher than one.

with the default risk premium which is opposite to each other, either if we consider the high or the low premium sub-sample.

We test this empirical hypothesis by constructing long-short portfolios of firm’s equity shares and CDS spreads. We implement our trading strategy in the last year of the time series (i.e., 252 daily observations). We start with an in-sample analysis, where we sort the firms according to the t -average default risk premium by using the market prices information up to t , but the estimation of the hyperparameters is based on full sample information, following the approach of Cochrane and Piazzesi (2005).

At each day t , and for each firm, we compute the average default risk premium until $t - 1$, by plugging in the equations (3-4) and (6) the estimated value of the state variable ($L_{i,t}$), and the hyperparameters. We split the sample in two sub-samples: the firms with average premium higher than one (HP-firms), and the firms with average premium lower one (LP-firms). For the HP-firms, an expected increase (decrease) in the premium should predict higher (lower) future price of the stock, and lower (higher) future CDS spread. Instead, for the LP-firms, an expected increase (decrease) in the premium should predict lower (higher) future price of the stock, and higher (lower) future CDS spread.

Then, at t , we buy (sell) the stocks and we sell (buy) the CDS of the HP-firms for which our estimation of the premium at $t + 1$ is higher (lower) than the current estimate of the premium at t . On the other hand, we sell (buy) the stocks and we buy (sell) the CDS of the LP-firms for which our estimation of the premium at $t + 1$ is higher (lower) than the current estimate of the premium at t . We can do that, as the filter generates a forecast for the state variable one-step ahead. Then, by using the equations (3-4), and the estimated hyperparameters, we can produce a forecast for the default probabilities one-step ahead, and thus for the default risk premium by using the equation (6). Table 7 (top-left) reports the average daily performance of the trading strategy, for the equity and the CDS portfolios, respectively. The trading strategy performed by using either the equity shares, or the CDS spread, shows a positive daily mean, which is very significant.

B. Out-of-Sample and Robustness

The last step concerns about supporting our previous results with a set of robustness checks, and an out-of-sample test, which corroborate our findings. First, we start constructing the strategy by excluding, from the feasible basket of firms, those with average default risk premium, up to the beginning of 2013, higher than 1000. Such a big value of the premium is primarily driven by a very low estimation of the physical default probability, which is the ratio of the premium. Table 7 shows that the previous results are not affected by narrowing the feasible set of firms for the strategy.

Moreover, we perform the portfolio strategy by trading in the opposite direction with respect to the approach described above. In other words, we buy (sell) the stocks and we sell (buy) the CDS of the LP-firms (instead of the HP-firms) for which our estimation of the premium at $t + 1$ is higher (lower) than the current estimate of the premium at t . On the other hand, we sell (buy) the stocks and we buy (sell) the CDS of the HP-firms for which our estimation of the premium at $t + 1$ is higher (lower) than the current estimate of the premium at t . The bottom part of table

7 shows that, in-sample, the strategy generates now negative and significant performance for both the portfolios, and even after excluding the outliers.

Finally, we strength our results with an out-of-sample analysis, where we still implement our trading strategy sorting the firms according to the t -average default risk premium, by using the market prices information up to t . However, the estimation of the hyperparameters is based now on the information up to the beginning of the trading strategy window. In practice, we perform again the non-linear filtering in conjunction with quasi-maximum likelihood estimation to extract the model parameters, and to reconstruct the dynamics of the state variable, but now we only use data on the observable market variables up to the beginning of 2013. Though, all the described results are confirmed, with the only exception of the negative performance of the opposite direction trading strategy in the case of the equity portfolio. This performance becomes now positive but not significant.

VI. Conclusion

In this paper we propose a new approach to estimate a barrier-dependent structural model, with only market data. By using information coming from the credit and the equity market, we obtain estimates on the firm's economic fundamentals, such as the market value of asset and debt, and the value of the barrier which triggers the firm's default. We show that our estimates are consistent with the market data observations, and are also able to simultaneously fit the two different markets dynamics.

Then, we exploit the results of the structural estimation to extract the default risk premium, which at the same time reflects the information conveyed by the two different markets. This premium arises from the difference between the actual and the market-implied evaluation of the default risk. We find that the default risk premium is time varying, and decreases during the crisis periods because of an increase in the actual default probability.

We try solving the well-known 'distress puzzle', by using the default risk premium to link the credit and the equity market securities. We show, in fact, that the dynamics of the premium is related in an opposite fashion to the equity and the credit market securities, which is consistent with the economic intuition and the financial theory of an opposite relationship between the credit and the stock market securities dynamics.

We believe that our estimation approach may also be addressed for different targets. Combining the result on the default boundary and the market value of the asset, we supply a new insight in the academic research on the corporate credit risk based on the well-known distance-to-default. In addition, we equip the corporate finance research with a new approach for the evaluation of the market value of the debt. It can be then primarily used in the firm's evaluation framework, and in the firm's profitability assessment debate, such as the discussion on the Tobin's Q .

We also contribute to open further directions for the asset and option pricing research. On one hand, if the price of a corporate security reflects the market evaluation of the corporate fundamentals, then our estimates of the market value of the assets and liabilities turns to be a key input for pricing purpose. On the other hand, if the firm's equity can be considered as an option on the

firm's assets, then a tradable option can be defined as a compound option on the same asset value, as already described in Geske (1979). Hence, the fresh information that we provide on the market value of the firm's economic indicators can be addressed to pricing options written on the firm's equity value.

Appendix A. Default Risk Premium: underlying theoretical framework

The model consists of $N + 1$ dates $t = \{0, 1, \dots, T - 1, T\}$, three agents $i = \{A, B, C\}$, and two securities $j = \{d, e\}$. $t = \{0, 1, \dots, T - 1\}$ are N trading dates, and $t = \{T\}$ is the final maturity. A is a risk-averse investor, whose the preferences structure is described by the utility function U_A , on the probability measure P , B is the firm issuing the security d , and C is an insurer selling the security e . Both B and C are risk-neutral, with utility functions U_B , and U_C , respectively.

Real-World Beliefs

We assume that the investor is price-maker, and the agents B and C are both price-takers. The security d at T payoffs X_T , if the firm does not default up to T , and 0 otherwise. Hence, the investor prices at $t = 0$ the security d as follows:

$$S_0^P = E_0^P[X_T] = X_T(1 - PD_0^P),$$

where PD_0^P is the probability that the firm defaults between 0 and T , under the real-world measure P . Then, S_0^P is the maximum price at which A is willing to buy d :

$$S_0^P : \max_{S_0} U_A(S_0) \geq 0,$$

that is S_0^P is maximum the price of the security that generates non-negative utility for the investor. Assuming that the investor is not able to extract net benefits from the trading, then $U_A(S_0) = 0$, and thus $S_0 = S_0^P$.

On the other side, the insurance e pays back to A , at any time up to T , an amount α , if the firm defaults up to T , and 0 otherwise. Hence, the investor prices at $t = 0$ the security e as follows:

$$K_0^P = E_0^P[\alpha] = \alpha PD_0^P,$$

Then, K_0^P is the maximum price at which A is willing to buy the insurance e :

$$K_0^P : \max_{K_0} U_A(K_0) \geq 0,$$

that is K_0^P is the maximum price of the insurance that generates non-negative utility for the investor. Assuming that the investor is not able to extract net benefits from the trading, then $U_A(K_0) = 0$, and thus $K_0 = K_0^P$.

Let suppose that, at $t = 1$, the investor updates her beliefs with a better evaluation of the firm's dynamics, such that $PD_1^P < PD_0^P$. Then, the maximum price at which A is willing to buy d ,

$$S_1^P : \max_{S_1} U_A(S_1) \geq 0,$$

where $S_1^P = E_1^P[X_T] = X_T(1 - PD_1^P)$, is higher than S_0^P . Therefore, the price of d increases as $S_1 > S_0$. At the same time, the maximum price at which A is willing to buy the insurance e ,

$$K_1^P : \max_{K_1} U_A(K_1) \geq 0,$$

where $K_1^P = E_1^P[\alpha] = \alpha PD_1^P$, is lower than K_0^P . Therefore, the price of e decreases as $K_1 < K_0$.

Risk-Neutral Beliefs

We assume here that the investor is price-taker, and the agents B and C are both price-makers. The firm B evaluates at $t = 0$ the security d as follows:

$$S_0^Q = E_0^Q[X_T] = X_T(1 - PD_0^Q),$$

where PD_0^Q is the probability that the firm defaults between 0 and T , under the risk-neutral measure Q . Then, S_0^Q is the minimum price at which B is willing to sell d :

$$S_0^Q : \min_{S_0} U_B(S_0) \geq 0,$$

that is S_0^Q is the minimum price of the security that generates non-negative utility for the firm. Assuming that the firm cannot extract net benefits from the trading, then $U_B(S_0) = 0$, and thus $S_0 = S_0^Q$.

On the other hand, the seller evaluates at $t = 0$ the security e as follows:

$$K_0^Q = E_0^Q[\alpha] = \alpha PD_0^Q,$$

Then, K_0^Q is the minimum price at which B is willing to sell the insurance e :

$$K_0^Q : \max_{K_0} U_C(K_0) \geq 0,$$

that is K_0^Q is the minimum price of the insurance that generates non-negative utility for the investor. Assuming that the insurer cannot extract net benefits from the trading, then $U_C(K_0) = 0$, and thus $K_0 = K_0^Q$.

Now, let suppose, instead, that, at $t = 1$, both the firm and the insurer update their risk-neutral beliefs with a worse evaluation of the firm's dynamics, such that $PD_1^Q > PD_0^Q$. Then, the minimum price at which B is willing to sell d ,

$$S_1^Q : \max_{S_1} U_B(S_1) \geq 0,$$

where $S_1^Q = E_1^Q[X_T] = X_T(1 - PD_1^Q)$, is lower than S_0^Q . Therefore, the price of d decreases as $S_1 < S_0$. At the same time, the minimum price at which C is willing to sell the insurance e ,

$$K_1^Q : \max_{K_1} U_C(K_1) \geq 0,$$

where $K_1^Q = E_1^Q[\alpha] = \alpha PD_1^Q$, is higher than K_0^P . Therefore, the price of e increases as $K_1 > K_0$.

Default Risk Premium

We define, at time $t = 0$, the default risk premium as the ratio between the risk-neutral and the real-world probability of default:

$$DRP_0 = \frac{PD_0^Q}{PD_0^P}$$

Either the investor updates the real-world beliefs with a better evaluation of the firm's dynamics, or the firm itself and the insurer update the risk-neutral beliefs with a worse evaluation of the firm's dynamics, then the DRP_1 is higher than DRP_0 . In the first case the increase is due to a lower denominator (lower real-world default risk), in the second case is due to a larger numerator (higher risk-neutral default risk). In fact,

$$DRP_1 > DRP_0 \Rightarrow \frac{PD_1^Q}{PD_1^P} > \frac{PD_0^Q}{PD_0^P} \quad (7)$$

By rearranging equation (1), we can see that

$$DRP_1 > DRP_0 \Rightarrow \frac{PD_1^Q}{PD_0^Q} > \frac{PD_1^P}{PD_0^P}, \quad (8)$$

that is, more in general, the risk premium may increase either because of a decrease in the real-world PD larger than the decrease in the risk-neutral PD , or of an increase in the risk-neutral PD larger than the increase in the real-world PD .

However, these two different drivers generate an opposite effect on the dynamics of the securities. In the first case, when the default risk premium increases, then the price of the security d increases, and the price of the insurance e decreases. In the second case, when the default risk premium increases, then the price of the security d decreases, and the price of the insurance e increases.

Appendix B. Kalman filter and Quasi-Maximum Likelihood Estimation

In a general formulation, with a non-linear relationship between the measurement and the state variables, the state-space model is defined by two sets of equations, the transition and the measurement equation, respectively:

$$X_{i,t+\delta t} = X_{i,t} + c_i + \epsilon_{i,t+\delta t},$$

$$Y_{i,t+\delta t} = \psi(X_{i,t+\delta t}) + u_{i,t+\delta t},$$

where $X_{i,t+\delta t}$ is the i -th observation of the state variable at time $t + \delta t$, c_i is the time-invariant component driving the evolution of the state variable, $\epsilon_{i,t+\delta t}$ is the transition error on the i -th observation of the state variable at time $t + \delta t$. On the other hand, $Y_{i,t+\delta t}$ is the i -th observation of the measurement variable at time $t + \delta t$, ψ is the measurement function which links the observable and the latent variable, and $u_{i,t+\delta t}$ is the measurement error.

For a Gaussian state-space model, under standard assumptions, the discrete Kalman filter is proved to be the minimum mean squared error estimator. However, in the case of non-linear relation between the measurement and the state variable, the classic linear Kalman filter is not longer optimal. One possible solution is to linearize the estimation around the current estimate by using the partial derivatives of the process and measurement functions.⁸ To linearize the measurement process, we need to compute the derivatives of ψ with respect to

(a) the state variable: $H_{i,j} = \frac{\partial \psi_i}{\partial X_j}(\tilde{X}_t, 0),$

where H is the Jacobian matrix of partial derivatives of the generic measurement function $\psi(\cdot)$ with respect to the state variable X , and \tilde{X}_t is the current estimate of the state.

(b) the measurement noise: $\check{H}_{i,j} = \frac{\partial \psi_i}{\partial \nu_j}(\tilde{X}_t, 0),$

where \check{H} is the Jacobian matrix of partial derivatives of $\psi(\cdot)$ with respect to the noise term ν .

Once the linearization has been completed, we can implement the discrete Kalman filter in the usual steps. First, we need to set the *initial conditions*:

$$\lambda_{i,0} \quad P_{i,0},$$

where $P_{i,t} := \text{var}[X_{i,t} - \lambda_{i,t}]$ is the variance of the estimation error, and $\lambda_{i,t}$ is the estimate of the state at time t based on the information available up to time t . Then, the filter implementation is based upon two sets of equations, the *predicting* equations, and the *updating* equations, that must be repeated for each time step in the data sample.

- *State Prediction*

$$\lambda_{i,t+\delta t/t} = \lambda_{i,t} + c_i,$$

and

$$P_{i,t+\delta t/t} = P_{i,t} + Q_i,$$

where $\lambda_{i,t+\delta t/t}$ is the estimate of the state at time $t + \delta t$ based on the information available up to time t , and Q_i is the covariance of the transition noise.

- *Measurement Update*

$$\lambda_{i,t+\delta t} = \lambda_{i,t+\delta t/t} + P_{i,t+\delta t/t} H'_{i,t+\delta t} Z_{i,t+\delta t}^{-1} (Y_{i,t+\delta t} - \psi(\lambda_{i,t+\delta t/t}))$$

$$P_{i,t+\delta t} = P_{i,t+\delta t/t} - P_{i,t+\delta t/t} H'_{i,t+\delta t} Z_{i,t+\delta t}^{-1} H_{i,t+\delta t} P_{i,t+\delta t/t}$$

$$Z_{i,t+\delta t} = H_{i,t+\delta t} P_{i,t+\delta t/t} H'_{i,t+\delta t} + R_i,$$

where H stands for the Jacobian matrix of partial derivatives of the generic measurement function ψ with respect to the state variable X , $Z_{i,t+\delta t}$ is the covariance matrix of the prediction errors at time $t + \delta t$. The prediction errors are defined as $v_{i,t+\delta t} = Y_{i,t+\delta t} - \psi(\lambda_{i,t+\delta t/t})$, where $Y_{i,t+\delta t}$ is the observation of the measurement variable at time $t + \delta t$.

The parameters that describe the dynamics of the transition and the measurement equations (i.e., *hyperparameters*) are unknown, and need to be estimated.

Let rewrite the state-space model as follows:

$$(y_{t+\delta t}, x_{t+\delta t}) = (x_t, \{\theta\}), \quad \{\theta\} = \{\theta^{(f)}; \theta^{(g)}\}$$

, where $y_{t+\delta t}$ is the observable variable at time $t + \delta t$, $x_{t+\delta t}$ is the state variable at time $t + \delta t$, $\{\theta^{(f)}\}$ is the set of unknown parameters in the transition equation, and $\{\theta^{(g)}\}$ is the set of unknown parameters in the measurement equation. The measurement and transition equations of the system are:

$$g(y_{t+\delta t}, \alpha) = \varphi(x_{t+\delta t}, \beta) + \epsilon_{t+\delta t}, \quad \epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2)$$

$$x_{t+\delta t} = f(x_t, \gamma) + \eta_{t+\delta t}, \quad \eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$$

Then,

$$\{\theta^{(f)}\} = \{\gamma, \sigma_\eta^2\}$$

$$\{\theta^{(g)}\} = \{\alpha, \beta, \sigma_\epsilon^2\}$$

We assume that the nonlinear regression disturbance, ϵ_t , is normally distributed:

$$f(\epsilon_t) = \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} \exp \left[-\frac{\epsilon_t^2}{2\sigma_\epsilon^2} \right]$$

By transformation of variable, the density of y_t is given by

$$f(y_t) = f(\epsilon_t) \left| \frac{\partial \epsilon_t}{\partial y_t} \right|, \quad \frac{\partial \epsilon_t}{\partial y_t} = \frac{\partial g(y_t, \alpha)}{\partial y_t}$$

Then, the density of y_t is

$$f(y_t) = \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} \exp \left[-\frac{(g(y_t, \alpha) - \varphi(x_t, \beta))^2}{2\sigma_\epsilon^2} \right] \left| \frac{\partial g(y_t, \alpha)}{\partial y_t} \right|$$

The log-likelihood function for observation t is

$$\ln \Omega_t(y_t; \{\theta\}) = -\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma_\epsilon^2) - \frac{(g(y_t, \alpha) - \varphi(x_t, \beta))^2}{2\sigma_\epsilon^2} + \ln \left| \frac{\partial g(y_t, \alpha)}{\partial y_t} \right|,$$

and the log-likelihood function for $t = 1, 2, \dots, T$ observations (i.e., $\delta t = 1$) is

$$\begin{aligned} \ln \Omega = \sum_{t=1}^T \ln \Omega_t(y_t; \{\theta\}) &= -\frac{T}{2} \ln(2\pi) - \frac{T}{2} \ln(\sigma_\epsilon^2) - \frac{1}{2\sigma_\epsilon^2} \sum_{t=1}^T (g(y_t, \alpha) - \varphi(x_t, \beta))^2 \\ &\quad + \sum_{t=1}^T \ln \left| \frac{\partial g(y_t, \alpha)}{\partial y_t} \right| \end{aligned}$$

As long as $g(y_t, \alpha) = y_t$, then

$$f(y_t) = f(\epsilon_t) \Rightarrow \ln \Omega_t(y_t; \{\theta\}) = \ln \Omega_t(\epsilon_t; \{\theta\})$$

The last term in the log-likelihood function is equal to zero, and the space of the hyperparameters to be estimated is reduced to:

$$\{\theta^{(f)}\} = \{\gamma, \sigma_\eta^2\}$$

$$\{\theta^{(g)}\} = \{\beta, \sigma_\epsilon^2\}$$

In practice, the iteration of the filter generates a measurement-system prediction error, and a prediction error variance at each step. Under the assumption that measurement-system prediction errors are Gaussian, we can construct the log-likelihood function as follows:

$$\begin{aligned} \ln \Omega(y_t; \{\theta\}) &= \ln \prod_{t=0}^{T-\delta t} p(y_{t+\delta t}/t) = \sum_{t=0}^{T-\delta t} \ln p(y_{t+\delta t}/t) = \\ &= -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \sum_{t=0}^{T-\delta t} \ln |Z_{t+\delta t}| - \frac{1}{2} \sum_{t=0}^{T-\delta t} v_{t+\delta t}' Z_{t+\delta t}^{-1} v_{t+\delta t}, \end{aligned}$$

where N is the number of time steps in the data sample. Finally, this function is maximized with respect to the unknown parameters vector $\{\theta\}$. This is known as the *Quasi-Maximum Likelihood* estimation, in conjunction with the non-linear Kalman filter.

Appendix C. Prices Observation Noise: Minimization by Model Calibration

A useful interpretation of the Kalman filtering is to think of it as an updating process, where we first form a prior preliminary guess about the unobservable state variable and then we perform a correction to this guess. It is a typical Bayesian procedure. The correction depends on how good has been the guess in predicting the next observation, and the weight of the correction to update our guess about the state variable primarily depends on how confident we are about the reliability of the observation. It is measured by the variance of the errors in the measurement equation, which links the state and the observable variable.

It follows that we are more confident about the observation of the CDS-PD and the equity prices when lower is the variance of the measurement errors. In the extreme case, when the error associated with the CDS-PD measurement equation has zero variance and the equity equation has high measurement error variance, we take into account only the CDS prices to reconstruct the dynamics of the market value of the leverage, and vice versa. We interpret this variance as a measure of the noise in the observation of the market data. This noise may be a consequence of the market microstructure effects, the model misspecification, or even the recording price procedure for the CDS spreads, which are traded on an OTC market, and the quotes may vary according to the data provider. It turns out that the impact of the market data on the estimated hyperparameters and state variable dynamics is inversely proportional to the observation noise measured by the measurement error variance.

In principle, we could impose an arbitrary prior on the variance of the measurement error either of the CDS-PD equation or the equity equation according to the weight that we want to assign to a particular market variable. It would be the case if we have an ex-ante conjecture on the informativeness of the credit or the equity market. However, we do not impose any prior constraint, and we include the variance of the measurement errors in the hyperparameters that we estimate, by using the quasi-maximum likelihood algorithm based on the non-linear filtering. Then, in a second stage, we implement a non-linear squares minimization to calibrate the values of the measurement error variances associated with the risk-neutral PD and the equity pricing equation, in order to fit simultaneously the observed dynamics of the risk-neutral PD implied by CDS spreads, and the equity value.

Driessen (2005) adopts a similar algorithm to derive the risk-premium component which translates the real-world probability measure of default, extracted from rating agency data, into the risk-neutral intensity. In practice, he performs a non-linear squares minimization by using the observed and the model-implied default probabilities, after estimated the hyperparameters with a Kalman filter. We search the value of the measurement errors variances which minimize the sum of the squared differences between the observed and the model-implied market data, where the sum is calculated over the sample time series.

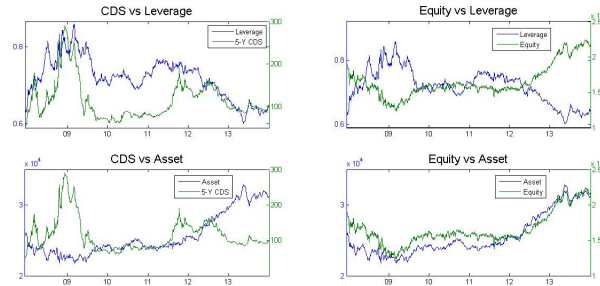
$$\min_{R_i, \omega_i} \sum_{t=1}^T \alpha_{i,t}^2,$$

where $\alpha_{i,t} = \begin{bmatrix} \hat{PD}_{i,t}^Q(\tau_a) - PD_{i,t}^Q(\tau_a) \\ \hat{E}_{i,t} - E_{i,t} \end{bmatrix}$

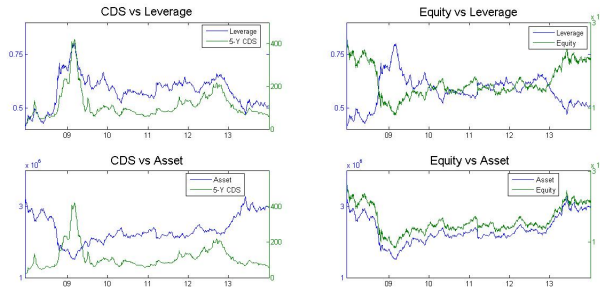
Finally, we iterate again the updating and the predicting equations of the non-linear Kalman filter to reconstruct the dynamics of the firm's market value of the leverage. Now, we do not perform the quasi-maximum likelihood estimation as we have already obtained the hyperparameters in the first step, and the measurement errors variances in the second stage. The result is the dynamics of the market value of the leverage which minimizes the distance between the implied and the observed market variables. It may be interpreted as the 'best-we-can-do' to reduce the noise in the prices observation, due to the model misspecification. We can attribute the residual error to the systematic noise implicitly contained in the market quotes observation.

Appendix D. Leverage and Asset against Market data: Other Regions

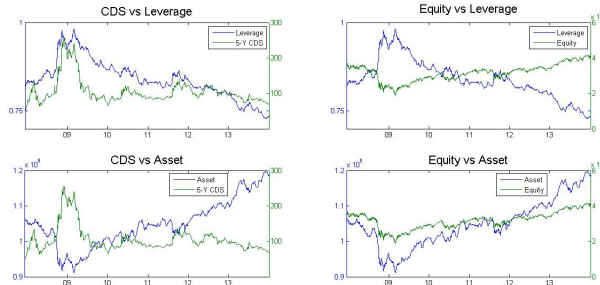
Leverage and Assets - Australia



Leverage and Assets - Japan



Leverage and Assets - United States



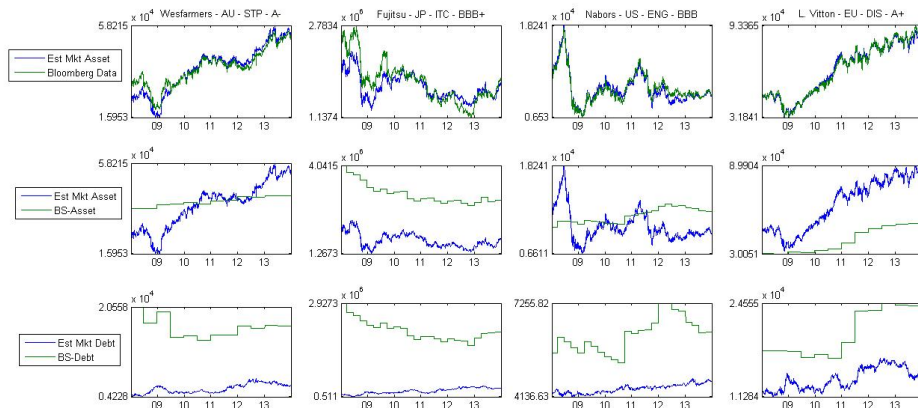
The plots report the same comparison between estimated average leverage and asset value against observed average market prices dynamics, as shown in the figure 3 for the Eurozone sample. See legend of figure 3.

Appendix E. Goodness of Fit: Bloomberg Data

The estimation of the dynamics of the market value of the leverage is performed for each firm one-by-one, and the hyperparameters of the model are firm-specific. As consequence, by using the set of equations (5), we can reconstruct the dynamics of the market value of asset and debt for each company. We can compare these results against the data provided by Bloomberg on the market value of asset, and the balance-sheet data of asset and debt. More precisely, Bloomberg gives information on the market value of the asset by gathering the data on the equity value, the market prices of the debt items traded on the market, and the balance-sheet data of the debt items not traded on the market. Then, especially for that companies with many debt items not traded on the market, Bloomberg needs a big amount of information from the balance-sheet to produce this kind of data. Instead, we use only market variables, which can be easily collected, to provide the same data. We are quicker in the production of the data, and we do not need to rely on any book information.

In the following figures, we show (first row) the comparison between the Bloomberg data on the market value of asset and our estimation of the market value of asset, (second row) the balance-sheet data on the value of the asset and our estimation of the market value of asset, and (third row) the balance-sheet data on the value of the debt and our estimation of the market value of debt. In particular, the first comparison is done between two time series of daily data, whilst the second and the third rows compare daily data (our estimation), and quarterly data (book information). We focus on the description of the first one, where we contrast two equivalent, in principle, sets of information. Nevertheless, the remaining two are useful to give a graphical intuition of the differences, in terms of value and frequency, between market and book evaluation of the same quantity, which we have underlined in the introduction, the motivation, and the contribution of the paper. We choose twelve illustrative firms, which belong to different regions, sectors, and ratings, in order to show that these results are robust across different firms' categories.

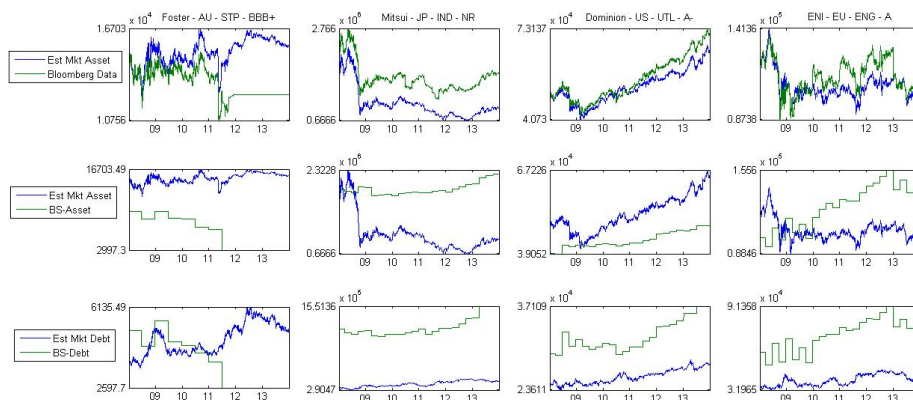
D-I



The figure D-I shows four examples where our model produces an estimation of the market value of the asset that is very similar to the data provided by Bloomberg. For almost the entire time series, the two dynamics seem to really overlap. It means that we and Bloomberg are providing

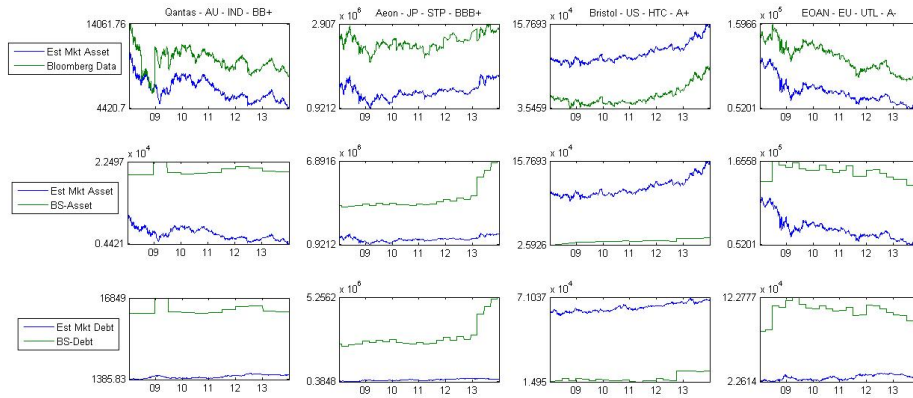
exactly the same data. Moreover, we are able to be quicker, and totally ignore the book information. However, if they are nearly equal, which is the point to collect data on the equity value and the CDS spreads, construct a proxy of the risk-free rate, and then implement our estimation model, if it would be possible to easily download the same result directly from a Bloomberg terminal? The answer is in the following graphs.

D-II



In the first plot of the figure D-II (Foster's Group), our estimation and Bloomberg data are very similar in the first part of the sample period, then Bloomberg would give stale data, while we keep providing fresh daily information. In the second and the third plot, the two series are similar in the first part, then the Bloomberg data is constantly larger than our estimation. In the last plot, this situation occurs only in specific time windows of the time series. More precisely, the two lines pretty overlap along the wider part of the time series, but Bloomberg reports a few jumps that we do not obtain in our results.

D-III



The figure D-III, finally, shows that the two sets of data can be really different for the entire time interval. The difference is not very noticeable in the trend, as for the both data sets there is a common and equal item (the equity value), but particularly in the levels. Such difference is due to the different evaluation of the firm's debt, which is highlighted in the last row of the figure D-III. When we obtain a market value of debt clearly lower than the book data of debt, we provide data on the market value of asset which is much lower than the Bloomberg data. The opposite case appears in the third plot. In this regard, we need to remind that Bloomberg uses the balance-sheet data when the debt items are not traded on the market. The conclusion is that we may be able to produce a more reliable and fresher information, by ignoring the book data and by taking into account only the market assessment.

Table 1 - Summary Statistics, CDS Spreads

STAT	1 year						3 years					
	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013
Mean	86.69	140.74	43.36	39.80	41.74	18.81	107.93	151.43	69.40	72.73	84.67	52.12
Standard Deviation	TS	71.84	88.29	11.21	19.18	11.12	65.10	78.97	11.23	23.48	12.13	7.63
	CS	166.38	300.91	37.34	27.09	48.26	167.02	274.38	50.89	40.43	70.35	44.10
Median	TS	60.38	107.44	40.92	28.08	39.78	86.00	121.56	65.95	57.75	81.14	52.18
	CS	56.81	83.70	34.34	32.98	27.20	75.61	93.73	54.98	64.14	62.78	41.50
	5 years						10 years					
STAT	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013
Mean	121.91	156.27	93.87	106.15	122.18	92.24	128.75	148.60	111.62	136.59	154.57	136.96
Standard Deviation	TS	60.49	70.16	11.36	24.68	12.45	54.42	58.39	9.79	25.19	12.13	7.74
	CS	159.98	251.92	60.66	52.03	85.45	143.89	216.25	63.77	58.13	88.68	74.67
Median	TS	102.52	127.58	93.34	90.71	118.41	112.20	119.15	111.89	125.61	154.81	138.43
	CS	89.88	101.93	75.55	94.53	98.07	99.54	101.27	91.88	122.19	131.77	117.72

Legend: Table 1 reports the summary statistics of the CDS spreads for all the 164 firms in the sample, and for the four time horizons. The statistics are calculated over two dimensions, the time series (TS), and the cross section (CS). The years refer to the time period going from the 20th December of the previous year to the 19th December of that year. The CDS spreads are expressed in basis points as annualized percentage of the notional value of the transaction.

Table 2 - Summary Statistics, Market Capitalization

		Australia										Japan												
STAT		2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013					
Standard Deviation	Mean	16106.98	14269.40	15830.27	15558.27	16615.72	20973.81	3306770.16	2187244.71	2374068.84	2312945.03	2354328.36	3650067.03	1388.69	1082.65	336.20	330.65	1026.57	934.35	167946.76	210075.19	150128.26	404024.02	
	TS	1388.69	1082.65	336.20	330.65	1026.57	934.35	702575.93	249284.28	249284.28	3337.60	3476.93	1934.45	16079.42	13902.67	14003.61	14192.08	16159.59	20936.58	4449327.34	3234826.62	3015261.81	2841162.46	5360640.13
	CS	16552.35	13902.67	14003.61	14192.08	16159.59	20936.58	4449327.34	3482359.81	2250207.16	2354792.22	2350307.91	3825030.35	6971.62	5591.93	7826.98	8502.39	8996.27	10797.14	1301167.07	1355906.53	1270331.88	1559423.72	
	Median	6971.62	5591.93	7826.98	8502.39	8996.27	10797.14	1594845.22	1047443.75	1301167.07	1355906.53	1270331.88	1559423.72											
		United States										Europe												
STAT		2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013	2008	2009	2010	2011	2012	2013					
Standard Deviation	Mean	31736.19	24972.26	29632.92	31879.01	33599.42	38801.01	37476.06	29748.36	36045.59	36186.81	35124.99	39957.96	4395.72	2568.67	1269.05	1566.59	815.32	1945.23	6002.41	3337.60	1556.23	3476.93	1934.45
	TS	4395.72	2568.67	1269.05	1566.59	815.32	1945.23	42760.72	33453.42	42475.56	42916.63	42344.26	47475.09	38637.15	32837.07	35168.41	36649.62	41794.40	44666.25	42760.72	33453.42	42475.56	42916.63	47475.09
	CS	33456.44	24420.28	29546.20	32264.76	33676.55	39087.60	39113.69	39113.69	28951.05	35924.19	37473.11	39421.99	18109.02	14066.85	17251.33	18248.14	18756.83	22731.48	21511.27	16238.91	20440.47	19406.24	22046.98
	Median	18109.02	14066.85	17251.33	18248.14	18756.83	22731.48	21511.27	16238.91	16238.91	20440.47	19406.24	22046.98											

Legend: Table 2 reports the summary statistics of the market capitalization across regions. The same structure in terms of time intervals as for the CDS table applies. The market capitalization is expressed in millions of the local currency.

Table 3: Empirical Results - Parameters Estimation

		Volatility				Barrier			
Regions	AUS	Mean	Barr/FV	Drift	Debt	Barrier			
		0.19	-0.39	-0.08	17119	11746			
	St. Dev.	0.03	0.06	0.04	17378	12133			
	JAP	0.19	-0.30	-0.10	841215	1137242			
	St. Dev.	0.04	0.10	0.09	676442	474817			
	USA	0.08	-0.21	-0.04	71826	86770			
	St. Dev.	0.02	0.08	0.02	84963	99737			
	EUR	0.15	-0.34	-0.06	33972	47644			
	St. Dev.	0.03	0.05	0.04	40132	55945			

Legend: The table reports the mean and the standard deviation of real data estimation on 164 firms divided, respectively, in four geographic regions, nine GICS sectors, and three Rating classes, for the unknown parameters σ_{L_i} , K_i , μ_{L_i} , F_i , C_i , R_i , ω_i , by using the univariate non-linear Kalman filter in conjunction with quasi-maximum likelihood estimation. The statistics for F_i , C_i are reported only for the four regions as the respective values are expressed in local currency.

Table 4: Structural Estimation - Fitting Data

Equity		1-Y CDS		3-Y CDS		5-Y CDS		10-Y CDS	
SME	Random	SME	Random	SME	Random	SME	Random	SME	Random
Mean	0.011***	0.014***	0.010***	0.008***	0.007***				
t-test	48.47	23.35	24.47	24.46	21.92				

Legend: The table reports the mean, and the t-test statistic, for the daily performance of the long-short portfolio trading strategy described in section 4, for the Equity and the CDS portfolios. The stars on the mean stand for the level of significance according to the t-test outcome (***) = 99% significance level, ** = 95%, * = 90%). The SME columns refer to the portfolio strategy constructed by using the structural model estimation, while the Random columns refer to the maximum performance achieved across the 1000 randomly constructed portfolios.

Table 5: The Default Risk Premium

Real-World PD		Risk-Neutral PD				Default Risk Premium						
1Y	3Y	5Y	10Y	1Y	3Y	5Y	10Y	1Y	3Y	5Y	10Y	
AUS	0.001	0.031	0.071	0.166	0.001	0.033	0.073	0.179	1.27	1.25	1.18	1.13
JAP	0.000	0.020	0.051	0.139	0.000	0.029	0.074	0.186	2.38	2.29	2.05	1.70
USA	0.000	0.006	0.013	0.032	0.001	0.028	0.068	0.173	8.78	10.03	10.35	8.28
EUR	0.000	0.023	0.063	0.181	0.001	0.035	0.082	0.186	2.02	1.88	1.53	1.02

Legend: The table reports the mean over the entire time series of the estimated median-firm risk-neutral and real-world default probability, and default risk-premium, across the four time horizons (1 year, 3,5, and 10 years), and the four geographic regions.

Table 6: Correlation DRP - Market Data

	5-th	25-th	50th	75-th	95th
corrEQ	-0.95	-0.28	0.31	0.88	0.89
corrCDS	0.77	0.08	-0.35	-0.49	-0.44
DRP-Equity					
	DRP<1	DRP>1	DRP<1	DRP>1	
Mean	-0.76	0.68	-0.69	0.03	
t-test Diff	-33.39				15.11

Legend: The upper table reports the sample correlation between the default risk premium and the equity prices, and the 10-years CDS spread, respectively, in correspondence of different firm-percentiles of the default risk premium distribution, after sorting the firms according to the average default risk premium. The lower table reports the mean correlation, across the high and low default risk premium sub-samples, between the default risk premium and the market variables. Moreover, the table reports the t-test outcome on the difference between the mean correlations across the high and low premium samples, for each market variable.

Table 7: Trading Strategy - Long-Short Portfolios

Correct Trading					
All Firms			Excluding Outliers		
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample	
	Equity	Equity	Equity	Equity	CDS
Mean	0.0015***	1.98E-04**	2.55E-04**	7.47E-04***	4.03E-04***
t-test	16.89	5.34	2.34	8.29	3.64
Opposite Trading					
All Firms			Excluding Outliers		
	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample	
	Equity	Equity	Equity	Equity	CDS
Mean	-0.0023***	-0.0011***	1.75E-04	-6.73E-04**	-8.21E-04***
t-test	-12.72	-3.65	0.91	-2.13	-5.11
					-8.24E-04
					-4.97E-04*
					-1.64

Legend: The table reports the mean, and the t-test statistic, for the daily performance of the long-short portfolio trading strategy described in section 5, for the Equity and the CDS portfolios. The stars on the mean stand for the level of significance according to the t-test outcome (*** = 99% significance level, ** = 95%, * = 90%). The table reports the results for the in-sample, and the out-of-sample approach, as described in the paper. The upper part of the table reports the results obtained by following the trading strategy scheme as described in the paper, while the lower part reports the results obtained by trading in the opposite direction. The left-side reports the results for the trading strategy performed by using all the sample firms, while the right-side reports the results for the trading strategy performed after excluding the firms with default risk premium higher than 1000.

Notes

¹We use CDS spreads as credit market indicator following previous papers which have shown the better performance of the CDS market to provide a reliable proxy of credit risk, with respect to bonds or loans spreads (Blanco, Brennen, and Marsh (2005), Almeida and Philippon (2007)). The CDS spreads are less affected by other sources of risk, in particular by liquidity risk (Longstaff, Mithal, and Neis (2005)).

²The original formulation for the default probability and the equity value in a first-time passage framework can be found, among others, in Perlich and Reisz (2007)

³See Longstaff et al. (2005) for an extensive description of the CDS contractual structure, and functioning

⁴The Markit iTraxx and CDX indices are constructed every six months, according to specified criteria and selections rules, which ensure the eligibility of an entity to be a constituent of the index, especially in terms of CDS contracts liquidity. We refer to the 20th list for the iTraxx indexes, and the 21th list for the CDX index. All have been issued on September 2013

⁵This term is also used for the conventional quarterly termination dates of credit default swaps, which fall on 20 March, 20 June, 20 September and 20 December. From late 2002, the CDS market began to standardize credit default swap contracts so that they would all mature on one of the four days of 20 March, 20 June, 20 September and 20 December. These dates are used both as termination dates for the contracts and as the dates for quarterly premium payments. So, for example, a five-year contract traded any time between 20 September 2005 and 19 December 2005 would have a termination date of 20 December 2010.

⁶See O’Kane and Turnbull (2003) for an extensive overview of the CDS valuation

⁷By adopting this procedure we also avoid the issue related to the insensitivity of the likelihood function with respect to the drift coefficient. Previous works have widely reported huge complexity in estimating the drift component in stochastic processes. We find that even trying to solve this problem by calibration is pretty useless. The impact of changing the drift coefficient of the state variable dynamics on the value of the sum of the squared errors is quite negligible. Instead, the likelihood function is very sensitive to the diffusion component, and we can directly estimate σ_{L_i} in the first step

⁸Instances of application of this filter deal in particular with interest rates term structure estimation. Duan and Simonato (1999) implement this technique to estimate an exponential-affine term structure models, while more recently Duffee and Stanton (2012) prove the robustness of the non-linear Kalman filter for a dynamics term-structure model estimation

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