The Determinants of the Correlation between Individual Stock and Corporate Bond Returns

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ABSTRACT

We study the correlations between individual bond and stock returns issued by the same firm using TRACE prices. We analyze the sources of the variation in correlations by panel data including variables representing cycle indicators, firm characteristics and specific bond characteristics. The results show that the correlations are both time and cross-sectional varying. Specifically, the correlations are higher when the stock idiosyncratic risk and/or the firm financial leverage increase, while for low levels of firm risk the two assets move differently. Also the correlations increase when investors have positive expectations about the future economic conditions. Although this is only true for firms that present low probability of default.

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1. Introduction

The correlation between bond and stock markets has been widely investigated from the investment perspective. The fact that these two markets co-move together, in the same or in the opposite direction, and also that both do so with a constant or with a time-varying response to changes in other variables, has important implications for asset allocation, risk management, and optimal portfolio management. The literature has estimated the correlation between the return of these two markets (or the yield in the case of bonds) going from pure data driven estimates to factor models based on macroeconomic equilibrium or asset pricing models. Conclusions drawn depend on the methodology used, the sample period and/or the country in each study.

In general, papers using data before the nineties find a small but positive long-term correlation between stocks and bonds (see for example Beltrati and Shiller, 1992, and Campbell and Ammer, 1993). However, equity and bond markets (corporate and treasury) behave very differently from the late 1990s onwards, displaying mostly a negative correlation (as in D'Addona and Kind, 2006). Authors have offered different explanations for both signs. On the one hand, under the present value models, we can justify a negative or zero correlation between bond and stocks, because variables that anticipate future economic growth could affect the stock prices positively (via higher expected dividends) while they do not have an effect on bond prices. On the other hand, a positive correlation could be expected, given that variables in the discount rate (interest rates and risk premium) are negatively related to both the prices of stocks and the prices of bonds.

Regardless of the sign, what empirical evidence shows is that this correlation is time varying. Gulko (2002) and Illmanen (2003) conclude that the stock-bond correlation can exhibit positive and negative levels in certain time periods, being positive in stable periods and decreasing significantly in a subsequent crisis period. This finding is justified by the "flight-to-quality" or "flight-to-safety" effect: accepting that risk aversion increases in stressed periods, the investors' fear of uncertainty is higher during recessions and this makes them shift their investments from stocks to bonds.[1] That is, contrary to what occurs in expansions, bonds are understood as a hedge instrument in recessions. In any case, the question of what drives the stock-bond correlation still remains open as is shown by the profuse research work surrounding this issue.[2]

[1] This argument also justifies the application of the external habit model of Campbell and Cochrane (1999) to bond pricing as in Wachter (2006) or in Baele et al. (2010).

[2] We can find papers ranging from econometric developments for measuring the co-movements between bond and stock markets or for testing the hypothesis of flight-to-quality (Baur and Lucey, 2009; Panchenko and Wu, 2009) and papers that show the important role of uncertainty in explaining the time-variation of this correlation (Connolly, et al., 2005), to other papers that propose a common model for pricing stocks and bonds (or a common factor model for the returns) which generates (and then explains) the correlation between both (Koijen et al., 2010; Baele et al., 2010).

In this paper we focus on the stock and bond return correlation but using a different approach. We are not interested in the co-movements of these two markets as a whole but we investigate the correlation between bond and stock returns at a firm level. In this sense, arguments related to portfolio diversification are not applicable. On the contrary, stocks and bonds issued by the same firm are securities representing the same productive assets, and therefore, the value of the equity and the value of the debt can be written as a function of the value of the assets of the firm. As a result, the correlation between them reflects common elements of firm-specific information that drives individual stock and bond prices. And, imposing some assumptions, it is possible to identify the sources of such correlation.

The main contribution of our paper relates to the analysis of these individual correlations. While studies on the correlation between aggregate indices representing the bond and stock markets are abundant, the correlation at the individual firm level has received little attention.[3] Our most related paper is Kwan (1996) which is the first paper analyzing the correlation between individual stock returns and changes in bond yields issued by the same firm. The author finds a negative correlation that could be driven by firm-specific information related to the mean of the firm's underlying assets. More recently, Schaefer and Strebulaev (2008) show that structural models, and specifically the Merton (1974) model, are useful in predicting sensitivities of corporate bond returns to changes in equity returns (also referred to as hedge ratio). Particularly related to our work is their finding of that estimated hedge ratios are positive, statistically significant, and increase with the firm's risk.

Our hypotheses are: i) individual stock and corporate bond returns are correlated, ii) this correlation is varying along time and across firms or across different bonds within the same firm, and iii) the level and the sign of such correlation depend on the investors' perception about what the determinants of the risk driving the prices of these two assets are. Thus, the first aim of our study is to estimate the dynamics of the correlation between individual stock and bond returns, and subsequently to find the sources of the variation behind these dynamics.

We use different approaches to estimate conditional correlations: a rolling sample correlation, a Dynamic Conditional Correlation (DCC) model as in Engle (2002), and a Regime Switching Conditional Correlation (RSDC) model as described in Pelletier (2006). In addition, we also consider corrected versions of these models that incorporate a non-synchronous trading adjustment initially proposed by Engle et al. (1996).

Once the dynamic correlations have been estimated we examine what the determinants of the correlation variability are in both the cross-sectional and time-series dimensions using panel

[3] In fact, papers using individual data of corporate bonds are scarce and are generally focused on explaining credit spreads.

data analysis. For this aim we consider a large set of potentially explanatory variables that include macroeconomic and financial aggregated factors related to economic cycles, variables representing both the operational and financial risks of the issuer, and variables representing bond characteristics or proxies for the specific risk of bondholders.

It is important to note that in this paper bond returns are computed from transaction prices. It is possible since the implementation of the Trade Reporting and Compliance Engine (TRACE) system allows all OTC corporate transaction in the secondary market from July 2002 to be recorded following the rules approved by the Security and Exchange Commission in January 2001. We use daily prices for the period between July 2002 and December 2009, which ensures time-series variation since this period includes the last part of an expansion cycle (2002-2006) and the recent and dramatic economic crisis (2007-2009). Secondly, we employ data for all stocks and bonds issued by the firms on the SP100, in order to pick up sufficient cross-sectional variability in the firm characteristics in relation to operational risk (all industries are represented) and financial risk (different capital structures), and also variability in the bond characteristics.

Our results indicate that the correlations between individual bond and stock returns are definitively time-varying. The dynamics in the correlations are reasonably well captured with models showing little persistence. On the other hand, very extensive cross-sectional dispersion is also found; the average correlation goes from a maximum of 30% to a minimum of -30% within all the pairs of stock-bond returns analyzed. Cross-sectional differences are significantly related to variables measuring issuer risk; specifically, the correlation is higher for firms with higher idiosyncratic risk, higher leverage ratio or firms in the industrial sector, and is lower for firms with a high probability of default. Finally, macroeconomic variables also determine the bond-stock correlation but only when the probability of default for a given firm is low. Therefore, economic conditions only explain the correlation when the firm risk of default is low. In other case, firm characteristics are the unique relevant variables.

The remainder of the paper is organized as follows. Section 2 presents a theoretical framework justifying the existence of common determinants for stock and bond prices that produce a non-zero correlation between these two assets. Section 3 describes the database used. Section 4 explains the methodologies and the results for the estimation of the dynamic correlations. In Section 5 we analyze the determinants of bond-stock correlations using panel data techniques. Summary and conclusions are presented in Section 6.

2. Bond-stock return co-movements

Structural models for pricing corporate debt, starting from Merton (1974), held the idea of a nonzero correlation between stock and bond returns. Although it is known that these structural models do a poor job in explaining bond prices, these models can be reasonably used for

predicting the common variation in the equity and debt returns for the same firm (see for example Schaefer and Strebulaev (2008)). The foundation of structural models is that the value of the equity and the value of the debt of the same firm can be written as functions of the firm value. Therefore, these values (and thus their returns) must be correlated. More specifically, let *B* be the market value of the debt of the firm *i* that promises to pay *D* on the date *T*, and let *S* be the market value of the equity of the same firm. Suppose that both values can be written as a function of the value of the firm, *V*, at any point in time *t*.

$$S_{it} = f(V_{it}, t) \quad ; \quad B_{it} = F(V_{it}, t) \tag{1}$$

Any change in the firm value will affect both the equity value and the debt value in

$$\frac{dS_{it}}{dV_{it}} = f_V(V_{it}, t) \quad ; \quad \frac{dB_{it}}{dV_{it}} = F_V(V_{it}, t) \tag{2}$$

where subscripts on *f* and *F* denote partial derivatives.

We can transform the equations in (2) in order to obtain the return on equity R_{it}^S and the return on debt R_{it}^B, respectively.

$$\frac{dS_{it}}{S_{it}} = \frac{f_V(V_{it},t)dV_{it}}{S_{it}V_{it}} V_{it} \leftrightarrow R_{it}^S = \frac{f_V(V_{it},t)}{S_{it}} R_{it}^V V_{it} \tag{3}$$

$$\frac{dB_{it}}{B_{it}} = \frac{F_V(V_{it},t)dV_{it}}{B_{it}V_{it}} V_{it} \leftrightarrow R_{it}^B = \frac{F_V(V_{it},t)}{B_{it}} R_{it}^V V_{it} \tag{4}$$

and combining (3) and (4),

$$R_{it}^S = \frac{f_V(V_{it},t)/S_{it}}{F_V(V_{it},t)/B_{it}} R_{it}^B \tag{5}$$

Equation (5) says that the equity and bond returns of the same firm are related by the elasticity of the equity value with respect to the debt value to changes in the firm value, supporting the idea of non-zero correlations.[4]

Many empirical studies underlay in this point for analyzing whether a variable related to one security is relevant in determining some characteristic about the other security. The most researched relationship in this sense is the effect of the equity volatility on the bond. Campbell and Taskler (2003) show that increases in corporate bond yields are associated with upward trends in idiosyncratic equity volatility. Cremers et al. (2006) focus on implied volatility from individual options on the equity, since unlike realized volatility it is a forward-looking measure of

[4] Note that the derivation of expression (5) requires neither distributional assumptions on the firm value nor the specification of the investor's preferences or the application of the Itô Lemma.

the investors' risk perception, for explaining credit spreads. They find that individual implied volatility can explain one third of the variation of credit spreads with a positive coefficient while, however, the implied volatility of an option on an equity index is negatively related to individual credit spreads. This finding reveals the opposite perspective from which the correlation between stocks and bonds must be addressed for aggregate or individual analysis. Finally, Zhang et al. (2009) revisited the relation between individual equity volatility and credit spreads by studying the benefits of using high-frequency equity returns for the identification of jumps in volatility, on the one hand, and measuring credit spreads from credit default swaps, on the other. Their results indicate that volatility risk and jump risk predict spread variations with a positive but non-linear relationship. In all of these papers the foundation is the same: the stock and the bond represent the productive assets of the firm.

The specific relationship between stock and bond returns requires imposing some conditions that may allow the functional form of the elasticity in (5) to be specified. Under the simplest structural model, the Merton (1974) model, the sole assumption that the firm value follows a diffusion process with constant instantaneous volatility and a standard Brownian motion, implies that this elasticity is

$$\frac{f_V(V_{it},t)/S_{it}}{F_V(V_{it},t)/B_{it}} = \frac{f_V(V_{it},t)/S_{it}}{\left(1-f_V(V_{it},t)\right)/B_{it}} = \frac{\phi(x_{it})}{1-\phi(x_{it})}\frac{B_{it}}{S_{it}} \tag{6}$$

where ϕ is the cumulative standard normal distribution at point $x_{it} = \left[\log(V_{it}/D_i) + \left(r_t + (\sigma_i^2/2)\right)\tau\right]/\sigma_i\sqrt{\tau}$, r is the risk free rate, σ is the volatility of the firm return, and $\tau = T - t$ is the length of time until maturity of the debt. Therefore, the model predicts a positive correlation between bond and equity returns.[5]

Additionally, as indicated in (6), this sensitivity can vary for firms with different volatility, "quasi" leverage ratio, or debt time to maturity. All of these variables determine $\phi(x_{it})$, on the one hand, but they also affect conversely the equity value and the debt value, on the other hand. Therefore, and a priori, the final effect on the elasticity is ambiguous.

In order to have some insights about how the cross-sectional differences between firm characteristics affect the elasticity, we simulate the paths for the equity and debt values under the Merton model using parameter values between the possible ranges observed in our sample. We find that the Merton model implies an equity-bond elasticity (equity-bond return covariance)

[5] The idea that a change in the value of the firm's assets produces changes in the same direction in both the equity value and the debt value, is common in structural models. As such, the positive correlation implied by equation (6) is not exclusively derived from the Merton model.

increasing with quasi leverage ratio, firm's volatility and time to maturity.[6] However, our simulations also show that this is not the case for the correlation; the increment in leverage or firm's volatility has a higher impact on the volatility of the bond return than on the covariance between the two returns, producing a decrease in the correlation for the same given leverage and time to maturity value. In contrast, independent of the volatility of the firm, the correlation increases with the bond's maturity, as can be seen in Figure 1.[7]

[Figure 1]

Regarding the time series dimension, literature indicates that both equity risk premium and credit spreads are countercyclical.[8] Thus, recent theoretical models for pricing risky debt recognize the importance of macroeconomic factors for generating cyclical movements, as in Hackbarth, et al. (2006) or Chen, et al. (2009). Although both equity risk premium and bond risk premium increase in bad times, this does not explain how the correlation between them moves along time. To that goal, it is necessary to simultaneously price both assets such that it will be possible to obtain the common response of the stock and the bond expected returns to changes in the economic conditions. The model proposed by Bhamra et al. (2010) does in this way. The model combines the cross-sectional implications of structural models with the time series variability of the bond and stock expected returns implied by an intertemporal equilibrium consumption-based asset pricing model. In the model, macroeconomic risks affect both assets by means of the recursive preferences assumed for the representative agent. For the debt value, changes in the economic conditions are reflected in the price of the Arrow-Debreu default claim; assuming a positive correlation between the Brownian motions in earnings an aggregate consumption, the price of the Arrow-Debreu claim is higher in bad times, reducing more the market debt value and, then, increasing more the credit spread in those moments. In the case of the equity, the macroeconomic risk has two effects. On the one hand, the marginal rate of substitution is higher in bad times, with a direct effect on expected equity returns. On the other hand, the increase on the price of the Arrow-Debreu default claim can have a positive effect on

[6] Our results are consistent with the simulations in Schaefer and Strebulaev (2008). Other studies underlying the equity-debt elasticity are Campello et al. (2008) and Elkamhi and Ericsson (2008). Although the aim of these papers is different, an intermediate step in Campello et al. (2008) is the estimation of the relation between the equity-debt elasticity and variables that potentially affect it. They find that this elasticity is not constant but it is positively affected by the volatility of the stock return and negatively affected by the risk free rate.

[7] We thank the anonymous referee of the JFQA the suggestion of exploring the correlation implied by the model. Results and specific details about these simulations are available upon request.

[8] On the side of the equity, theoretical intertemporal asset pricing models, since the model by Merton (1973), are defined in order to capture this observed pattern in the price of risk. On the side of the debt price, Giesecke et al. (2011), by using an extensive data set starting in 1866, conclude that corporate default rates are only moderately related to business cycles and that macroeconomic indicators are not useful for explaining changes in credit spreads. And Gilchrist and Zakrajsek (2011) show that the ability of credit spreads for forecasting economic cycles is mainly due to unexpected default component.

equity value since shareholders no longer have to pay coupons in the case of default. Moreover, if the model incorporates the possibility of a dynamic capital structure, this positive effect is increased because of the benefits of refinancing options for shareholders. Therefore, although the model implies both equity and bond risk premium to be countercyclical, the correlation between them would be negative if the opposite effect that the risk-neutral probability of default plays in the price of the two assets is predominant.

The aim of our paper is to analyze how the correlation between stock and bond moves and what variables are responsible for such variation along the time and across different firms and/or specific bond characteristics. It must be note that our study is totally empirical and does not relay in any model for pricing risky debt. The previous discussion about what are the implications of some models on the correlation is just to generate predictions with theoretical support. Next, the empirical results will confirm or not these predictions.

3. Data

We employ the transaction database TRACE which compiles information about all corporate bond transactions. TRACE is a system by which all members must report an OTC corporate transaction in the secondary market following the rules approved by the Security and Exchange Commission in January 2001. The actual reporting started in July 2002, with the dissemination of all trades in bonds with an initial issuance above $1 billion and in the 50 high yield bonds. In March 2003 the dissemination was extended to trades in bonds with an initial issuance above $100 million and a rating of at least A-. Finally, the dissemination was completed in October 2004 with 99% of all trades reported in real time.[9] The increase in the quantity and the quality of the information provided by the TRACE system invites empirical studies of the U.S. corporate bond market and this is reflected in the increasing number of papers using this database. However (although expected) these papers are mainly focused on the transparency and the liquidity of the corporate bond market. On one hand, the implementation of the new system provides the opportunity to analyze improvement on the transparency or (and therefore) on the liquidity of the market and, on the other hand the new database provides intraday information that allows liquidity measures and their components to be estimated more efficiently.[10]

Although we are not going to benefit from the dissemination of the intraday information in TRACE, this database allows us to identify exactly the last trade in each day and thus to match this “close” price to the corresponding close price in the stock market. We collect all transactions regarding bonds issued by the firms on the SandP100 and, after applying the filters proposed by

[9] As of July 2005 real time means that trades must be reported within 15 minutes.
[10] Edwards, et al. (2007), Bessembinder et al. (2006), Goldstein et al. (2007), and Dick-Nielsen et al. (2012) are relevant examples.

Dick-Nielsen (2009) to eliminate erroneous data in the reported transactions, we save the daily close prices.[11] In the same way, daily close prices for the stocks of the firms on the SP100 Index are collected from the Center for Research in Security Prices (CRSP). Next, some filters reduce the final number of bonds in our sample. Firstly, we only use bonds with fixed coupon rates, noncallable, nonputable, nonsinking funds and which are nonconvertible in order to avoid simultaneity effects on their prices. Secondly, we eliminate bonds that do not fulfill both a sample length criterion of at least three years of data, and a liquidity criterion of 10 observations per month.[12] This results in a final number of 467 bond issues of 72 firms. Therefore, 467 correlations are estimated and analyzed.

The sample period goes from July 2002 to December 2009, which promises substantial time series variation since it includes the last part of an expansion cycle (2002-2006) and the recent and dramatic economic crisis (2007-2009).

Daily returns obtained from daily prices of stock and bonds are used to estimate a series of monthly dynamic correlation for each pair of stock-bond returns. Once again, studies about which model provides the best estimate for the correlation between aggregate stock and bond returns are abundant whereas that is not the case for individual corporate bond-stock co-movements. And what seems clear is that the dynamics of the correlation in aggregate markets are different as compared to the individual case. Given this, instead of assuming a determined model for the correlations and after testing its performance, we estimate in the next section the correlations with pure data driven methods. After that, we attempt to explain their cross-sectional and time series variations with variables that can potentially do so.

4. Bond-Stock Correlations

4.1. Conditional Correlation Models

The dynamics of time varying correlations between financial variables have been extensively studied in the literature. The most employed estimation methods are versions of Multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. A survey of Multivariate GARCH models is given by Bauwens et al. (2006).

However, the estimation of GARCH models becomes intractable when the number of series being modeled is high. The Dynamic Conditional Correlation (DCC) of Engle (2002) and the Regime Switching Conditional Correlation (RSDC) of Pelletier (2006) deal with this problem

[11] We would like to thank Jens Dick-Nielsen for his help in answering all our doubts about the implementation of the filters.

[12] If the latter condition is not reached, we relax this constraint to observe at least 30 observations in the quarter to which the month belongs.

allowing a two-step estimation of the correlation matrix. In the first step the univariate model of the volatility is estimated for each asset and in the second step that estimation is used to obtain the dynamic of the correlation.

In our DCC model we assume that bond and stock returns follow a GARCH(1,1) process,

$$r_{it} = \mu_i + \epsilon_{it} \qquad i = 1,2$$

$$\epsilon_i \sim N(0, \sigma_i) \tag{7}$$

$$\sigma_{it}^2 = \gamma_{0i} + \gamma_{1i}\epsilon_{it-1}^2 + \gamma_{2i}\sigma_{it-1}^2,$$

where μ_i is the mean return of asset *i*,, that is the stock or the bond, and ϵ_{it} is the error term, which follows a conditional normal distribution with zero mean but which shows heteroskedasticity.

The estimator of the conditional correlation,

$$\rho_{12t} = \frac{q_{12t}}{\sqrt{q_{11t}}\sqrt{q_{22t}}}\ , \tag{8}$$

is obtained in the second step from the estimation of the following process,

$$q_{12t} = (1 - \alpha - \beta)\bar{\rho}_{12} + \alpha z_{1t-1}z_{2t-1} + \beta q_{12t-1}\ , \tag{9}$$

where $\bar{\rho}_{12}$ is the unconditional correlation coefficient and z_{it-1} are normalized error terms in the mean equation,

$$z_{it} = \frac{\epsilon_{it}}{\sigma_{it}} \quad i = 1,2. \tag{10}$$

The hypothesis of normality in equation (7) gives rise to a likelihood function. As Engle (2002) points out, if we denote by θ the set of the parameters of the univariate GARCH model in (7) and $\emptyset$ the set of the parameters in (10), the log likelihood $L(\theta, \emptyset)$ can be written as the sum of two components: one for the volatility part and the other one for the correlation part,

$$L(\theta, \emptyset) = L_v(\theta) + L_c(\theta, \emptyset)\ . \tag{11}$$

The two-step approach consists of finding the parameters in (7) such as

$$\hat{\theta} = argmax\{L_v(\theta)\} \tag{12}$$

and then

$$\max_{\emptyset}\ \{L_c(\hat{\theta}, \emptyset)\}. \tag{13}$$

In addition to the DCC model we also consider a RSDC model in the spirit of that of Pelletier (2006). Our RSDC model assumes again that the bond and stock return variance follows a GARCH (1,1) process as in (7), and the covariance matrix for the two asset returns, Σ_t, can be decomposed as follows

$$\Sigma_t = \mathrm{D}_t \Gamma_t \mathrm{D}_t \ , \tag{14}$$

where $\mathrm{D_t}$ is a diagonal matrix containing the standard deviations and Γ_t is the correlation time varying matrix that is modeled in a dynamic framework by using

$$\Gamma_t = \sum_{k=1}^{K} I_{\{S_t=k\}} \Gamma_k \ , \tag{15}$$

where I is the indicator function, S_t is an unobserved Markov chain process which can take K possible values and Γ_k are correlation matrices with $\Gamma_k \neq \Gamma_{k'}$ for $k \neq k'$. In this sense, the model is presented as an intermediate model between the CCC model of Bollerslev (1990) that assumes constant correlation and the DCC model of Engle (2002), where correlations change for every t. Under this model, changes in the correlation only occur when there is a regime change, while the correlation remains constant within the same regime.

Regime switches in the state variable S_t are assumed to be governed by the transition probability matrix Π . The transition probabilities between states are assumed to follow a first order Markov chain and remain constant through time,

$$Pr(S_t = j | S_{t-1} = i, S_{t-2} = l, \dots) = Pr(S_t = j | S_{t-1} = i) = \pi_{ij} \qquad i,j=1,2\dots K \tag{16}$$

We consider two regimens in our empirical estimation: K=2.

The estimation of the RSDC model is achieved by using again the two–step procedure of Engle (2002). In the first step we estimate the univariate GARCH model for the conditional variances and, in the second step, we estimate the parameters in the correlation matrix and the transition probabilities given the first step estimates. Details of the estimation procedure can be found in Pelletier (2006).

As a robustness check, we also compute monthly estimations of moving sample correlations by using a rolling and overlapped window of three month-data such as in Andersson et al. (2008) or Demiralp and Hein (2010).

4.2. The non-trading days' issue

Typically, papers estimating financial correlations where individual bonds are involved have been based on monthly returns. Higher frequency data are only used in the case of correlations based

on market indices.[13] Our TRACE database allows us to calculate daily individual bond returns. However, corporate bonds are not very liquid assets and therefore it is common to find non-trading days without information about the bond price. We treat this problem in two different ways.

1. Calculating log-returns as if prices were consecutive, but adjusting them by dividing by the number of days in which there was no price: $\frac{1}{h}\left[log\left(\frac{p_t}{p_{t-h-1}}\right)\right]$.

2. Calculating log-returns without adjustment $log\left(\frac{p_t}{p_{t-h-1}}\right)$ and making the adjustment in the methodology for estimating the variance and the correlation. In doing so we follow and extend the proposal of Engle et al. (1996) to account for weekends in GARCH-type models, for the case of any *h*-days gap between prices:

$$\sigma_{it}^2 = d_t^{\delta}\left(\gamma_{0i} + d_{t-h-1}^{-\delta}\left(\gamma_{1i}\varepsilon_{i,t-h-1}^2 + \gamma_{2i}\sigma_{it-h-1}^2\right)\right) \tag{17}$$

$$q_{12t} = d_t^{\delta}\left((1-\alpha-\beta)\bar{\rho}_{12} + d_{t-h-1}^{-\delta}(\alpha z_{1t-h-1}z_{2t-h-1} + \beta q_{12t-h-1})\right) \tag{18}$$

This specification captures how the variance and the correlation can slow or speed up when gaps due to non-trading days occur, where δ is the speed parameter.

The correlations estimated with the standard DCC and RSDC methods applied to the returns from alternative 1 are termed DCC and RSDC, while the correlations estimated with the specifications (17) and (18) applied to standard returns are called DCCD and RSDCD.[14] Therefore, we obtain four different estimated procedures for each of the 467 pairs of bond-stock returns plus the historical rolling estimation.[15]

4.3. Correlations estimates

The high numbers of correlations that we estimate prevent us from considering a detailed examination of the parameter values. Instead, we summarize them by using frequency histograms in Figure 2.

[Figure 2]

[13] See for example Campbell and Ammer (1993) and Campbell and Taksler (2003).

[14] The estimation procedure for estimating RSDCD uses the Engle et al. (1996) correction only in the estimation of the variances, i.e. in the first step. In the second step, the correlation matrix estimation proceeds in the same manner as the standard RSDC procedure.

[15] It must be pointed out that the stock returns are computed introducing the same gaps as in bond prices in order to have equivalent series for estimating their correlation.

Figure 2 shows that, in the case of DCC models, α and β estimates seem to be concentrated in the whereabouts of one and zero respectively. This means that the correlation seems to be governed mostly by the short-term shocks and shows little persistence. This evidence is contrary to what is usually observed in the dynamics of GARCH volatility models where volatility clustering is better gathered by high lagged volatility parameter values. The δ values, which determine the average speed of the correlation rate, are mainly close to zero, meaning that non-trading days seem to have little effect on the conditional correlation; although we cannot discard other values of this parameter (given the dispersion of the values) that may significantly affect the way the correlation evolves throughout non-trading days.

In the RSDC models, the estimates for the transition probabilities show that regimes are not persistent in time, given that these parameters are neither close to one or to zero. This fact may be in keeping with the low persistence shown in the GARCH parameters. On the other hand, correlation values in each regime seem to naturally delimit a high and low correlation regime, as these values are concentrated in the upper and lower value buckets of the histograms.

An overview of the parameter values helps to discern how the correlation dynamics behave on a general basis, but says little about the performance of each model. Now we focus on the estimated correlations on a descriptive basis. Table 1 shows descriptive statistics regarding the average (Panel A) and the standard deviation (Panel B) through time of the 467 estimated correlations.

[Table 1]

In general, the different methods produce similar results. The correlation is on average close to zero, showing slightly negative values, for the DCC and RSDC models, and a positive value for the sample correlation. Adjusted models present higher dispersion.

An alternative perspective can be obtained by viewing the average correlation at a time series level. Figure 3 plots the mean of the correlations across the 467 pairs at each point in time.

[Figure 3]

As seen, all four models perform similarly through time on average, though RSDC is less spiky. Although centered on zero, with little time dispersion, the average correlation seems to be negative in the first part of the sample (expansion period), and slightly increases towards positive values in the last part of the sample (crisis period).[16] We point out that this figure plots the average among our 467 correlations between stock and bond return pairs; therefore, the

[16] In fact, the average correlation moves from -0.017 to -0.012 during the expansion periods while from 0.004 to 0.01 in recessions.

variability of the series is going to be smoothed down. In order to illustrate that the time variation is much higher in individual correlations, Figure 4 shows two representative bond-stock return correlation series for the industrial and financial sector.

[Figure 4]

An overview of the global patterns in the estimated correlations is provided above, although we note that conclusions on this basis can only be drawn in an aggregate level, while we are interested in the explanation of each individual correlation. In that sense, we point out that our aim is not to identify the best process for the dynamics under the correlations; in fact, we find that one model is able to adjust the correlation of one specific pair better but the other method produces a higher adjustment for another different individual correlation. Since the process driving the true correlation is unknown, the utilization of different methodologies for estimating the correlation must be understood as a way of giving robustness to the analysis.

5. The determinants of the correlations

5.1. Explanatory variables

In this section we use the correlations estimated before analyzing their cross-sectional and time series variation at a monthly frequency with panel data regression analysis. To do so, we include macro variables, firm specific variables as well as bond specific variables in the model. The selection of these explanatory variables responds to both theoretical insights and empirical findings in the literature.

In the group of macroeconomic, aggregate or state variables we consider nine potential cycle indicators based on both the financial and the real side of the economy. Specifically, we use the following variables indicating economic growth: gross domestic product growth rate (ΔGDP), the industrial production index growth rate (ΔIPI), the aggregate consumption growth rate (Δ_c), and a dummy for crisis (NBER). We employ a group of variables related to uncertainty in both real and financial markets that are expected to anticipate recessions: the volatility of the aggregate consumption growth rate (σ_c), the volatility of SP100 return (σ_{SP}), the implied volatility computed from prices of options written on the S&P index (VIX), and a default spread (Default). Also we include the term structure of interest rates (Term) as indicator of future good conditions. And finally, the short-term interest rate (TBill) is considered since both the theoretical model and the empirical evidence provided in Campello et al. (2008) indicate that increases in the risk free rate produces decreases in the correlation between the two assets.

As we have argued before, the value of the firm, which is indirectly related to its risk, is a common determinant in the firm bond and stock returns. We consider different variables for

approximating firm-specific risk. The group of variables indicating individual stock uncertainty includes: total risk (σ^{Tot}), systematic risk (β) and idiosyncratic risk (σ^{Id}). In the group of variables representing the financial component of the firm risk are the leverage ratio (Lev) and the default probability (Default Prob). As measures of firm operational risk we use industry dummy variables (Ind1 and Ind2) and the unlevered beta (β^{UN}). Finally, a covenants indicator for each bond (Cov) is included for considering the effect of potential agency problems.

Finally, as control variables we include two characteristics of the debt issue, the coupon level (Coupon) and the time to maturity (time), and given the importance of illiquidity risk in both the stock and bond returns, we also consider a measure of illiquidity for each asset in the pair (Ami_S and Ami_B).

All data for the construction of these variables are collected from CRSP U.S. Database, U.S. Federal Reserve, and COMPUSTAT. The details about the specific data sources, the computation or estimation methodologies for constructing the variables and their descriptive statistics can be found in Appendices I and II.

5.2. Panel Estimation: Methodology

Once the dynamic correlations between bond and stock returns have been estimated, as indicated in the previous section, we enter into the main focus of this paper: the analysis of the variation of stock-bond return correlation on both a time series and cross-sectional basis. To this extent, we conduct a regression analysis using panel data estimation techniques. These procedures will be briefly introduced in the following lines.

In order to be consistent with the techniques used to estimate the dynamic correlations, we admit potential persistence in the dependent variable.[17] The regression to be estimated is

$$y_{it} = \alpha y_{it-1} + \mathbf{x}'_{\mathbf{it}}\beta + \varepsilon_{it} \tag{19}$$

where y_{it} is the dynamic correlation for bond-stock returns pair *i* and month *t* and $\mathbf{x_{it}}$ is the vector of exogenous and potentially predetermined variables which includes state variables, firm-specific risk variables, and bond-specific risk or characteristic variables.

In order to deal with the potential fixed effects in the error term, equation (19) can be differentiated and estimated by the so-called Difference GMM model proposed by Arellano and Bond (1991). However, this estimation methodology does not allow for independent variables constant in time. The System GMM estimator, first proposed by Arellano and Bover (1995) and later developed by Blundell and Bond (1998), deals with this issue by including a new set of

[17] Results from a static panel model are qualitatively similar to those displayed in this paper, and are available upon request.

moment conditions in addition to the ones included under the Difference GMM procedure, which come from the use of differenced lagged values of the dependent variable as instruments. In any case, both techniques, Difference GMM and System GMM, imply taking decisions about how valid the instruments are, and especially how many instruments have to be included.

As reported in numerous papers (Sargan, 1958; Bowsher, 2002; or Roodman, 2009), too many instruments can induce estimation problems, such as difficulty in calculating the inverse of the estimated variance matrix in the two-step procedures, potential bias in the two-step estimated standard errors, or weakness in the test of Hansen (1982) for instrument validity. In the first case, a generalized inverse is performed, whilst the second issue is addressed by Windmeijer (2005) who computes a correction in the variance of the estimator that performs well in simulations. However, the potential weakness in the Hansen test has no reliable solution. In the end, regarding this issue the researcher mainly has two options. The first is to cut through the number of instruments, limiting *ad hoc* the instrument set. Of course this poses the same problem of knowing how many instruments are "too much". Secondly, one can accumulate the moment conditions in a smaller number of these, thus collapsing the instrument set (Roodman, 2009a), creating far less moment conditions, although potentially reducing efficiency. Both methods can be combined to yield better results.

Regarding the validity of the chosen instruments, two tests can be used. The first one is from Arellano and Bond (1991) and is based on the key assumption of absence of autocorrelation in the idiosyncratic error term. If the error term has first order autocorrelation, then the second lag of the dependent variable would not be an appropriate instrument because it would be correlated with the error term. In this case, only lags 3 and longer would be available as valid instruments. Therefore, the Arellano-Bond test is used to value the appropriateness of the instruments by means of analyzing the autocorrelation of the residuals.

On the other hand, and despite the persistence in the residuals, a set of valid instruments must also be assumed as exogenous to conclude on the validity of System GMM. In an attempt to verify this assumption, the Sargan (1958) or the Hansen (1982) tests can be applied. In both cases, the null is that the set of sample moment conditions holds, which is tested by a quadratic form statistic that is asymptotically chi-square distributed where the degrees of freedom are equal to the degrees of overidentification, that is, the number of instruments exceeding the variables to be instrumented.[18] Although the Hansen tests is itself robust, it is weakened by instrument proliferation, whereas the Sargan test is not weakened in this case, but is also not robust. Numerous authors have cited this issue of including too many instruments as we have already commented, and thus we henceforth take this fact into account.

[18] In the case where instruments are equal in number to the variables to be instrumented, the Sargan or the Hansen tests are not computed since their values are always zero.

5.3. Panel Estimation: Results

We estimate the parameters of equation (19) by OLS, Within-Groups estimation, Difference GMM and System GMM employing as the dependent variable each of the five groups of the estimated correlations: DCC, DCCD, RSDC, RSDCD, and rolling sample correlation. Tables 2 - 6 show results, respectively, for the case of System GMM methodology.[19] We choose to provide only these results for two reasons. First, Flannery and Watson (2010) recently found this to be the best panel estimation methodology, based on their results for simulations of specifications with different panel lengths that include potentially arising issues such as serial correlation and highly autocorrelated exogenous variables. Secondly, qualitatively speaking, the results are robust to the different estimation techniques.

As indicated in equation (19), we only include the first lag of the correlation as an independent variable. We have checked that an autoregressive process of order 1 is sufficient for capturing the persistence for all the estimated correlations except for the sample case in which more lags may be needed. For the sake of homogeneity in comparisons and in order to be parsimonious in the number of instruments, we choose to include only one lag of the dependent variable for all five cases.

The vector of exogenous variables ($\mathbf{x_{it}}$) includes a priori all the variables described in section 5.1. However, in order to save space, Tables 2 - 6 show results for models that only include a subset of this total set. This selection has been made following two criteria: a variable is excluded from the model if it is either not relevant for any of the five groups of correlations or if its information is already contained in another exogenous variable. Therefore, by running successive regressions using different combinations of variables, we obtain the following general results that allow us to discard certain groups of explanatory variables.

- In the group of state or macroeconomic variables, we find that GDP growth, IPI growth, consumption growth and the volatility of the market index are not useful in explaining the variation in correlations and that the information in short-term interest rates is already included in term spread and default spread.
- In the group of variables related to stockholders risk, we find that unlevered betas have a negative relationship with correlations but their significance disappears when the two industry dummy variables are included in the model, despite the method used for estimating taxes (see Appendix I). Therefore, it seems that the only relevant information in these betas is just the type of the business of the assets' issuer. On the other hand, the results are practically the same assuming the CAPM or the Fama-French model. Consequently, we only show results for the standard market beta. Finally, the total risk

[19] Results due to the other estimation methodologies are available upon request.

and the idiosyncratic risk share an important part of common information and the former is not significant when the non-systematic risk is considered in the model.

- None of the illiquidity measures either for the stock or for the bond in the pair are significantly related to the correlations nor does the level of the bond coupon contain relevant information.

Therefore, Tables 2 - 6 show results regarding different models that combine the exogenous variables of the subset indicated in the first column: volatility of consumption growth, default spread, implied volatility for the stock index, term spread, the dummy for recessions, market beta for each stock, leverage ratio for each issuer, default probability for each issuer, idiosyncratic risk for each stock, the covenants indicator for each bond, the time to maturity for each bond, and the two dummy variables representing the issuer industry group.[20]

As stated before, Tables 2 - 6 show the estimation results using the two-step System GMM.[21] Given the instrument proliferation issue discussed in the previous section, in the first five columns we provide the estimates using as instruments lags 2 to 4 of the dependent variable (except in the case of the sample correlation, for which the Arellano-Bond test is rejected until the fifth order, and thus we use lags from 5 to 7). This number of instruments seems to be a reasonable threshold for the acceptance of the Hansen test as reasonable p-values for the test are observed. The next five columns show the results from the estimation of the same models but collapsing the whole instrument set, following Roodman (2009a), in order to create a smaller number of moment conditions. In all cases we have assumed that the variables in vector $\mathbf{x_{it}}$ are strictly exogenous, and therefore no instrumentation of these variables is needed. The number of instruments is also reported at the top of each column, and different order Arellano-Bond tests, the Sargan test and the Hansen test are reported at the end. Finally, p-values (in parenthesis) are based on standard errors that have been calculated using the Windmeijer (2005) implementation, which attempts to correct the downward bias that potentially arises in two-step estimations.

We begin our analysis by examining the results from a global specification point of view. For correlations estimated with DCC, DCCD, RSDC, and RSDCD methods, the Arellano-Bond test is not rejected for orders 2 and higher, which in principle suggests that the second and further lags of the correlation are valid instruments. A notable exception is the sample correlation; it is not until the AR(5) when the null of absence of residual autocorrelation is not rejected, and thus only lags from 5 onwards can be used as valid instruments. Regarding the Hansen test of

[20] Although the covenants indicator is almost never statistically significant we decide to keep it in the model because it is the only variable directly related to agency problems in our sample and it does not produce multicolinearity problems with the rest of variables.

[21] Estimations have been run using the xtabond2 procedure developed by David Roodman for Stata, whom we would like to thank for sharing this useful tool with researchers.

overidentifying restrictions, the null is not rejected in all regressions and for all estimated correlations, with the exception of the collapsed instrumentation in the case of the sample correlations. Thus, it seems that the instruments used are exogenous and therefore valid, keeping in mind that this test may be weakened, given the instrument proliferation. Given this, the Sargan test is also provided. Although the Sargan test is not robust, it can indeed give us some intuition about how much the Hansen test may be weakened. As seen in Tables 2–6, the Sargan test is always rejected when using lags from 2 to 4 for the instrumentation (first five columns), which leads to a very high number of instruments. However, when we collapse the instrument set, the Sargan test is not rejected for the DCCD and RSDCD cases. On the one hand, this is an important point in favor of collapsing the instrument set, and, on the other hand, this result inspires confidence about the specification of the models used when the correlations have been estimated taking into account the problem of the non-trading days'.

[Tables 2, 3, 4, 5 and 6]

Regarding the estimates of the model parameters and starting with the autoregressive component, we find that it is always significant for all models in Tables 2 and 6. In contrast, one lag of the correlation is never significant when correlations are estimated by using DCCD and RSDCD (Tables 3 and 5). This suggests that the correction for controlling the non-trading days eliminates the persistence in the resulting series estimates.

With respect to the set of state variables, we find a high and significant value for the parameter associated to the volatility of consumption growth that is quite remarkable. With the exception of some models for the case of the sample correlation, this result is robust for all models and the other four estimated correlations. Therefore, it seems that the consumption risk determines not only stock prices but also bond prices, being a relevant factor for explaining the correlation between the two assets. This result is in favor of a consumption-based model that price simultaneously stock and corporate bonds, as the one of Bhamra et al. (2010). Curiously enough, Augustin and Tédongap (2011) also find that an important part of the variability of sovereign credit default swaps can be explained by the volatility of aggregate consumption growth. We also find that the sign of this coefficient is negative, indicating that when the volatility of aggregate consumption growth is low the correlation between the return on bonds and stocks with the same issuer is higher. That is, only when investors have positive expectations about future economic conditions do the returns of the two assets move together, reflecting the common effect of the firm value under both financing assets. However, when the future expectations are negative, it seems that the shareholders call option value increases at the same time that the debt value decreases making the correlation to be lower. We will come back to this finding later.

The other variables representing economic cycles produce the same conclusion. The aggregate default spread shows a negative and significant effect on correlations for the cases of DCC, DCCD and the sample. This result is consistent with the evidence reported in Chiang and Li (2009), although they use corporate bond and stock market indices. The coefficient of the dummy for recession (NBER) is always negative and statistically relevant regardless of including or not other state variables. And, finally, the term structure slope displays a positive and significant relation with all the dynamic correlations, but only when NBER indicator is also included in the model. Therefore, on the one hand, we find that the information in term is only relevant in crisis periods and, on the other hand, that the correlation between the returns of bond and stocks is systematically lower during recessions. Finally, the implied volatility of the stock market (VIX) is generally not significant. This would be consistent with the fact that the volatility of the whole stock market can be useful for explaining the correlation between the two markets (as in Chiang and Li, 2009, or Conolly et al., 2005) but not for explaining correlations between individual assets (as found by Campbell and Taskler, 2003). [22]

Summarizing the results regarding all the variables that convey information about the economic cycles, we find that positive expectations about the future economic conditions increase the correlation between the return on individual stock and bond returns. Thus, our results suggest that stocks and bonds issued by the same firm react differently depending on the type of news. Good news could be interpreted as a signal of an increase in the firm value, and thus both the equity and debt values would increase producing an increment in the correlation between their returns. However, bad news would affect the two assets asymmetrically.

Regarding variables with cross-sectional information, the most important feature is the strong role of the stock idiosyncratic risk in all regressions, no matter the specification. We find that increases in the non-systematic volatility of the firm equity lead returns on bonds and stocks of the same firm to behave more similarly. In the same sense, increases in the financial risk of the issuer, measured by the leverage ratio, are also positively associated with higher the correlations. These findings are consistent with previous empirical evidence confirming that the relation between the two assets strengthens as the issuer risk increases. Campbell and Taksler (2003), Campello et al. (2008) or the simulations reported in Schaefer and Strebulaev (2008) are examples.

Therefore, our results agree with structural models since they suggest that the equity-bond return covariance increases with these firm characteristics. However, they also indicate that the specific model by Merton (1974) would not be appropriated for measuring the correlation

[22] The models in columns 2, 3 and 4 have been estimated including one lag of default in the two first cases and one lag of term in the last one, in order to control for a potential problem of persistence in repressors or to consider the anticipated information that these variables contain. The conclusions remain unchanged.

between these two assets; remember that the model simulations produce contrary results regarding leverage or firm volatility.

Other variables that also proxy for the firm risk induce different conclusions. Systematic risk, measured by beta, or the default probability of the issuer show negative and generally significant coefficients. These results are consistent with the theoretical predictions of the Merton model; for sufficiently high values of financial leverage, an increase in the firm risk (i.e. firm beta or default probability) would increase the equity value while decreasing the debt value. Our evidence coincides with Kwan (1996), who finds no correlation between changes in individual bond yields and stock returns for AAA-rated bonds but a negative correlation and increasing (in absolute value) when the credit rating rates diminish.

Regarding operational risk, we also find that the type of industry appears as an important determinant of the correlation, as shown by the results related to the two industry dummies for all Tables 2 – 6. In the cases where NBER is not included, the constant term represents firms in industry 3. We find that the correlation is higher for utility firms than for the other two industries and it is significantly reduced especially for industrial firms.

Finally, the number of covenants in the bond contract is not significant in any of the specifications, although it showed certain explanatory power in previous regressions. And, only in some specific cases do we find a positive influence of the bond's time to maturity on correlations; essentially, bonds that are farther from maturing display higher correlation with their stock pairs.

5.4. Robustness: Fama-MacBeth Estimation

To ensure the reasonableness of our conclusion from the panel data estimation in the previous section, we run cross-sectional regressions each month and compute estimates and standard errors following Fama-MacBeth (1973) methodology. In this case, state variables cannot be included in the regression and we consider different combinations of all the variables with cross-sectional dimension. Estimation results for the cases in which DCC, DCCD, RSDC and RSDCD correlations are the dependent variable are reported in Table 7.

[Table 7]

The Fama-MacBeth methodology allows us to confirm the robustness of some of the results from the panel data analysis. None of the variables that approximate illiquidity risk are significant nor does the coupon contain relevant information. The two dummies for industry groups are highly significant, and it seems that the information enclosed in both the market beta and the unlevered market beta is insignificant when the two industry dummies are considered.

Stronger and more conclusive results are now obtained for the default probability and the time to maturity variables for which the slopes are positive and significant for the four correlation estimations and for all combinations of variables in the model. In the same way, the covenants indicator is also generally relevant showing that the correlation diminishes when the bondholders' risk is controlled by covenants in the bond contract. Finally, the strong results obtained before for the idiosyncratic risk and the leverage ratio are now slightly controversial. While idiosyncratic risk is a relevant variable only for the cases of DCC and DCCD correlations, the leverage ratio is statistically significant when the two RSDC methods are employed for estimating correlations. In any case, the signs of the coefficients are the same as before indicating that increases in the firm's risk are contemporaneously associated with increases in the correlation between its bond and stock returns.

5.5. Interactions

The most surprising results in Tables 2 – 6 are regarding the variables indicating economic cycle and the firm default probability because we find the contrarian relations that would be expected a priori. On the one hand, under the basement of structural models, in the same way that we find that the correlation increases with leverage or firm volatility, it would also be expected higher correlation associated with higher default probability. On the other hand, evidence has shown that both stock and corporate bond returns are countercyclical and that their responses to changes in economic conditions are stronger in recessions than in expansions. These premises suggest that the correlation between them should be higher in bad moments. However, these statements are not taking into account the potential interactions between the economic cycle and the risk position of individual firms. In this subsection we analyze more carefully our previous results with the theoretical support of a model that combines the time-series and the cross-sectional dimensions of the problem: the intertemporal-structural model proposed by Bhamra et al. (2010).

Under this model, the sources of risk for both, the stock and the bond, are the aggregate consumption and the individual firm's earnings. On the one hand, negative changes in the next period consumption growth or a negative revision in the expectations about the consumption growth in future increase the price of risk. On the other hand, the volatility in the firm earnings is responsible of the firm probability of default. And these two sources of risk are positively correlated.[23] Therefore, with this framework in mind, we would expect interactions between the two variables in our panel estimations. In order to analyze if this is the case, we divide our sample into two subsamples of firms according to the mean average in the default probability and estimate the same models as in Table 2 for the two subsamples separately.[24] Estimated results are

[23] The parameters estimations in Bhamra et al. (2010) produce a correlation of 20% between the Brownian motion in the consumption growth dynamics and the systematic shocks to the firm's earnings growth.
[24] In this case, we only present the results related to DCC correlation and without collapsing instruments.

reported in Table 8, for the subsample containing the stocks and bonds of firms with low probability of default, and Table 9, for the subsample of firms with high probability of default.

[Tables 8 and 9]

The results in Tables 8 and 9 confirm the interaction between the aggregate cycle indicators and the firm's probability of default. While cycle indicators are highly significant for firms with low probability of default, no state variable is relevant when the firms have high probability of default. In this case, the probability of default is significant with negative slope, implying the contrarian role that this variable plays in pricing equity and debt. Only when the probability of default is low, and therefore the firm default risk does not matter, the effect of the economic cycle appears in the stock-bond correlation. We find again that the correlation diminishes during or before recessions. This result is reasonable because if the default risk is actually low, the effect of an economic downturn would be almost imperceptible for the debt price while it would be important for the equity price. All these results are compatible with the model proposed by Bhamra et al. (2010). Also, the negative slope for both the volatility of consumption and the firm's probability of default confirms the positive correlation between the two sources of risk of this model.

6. Conclusions

The correlation between bond and stock returns at the aggregate-market level is a widely investigated topic. However, papers seeking to explain the commonality between bond and stock returns of assets issued by the same firm are scarce because of the lack of a continuous and reliable data base for corporate bond transaction prices. We attempt to cover this gap by estimating and analyzing the dynamics of the correlations between individual stock and bond returns. We employ corporate bond transaction prices coming from TRACE, a system by which all members must report OTC corporate transactions in the secondary market starting in July 2002.

The first part of the paper estimates the correlation series for each stock-bond pair in our sample, using different approaches: a rolling window sample correlation, a Dynamic Conditional Correlation model, a Regime Switching Conditional Correlation model and the two corresponding adjusted models to incorporate the non-synchronous trading problem. Our results indicate that the correlations between individual bond and stock returns are definitively time-varying. The dynamics in the correlations are reasonably well captured by models showing little persistence that diminishes when the non-trading effect in bonds is accounted for.

The aim of the second part of the paper is to identify the sources of the variability of these correlations over time and across firms and/or bond issues. For this purpose we consider a large set of potential explanatory variables including cycle indicators, different measures of the issuer's

risk, and also characteristics regarding the specific bond contract. We employ both panel data analysis and the Fama-MacBeth cross-sectional estimation methodology.

Our results are quite robust to the five sets of estimated correlations, and for the alternative estimation methods and model specifications employed. On the one hand, the correlation between the two assets returns increases when investors have positive expectations about future economic conditions, reflecting a positive elasticity equity-debt to changes in the firm value. This conclusion is especially stronger and consistent when we use the volatility of aggregate consumption growth to measure economic cycles. However, this cycle effect on the correlation is only observed for stocks and bonds of firms with low probability of default. In other case, aggregate state variables do not explain changes in the correlation.

On the other hand, we also find relevant variables when explaining the cross-sectional variation of the correlations. Consistently with the foundation of structural models that both financial assets represent the same productive assets, the correlation tends to be higher with the stock idiosyncratic risk and the firm financial leverage. However, when the firm's probability of default achieves high levels, the stock-bond correlation decreases as this variable increases, reflecting the opposite effect that a potential default has for the prices of equity and debt.

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Appendix I: Explanatory Variables

State Variables

ΔGDP: The growth rate of GDP comes from monthly real Gross Domestic Product Index provided for Macroeconomic Advisers.

ΔIPI: The Industrial Production Index growth rate is computed from the monthly index provided in Table G.17 of the Federal Reserve Data Base, which is constructed with the major industry groups.

Δc: The aggregate consumption growth is computed from seasonally adjusted monthly data on real consumption expenditures on nondurable goods and services from NIPA Table 2.8.6.

NBER: Is a dummy variable equals one during recessions and it is constructed from the recession dates provided for the National Bureau of Economic Research.

σ_c: The volatility of aggregate consumption growth is computed using a rolling window of 36 previous months.

σ_{SP}: The volatility of the stock market is computed monthly from daily stock returns of the SandP100 and a past rolling window of 60 observations.

VIX: As a proxy for the aggregate stock market risk we use monthly data for the volatility index (VIX) obtained from the Chicago Board of Options Exchange.

Default: The Default premium proxy variable is computed as the spread between Moody's yield on BAA corporate bonds and the yield on U.S. Treasury securities at 10-year maturity.

Tbill: As a proxy for the risk free rate we use the 3-month Treasury bill secondary market rate. From the Federal Reserve Data Base, Table H.15

Term: The term structure variable is computed as the difference between the market yield on U.S. Treasury securities at 10-year constant maturity and the 3-month Treasury bill rate.

Individual Stock Uncertainty

The different monthly measures of stock risk use daily stock returns and a past rolling window of 60 observations.

σ^{Tot}: As a measure of the stock total risk we use the standard deviation of the stock return.

β and β_{FF}: We measure stock systematic risk by market beta estimates from two generating return processes: the market model and the Fama and French (1993) three factor model.

σ^{Id} and σ^{Id}_{FF}: Correspondently to the two measures of systematic risk, for each stock, idiosyncratic risk is computed as the standard deviation of the residuals from the market model or the Fama and French model.

Firm Financial Risk

Lev: As a direct measure of the liabilities value in relation to the firm owned resources, we employ the leverage ratio measured as the ratio between the book value of firm debt[25] from COMPUSTAT and the market value of the stocks of the firm from CRSP. The debt value is reloaded quarterly because of availability reasons while the shares market value is measured monthly as the number of shares outstanding multiplied by the price at the end of the month.

Default Prob: Monthly series for the default probability of each firm from Moody's.

Firm Operational risk

We employ two variables representing the firm operational risk: industry dummies and un-levered beta.

Ind1 and **Ind2**: To control for commonality in operational risk between issuers we include 2 dummy variables for distinguishing the 3 industries that are represented in our sample: industrial firms, financial firms and utility firms. Ind1 takes a value of one if the issuer is an industrial firm, including Manufacturing, Communications, Oil and Gas, Retail, Service/Leisure and Transportation. Ind2 represents financial issuers including Banking, Credit/Financing, Financial Services and Insurance. In the third industrial group (without dummy representation) are Electric, Gas and Telephone services suppliers.

$\boldsymbol{\beta}^{\mathbf{UN}}$ and $\boldsymbol{\beta}^{\mathbf{UN}}_{\mathbf{FF}}$: The second variable that we use to proxy operational risk is the unlevered beta which is computed from the market beta using the Modigliani and Miller (1963) relationship,[26]

$$\beta_{it}^{U} = \frac{\beta_{it}}{1+(1-T_{it})L_{it}},$$

where T_{jt} and L_{jt} are the tax rate and the financial leverage ratio, respectively, for firm i at month *t*.

Given that we have two measures of market betas –estimated assuming the CAPM or the Fama-French model-, we will estimate the two correspondent unlevered betas. We measure the financial leverage using our variable Lev. Regarding the firm tax rate, we estimate corporate marginal tax rates annually and use these estimations for all months within this year. The dynamic features of the tax code makes it not realistic to compute the marginal tax rate for a given firm and year as the rate between taxes and taxable earnings. The tax code allows firms to carry backward and forward the losses. This means that if current taxable income is shielded by current interest deductions, an extra dollar of interest leads to a loss today which can be carried backward to obtain a refund of taxes paid in the past or can be carried forward to shield profits in the future years. Then, it is important to consider an uncertain scenario with past and future earnings to estimate the marginal tax rate (MTR) for each firm and year. We estimate the MTR employing the

[25] Specifically, we employ Long Term Debt and not Total Liabilities because some quarterly data for some firms about Debt in Current Liabilities are not available in Compustat.
[26] This equation is just an approximation because it assumes non risky debt.

original technique proposed by Graham (2000) and also used more recently in Binsbergen et al. (2010). Now we briefly describe the idea behind this technique.

For each firm and year, a scenario containing past and future earnings is simulated from the observed current taxable income. Given this simulated scenario, the tax bills for all years in the scenario are computed. Next, the current taxable income is increased by one unit ($10,000 in terms of COMPUSTAT units) and the tax bills for all simulated years are recalculated. The present value of the difference between the tax bills in the first simulation and the tax bills in the incremental simulation represents the MTR rate for this firm and year and this specific scenario. The exercise is repeated for a number of different scenarios or paths and the average across the MTRs is the estimation of the expected marginal tax rate.

The specific details for the application of the estimation technique are the following. The simulated taxable incomes paths are generated assuming that they change following a normal distribution with mean and variance equal to the historic mean and variance of the series.[27] These historical moments are computed each year *t* using historical data from 1979 to year *t*-1.[28] Each simulated scenario contains 23 years: the current year with the observed taxable income, 2 years back and 20 years forward.[29] Based on the current statutory federal tax schedule, the deduction for $1 initial interest is 0,35.[30] For computing present values, taxes in years *t*+1 through *t*+20 are discounted using the yield of corporate bonds at year *t*. Specifically, we employ as the discount rates two indexes of yield corporate bonds provided by the Federal Reserve for the period 2002-2009: the Moody's yield on seasoned corporate bonds AAA and the Moody's yield on seasoned corporate bonds BAA. The first index is use for discounting the estimated future differences in tax bills for firms which rating classification is in the level A for all the years in our sample and the second index is employed for firms that present a rating level lower than A in any year of our sample. The difference in tax bills for years *t*-1 and *t*-2 are not grossed-up because tax refunds are not paid with interest. Finally, following Graham (2000) we consider 50 paths.

For robustness reasons we also use two alternative measures of the corporate tax rates in computing the unleveraged betas: the tax rate directly provided by COMPUSTAT, which is computed annually as the rate between total taxes and pretax income, and we also compute the rate between total taxes and EBIT. In both cases, a zero tax rate has been imposed when it is negative.

We have then 3 measures of tax rates that produce 3 series for $\boldsymbol{\beta}^{UN}$ and 3 series for $\boldsymbol{\beta}^{UN}_{FF}$.

[27] Blouin et al. (2010) show that the random walk based on historical moments used here to forecast future taxable income underestimates its future volatility and they propose a non-parametric method for simulating the entire distribution of future income. However, Binsbergen et al. (2010) proved that the results are qualitatively the same using this alternative.

[28] When the historic mean is negative, the mean of the normal distribution is assumed to be zero.

[29] From 1997, tax law allows firms to carry losses back two years or forward 20 years.

[30] We do not incorporate state taxes in the estimation of MTR because a lot of additional assumptions may be made since each state has its own graduated rate structure and its own definition of variables to compute state taxes.

Bond Agency Problem

Cov: We measure the financial risk for each bond, in this case, by using a covenants indicator. Since Jensen and Meckling (1976) and Myers (1977) we know that incentive conflicts between equity and debt holders increase the firm's cost of debt. A partial solution to overcome this problem is to restrict the actions of the firm's equityholders by adding debt covenants. We construct a covenant intensity index following Bradley and Roberts (2004) and Demiroglu and James (2010). It is defined as the sum of the number of covenants for each bond contract including both those covenants that restrict the ability of the issuer to take part in a transaction that may be detrimental to bondholders and those covenants designed to directly protect bondholders.

Bond and Stock Illiquidity

We are also concerned about liquidity risk affecting both the stock and the bond in each correlation. For this reason, we compute the individual illiquidity ratio proposed by Amihud (2002) for both assets in each pair.[31]

Ami_S and **Ami_B**: The illiquidity ratio is daily calculated as the ratio of the absolute value of daily return over the dollar volume, which is closely related to the notion of price impact,

$$Illiq_{id} = \frac{|R_{id}|}{DVol_{id}}$$

where $|R_{id}|$ and $DVol_{id}$ are the absolute return and the dollar trading volume of asset *i* during day *d*. This measure is averaged monthly to obtain an individual illiquidity measure for each asset at month *t*,

$$Illiq_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{id}|}{DVol_{id}}$$

where $D_{j,t}$ is the number of days for which data about asset *i* are available in month *t*. Daily returns and trading volumes (million dollars) for the stocks in our sample are collected from CRSP. In the case of bonds, daily returns and volumes come from TRACE Database.

Bond Issue Characteristics

To control for bond characteristics regarding interest rate risk, we also consider for each bond:

Time: The time to maturity is computed monthly as the number of days until maturity.

Coupon: Is the coupon level and it is constant in time.

[31] The main advantage of Amihud´s illiquidity ratio is that it can be easily computed using daily data during long periods of time. Moreover, Hasbrouck (2009) shows that, at least for US data, Amihud´s ratio better approximates Kyle´s lambda relative to competing measures of illiquidity.

Appendix II: Descriptive Statistics

This table shows some descriptive statistics of the explanatory variables described in this Appendix. The first panel relates to state variables, which are in aggregate terms and, therefore, the descriptive statistics refer to the time dimension. The second panel refers to variables that have cross-sectional scope and the statistics are applied to both the time dimension for each individual and then the cross-section dimension across all individuals. The only exceptions are Coupon and Cov that are constant in time and then statistics are refer only to the cross-sectional variation.

State Variables							
	Mean	St.Dev.	Skewness	Kurtosis	1st Quartile	Median	3rd Quartile
Δc	0.001	0.002	-0.218	3.029	0.000	0.002	0.003
σ_c	0.002	0.001	1.253	3.918	0.002	0.002	0.003
Default	0.026	0.011	1.427	4.544	0.018	0.023	0.032
ΔGDP	0.001	0.006	-0.644	4.279	-0.002	0.001	0.005
ΔIPI	0.000	0.008	-1.854	9.278	-0.003	0.001	0.005
Tbill	0.022	0.017	0.406	1.739	0.009	0.017	0.039
Term	0.019	0.013	-0.361	1.686	0.006	0.023	0.030
VIX	0.213	0.102	1.540	5.410	0.133	0.179	0.260

Firm or Bond Issue Variables							
	Mean	St.Dev.	Skewness	Kurtosis	1st Quartile	Median	3rd Quartile
β	0.931	0.319	0.485	3.628	0.715	0.899	1.107
β_{FF}	0.962	0.323	0.391	3.857	0.759	0.937	1.145
β^{UN1}	0.728	0.241	0.392	3.373	0.562	0.710	0.875
β^{UN2}	0.720	0.267	0.407	3.675	0.547	0.697	0.862
β^{UN3}	0.734	0.239	0.366	3.339	0.568	0.717	0.882
β^{UN1}_{FF}	0.761	0.259	0.273	3.587	0.592	0.745	0.918
β^{UN2}_{FF}	0.753	0.284	0.318	3.868	0.577	0.732	0.909
β^{UN3}_{FF}	0.768	0.259	0.261	3.537	0.601	0.752	0.927
σ^{Tot}	1.882	1.146	1.863	6.434	1.164	1.454	2.141
σ^{Id}	1.438	0.754	1.548	5.324	0.959	1.168	1.647
σ^{Id}_{FF}	1.365	0.691	1.540	5.326	0.919	1.122	1.570
Lev	0.567	0.393	1.265	5.113	0.343	0.432	0.650
Default Prob	0.302	0.559	2.018	7.749	0.029	0.071	0.240
Cov	4.417	2.265	-0.881	2.594	3.000	5.000	6.000
Ami_S	0.278	0.131	1.464	5.764	0.191	0.259	0.307
Ami_B	0.139	0.259	4.087	25.637	0.018	0.056	0.160
Time	1924.9	690.1	0.274	1.917	1314.6	1841.0	2515.5
Coupon	6.050	1.378	-1.047	7.321	5.320	5.975	6.875

Table 1: Cross-sectional descriptive statistics for the average and the standard deviation of the estimated correlations

The table shows some descriptive statistics for the average (Panel A) and the standard deviation (Panel B) of the estimated correlation of each bond through time. Then, the reported statistics refer to a sample of 467 average correlations and 467 standard deviations of the correlations, respectively. DCC and RSDC denote the correlations estimated by using standard DCC and RSDC methods, DCCD and RSDCD refer to estimations that include a non-trading adjustment in the specification of the variance and the correlation of the series, and SMPL denotes the 3-month rolling sample correlation.

	Panel A					**Panel B**				
	DCC	DCCD	RSDC	RSDCD	SMPL	DCC	DCCD	RSDC	RSDCD	SMPL
Mean	-0.0013	-0.0029	-0.0055	-0.0084	0.0035	0.1664	0.1746	0.1491	0.1729	0.1587
Maximum	0.3058	0.3227	0.5078	0.3411	0.2993	0.2872	0.2847	0.2351	0.2895	0.273
Minimum	-0.1504	-0.1423	-0.2494	-0.3096	-0.1857	0.0998	0.0932	0.0801	0.1002	0.0891
25th Perc.	-0.0351	-0.0340	-0.0559	-0.0633	-0.0306	0.1363	0.1494	0.1296	0.1464	0.137
Median	-0.0047	-0.0061	-0.0049	-0.0106	-0.0023	0.1608	0.1719	0.1464	0.1678	0.1553
75th Perc.	0.0211	0.0198	0.0363	0.0422	0.0329	0.1938	0.1959	0.1647	0.1942	0.1762
Std Dev.	0.0527	0.0504	0.0869	0.0916	0.0558	0.0379	0.0359	0.0271	0.0354	0.0308
Skewness	1.8274	1.8311	0.7794	0.2328	1.2078	0.6034	0.4759	0.5213	0.687	0.6714
Kurtosis	11.2585	11.7588	6.3793	4.1957	7.9758	2.8041	3.032	3.3547	3.2496	3.7301

Table 2: DCC Correlation Panel Estimation

The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic DCC stock-bond return correlations for different specifications according to the variables indicated in the left column. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. For the first five columns, the System GMM is used by instrumenting the endogenous variable with lags from 2 to 4, while in the last five columns the system of moment conditions is collapsed using lags 2 onwards. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	359	360	361	361	356	99	100	101	101	96
y_{t-1}	**0.020**	**0.020**	**0.019**	**0.019**	**0.023**	**0.018**	**0.018**	**0.017**	**0.016**	**0.022**
	(0.015)	**(0.016)**	**(0.017)**	**(0.023)**	**(0.006)**	**(0.025)**	**(0.024)**	**(0.026)**	**(0.036)**	**(0.006)**
σ_c	**-21.838**	**-15.736**	**-15.137**	**-35.005**	--	**-25.201**	**-19.143**	**-18.724**	**-40.482**	--
	(0.000)	**(0.001)**	**(0.001)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Default	--	**-6.297**	**-8.410**	--	--	--	**-6.242**	**-7.695**	--	--
	--	**(0.001)**	**(0.006)**	--	--	--	**(0.004)**	**(0.019)**	--	--
VIX	--	--	2.631	--	--	--	--	1.827	--	--
	--	--	(0.348)	--	--	--	--	(0.540)	--	--
Term	--	--	--	**5.340**	--	--	--	--	**6.350**	--
	--	--	--	**(0.005)**	--	--	--	--	**(0.001)**	--
NBER	--	--	--	**-1.824**	--	--	--	--	**-2.056**	--
	--	--	--	**(0.000)**	--	--	--	--	**(0.000)**	--
β	**-1.105**	**-1.227**	**-1.217**	**-1.100**	**--**	**-0.786**	**-0.897**	**-0.881**	**-0.767**	--
	(0.002)	**(0.001)**	**(0.001)**	**(0.003)**	**--**	**(0.031)**	**(0.014)**	**(0.015)**	**(0.034)**	--
Lev	**0.339**	**0.310**	**0.313**	**0.323**	**--**	**0.292**	**0.266**	**0.269**	**0.281**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**--**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Default Prob.	**-0.173**	**-0.185**	**-0.187**	**-0.176**	**0.121**	**-0.168**	**-0.175**	**-0.177**	**-0.170**	**0.126**
	(0.002)	**(0.001)**	**(0.001)**	**(0.001)**	**(0.029)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.018)**
σ^{ld}	**0.970**	**1.371**	**1.362**	**1.232**	**--**	**1.073**	**1.447**	**1.436**	**1.337**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**--**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Cov	-0.136	-0.142	-0.142	-0.141	-0.176	-0.139	-0.138	-0.138	-0.144	-0.190
	(0.113)	(0.097)	(0.098)	(0.100)	(0.043)	(0.137)	(0.139)	(0.140)	(0.125)	(0.050)
Time	**0.133**	**0.132**	**0.130**	**0.135**	**0.111**	0.096	0.100	0.100	0.105	0.067
	(0.037)	**(0.038)**	**(0.041)**	**(0.034)**	**(0.080)**	(0.141)	(0.124)	(0.123)	(0.105)	(0.298)
Ind1	**-5.286**	**-5.363**	**-5.346**	**-5.392**	**-5.526**	**-5.143**	**-5.203**	**-5.194**	**-5.230**	**-5.309**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ind2	**-3.306**	**-3.459**	**-3.445**	**-3.503**	**-2.714**	**-3.600**	**-3.714**	**-3.719**	**-3.783**	**-2.853**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.002)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.003)**
Constant	**7.779**	**7.881**	**7.756**	**9.843**	**7.462**	**8.277**	**8.311**	**8.217**	**10.592**	**7.996**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Are-Bond	-17.830	-17.830	-17.830	-17.800	-17.830	-18.350	-18.350	-18.350	-18.340	-18.360
AR(1) Test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond	-0.810	-0.820	-0.810	-0.880	-0.520	-1.040	-1.030	-1.040	-1.140	-0.640
AR(2) Test	(0.421)	(0.414)	(0.417)	(0.377)	(0.602)	(0.298)	(0.302)	(0.298)	(0.256)	(0.521)
Are-Bond	1.560	1.560	1.570	1.600	1.500	1.550	1.560	1.560	1.610	1.500
AR(3) Test	(0.120)	(0.118)	(0.116)	(0.109)	(0.135)	(0.120)	(0.119)	(0.118)	(0.108)	(0.134)
Are-Bond	-0.280	-0.310	-0.320	-0.310	-0.280	-0.270	-0.300	-0.300	-0.300	-0.280
AR(4) Test	(0.777)	(0.756)	(0.752)	(0.760)	(0.776)	(0.785)	(0.763)	(0.761)	(0.765)	(0.777)
Are-Bond	-0.820	-0.800	-0.800	-0.870	-0.850	-0.820	-0.800	-0.810	-0.880	-0.850
AR(5) Test	(0.415)	(0.425)	(0.422)	(0.387)	(0.395)	(0.413)	(0.422)	(0.420)	(0.380)	(0.394)
Sargan Test	634.200	630.760	633.620	628.930	641.920	113.990	114.980	116.450	112.930	124.440
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.033)	(0.028)	(0.023)	(0.038)	(0.006)
Hansen Test	370.870	369.840	370.090	371.010	368.600	97.760	98.270	98.190	98.160	105.020
	0.191	(0.201)	(0.199)	(0.190)	(0.214)	(0.224)	(0.213)	(0.215)	(0.215)	(0.104)

Table 3: DCCD Correlation Panel Estimation

The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic DCCD stock-bond return correlations for different specifications according to the variables indicated in the left column. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. For the first five columns, the System GMM is used by instrumenting the endogenous variable with lags from 2 to 4, while in the last five columns the system of moment conditions is collapsed using lags 2 onwards. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	359	360	361	361	356	99	100	101	101	96
y_{t-1}	0.011	0.011	0.010	0.010	0.014	0.007	0.007	0.007	0.006	0.010
	(0.202)	(0.194)	(0.219)	(0.243)	(0.106)	(0.369)	(0.366)	(0.378)	(0.463)	(0.215)
σ_c	**-22.996**	**-16.420**	**-15.380**	**-38.599**	--	**-23.656**	**-17.220**	**-16.675**	**-40.007**	--
	(0.000)	**(0.000)**	**(0.001)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Default	--	**-6.874**	**-11.196**	--	--	--	**-6.671**	**-9.172**	--	--
	--	**(0.001)**	**(0.001)**	--	--	--	**(0.002)**	**(0.008)**	--	--
VIX	--	--	5.258	--	--	--	--	3.102	--	--
	--	--	(0.102)	--	--	--	--	(0.334)	--	--
Term	--	--	--	**6.489**	--	--	--	--	**6.948**	--
	--	--	--	**(0.002)**	--	--	--	--	**(0.001)**	--
NBER	--	--	--	**-2.220**	--	--	--	--	**-2.280**	--
	--	--	--	**(0.000)**	--	--	--	--	**(0.000)**	--
β	**-0.906**	**-1.029**	**-0.994**	**-0.921**	--	**-1.072**	**-1.199**	**-1.176**	**-1.035**	--
	(0.016)	**(0.006)**	**(0.007)**	**(0.014)**	--	**(0.004)**	**(0.001)**	**(0.002)**	**(0.006)**	--
Lev	**0.332**	**0.301**	**0.307**	**0.318**	--	**0.342**	**0.317**	**0.321**	**0.330**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Default Prob.	**-0.152**	**-0.165**	**-0.168**	**-0.161**	**0.165**	**-0.195**	**-0.203**	**-0.204**	**-0.198**	**0.125**
	(0.008)	**(0.005)**	**(0.004)**	**(0.006)**	**(0.006)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.017)**
σ^{Id}	**0.983**	**1.412**	**1.394**	**1.299**	--	**1.137**	**1.537**	**1.518**	**1.424**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Cov	-0.113	-0.122	-0.125	-0.121	-0.156	-0.123	-0.121	-0.121	-0.127	-0.177
	(0.184)	(0.151)	(0.142)	(0.156)	(0.075)	(0.159)	(0.165)	(0.165)	(0.148)	(0.050)
Time	0.098	0.096	0.094	0.101	0.076	0.065	0.070	0.070	0.075	0.035
	(0.128)	(0.135)	(0.143)	(0.114)	(0.240)	(0.321)	(0.283)	(0.283)	(0.251)	(0.594)
Ind1	**-4.814**	**-4.961**	**-4.958**	**-5.005**	**-4.993**	**-5.295**	**-5.376**	**-5.370**	**-5.415**	**-5.386**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ind2	**-3.291**	**-3.527**	**-3.559**	**-3.595**	**-2.614**	**-4.006**	**-4.145**	**-4.152**	**-4.240**	**-3.132**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.003)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Constant	**7.421**	**7.611**	**7.452**	**9.928**	**7.241**	**8.156**	**8.213**	**8.110**	**10.634**	**7.718**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Are-Bond AR(1) Test	-17.900	-17.910	-17.910	-17.900	-17.900	-18.580	-18.580	-18.580	-18.570	-18.580
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond AR(2) Test	-0.500	-0.490	-0.510	-0.580	-0.240	-0.820	-0.820	-0.810	-0.930	-0.530
	(0.619)	(0.621)	(0.611)	(0.563)	(0.814)	(0.413)	(0.414)	(0.416)	(0.354)	(0.598)
Are-Bond AR(3) Test	1.110	1.110	1.130	1.170	1.050	1.100	1.110	1.120	1.170	1.040
	(0.269)	(0.266)	(0.259)	(0.243)	(0.294)	(0.269)	(0.266)	(0.262)	(0.242)	(0.296)
Are-Bond AR(4) Test	-0.340	-0.370	-0.370	-0.360	-0.330	-0.340	-0.370	-0.380	-0.370	-0.330
	(0.735)	(0.714)	(0.710)	(0.715)	(0.743)	(0.731)	(0.711)	(0.708)	(0.711)	(0.741)
Are-Bond AR(5) Test	-0.910	-0.900	-0.910	-0.970	-0.950	-0.900	-0.890	-0.900	-0.970	-0.940
	(0.363)	(0.367)	(0.360)	(0.331)	(0.344)	(0.367)	(0.371)	(0.367)	(0.334)	(0.346)
Sargan Test	577.500	574.830	576.760	570.600	582.870	103.370	105.460	106.550	102.080	116.540
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.126)	(0.099)	(0.087)	(0.145)	(0.023)
Hansen Test	386.220	384.230	384.250	385.480	389.610	100.360	102.060	102.050	101.140	107.160
	(0.077)	(0.088)	(0.088)	(0.081)	(0.061)	(0.173)	(0.145)	(0.145)	(0.160)	(0.081)

Table 4: RSDC Correlation Panel Estimation

The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic RSDC stock-bond return correlations for different specifications according to the variables indicated in the left column. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. For the first five columns, the System GMM is used by instrumenting the endogenous variable with lags from 2 to 4, while in the last five columns the system of moment conditions is collapsed using lags 2 onwards. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	359	360	361	361	356	99	100	101	101	96
y_{t-1}	**0.017**	0.017	**0.017**	0.017	**0.020**	0.006	0.006	0.006	0.004	0.008
	(0.048)	(0.050)	**(0.049)**	(0.058)	**(0.021)**	(0.481)	(0.470)	(0.477)	(0.575)	(0.305)
σ_c	**-22.698**	**-20.320**	**-19.961**	**-35.811**	--	**-20.498**	**-17.504**	**-17.339**	**-35.447**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.005)**	**(0.006)**	**(0.000)**	--
Default	--	-2.318	-4.687	--	--	--	-3.211	-3.808	--	--
	--	(0.353)	(0.161)	--	--	--	(0.214)	(0.248)	--	--
VIX	--	--	2.993	--	--	--	--	0.770	--	--
	--	--	(0.372)	--	--	--	--	(0.804)	--	--
Term	--	--	--	**5.614**	--	--	--	--	**6.352**	--
	--	--	--	**(0.004)**	--	--	--	--	**(0.001)**	--
NBER	--	--	--	**-1.450**	--	--	--	--	**-1.796**	--
	--	--	--	**(0.006)**	--	--	--	--	**(0.001)**	--
β	-0.904	-0.944	-0.925	-0.910	--	**-1.222**	**-1.275**	**-1.273**	**-1.216**	--
	(0.066)	(0.057)	(0.062)	(0.065)	--	**(0.008)**	**(0.006)**	**(0.006)**	**(0.008)**	--
Lev	**0.316**	**0.308**	**0.311**	**0.315**	--	**0.351**	**0.336**	**0.336**	**0.343**	--
	(0.005)	**(0.006)**	**(0.006)**	**(0.006)**	--	**(0.001)**	**(0.002)**	**(0.002)**	**(0.001)**	--
Default Prob.	**-0.216**	**-0.222**	**-0.224**	**-0.228**	0.091	**-0.199**	**-0.202**	**-0.203**	**-0.203**	0.073
	(0.010)	**(0.008)**	**(0.008)**	**(0.007)**	(0.255)	**(0.014)**	**(0.013)**	**(0.012)**	**(0.014)**	(0.354)
σ^{Id}	**0.943**	**1.083**	**1.074**	**1.118**	--	**0.911**	**1.106**	**1.101**	**1.128**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Cov	-0.081	-0.083	-0.077	-0.081	-0.135	0.001	-0.002	-0.003	0.001	-0.072
	(0.604)	(0.596)	(0.621)	(0.602)	(0.387)	(0.997)	(0.988)	(0.987)	(0.996)	(0.666)
Time	**0.256**	**0.257**	**0.256**	**0.264**	**0.233**	**0.256**	**0.258**	**0.258**	**0.262**	0.230
	(0.022)	**(0.021)**	**(0.022)**	**(0.017)**	**(0.036)**	**(0.029)**	**(0.027)**	**(0.027)**	**(0.024)**	(0.051)
Ind1	**-7.346**	**-7.254**	**-7.182**	**-7.333**	**-7.592**	**-9.117**	**-9.159**	**-9.161**	**-9.251**	**-9.264**
	(0.003)	**(0.003)**	**(0.003)**	**(0.003)**	**(0.002)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Ind2	-4.602	-4.558	-4.512	-4.650	-4.044	**-6.085**	**-6.171**	**-6.162**	**-6.274**	**-5.411**
	(0.069)	(0.069)	(0.071)	(0.061)	(0.109)	**(0.018)**	**(0.016)**	**(0.015)**	**(0.014)**	**(0.038)**
Constant	**8.759**	**8.655**	**8.501**	**10.596**	**8.536**	**9.745**	**9.821**	**9.791**	**12.030**	**9.276**
	(0.002)	**(0.002)**	**(0.002)**	**(0.000)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.000)**	**(0.001)**
Are-Bond AR(1) Test	-18.260	-18.270	-18.270	-18.250	-18.270	-19.050	-19.050	-19.050	-19.050	-19.050
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond AR(2) Test	-0.550	-0.560	-0.550	-0.600	-0.290	-1.300	-1.300	-1.300	-1.390	-1.020
	(0.579)	(0.572)	(0.584)	(0.547)	(0.768)	(0.192)	(0.195)	(0.194)	(0.165)	(0.306)
Are-Bond AR(3) Test	1.820	1.820	1.820	1.850	1.750	1.810	1.820	1.820	1.850	1.740
	(0.069)	(0.069)	(0.069)	(0.064)	(0.080)	(0.070)	(0.069)	(0.069)	(0.064)	(0.081)
Are-Bond AR(4) Test	-1.310	-1.320	-1.330	-1.330	-1.330	-1.320	-1.320	-1.330	-1.330	-1.330
	(0.189)	(0.187)	(0.185)	(0.184)	(0.184)	(0.188)	(0.186)	(0.185)	(0.182)	(0.184)
Are-Bond AR(5) Test	0.100	0.100	0.100	0.070	0.070	0.100	0.110	0.110	0.070	0.070
	(0.922)	(0.918)	(0.916)	(0.944)	(0.947)	(0.918)	(0.913)	(0.913)	(0.945)	(0.941)
Sargan Test	709.230	711.220	711.290	709.670	736.760	118.970	119.400	119.710	116.190	123.010
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.015)	(0.014)	(0.024)	(0.008)
Hansen Test	380.970	382.170	381.860	382.540	379.950	98.650	98.260	98.220	97.250	102.990
	(0.108)	(0.100)	(0.102)	(0.098)	(0.115)	(0.205)	(0.213)	(0.214)	(0.234)	(0.131)

Table 5: RSDCD Correlation Panel Estimation

The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic RSDCD stock-bond return correlations for different specifications according to the variables indicated in the left column. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. For the first five columns, the System GMM is used by instrumenting the endogenous variable with lags from 2 to 4, while in the last five columns the system of moment conditions is collapsed using lags 2 onwards. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	359	360	361	361	356	99	100	101	101	96
y_{t-1}	0.007	0.007	0.007	0.006	0.009	-0.002	-0.002	-0.002	-0.003	0.001
	(0.437)	(0.431)	(0.438)	(0.512)	(0.314)	(0.811)	(0.829)	(0.811)	(0.715)	(0.918)
σ_c	**-15.419**	-11.221	-10.919	**-32.477**	--	**-17.546**	**-13.878**	**-13.730**	**-35.453**	--
	(0.003)	(0.055)	(0.062)	**(0.000)**	--	**(0.001)**	**(0.020)**	**(0.021)**	**(0.000)**	--
Default	--	-4.405	-5.728	--	--	--	-3.769	-4.150	--	--
	--	(0.112)	(0.122)	--	--	--	(0.180)	(0.260)	--	--
VIX	--	--	1.656	--	--	--	--	0.429	--	--
	--	--	(0.595)	--	--	--	--	(0.890)	--	--
Term	--	--	--	**7.328**	--	--	--	--	**7.752**	--
	--	--	--	**(0.001)**	--	--	--	--	**(0.000)**	--
NBER	--	--	--	**-1.943**	--	--	--	--	**-1.950**	--
	--	--	--	**(0.002)**	--	--	--	--	**(0.002)**	--
β	**-1.692**	**-1.789**	**-1.779**	**-1.719**	--	**-1.071**	**-1.134**	**-1.138**	**-1.062**	--
	(0.001)	**(0.001)**	**(0.001)**	**(0.001)**	--	**(0.042)**	**(0.031)**	**(0.032)**	**(0.044)**	--
Lev	**0.518**	**0.500**	**0.502**	**0.515**	--	**0.427**	**0.411**	**0.410**	**0.425**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Default Prob.	**-0.246**	**-0.254**	**-0.256**	**-0.256**	0.090	**-0.232**	**-0.236**	**-0.236**	**-0.242**	0.135
	(0.023)	**(0.018)**	**(0.018)**	**(0.018)**	(0.385)	**(0.030)**	**(0.027)**	**(0.028)**	**(0.025)**	(0.180)
σ^{Id}	**0.878**	**1.164**	**1.157**	**1.114**	--	**0.951**	**1.181**	**1.180**	**1.166**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Cov	-0.166	-0.163	-0.164	-0.166	-0.247	-0.082	-0.081	-0.079	-0.089	-0.161
	(0.322)	(0.330)	(0.330)	(0.325)	(0.149)	(0.604)	(0.609)	(0.619)	(0.572)	(0.316)
Time	0.246	0.242	0.242	0.252	0.210	0.180	0.178	0.176	0.191	0.125
	(0.074)	(0.078)	(0.078)	(0.063)	(0.140)	(0.190)	(0.197)	(0.201)	(0.160)	(0.369)
Ind1	**-4.134**	**-4.157**	**-4.150**	**-4.251**	**-4.151**	**-4.861**	**-4.913**	**-4.880**	**-5.011**	**-5.115**
	(0.015)	**(0.014)**	**(0.014)**	**(0.013)**	**(0.013)**	**(0.008)**	**(0.007)**	**(0.008)**	**(0.006)**	**(0.006)**
Ind2	-2.808	-2.896	-2.900	-3.008	-1.760	-3.396	-3.496	-3.458	-3.649	-2.552
	(0.119)	(0.108)	(0.107)	(0.098)	(0.318)	(0.080)	(0.071)	(0.075)	(0.059)	(0.192)
Constant	**5.661**	**5.704**	**5.643**	**8.249**	**4.969**	**5.697**	**5.735**	**5.687**	**8.399**	**5.662**
	(0.006)	**(0.005)**	**(0.006)**	**(0.000)**	**(0.015)**	**(0.010)**	**(0.009)**	**(0.010)**	**(0.000)**	**(0.012)**
Are-Bond AR(1) Test	-17.580	-17.580	-17.580	-17.570	-17.580	-18.350	-18.350	-18.350	-18.350	-18.360
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond AR(2) Test	-0.980	-0.970	-0.970	-1.050	-0.790	-1.650	-1.630	-1.640	-1.730	-1.380
	(0.329)	(0.331)	(0.331)	(0.294)	(0.430)	(0.100)	(0.102)	(0.100)	(0.084)	(0.166)
Are-Bond AR(3) Test	2.000	2.000	2.010	2.050	1.940	2.000	2.000	2.000	2.050	1.940
	(0.046)	(0.045)	(0.045)	(0.040)	(0.052)	(0.046)	(0.045)	(0.045)	(0.040)	(0.052)
Are-Bond AR(4) Test	-1.190	-1.200	-1.200	-1.200	-1.160	-1.170	-1.180	-1.180	-1.190	-1.160
	(0.236)	(0.231)	(0.230)	(0.229)	(0.245)	(0.242)	(0.238)	(0.237)	(0.235)	(0.245)
Are-Bond AR(5) Test	-0.570	-0.570	-0.570	-0.630	-0.610	-0.580	-0.580	-0.580	-0.650	-0.610
	(0.569)	(0.572)	(0.570)	(0.529)	(0.544)	(0.560)	(0.562)	(0.561)	(0.517)	(0.539)
Sargan Test	641.620	639.810	640.100	638.700	646.890	91.320	91.570	91.700	90.060	91.720
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.383)	(0.376)	(0.372)	(0.419)	(0.372)
Hansen Test	372.580	372.710	372.730	373.420	373.750	91.480	91.230	91.440	91.270	92.740
	(0.175)	(0.173)	(0.173)	(0.167)	(0.164)	(0.379)	(0.386)	(0.380)	(0.385)	(0.344)

Table 6: Sample Correlation Panel Estimation

The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic sample stock-bond return correlations for different specifications according to the variables indicated in the left column. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. For the first five columns, the System GMM is used by instrumenting the endogenous variable with lags from 2 to 4, while in the last five columns the system of moment conditions is collapsed using lags 2 onwards. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	347	348	349	349	344	96	97	98	98	93
y_{t-1}	**0.706**	**0.684**	**0.683**	**0.681**	**0.706**	**0.595**	**0.611**	**0.614**	**0.575**	**0.783**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
σ_c	**-7.511**	-1.732	0.245	**-17.855**	--	**-11.581**	-4.064	-2.103	**-18.743**	--
	(0.002)	(0.504)	(0.925)	**(0.000)**	--	**(0.026)**	(0.349)	(0.626)	**(0.010)**	--
Default	--	**-6.900**	**-16.563**	--	--	--	**-7.148**	**-16.159**	--	--
	--	**(0.000)**	**(0.000)**	--	--	--	**(0.000)**	**(0.000)**	--	--
VIX	--	--	**11.871**	--	--	--	--	**11.086**	--	--
	--	--	**(0.000)**	--	--	--	--	**(0.000)**	--	--
Term	--	--	--	**3.952**	--	--	--	--	**2.821**	--
	--	--	--	**(0.002)**	--	--	--	--	**(0.046)**	--
NBER	--	--	--	**-1.405**	--	--	--	--	**-1.507**	--
	--	--	--	**(0.000)**	--	--	--	--	**(0.003)**	--
β	**-0.716**	**-0.891**	**-0.821**	**-0.755**	--	**-0.959**	**-1.056**	**-1.002**	**-0.974**	--
	(0.011)	**(0.002)**	**(0.005)**	**(0.008)**	--	**(0.006)**	**(0.003)**	**(0.005)**	**(0.005)**	--
Lev	-0.045	-0.077	-0.062	-0.050	--	-0.031	-0.061	-0.047	-0.037	--
	(0.271)	(0.078)	(0.157)	(0.242)	--	(0.518)	(0.192)	(0.306)	(0.430)	--
Default Prob.	**-0.068**	**-0.087**	**-0.094**	**-0.079**	0.050	-0.075	**-0.081**	**-0.087**	**-0.076**	0.032
	(0.043)	**(0.015)**	**(0.009)**	**(0.024)**	(0.088)	(0.052)	**(0.039)**	**(0.025)**	**(0.049)**	(0.354)
σ^{ld}	**0.867**	**1.379**	**1.332**	**1.131**	--	**1.100**	**1.483**	**1.434**	**1.355**	--
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	--	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	--
Cov	0.001	-0.003	-0.004	-0.003	-0.002	-0.029	-0.030	-0.034	-0.035	-0.017
	(0.971)	(0.940)	(0.908)	(0.936)	(0.946)	(0.469)	(0.436)	(0.375)	(0.400)	(0.547)
Time	-0.008	-0.008	-0.008	-0.004	-0.002	-0.013	-0.010	-0.009	-0.009	-0.006
	(0.780)	(0.800)	(0.798)	(0.894)	(0.950)	(0.666)	(0.726)	(0.764)	(0.778)	(0.767)
Ind1	**-1.160**	**-1.439**	**-1.398**	**-1.395**	**-1.244**	**-2.131**	**-2.110**	**-2.063**	**-2.331**	-1.054
	(0.016)	**(0.004)**	**(0.005)**	**(0.006)**	**(0.009)**	**(0.010)**	**(0.011)**	**(0.012)**	**(0.009)**	(0.076)
Ind2	-0.074	-0.362	-0.358	-0.307	-0.253	-0.741	-0.838	-0.862	-0.982	-0.272
	(0.867)	(0.445)	(0.441)	(0.518)	(0.571)	(0.247)	(0.196)	(0.175)	(0.164)	(0.515)
Constant	**1.817**	**2.186**	**1.791**	**3.528**	**1.370**	**3.474**	**3.391**	**3.038**	**4.744**	0.981
	(0.011)	**(0.003)**	**(0.015)**	**(0.000)**	**(0.039)**	**(0.017)**	**(0.019)**	**(0.034)**	**(0.007)**	(0.304)
Are-Bond	-12.930	-12.460	-12.450	-12.350	-13.010	-5.280	-5.450	-5.490	-4.920	-9.060
AR(1) Test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond	14.300	14.210	14.290	14.220	14.330	13.470	13.550	13.650	13.300	14.440
AR(2) Test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond	-17.080	-17.030	-17.000	-17.010	-17.140	-13.390	-13.340	-13.280	-13.220	-14.790
AR(3) Test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond	10.090	9.780	9.720	9.680	10.110	4.480	4.640	4.630	4.170	7.490
AR(4) Test	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Are-Bond	0.880	0.890	0.790	0.860	0.860	0.850	0.870	0.780	0.830	0.870
AR(5) Test	(0.380)	(0.375)	(0.428)	(0.390)	(0.392)	(0.397)	(0.386)	(0.436)	(0.406)	(0.383)
Sargan Test	599.940	600.980	596.980	605.150	596.100	123.750	125.940	126.740	125.770	122.620
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.003)	(0.002)	(0.003)	(0.005)
Hansen Test	343.740	342.990	342.780	344.660	343.120	117.650	119.710	120.050	116.540	126.230
	(0.374)	(0.385)	(0.388)	(0.361)	(0.383)	(0.011)	(0.008)	(0.007)	(0.013)	(0.002)

Table 7: Fama-MacBeth estimation

The table displays results from the cross-sectional estimation of the correlation on the variables indicated in the first column. The methodology is the Fama-MacBeth estimation applied to each of the 90 months between July 2002 and December 2009. P-values for individual significance are reported in parenthesis. The last row provides a pseudo-R square computed with the sum of the 90 residual sums and the 90 total sums.

	DCC				DCC with non-trading adjustment				RSDC				RSDC with non-trading adjustment			
	2.193	**2.824**	**2.921**	-0.228	**1.967**	**2.773**	**2.866**	-0.210	**2.898**	**2.698**	**2.229**	-1.746	1.190	-0.796	-1.278	**-5.161**
B	**(0.003)**	**(0.027)**	**(0.019)**	(0.880)	**(0.009)**	**(0.050)**	**(0.039)**	(0.894)	**(0.000)**	**(0.018)**	**(0.044)**	(0.164)	(0.153)	(0.582)	(0.358)	**(0.002)**
	-4.786	**-4.885**	**-5.177**	-1.700	**-4.600**	**-4.882**	**-5.155**	-1.777	**-5.493**	**-4.298**	**-4.096**	0.217	**-4.254**	-0.349	0.151	4.273
β^{UN}	**(0.000)**	**(0.004)**	**(0.002)**	(0.401)	**(0.000)**	**(0.009)**	**(0.005)**	(0.400)	**(0.000)**	**(0.006)**	**(0.006)**	(0.901)	**(0.000)**	(0.851)	(0.933)	(0.051)
		-0.079	-0.086	0.292		-0.113	-0.118	0.237		0.064	0.093	**0.548**		**0.777**	**0.841**	**1.290**
Lev		(0.786)	(0.767)	(0.371)		(0.734)	(0.723)	(0.497)		(0.803)	(0.714)	**(0.039)**		**(0.017)**	**(0.011)**	**(0.000)**
	9.363	**9.212**	**10.815**	1.969	**9.174**	7.886	**10.159**	2.895	**16.824**	**23.187**	**26.768**	**14.383**	**22.312**	**17.434**	**17.976**	**7.915**
Default Prob.	**(0.000)**	**(0.043)**	**(0.022)**	(0.680)	**(0.001)**	(0.094)	**(0.028)**	(0.496)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.034)**
	1.437	**1.506**	**1.495**	**2.256**	**1.444**	**1.451**	**1.387**	**2.005**	0.431	0.138	0.059	**1.139**	0.242	-0.139	-0.519	0.394
σ^{Id}	**(0.001)**	**(0.001)**	**(0.002)**	**(0.000)**	**(0.002)**	**(0.004)**	**(0.006)**	**(0.000)**	(0.305)	(0.746)	(0.897)	**(0.017)**	(0.618)	(0.782)	(0.326)	(0.443)
	-0.108	**-0.113**	**-0.102**	**-0.100**	**-0.137**	**-0.143**	**-0.135**	**-0.134**	**-0.140**	**-0.151**	**-0.144**	**-0.134**	-0.068	-0.084	-0.067	-0.060
Cov	**(0.016)**	**(0.014)**	**(0.021)**	**(0.025)**	**(0.008)**	**(0.007)**	**(0.008)**	**(0.009)**	**(0.003)**	**(0.001)**	**(0.002)**	**(0.004)**	(0.160)	(0.081)	(0.152)	(0.203)
			2.448	2.516			2.802	3.134			3.127	2.849			4.084	4.612
Ami_S			(0.349)	(0.403)			(0.327)	(0.326)			(0.218)	(0.285)			(0.102)	(0.110)
			0.031	0.011			0.068	0.025			-0.598	-0.703			0.777	0.736
Ami_B			(0.960)	(0.985)			(0.916)	(0.970)			(0.275)	(0.204)			(0.259)	(0.293)
			-0.078	-0.064			-0.098	-0.095			-0.114	-0.103			0.169	0.178
Coupon			(0.535)	(0.617)			(0.403)	(0.430)			(0.494)	(0.552)			(0.236)	(0.213)
	0.155	**0.160**	**0.210**	**0.180**	**0.128**	**0.133**	**0.184**	**0.162**	**0.364**	**0.376**	**0.442**	**0.399**	**0.261**	**0.280**	**0.275**	**0.249**
Time	**(0.003)**	**(0.003)**	**(0.001)**	**(0.004)**	**(0.024)**	**(0.023)**	**(0.007)**	**(0.019)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**
				-5.172				**-4.750**				**-5.925**				**-5.487**
Ind1				**(0.000)**				**(0.001)**				**(0.000)**				**(0.000)**
				-3.690				**-3.422**				**-3.730**				**-3.691**
Ind2				**(0.018)**				**(0.045)**				**(0.007)**				**(0.009)**
	-3.062	**-3.467**	**-0.033**	1.105	**-2.825**	**-3.154**	**-0.028**	1.293	**-3.254**	**-3.628**	**-0.033**	1.541	**-2.638**	**-3.306**	**-0.043**	0.232
Const.	**(0.000)**	**(0.000)**	**(0.005)**	(0.508)	**(0.001)**	**(0.000)**	**(0.011)**	(0.481)	**(0.000)**	**(0.000)**	**(0.021)**	(0.343)	**(0.004)**	**(0.000)**	**(0.002)**	(0.902)
R^2 (%)	6.995	7.755	9.404	11.039	6.778	7.665	9.330	10.892	6.782	7.499	9.291	10.901	6.469	7.265	8.822	10.105

Table 8: DCC Correlation Panel Estimation. Firms with low probability of default

The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic DCC stock-bond return correlations for the subsample of firms with low probability of default using the mean of the firm's probability of default for dividing the sample. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. The System GMM is used by instrumenting the endogenous variable with lags from 2 to 4. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	358	358	359	359	360	360
y_{t-1}	0.010	0.010	0.010	0.010	0.009	0.010
	(0.259)	(0.265)	(0.269)	(0.241)	(0.305)	(0.266)
σ_c	**-25.098**	**-25.986**	**-18.162**	**-18.057**	**-48.569**	**-48.006**
	(0.000)	**(0.000)**	**(0.009)**	**(0.004)**	**(0.000)**	**(0.000)**
Default	--	--	**-8.755**	**-9.922**	--	--
	--	--	**(0.002)**	**(0.001)**	--	--
Term	--	--	--	--	**8.012**	**7.839**
	--	--	--	--	**(0.004)**	**(0.006)**
NBER	--	--	--	--	**-2.608**	**-2.480**
	--	--	--	--	**(0.000)**	**(0.000)**
B	-0.972	-0.941	**-1.211**	-1.059	-0.858	-0.747
	(0.220)	(0.118)	**(0.049)**	(0.249)	(0.387)	(0.443)
Lev	0.370	**0.493**	0.269	0.257	0.108	0.209
	(0.191)	**(0.043)**	(0.359)	(0.319)	(0.732)	(0.452)
Default Prob.	0.707	--	0.602	--	0.697	--
	(0.200)	--	(0.298)	--	(0.217)	--
σ^{Id}	**0.611**	**0.684**	**1.359**	**1.561**	**1.233**	**1.243**
	(0.047)	**(0.024)**	**(0.001)**	**(0.000)**	**(0.001)**	**(0.001)**
Cov	**-0.254**	**-0.269**	**-0.277**	**-0.259**	-0.217	-0.213
	(0.034)	**(0.036)**	**(0.032)**	**(0.037)**	(0.073)	(0.082)
Time	0.075	0.077	0.067	0.064	0.083	0.081
	(0.295)	(0.285)	(0.368)	(0.379)	(0.252)	(0.265)
Ind1	-5.093	-3.658	-4.648	**-6.132**	-5.627	**-6.109**
	(0.123)	(0.289)	(0.147)	**(0.049)**	(0.066)	**(0.042)**
Ind2	-3.672	-2.428	-3.319	-4.580	-3.654	-4.141
	(0.238)	(0.468)	(0.272)	(0.148)	(0.260)	(0.201)
Constant	**9.107**	**7.856**	**8.990**	**10.250**	**12.624**	**12.864**
	(0.008)	**(0.032)**	**(0.009)**	**(0.002)**	**(0.000)**	**(0.000)**
Are-Bond AR(1) Test	**-14.79**	**-14.78**	**-14.79**	**-14.81**	**-14.79**	**-14.81**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Are-Bond AR(2) Test	-0.41	-0.4	-0.41	-0.37	-0.48	-0.43
	(0.681)	(0.689)	(0.684)	(0.712)	(0.630)	(0.669)
Are-Bond AR(3) Test	0.60	0.56	0.63	0.6	0.68	0.63
	(0.547)	(0.576)	(0.529)	(0.549)	(0.498)	(0.530)
Are-Bond AR(4) Test	0.60	0.61	0.55	0.55	0.58	0.59
	(0.550)	(0.540)	(0.583)	(0.584)	(0.564)	(0.555)
Are-Bond AR(5) Test	-1.11	-1.1	-1.10	-1.09	-1.17	-1.16
	(0.269)	(0.272)	(0.273)	(0.277)	(0.241)	(0.246)
Sargan Test	**584.17**	**583.94**	**581.00**	**580.76**	**575.59**	**575.23**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Hansen Test	319.24	317.25	319.49	319.96	315.75	317.55
	(0.864)	(0.880)	(0.861)	(0.857)	(0.892)	(0.878)

Table 9: DCC Correlation Panel Estimation. Firms with high probability of default

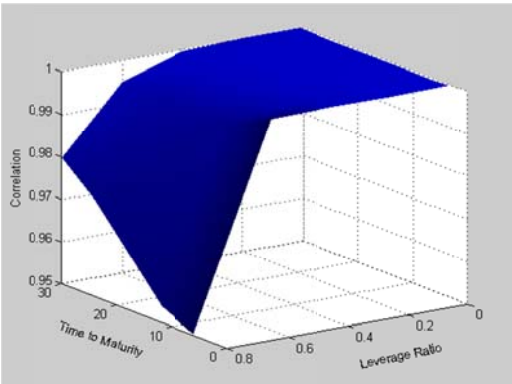
The table displays System GMM two-step estimated coefficients using as dependent variable the dynamic DCC stock-bond return correlations for the subsample of firms with high probability of default using the mean of the firm's probability of default for dividing the sample. The values in parenthesis are the p-values associated to each coefficient or test, and characters in bold denote significant coefficients at the 95% confidence level. The standard errors are calculated using the Windmeijer (2005) correction for potential downward bias in two-step estimates. The System GMM is used by instrumenting the endogenous variable with lags from 2 to 4. The number of instrument is reported at the top, the Arellano-Bond test for residual autocorrelation is reported below for orders 1 to 5, and the Hansen and Sargan tests are at the bottom.

# Instrum.	358	358	359	359	360	360
γ_{t-1}	**0.046**	0.036	**0.047**	**0.049**	**0.049**	**0.040**
	(0.011)	(0.061)	**(0.011)**	**(0.005)**	**(0.008)**	**(0.029)**
σ_c	-14.815	-41.759	-15.267	-15.848	-62.966	-22.270
	(0.649)	(0.249)	(0.694)	(0.704)	(0.238)	(0.486)
Default	--	--	1.532	-0.867	--	--
	--	--	(0.927)	(0.958)	--	--
Term	--	--	--	--	9.125	2.907
	--	--	--	--	(0.353)	(0.697)
NBER	--	--	--	--	-1.290	-0.183
	--	--	--	--	(0.686)	(0.941)
β	-0.020	-0.811	-0.071	-1.898	-0.738	-2.031
	(0.992)	(0.680)	(0.972)	(0.286)	(0.753)	(0.473)
Lev	**0.265**	0.229	**0.283**	**0.398**	**0.353**	0.295
	(0.044)	(0.109)	**(0.042)**	**(0.007)**	**(0.012)**	(0.089)
Default Prob.	**-0.314**	--	**-0.303**	--	-0.239	--
	(0.002)	--	**(0.006)**	--	(0.094)	--
σ^{Id}	**1.475**	**1.125**	**1.325**	0.911	**1.329**	**1.093**
	(0.000)	**(0.020)**	**(0.024)**	(0.218)	**(0.004)**	**(0.028)**
Cov	-0.332	-0.236	-0.292	-0.166	-0.127	0.076
	(0.437)	(0.521)	(0.552)	(0.651)	(0.782)	(0.847)
Time	0.090	0.046	0.099	0.280	0.139	0.354
	(0.806)	(0.893)	(0.791)	(0.374)	(0.733)	(0.260)
Ind1	-5.453	-3.634	-5.946	-2.939	-9.199	1.385
	(0.510)	(0.624)	(0.492)	(0.736)	(0.462)	(0.859)
Ind2	-6.783	-4.465	-6.877	-4.730	-9.097	2.602
	(0.407)	(0.524)	(0.403)	(0.608)	(0.409)	(0.705)
Constant	8.226	12.837	8.219	7.950	18.965	1.799
	(0.488)	(0.229)	(0.490)	(0.474)	(0.255)	(0.834)
Are-Bond AR(1) Test	**-9.75**	**-9.62**	**-9.74**	**-9.78**	**-9.74**	**-9.7**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Are-Bond AR(2) Test	-0.77	-0.92	-0.75	-0.62	-0.70	-0.84
	(0.441)	(0.356)	(0.454)	(0.533)	(0.486)	(0.398)
Are-Bond AR(3) Test	1.80	1.75	1.82	1.79	1.88	1.75
	(0.071)	(0.081)	(0.069)	(0.074)	(0.060)	(0.080)
Are-Bond AR(4) Test	-1.29	-1.18	-1.29	-1.21	-1.34	-1.21
	(0.199)	(0.237)	(0.198)	(0.225)	(0.181)	(0.224)
Are-Bond AR(5) Test	0.18	0.05	0.17	0.06	0.11	0.04
	(0.855)	(0.960)	(0.863)	(0.951)	(0.909)	(0.964)
Sargan Test	**525.13**	**533.65**	**524.90**	**533.46**	**526.04**	**534.49**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Hansen Test	138.61	140.19	138.61	139.27	137.01	138.49
	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)

Figure 1: Simulated Correlations and firm characteristics

This figure displays the simulated correlations obtained from the Merton model and different parameter values. Specifically, this figure plots how stock-bond return correlation behaves regarding the leverage ratio of the firm, the time to maturity of the bond, and the firm volatility. We show the pictures for the two extreme values that we consider for the firm volatility: 0.1 and 0.5.

Firm volatility = 0.1



Firm volatility = 0.5

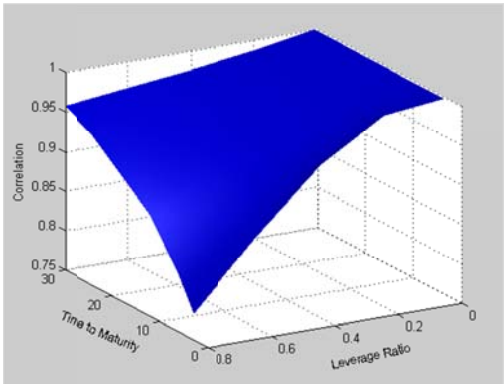


Figure 2: Estimated parameter frequencies

The figure shows histograms for the parameter values associated to the four models employed to estimate correlations: standard DCC and RSDC methods and the corresponding adjusted versions for non-trading days (DCCD and RSDCD). For each parameter involved in the second step estimation, we take the values of the 476 estimations and divide the whole range of values into 20 equally spaced buckets. Each histogram represents the number of parameters that fall in each bucket, for each model.

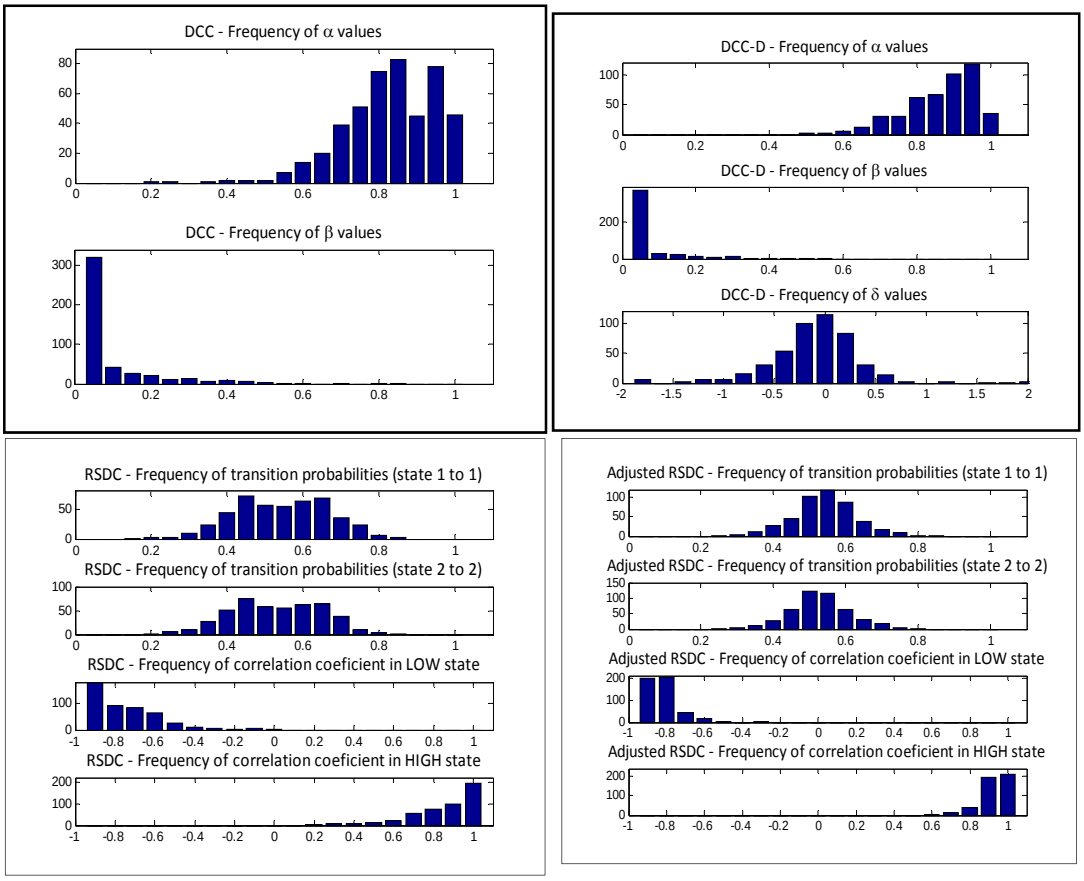


Figure 3: The time series of the mean among individual correlations

The figure shows the average across the 467 estimated correlations at each point in time and for the 5 estimation methodologies. DCC and RSDC denote the correlations estimated by using standard DCC and RSDC methods, DCCD and RSDCD refer to estimations that include a non-trading adjustment in the specification of the variance and the correlation of the series, and SMPL denotes the 3-month rolling sample correlation.

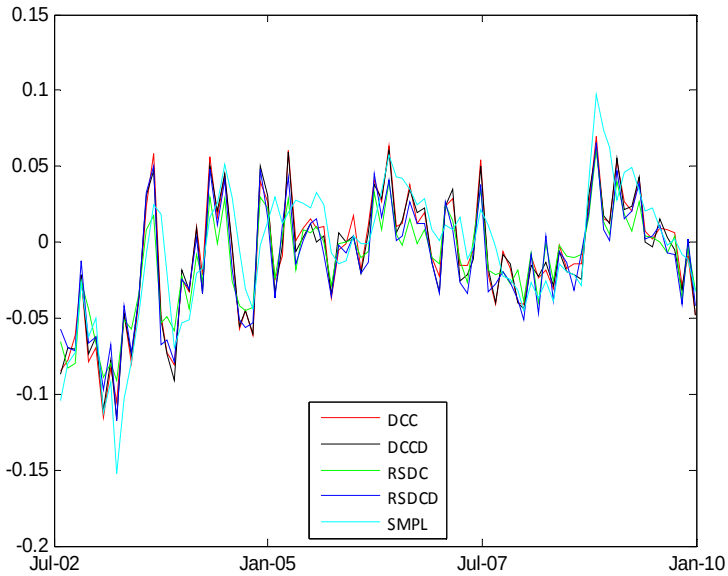
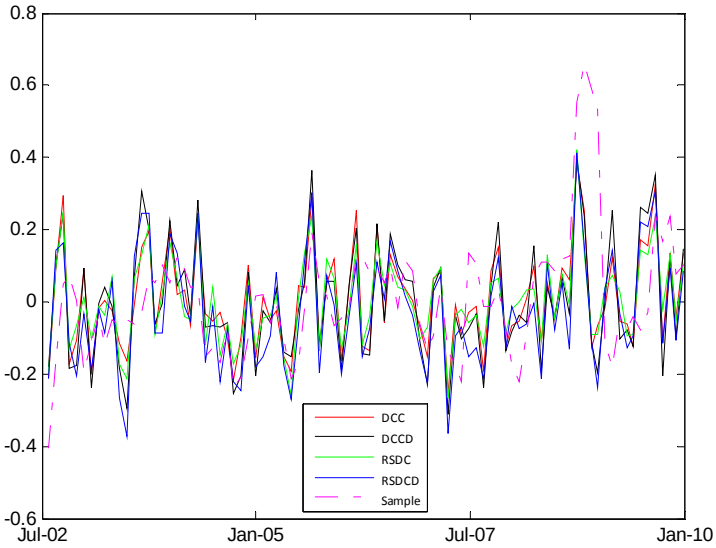
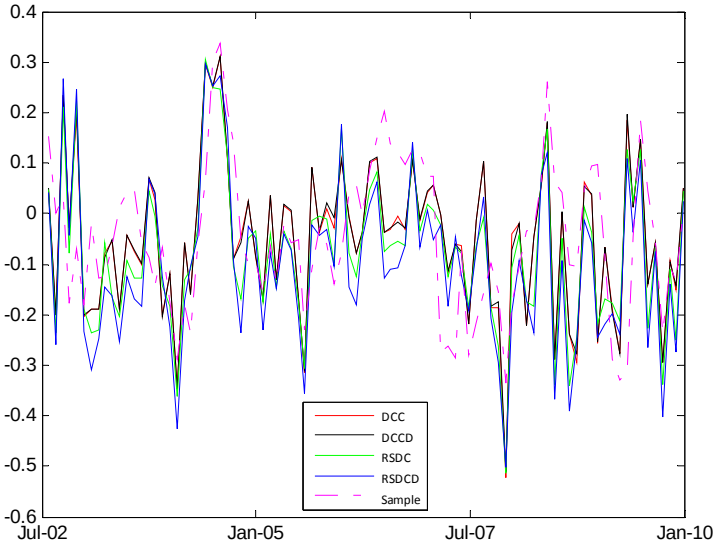


Figure 4: The time series of two representative individual correlations

The figure displays the time series of the correlation between the bond and the stock return issued by an industrial firm (on the top) and issued by a financial firm (on the bottom). DCC and RSDC denote the correlations estimated by using standard DCC and RSDC methods, DCCD and RSDCD refer to estimations that include a non-trading adjustment in the specification of the variance and the correlation of the series, and SMPL denotes the 3-month rolling sample correlation.