Euro Corporate Bonds Risk Factors*

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This version: October 2, 2006

Abstract

This paper investigates the determinants of credit spread changes on bonds denominated in Euro. The analysis is carried out using a panel data on Euro bonds. We try to asses the relative importance of market and idiosyncratic factors in explaining the movements in credit spread. Because credit spread changes can be easily viewed as an excess return of corporate bonds over treasury, we adopt a factor model framework. We consider different approaches to the estimation of common factors using a panel of monthly redemption yields on a set of corporate bonds for a time span of three years. Our results suggest that the Euro corporate market is widely heterogeneous and illiquid. Neither the issue specific factors nor the aggregate common factors appear important in determining credit spread changes. However, an unobserved common factor, identified as a liquidity factor seems to drive a relevant component of the systematic changes in credit spreads.

Keywords: Euro Corporate Bonds, Cross Section Dependence, Common Correlated Effects, Yield Curve, Latent Variables.
JEL - Classification: G10,C33

*This is a revised version of a paper presented at the Panel Data Conference 2006, Robinson College, Cambridge UK, July 8-9 and at the ESEM, Vienna, August 2006. We are indebted to Paolo Baldessari and Cristian Grigatti for helpful comments. Most of the database used in this paper was collected when Carolina Castagnetti was working at Fideuram Investimenti SGR. We are grateful to the quantitative group and the risk management group of Fideuram Investimenti SGR for very useful discussions and suggestions. We are also grateful to Giovanni Urga for very helpful comments. We thank Phil Galdi for providing us with the Merryll Lynch Database. Financial support from PRIN 2004 is gratefully acknowledged.

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1 Introduction

The credit risk, or risk of default, of a bond arises for two reasons: the magnitude and the timing of payoffs to investors may be uncertain. In other words, the risk of default of the issuer is accompanied by the recovery rate uncertainty. The effects of default risks on prices depend on how the default event is defined and the specification of the recovery in the event of a default.

Because of this uncertainty, the corporate bonds should offer higher yields than comparable default-free bonds, i.e. government bonds. Consequently, a corporate bond trades at a lower price than a corresponding (in terms of maturity and coupon) government bond. The difference between the yield on the risky bond and the yield of the corresponding default-free bond is called the credit spread.

Theoretical credit risk models tackle with the default risk in different ways. Structural models, in their most basic form, assume default at the first time that some credit indicator falls below a specified threshold value. In the Merton's model (Merton (1974)) default occurs at the maturity date of debt provided the issuer's assets are less than the face value of maturing debt at that time.

Reduced-form models treat default as governed by a counting (jump) process with associated (possibly state-dependent) intensity process and, as such, whether or not an issuer actually defaults is an unpredictable event.

Several works deal with the empirical estimation of the structural models. Among others, Eom, Helwege, and Huang (2003) empirically test five structural models of corporate bond pricing using data on the US market. They consider Merton (1974), Geske (1977), Leland and Toft (1996), Longstaff and Schwartz (1995) and Collin-Dufresne, Goldstein, and Martin (2001). They clearly show that all the five models considered have relevant spread prediction errors. In particular all the models tend to underestimate the spread of higher rated corporate bonds while they overestimate the spread of bonds which are considered riskier. A less structural approach has addressed the question of which variables are most correlated with the credit spread movements following a data-driven approach. In this framework Duffee (1999) investigates the effect of the term structure on callable and non callable credit spread. Campbell and Taksler (2003) evaluate the volatility effect, after controlling for other factors, on the variation, across companies and over time, in corporate bond yields spreads. They find that equity volatility and credit ratings each explain about one third of the movements in corporate bond spreads. This finding is robust also to the use of issuer fixed effects.

The purpose of this paper is to study the determinants of credit spread changes in the Euro Corporate Bond Market. In particular, we are interested in understanding in which measure the implications for credit spread changes of structural credit risk models are verified in the context of Euro corporate bond market. The delta credit spread is given by the first difference of the spread between the corporate bond redemption yield and the government bond redemption yield with the same maturity. As will be shown in the next Section, the delta credit spreads can be considered as a measure of the excess return of corporate bonds over government bonds. Despite of their increasing importance[1], only recently the literature has started to investigate the determinants of their behavior.

Collin-Dufresne, Goldstein, and Martin (2001) show that variables that in theory determine the credit spreads changes have a rather limited explanatory power. They consider other variables than those prescribed by the structural-approach models in order to catch other effects as liquidity premium and the dynamic of interest rates. For this scope they adopt an heterogenous parameter model for each issue and find out that the residuals from these regressions are highly cross correlated. A principal component analysis of the residuals shows that the first component is able to explain over the 75 percent of the total variation of credit spreads. They also find that this large systematic component is not explained by several financial as well as macroeconomic variables. The authors conclude that the common systematic factor that drives the credit spread changes is a local domand/supply factor shock that is independent of traditional credit risk factors.

Elton, Gruber, Agrawal, and Mann (2001) move in a different direction. They point out that credit spread changes are determined not only by credit risk but also by risk premium. Credit spread changes can be easily viewed as an excess return of corporate bonds over treasury, i.e. risk free bond proxy. Therefore, they approach the problem in the framework of a traditional equity factor model to assess the influences of stock return common factors on credit spread.

Even though the empirical analysis of US corporate bond market is an obvious reference, the European market is characterized by marked differences. In this paper we provide some empirical evidence that the factors that are supposed to drive the American market are not so decisive in the European market.

We consider monthly delta credit spread over the period January 2001 through November 2004 for more than 200 issuers. Using a panel data model, we try to assess the relative importance of market and idiosyncratic factors in explaining the movement of credit spreads. We consider different approaches to the estimation of common factors using a panel of monthly redemption yields on a set of corporate bonds for a time span of three years. First, we find that the influence of the equity market factor, measured by the corresponding equity volatility, is much less evident and strong than that found by Campbell and Taksler (2003) for the US corporate market. Second, we find evidence of a systematic risk factor in the Euro corporate bond market that is independent of the main common factors predicted by the theory, that in our case also include the government bond common factors. We show that this common risk factor is correlated with a market liquidity effect variable, which could be interpreted as a supply/demand shock. This factor seems to drive a relevant component of the systematic changes in credit spreads.

[1]Collin-Dufresne, Goldstein, and Martin (2001) stress the hedge funds trading strategy of taking highly leverage positions in corporate bonds while hedging away interest rate risk by shorting government bonds. Another example is the increasing supply of financial products from the European mutual funds which invest both in corporate and government bonds. As a consequence, their portfolios are extremely sensitive to changes in credit spreads rather than changes in bond yields.

In section 2 we discuss the meaning of the credit spreads changes. In section 3 we describe the data. Preliminary analysis is presented in section 4. The econometric model is introduced in section 5, and results discussed is section 6. Section 7 concludes.

2 Delta Credit Spread and Excess Returns

We define credit spread as the difference between the yield to maturity on a corporate bond and the yield to maturity on a government bond of the same maturity:

$$cs_t = c_t - g_t \tag{1}$$

where c_t is the redemption yield of a corporate bond at time t and g_t is the corresponding (i.e. with the same maturity) redemption yield on a government bond.[2]

The starting point is that the change in credit spreads, i.e. the *delta credit spread*, δ_t:

$$\delta_t = cs_t - cs_{t-1} \tag{2}$$

represents a proxy for corporate bond excess loss, that is, the return on government bond minus the return on corporate bond with the same maturity. The return on a coupon bond j for an holding period equal to one is given by

$$r_{j,t} = \frac{P_{j,t} - P_{j,t-1}}{P_{j,t-1}}$$

where $P_{j,t}$ is the gross price at time t for bond j. Using the first-order Taylor's approximation of the bond price with respect to the redemption yield, we obtain that the holding-period return is proportional to the change in the redemption yield:

$$r_{j,t} \cong -d_{j,t}(y_{j,t} - y_{j,t-1}) \tag{3}$$

where $d_{j,t}$ is the modified duration of bond j at time t and $y_{j,t}$ is the redemption yield of bond j at time t. Therefore, the difference between the return on corporate bond and the government position is given by

$$r_{c,t} - r_{g,t} \cong -d_{c,t}(c_t - c_{t-1}) + d_{g,t}(g_t - g_{t-1}) \tag{4}$$

where $r_{g,t}$ and $r_{c,t}$ are the return on the government and corporate bond, respectively.

We know that holding other factors constant, higher the duration lower the yield to maturity and the coupon rate. In general, the corporate bonds have higher coupon and higher yield than the government bond with the same maturity. Hence, the duration of government bonds can be thought of the duration of corporate bonds plus a positive spread, $\gamma(t)$:

$$d_{g,t} = d_{c,t} + \gamma(t)$$

[2] In particular, g_t is given by the redemption yield on the estimated euro government curve. See next section.

Then, expression (13) becomes:

$$r_{c,t} - r_{g,t} \cong -d_{c,t}\delta_t + \gamma(t)(g_t - g_{t-1}) \qquad (5)$$

where the second term on the RHS is negligible with respect to the excess return:

$$r_{c,t} - r_{g,t} \cong -d_{c,t}\delta_t \qquad (6)$$

The excess return of corporate bonds over government bonds is proportional to the change in credit spread. So credit spread changes can be viewed as a proxy of the excess return of corporate bond over government bond. This implies it would be reasonable to analyze the credit spread changes in a factor model framework.

3 Individual and common factors

In this paper we refer to structural-model approach and to risk premia theory in order to identify the main factors that drive credit spread changes. The seminal paper of Merton (1974) was the first model of the structural-form approach. Built on the arbitrage-free pricing methodology, credit risk arises from the potentiality of default which occurs when the value of the assets fall below a certain threshold value.[3]

Structural credit risk models show important drawbacks. They mainly focus on the value and the capital structure of the firm, which is a difficult process to represent, and they do not allow for credit rating changes. Besides that, the structural approach provides an intuitive framework to determine the main factors that drive credit spread changes. In our investigation we focus on the following determinants of credit spread changes.

1. *Changes in the government bond rate level.* This variable represents both a proxy for, the so called, *flight to quality* flows and a proxy for business cycle. From one side, a lower level of government rates implies a market preference for less risky asset, i.e. wider credit spreads. From the other side, lower rates also imply a higher loan demand which widens the credit spreads. Empirical evidence that there exists a negative relationship between changes in credit spreads and interest rates has been shown by Longstaff and Schwartz (1995), Duffee (1998) and Collin-Dufresne, Goldstein, and Martin (2001).

[3] However, the Merton model contains many flaws. First, it requires inputs related to the value of firms that are hardly available. Second, it allows default only at the maturity date of the bond. Third, it assumes independence between interest rates and credit risk. Last but not least, because it assumes that the value of the asset follows a geometric Brownian motion, the model implies that the default is predictable shortly before default. The first structural model has been widely improved by relaxing some of its restrictive assumptions, see, among others, Black and Cox (1976), Turnbull (1979), Leland (1994), Longstaff and Schwartz (1995), Briys and De-Varenne (1997) Collin-Dufresne and Goldstein (2001).

2. *Changes in the slope of the government yield curve.* It's a proxy of the movement in the supply and demand of government bonds. Hence a flat term structure of interest rates curve reduces the incentives to invest in the government sector and therefore causes a corporate spread widening. Duffee (1998) tests this relation for the US corporate bond market.

3. *Changes in the convexity of the government yield curve.* We include also the convexity of the government yield curve to capture potential non linear effects.

4. *Changes in liquidity.* Collin-Dufresne, Goldstein, and Martin (2001) stressed the fact that the corporate bond market tends to have relatively high transactions costs and low volume. These findings suggest to check for the existence of a liquidity premium. Because of the strong link between swap market and corporate market,[4] we expect that a change in the swap market liquidity would reflect a change in the same direction in the corporate market liquidity. Therefore we consider the five year delta swap spread as a proxy of the liquidity on credit market. A decrease in the liquidity in the corporate market implies a market preference for less risky asset. Hence we expect the factor loading of liquidity proxy to be positive.

5. *Mean and Standard Deviation of daily excess return of firm's equity.* These variables summarize the firm-level risk and return. Equity data reflect up-to-date information on firm value and should anticipate bond prices[5]. An increase in the equity daily excess return means a higher firm's profitability. In line with the analysis of Kwan (1996) we expect stock returns to have a negative effects on credit spreads. We note also that previous studies of yield changes have often used the firm's equity return instead of changes in leverage as proxy for changes in the firm's health. From the other side it is well known that the equity volatility of a firm increases its probability of default. Hence, firm's volatility should drive up the yields on corporate bonds and widen the credit spreads.

6. *Changes in Credit Quality.* Changes in credit quality which also includes downgrading or upgrading in rating is part of credit risk. A general process of improvement or worsening in the credit quality should inversely move the credit spreads: a better credit quality reduces credit spread.

7. *Changes in the Business Climate.* Even if the probability of default remains constant for a firm, changes in credit spreads can occur due to changes in the expected recovery rate. The expected recovery rate in turn should be a

[4]The issuers of corporate bonds typically fund on the swap market. Thus, if swap spreads widen, long-term funding costs of corporate bonds'issuers should increase, and investor demand for credit bonds should reduce. Assuming a constant supply of bonds, the decline in demand for credit products will cause prices to decline and the spread to Treasury to widen

[5]Ederington, Yawitz, and Roberts (1987) claim that all data going into ratings prices should be anticipated by equity prices. Moreover they argue that investors fully anticipate rating changes which almost never affect bond returns.

function of the overall state business climate. We use stock indices return as proxies for the overall state of the economy and we expect an increase in the index return reduces the credit spreads.

8. *Changes in Credit Market Factors.* We test whether credit spread changes depend on bond characteristics such as rating and industrial sector.

9. *Credit Spread.* To investigate the presence of a mean-reverting behavior in credit spreads, we include the beginning-of-month level of credit spread. In case of a mean-reverting behavior this variable should contain information about the current month's change in credit spread.

10. *Accounting variables.* We don't consider accounting variables to explain the credit spread changes. This choice is driven by two consideration. First, accounting data have in general either quarterly or yearly frequency. We think that interpolating the data to obtain higher frequency don't bring as much information to credit spread changes. Second, most of the works which use accounting variables do not found empirical any statistical evidence of their explanatory power for the credit spread changes and conclude that they can hardly explain the observed movements in credit spread.

4 Data Description

4.1 Data

Our corporate bond data are extracted from the IBOOX Euro Bond Index. This index is issued by seven major investment banks[6]. Each bank is due to sell and buy every single asset belongs to the index. The index bond prices are determined by the following criteria. First, the highest and the lowest prices are excluded and then the price is given by the average of the other five prices. Moreover each asset included should have at least 500 millions Euros of amount outstanding and its time to maturity should be bigger than one year. Such criteria should guarantee to deal with assets tradable and liquid. In this way we try to reduce the liquidity premium of Euro corporate market.

The IBOOX database[7] contains issue- and issuer-specific variables such as callability, maturity, coupon, industrial sector, rating, subordination level, issuer country, duration and several measures of credit spread. The IBOOX Euro Index is composed both of Euro government bond and investment grade Euro corporate bonds. We consider only the Euro corporate bonds. We start considering monthly observations for the period January 2000 trough November 2004.

Because our goal is to explain the behavior of investment grade Euro corporate bond we eliminate all the bonds downgraded to high yield debt. The bonds under

[6]ABN AMRO, Barclays Capital, BNP Paribas, Deutsche Bank, Dresdner Kleinwort Wasserstein, Morgan Stanley and UBS Investment Bank.

[7]The database have been built by the optimization group at Fideuram Investimenti SGR, Milan.

consideration have standard cashflows - fixed rate coupon and principal at maturity. We exclude all bonds not rated, step-up notes, floating rate debt and convertible bonds. We also exclude bond with call options, put options or sinking fund provisions. Moreover, we must have issuer with publicly traded stock in order to estimate equity volatility and equity excess return.

To match corporate bonds by corresponding stock we first match corporate ISIN by Bloomberg ISIN of the underline stock and we use the latter to extract equity data from DataStream. We also require that a issue have six months of stock price data prior to the bond trade.

Last, in order to undertake principal component analysis of the residuals we restricted our sample to a balanced panel. We take into account only issues which belong uninterruptedly to the index from the last observation backward. We ended up with 207 bonds for 33 monthly observations.

We use the fitted government curve spread provided by IBOOX database. This spread is equal to the difference between the yield to maturity of the corporate bond and the corresponding (i.e. with the same maturity) yield to maturity on the estimated Euro government curve[8].

Elton, Gruber, Agrawal, and Mann (2001) suggest to use spot rates rather than yield to maturity because arbitrage arguments hold with spot rates. The procedure of Elton, Gruber, Agrawal, and Mann (2001) consists of computing the corporate spread as the difference between the spot rate on corporate bonds in a particular rating class and the spot rate for Treasury bonds of the same maturity. Both zero curve are usually estimated by standard methods as the Nelson-Siegel procedure or Spline functions.

Campbell and Taksler (2003) follow the procedure of Elton, Gruber, Agrawal, and Mann (2001) to eliminate coupon effects from corporate bond yields. First, they estimate the corporate bond spot curves for sector and credit rating. Then they use the zero-coupon curve to estimate the corporate bond prices. Last, for each bond, they obtain the redemption yield from the estimated prices. As a consequences of their analysis, Campbell and Taksler (2003) raise some doubts on the need to measure corporate bond yield spreads in relation to a zero-coupon curve. In fact even though their analysis make use of both "redemption yield spread" and "estimated redemption yield spread" they obtain very similar results.

The use of "estimated redemption yield spread" makes sense only if the approximated corporate bond prices are truly closed to the observed one. In general in Euro bond market this is not the case. In fact whatever is the interpolated technique used (Nelson-Siegel, Cubic Spline with 5 knots) the results are quite poor. In Appendix A, we present some evidence on the magnitude of the estimation errors of redemption yield spread based on estimated corporate spot rate.

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[8] The Euro government curve is estimated by a cubic spline. Moreover, only German and French government bonds enter the term structure estimation process.

4.2 Variables

Below are described the data used to explain the movements in the corporate spread.

1. *Changes in the government bond rate level.* For the treasury rate level we use DataStream's monthly series of 10-year Benchmark German Treasury rates.

2. *Changes in the slope of the government yield curve.* We define the slope of the yield curve as the difference between DataStream's 10-year and 2-year Benchmark German Treasury rates.

3. *Changes in the convexity of the government yield curve.* The convexity of the interest rate term curve is defined as the difference between the 5-year German Treasury rate and the average of the 10-year and the 2-year Benchmark German Treasury rates[9].

4. *Changes in liquidity.* As a proxy of the change in the corporate bond market liquidity we consider the monthly change in the five year Euro swap spread. The Euro swap spread is given by the difference between yields on the 5-year swap index and 5-year Benchmark German Treasury rate.

5. *Mean and Standard Deviation of daily excess return of firm's equity.* Following Campbell and Taksler (2003) we match bond data with equity data to explicitly evaluate the effects of equity volatility on corporate bond yield spreads. We consider only the corporate bonds issued by firms included in the Morgan Stanley World All Country Index[10]. To compute the daily excess return of each firm's equity we consider the Morgan Stanley Indices of the country where the stock is exchanged[11]. For each firm's equity we compute the mean and standard deviation of daily excess returns over the 180 days prior to (not including) the bond trade.

6. *Changes in Credit Quality.* We proxy the change in credit quality by monthly changes in rating downgrading and upgrading of the Merrill Lynch Global High Grade Corporate Index[12].

7. *Changes in the Business Climate.* We use monthly Morgan Stanley Euro Index price return as a proxy of the overall state of the economy.

[9]The data source is DataStream.

[10]The data source is DataStream.

[11]We end up to consider the following Morgan Stanley Indices: Msci Emu, Msci Denmark, Msci Finland, Msci Norway, Msci Sweden, Msci Switzerland, Msci Uk, Msci Usa, Msci Canada, Msci Japan And Msci Hong Kong.

[12]We take into account only Euro denominated bonds and the monthly changes are computed with respect to the index par amount. The data come from the Merrill Lynch Index Rating Migration Databook. This databook resume relevant information on the composition of the main Merrill Lynch Corporate Bond Indices.

8. *Changes in Credit Market Factors.* We consider also market factors for rating categories and industrial sectors. Each bond is assigned to an IBOXX sub-indices based on the bond's beginning of month rating or sector. We consider four rating categories, (AAA, AA, A, BBB) and three industrial sectors, (Industrial, Financial, Utility) and for each sub-index we consider the index monthly delta spread.

Table 3 presents summary statistics on the bonds and issuers in the sample. Because of the reduction of the sample to match the equity data and to deal with a balanced panel data set one may wonder if these bonds are representative of the overall Euro corporate market. A comparison of our sample to the 790 noncallable and nonputable bonds included in the IBOOX index for the period considered suggests that they are very close. In Table 4 bonds in the sample and bonds included in the IBOOX index are compared. The two samples have very similar distribution across credit ratings (panel A) and industrial sectors (panel B). In Table 5 the distribution across the industries stresses the fact that the banks are almost the 28% of the entire sample (panel A). The distribution across maturity bucket of our sample has a slight tendency toward medium and short term bonds (panel B). Though the average bond maturity in our sample is very closed to the average bond maturity of the full sample (5.66 in Table 3).

Although the criteria of IBOOX index should guarantee the liquidity of their components, Table 3 shows that the full sample contains outliers. The standard deviation of the full sample is twice our sample standard deviation. The maximum monthly credit spread change is about 466 basis points for our sample and 2530 basis points for the full sample. Therefore the extra return of a corporate bond with respect to a government bond can be 25 % in a month if we consider the full sample.

5 Cross-section dependence in credit spread changes

In this section we evaluate the presence of cross-section dependence in credit spread changes. First, we compute the average and absolute correlation of the corporate bond delta spread which are shown in Panel A of Table 6. The correlation serves as an indication of a cross-section dependence. Moreover the first two principal components of delta credit spreads account for 62% of the total variance. Both measures seem to confirm the presence of a cross-section dependence. We start from a simple model where the delta credit spread depend on common observed factors, $\boldsymbol{d_t}$, and individual specific components, $\boldsymbol{x_{it}}$:

$$y_{it} \quad = \quad \boldsymbol{\alpha_i}'\boldsymbol{d_t} + \boldsymbol{\beta}_{\boldsymbol{i}}'\boldsymbol{x_{it}} + e_{it} \qquad t = 1, \ldots, T \tag{7}$$

We estimate each regression separately by OLS and then compute the correlation among the residuals. The results are presented in Panel B of Table 6. Third, we consider all the panel data and estimate a dummy variable model:

$$y_{it} \quad = \quad \boldsymbol{\alpha_i}'\boldsymbol{d_t} + \boldsymbol{\beta}_{\boldsymbol{i}}'\boldsymbol{x_{it}} + e_{it} \qquad t = 1, \ldots, T \;\; i = 1, \ldots, I \tag{8}$$

Table 6 also reports the average and absolute correlation of the estimated residuals of a fixed effects (hereafter FE) panel data model. In Table 7 we illustrate the expected coefficient signs while in Table 8 we present the estimation results of the fixed effects model. Two different specifications are presented for pooling OLS and FE model. [13] The average absolute correlation between OLS residuals is 0.34. Using the fixed effects estimator reduces the average absolute correlation which becomes 0.28. There is little difference between the average absolute correlation and the average correlation for both the delta credit spreads and the residuals since while the former are mainly positively correlated, the latter are mainly negatively correlated. Table 6 reports the test statistic for cross dependence by Pesaran (2004). Pesaran (2004) proposes a test for cross-section dependence based on a simple average of the all pairwise correlation coefficients of the Ordinary Least Square (OLS) residuals from the individual regressions in the panel. This test is applicable to a variety of panel data models and despite of the Breusch and Pagan Lagrange Multiplier test, it can be applied when the cross section dimension is large relatively to the time series dimension. The Cross Section Dependence statistic (CD stat) is computed as:

$$CD = \sqrt{\frac{2T}{I(I-1)}}\left(\sum_{i=1}^{I-1}\sum_{j=i+1}^{I}\widehat{\rho}_{ij}\right)$$

where $\widehat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals:

$$\widehat{\rho}_{ij} = \widehat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\widehat{e}_{it}\widehat{e}_{jt}}{(\sum_{t=1}^{T}\widehat{e}_{it}^{2})^{1/2}(\sum_{t=1}^{T}\widehat{e}_{jt}^{2})^{1/2}}$$

and:

$$\widehat{e}_{it} = y_{it} - \widehat{\boldsymbol{\alpha}}_i^{'}\boldsymbol{d}_t - \widehat{\boldsymbol{\beta}}_i^{'}\boldsymbol{x}_{it}$$

with $\widehat{\boldsymbol{\alpha}}_i$ and $\widehat{\boldsymbol{\beta}}_i$ being the OLS estimates of $\boldsymbol{\alpha}_i$ and $\boldsymbol{\beta}_i$ computed regressing y_{it} on the observed common effects (including the constant term), $\mathbf{d}_t$, and the observed individual specific regressors, $\mathbf{x}_{it}$, for each i separately. Under the null hypothesis of no cross section dependence the CD statistics is distributed (as I and $T \to \infty$ with no particular order) as a standard normal distribution. Moreover Pesaran (2004) shows by means of Monte Carlo experiments that the test has also good small sample properties (for both N and T small). The result of the test is summarized in Table 6. The hypothesis that the residual credit spread changes are cross sectionally independent is strongly rejected. Finally, this analysis shows that cross-section dependence is a feature of Euro delta credit spread. This evidence is in line with the analysis conducted by Collin-Dufresne, Goldstein, and Martin (2001) for the the US corporate bond market.

6 Econometric Model

Collin-Dufresne, Goldstein, and Martin (2001) remark that if there are omitted explanatory variables these must be searched among non-firm-specific factors. They

[13] The residuals from the first FE specification are used for the cross-section dependence analysis.

find that the unexplained component of the movement in credit spread changes can be ascribed to the presence of a single common factor. And they identify this variable as local supply/demand shocks. They estimate this single-common component from a principal analysis of the residuals from individual OLS regressions. Following this idea, we consider a linear heterogeneous panel data model where y_{it} is the observation on the delta credit spread at time t for the i^{th} issue for $i = 1, 2, \ldots, I$ and $t = 1, 2, \ldots, T$:

$$y_{it} = \boldsymbol{\alpha_i}'\boldsymbol{d_t} + \boldsymbol{\beta}_{\boldsymbol{i}}'\boldsymbol{x_{it}} + e_{it} \tag{9}$$

$$e_{it} = \boldsymbol{\gamma}_{\boldsymbol{i}}'\boldsymbol{f_t} + \epsilon_{it} \tag{10}$$

where $\boldsymbol{d_t}$ is a $n \times 1$ vector of observed common effects, $\boldsymbol{x_{it}}$ is a $k \times 1$ vector of observed individual specific regressors, $\boldsymbol{f_t}$ is the $m \times 1$ vector of unobserved common factors and ϵ_{it} are the idiosyncratic errors assumed to be independently distributed of $(\boldsymbol{d_t}, \boldsymbol{x_{it}})$.

To allow for correlation between $\boldsymbol{f_t}$ and $(\boldsymbol{d_t}, \boldsymbol{x_{it}})$ we suppose that the individual specific factors are correlated with common (observed and unobserved) factors through:

$$\boldsymbol{x_{it}} = \boldsymbol{A_i}'\boldsymbol{d}_t + \boldsymbol{\Gamma_i}'\boldsymbol{f_t} + \boldsymbol{v_{it}} \tag{11}$$

where $\boldsymbol{v_{it}}$ are the specific components of $\boldsymbol{x_{it}}$ distributed independently of the common effects and across i. Following Pesaran (2006) we can combine the expressions (9) and (11) in a system

$$\boldsymbol{z_{it}} = \begin{bmatrix} y_{it} \\ \boldsymbol{x_{it}} \end{bmatrix} = \boldsymbol{B}_i'\boldsymbol{d}_t + \boldsymbol{C}_i'\boldsymbol{f}_t + \mathbf{u}_{it}$$

where

$$\mathbf{u}_{it} = \begin{bmatrix} \epsilon_{it} + \boldsymbol{\beta_{i}}_i'\boldsymbol{v_{it}} \\ \boldsymbol{x_{it}} \end{bmatrix}$$

$$\boldsymbol{B}_i = \begin{bmatrix} \boldsymbol{\alpha_i} & \mathbf{A}_i \end{bmatrix} \begin{bmatrix} 1 & 0 \\ \boldsymbol{\beta_i} & \mathbf{I}_k \end{bmatrix} \qquad \boldsymbol{C}_i = \begin{bmatrix} \boldsymbol{\gamma_i} & \boldsymbol{\Gamma_i} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ \boldsymbol{\beta_i} & \mathbf{I}_k \end{bmatrix}$$

Pesaran (2006) put forward, using cross section averages of y_{it} and $\boldsymbol{x_{it}}$ as proxies for the latent factors, $\boldsymbol{f_t}$, a consistent estimator for $\boldsymbol{\beta_i}$. The basic idea behind the proposed estimation procedure, the Common Correlated Effects (CCE) estimator, is to filter the individual specific regressors by means of cross section aggregates such that asymptotically (as $I \to \infty$) the differential effects of unobserved common factors are eliminated.

For the individual slope coefficients the CCE estimator is given by augmenting the OLS regression of y_{it} on $\boldsymbol{x_{it}}$ and $\boldsymbol{d_t}$ with the cross-section averages $\overline{\boldsymbol{z}}_{\boldsymbol{t}} = \frac{1}{I}\Sigma_{i=1}^{I}\boldsymbol{z_{it}}$. Although $\overline{y}_t$ and ϵ_{it} are not independent (i.e. endogeneity bias), their correlation goes to zero as $I \to \infty$.

Efficiency gains from pooling of observations over the cross section units can be achieved when the individual slope coefficients are the same: $\boldsymbol{\beta_i} = \boldsymbol{\beta}$ for $i = 1, \ldots I$

(Pesaran (2006)). Such a pooled estimator of $\boldsymbol{\beta}$, Common Correlated Effects Pooled (CCEP) estimator, is given by:

$$\widehat{\boldsymbol{\beta}}_P = (\sum_{i=1}^{I} \boldsymbol{X_i}'\overline{\boldsymbol{M}}\boldsymbol{X_i})^{-1} \sum_{i=1}^{I} \boldsymbol{X_i}'\overline{\boldsymbol{M}}\boldsymbol{y_i} \tag{12}$$

$$\overline{\boldsymbol{M}} = \boldsymbol{I_T} - \overline{\boldsymbol{H}}(\overline{\boldsymbol{H}'\boldsymbol{H}})^{-1}\overline{\boldsymbol{H}'}$$

where $\overline{\boldsymbol{H}} = (\boldsymbol{D}, \overline{\boldsymbol{Z}})$, $\boldsymbol{D}$ and $\overline{\boldsymbol{Z}}$ being, respectively, the $(T \times n)$ and $(T \times (k+1))$ matrices of observations on $\boldsymbol{d_t}$ and $\overline{\boldsymbol{z}}_t$.[14]

In contrast to Pesaran (2006), which focus only on $\boldsymbol{\beta}_i$, the individual specific coefficients, our analysis is also concerned with observed and unobserved factors effects, i.e. $\boldsymbol{\alpha_i}'\boldsymbol{d_t}$ and $\boldsymbol{\gamma_i}'\boldsymbol{f}_t$. To this end is important to rely on a consistent estimator of $\boldsymbol{\beta}_i$, which is obtained using suitable proxies for the unobservable factors. Based on these estimates is possible to compute consistent estimates of the errors e_{it}, which can be used as observed data to obtain estimates of the unobserved factors, $\boldsymbol{f_t}$.

We estimate the following model:

$$y_{it} = \theta_i + \boldsymbol{\alpha}'\boldsymbol{d_t} + \boldsymbol{\beta}'\boldsymbol{x_{it}} + e_{it} \tag{13}$$

$$e_{it} = \boldsymbol{\gamma}_{\boldsymbol{i}}'\boldsymbol{f_t} + \epsilon_{it} \qquad i = 1, \ldots, I \;\; t = 1, \ldots, T \tag{14}$$

with the hypothesis that the observed common factors are uncorrelated with unobserved ones, i.e. $E[\boldsymbol{f_t}\boldsymbol{d_t}'] = \boldsymbol{0}$, $\forall t$. In order to deal with error cross section dependence due to unobserved common factors we adopt the following procedure:

1. we consistently estimate the slope parameter $\widehat{\boldsymbol{\beta}}_P$ by means of the CCEP estimator of equation (12), based on an estimate of $\boldsymbol{f_t}$ by means of cross-section averages, $\overline{\boldsymbol{z}}$.

2. for $i = 1, \ldots, I$ we estimate the residuals as: [15]

$$\widehat{\boldsymbol{e}}_i = \overline{\boldsymbol{M}}_d(\boldsymbol{y_i} - \boldsymbol{X_i}\widehat{\boldsymbol{\beta}}_P) \tag{15}$$

[14] Coakley, Fuertes, and Smith (2002) propose a common factor specification for the error term in order to restrict the dimension of the variance covariance structure. They propose a principal component estimator by augmenting the regression of each dependent variable y_{it} on $\boldsymbol{d_t}$ and $\boldsymbol{x_{it}}$ with one or more principal components of the estimated OLS residuals $\widehat{e}_{it}$, for $i = 1, \ldots, I$ and $t = 1, \ldots, T$ obtained from a first stage OLS regression of y_{it} on $\boldsymbol{d_t}$ and $\boldsymbol{x_{it}}$ for each i. Pesaran (2006) shows that this procedure leads to inconsistent estimation when the included regressors and unobserved factors are correlated.

[15] Pesaran (2006) suggests to use $\widetilde{\boldsymbol{e}}_i = \overline{\boldsymbol{M}}(\boldsymbol{y_i} - \boldsymbol{X_i}\widehat{\boldsymbol{\beta}}_P)$, the consistent estimates of the errors e_{it} in (9), to obtain consistent estimates of the factors, $\widehat{\boldsymbol{f}}_t$. Last, the factor loadings can be easily estimated in the regression equation:

$$y_{it} = \boldsymbol{\alpha_i}'\boldsymbol{d_t} + \boldsymbol{\beta_i}'\boldsymbol{x_{it}} + \boldsymbol{\gamma_i}'\widehat{\boldsymbol{f}}_t + \zeta_{it}$$

However, the estimates of the unobserved common factors $\widehat{\boldsymbol{f}}_t$, obtained as linear combinations of the vectors $\hat{\boldsymbol{e}}_t$, are by construction orthogonal to $\overline{\boldsymbol{z}}_t$.

where $\overline{\boldsymbol{M}}_d$ is given by

$$\overline{\boldsymbol{M}}_d = \boldsymbol{I_T} - \boldsymbol{D}(\boldsymbol{D}'\boldsymbol{D})^{-1}\boldsymbol{D}'$$

the presence of unobserved common factors correlated with the individual specific regressors do not cause the inconsistency of the parameter estimates of the observed common effects part. Though the assumption is that the unobserved common effects are uncorrelated with the observed common effects.[16] This hypothesis seems reasonable and moreover our estimated factors are, by construction, orthogonal to the observed common effects.

3. The unobserved common factors can be consistently estimated from the principal components of residuals $\hat{\boldsymbol{e}}_{\boldsymbol{i}}$ (up to a non-singular transformation, i.e. *rotation indeterminacy*). We extract the J largest residual principal components via the spectral decomposition of the $(T \times T)$ cross-product matrix

$$\hat{\boldsymbol{\Sigma}} = \frac{1}{I}\hat{\boldsymbol{E}}\hat{\boldsymbol{E}}'$$

where $\hat{\boldsymbol{E}}$ is the $(T \times I)$ matrix: $\hat{\boldsymbol{E}} = (\widehat{\boldsymbol{e}}_1, \widehat{\boldsymbol{e}}_2, \ldots, \widehat{\boldsymbol{e}}_I)$. In order to consistently estimate the number of factors we make use of the information criteria proposed by Bai and Ng (2002).

4. Bai (2003) shows that as long as $\sqrt{T}/I \to 0$ the error in the estimated factor is negligible. For large I, $\boldsymbol{f_t}$ can be treated as known. In Appendix B we show by means of a Monte Carlo simulation that $\boldsymbol{f_t}$ is consistently estimated using the principal components. Finally, these estimates are used as regressors in the model:

$$y_{it} = \theta_i + \boldsymbol{\alpha}'\boldsymbol{d_t} + \boldsymbol{\beta}'\boldsymbol{x_{it}} + \boldsymbol{\gamma}'\widehat{\boldsymbol{f}}_{\boldsymbol{t}} + \varsigma_{it} \qquad (16)$$

where ς_{it} is the idiosyncratic error and $\widehat{\boldsymbol{f}}_{\boldsymbol{t}}$ is the $(J \times 1)$ vector of the first J principal components of $\hat{\boldsymbol{\Sigma}}$. We observe that, given $\widehat{\boldsymbol{f}}_{\boldsymbol{t}}$[17], the estimate of $\boldsymbol{\gamma}$ in the equation (16) correspond to the cross-section mean of the estimates of the factor loadings $\boldsymbol{\gamma_i}$ in the equation (14) which are consistently estimated by principal components (Bai (2003)). This is justified by the fact that our main concern is to estimate the unobserved factors.

7 Results

Our estimation proceeds as follows. Following the estimation procedure outlined in section 6, first, we estimate a Fixed Effects (FE) model, as well as a two-way Fixed Effects (2FE) model by including monthly dummies, to evaluate the impact that observed common factors and observed individual components have on credit

[16] See the Appendix A.

[17] Or any linear combination of them, i.e. $\boldsymbol{H}\widehat{\boldsymbol{f}}_{\boldsymbol{t}}$, where $\boldsymbol{H}$ is an invertible matrix such that $\widehat{\boldsymbol{f}}_{\boldsymbol{t}}$ is an estimator of $\boldsymbol{H}\boldsymbol{f_t}$ and $\boldsymbol{H}^{-1}\widehat{\gamma}_i$ is an estimator of γ_i.

spread changes. We observe (table 8) that both models poorly explain the variation of Euro credit spreads and the estimated residuals show a certain degree of cross-section dependence (table 6). Second, as noted by Collin-Dufresne, Goldstein, and Martin (2001), we suppose that possibly unobserved common factors may drive the unexplained systematic component of movements in credit spreads. Hence we undertake a Principal Component Analysis on the residuals to proxy the unobserved common components, in line with the analysis of Coakley, Fuertes, and Smith (2002).

Table (8) reports the results of two pooling OLS specifications which have then been augmented for issue fixed effects. We consider all the economic variables implied by the structural models as listed in section 2. We also add some variables suggested by the empirical research on credit spreads.[18] We report the two specifications more sensible in terms of economic theory predictions and more parsimonious in terms of number of variables considered. Then, by estimating fixed effect for each issue we remove pure cross sectional variation in issue quality.

We include dummy variables for rating and maturity bucket. For rating the AAA/AA rating is the reference group. Table (8) shows that, on average, bonds with lower rating have higher delta credit spread. The reference group for maturity bucket is the short term (i.e. below three years maturity). Similarly to the rating dummies we observe that the credit spread changes are higher for longer corporate bonds.

In some specifications we also consider as explanatory variable the bond rating. We assign a value to each rating in a range from 1 to 10 for rating going from $BBB-$ to AAA, respectively. When the bond rating increases (i.e. lower risk) the corresponding excess return should decrease and, therefore, the delta credit spread (which approximates *minus* the corporate bond excess return with respect to the corresponding government bond) should increase.[19]

In general, the variables suggested by the theory are both economically and statistically significant in explaining variations in individual issues' credit spreads. We observe that the change in the government bond rate level is significant although it is positive, but this is in contrast with what has been found for the American corporate bond market (see Longstaff and Schwartz (1995), Duffee (1998), Collin-Dufresne, Goldstein, and Martin (2001)), where the expected sign is negative. This finding is in accordance with the observation that lower government rates (that can be considered as a proxy for a *flight-to-quality* strategy) imply market preference for less risky assets. From an other point of view, that of the firm's liability side, an increase in the government bond rates may induce a worsening in the financial position of the issuer. The market reaction to the firm's riskier position could be such that an increase in the credit spreads is necessary in order to restore the equilibrium. This is more likely in the European market where the long and short debt positions

[18]We consider as explanatory variables the coupon, the maturity, sector and sub-sector dummies, rating dummies, maturity bucket dummies, the issue size, issuer dummies, issuer country dummies in line with the analysis of Duffee (1998), Campbell and Taksler (2003), Collin-Dufresne, Goldstein, and Martin (2001) and Elton, Gruber, Agrawal, and Mann (2001).

[19]This motivates the predicted effect of change in rating on the credit spread changes. See Table 7.

heavily depends on the credit market conditions.

We notice that all the variables are statistically significant except of the change in *rating upgrading* and the change in the *government curve slope* though they have the predicted right signs. We also observe that while the change in rating downgrade is always strongly significant the change in rating upgrade is not. However, the presence of an asymmetric effect of shocks in the credit market seems to be sensible and realistic. Unlikely, the liquidity proxy (*delta swap spread*) considered is not significant at the 5% significance level. This is in contrast with the observation that each euro corporate bonds is characterized by different liquidity conditions. This seems to suggest the inadequacy of this proxy to catch the influence of liquidity conditions on the movements of the delta credit spreads.

We also run a 2FE model by including *monthly dummies*. The *monthly dummies* represent unexplained time-series variation in average corporate delta spreads. The inclusion of time dummies does not change the results except that of lowering the significance of common effects.[20]

Table 8 shows that at most the variables considered capture only around 20 percent of the variation as measured by adjusted R^2. Moreover the residuals obtained from the above regressions show a certain degree of cross-section dependence.[21] Both results are very similar to those found by Collin-Dufresne, Goldstein, and Martin (2001) for the US market.

In line with their analysis we look for a factor structure in order to explain the delta credit spreads. First, we consistently estimate the slope parameters of the individual specific components by means of the CCEP estimator of Pesaran in (12). Second, with the variance-covariance matrix of the consistently estimated residuals of equation (15), we obtain the principal components. Third, we select the common factors according to the information criteria of Bai and Ng (2002). The results (see Table 9) suggest to include just one factor in our model. Hence we augment our regressions with the first principal component.

Table 10 shows regressions of delta credit spreads when we include the estimated factor. We consider four different specifications. All the specifications show that the results are coherent in terms of R-square, expected signs and statistical significance of the estimated parameters. These results also address the robustness of our findings. In fact, either by adding or excluding explanatory variables our results, in terms of magnitude, sign and statistical significance of the estimated parameters do not considerably change. Moreover, the partial coefficients of determination, computed for each group of regressors, show that the individual specific regressors are responsible for the 75% of the model fit. More interestingly the unobserved factor contributes, in terms of R-square, to the overall fit as the observed factors, which are considered as the main common drivers of the corporate bond market.

We observe that while the parameter of *average daily stock excess return* is always significantly negative, the coefficient on equity volatility is not significant although

[20]The results of the 2FE models are available on request from the authors.

[21]See Table 6 which reports the residual average and absolute average cross section correlation for the first FE specification.

it is positive, as expected. This is in contrast with the analysis of Campbell and Taksler (2003) for the US market. We also consider changes in the number of days used to compute equity volatility but the result is unaffected.[22]

It is important to note that the explanatory power of the regressions is clearly higher when the estimated factor is included. The adjusted R-square considerably rises: from about 20 percent to about 25 percent. The regression results indicate that the inclusion of estimated factor does not alter the coefficient estimates. The only effect of the factor inclusion is the strengthening of the parameter of the stock market index return and the weakening of the parameter for the single firm's equity excess return.

So far our analysis shows that there exists a systematic risk factor in the Euro corporate bond market that is independent of the main common factors predicted by the theory and that seems to drive a relevant component of the systematic changes in credit spreads. What is left is to investigate the nature of the unobserved common factor. Our suspect is that the estimated factor, which improves so remarkably the fit in the delta spread equation, accounts for 'latent' liquidity effects. This is reinforced by the observation that the liquidity proxy (*delta swap spread*) is unable to control for liquidity effects (See Table 8). Moreover we argue that liquidity distortions are possibly induced by the presence of imperfections in Euro corporate bond market. This idea comes mainly from the evidence, stressed in section 4, that corporate bonds in the Euro market could be mispriced.[23]

Hence, we think that potentially an aggregate factor driving liquidity in the bond market could be correlated with the common factor we find, in line with the findings of Collin-Dufresne, Goldstein, and Martin (2001). Moreover, we check out the robustness of our findings by regressing the systematic factor on liquidity proxies. Every month we compute for each bond and for the index as a whole the rolling, six month window, variance of the corresponding price. Given the relations between variance and trading volume we measure bond liquidity by the corresponding price variance. Table 11 shows the average slope t-statistics in the regressions of the estimated factor on a constant and the price variance of each bond in the sample. The same regression is also run for the aggregate price index whose variance has been computed using the same rolling window. In both cases the price variance parameter is statistically significant in explaining the estimated systematic factor. For robustness checks, we also run the same regressions for the second factor, i.e the second principal component of residuals in (15), and, as expected, we find that the slope coefficients are not statistically significant.

Table 12 reports the average partial correlation between the delta credit spreads and the estimated factor, after having controlled for all the explanatory variables contained in Table 10. As expected, the average partial correlation increases as the credit rating decreases, i.e. as the liquidity conditions worsen.

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[22]We also run the procedure to compute the standard deviation of equity daily excess return by using the preceding 90, 270 and 360 days prior the bond trade.

[23]See Table 2.

8 Conclusion

In this paper we investigate the determinants of credit spread changes denominated in Euro. We point out that the change in credit spreads can be viewed as a proxy of the excess return of the corporate bonds over government bonds. For this reason we conduct our empirical analysis in a factor model framework. We also follow a data-driven approach recently developed for the US market which address the question of which variables are mostly correlated with the credit spread movements. The end of the analysis is to show that known and observed factors, individual and common, are unable to account for the observed credit spreads variation. The empirical analysis is carried out using a panel data model. We estimate the individual factors influences using a recently developed estimator (Pesaran (2006)), and starting from these estimates we can consistently estimate the unobserved common factors. These factors could be correlated with the individual observed factors but are orthogonal, by assumption and construction, to the observed common factors. Overall our analysis shows that there exists a systematic risk factor in the Euro corporate bond market that is independent of the main common factors predicted by the theory and that seems to drive a relevant component of the systematic changes in credit spreads. Moreover we show that this systematic factor is correlated with variables that are proxies of liquidity in the bond market. This sort of liquidity bias can be thought of being caused by the lack of a fully developed market. This interpretation seems to be supported also by the misalignments found in Euro bond corporate prices. Even if our database has been built up following criteria which should guarantee the liquidity of the issues included, we guess the market is widely heterogeneous and illiquid. A hint of this problem was the huge difference between the bond market prices and the estimated prices obtained from the corporate bond spot curve.

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9 Appendix A

For each month, we estimate the zero coupon yield curves for each rating category[24] by a smoothed cubic spline. We then use these spot rates to discount the coupon corporate bonds cash flows and obtain fitted price for each bond. We observe that the difference between actual prices and estimated prices are quite consistent[25]. While for the government bonds the absolute average error is about 1 cent, for the corporate bonds is about 20 cents for all rating categories.

Figure 1 and 2 show respectively the difference between the market prices and the fitted prices for the German government bonds and for the A rated euro corporate bonds at the same date. The average error over all the months considered is much bigger than the average error found in other studies (see among others Elton, Gruber, Agrawal, and Mann (2001) and Campbell and Taksler (2003)) on the US corporate bond market but is comparable to the average error found for the Euro market according to the analysis conducted by Van-Landschoot (2003).

Van-Landschoot (2003) extend the Nelson-Siegel method to estimate the European term structure of credit spreads for different sub-rating categories. The analysis shows that the Nelson-Siegel method results in systematic errors that depends on liquidity, coupon and subcategories within the rating category (plus, flat, minus rating). Therefore Van-Landschoot (2003) extends the model with four additional factors in order to take into account the underline effects. The average yield error of the extended Nelson-Siegel model is quite consistent. For example, the yield error for an A rated bond is close to 16 basis points for a two years maturity bond and to 15 basis point for a five years maturity bond. Such yield errors cause the price errors to be quite consistent. Table II illustrates this point. Table II shows the error between the observed market price and the estimated price for any two corporate bonds included in the IBOOX index on August 25, 2005. The first one is a two year maturity bond issued by Lehman Brothers while the second one is a five year maturity bond issued by France Telecom. Both bonds have an A rating. First, we compute the "estimated redemption yield" by adding the yield error to the observed redemption yield. Then we obtain the "estimated price" from the "estimated redemption yield". Table II shows that for the two bonds the error between the actual price and the estimated price is about 30 cents and 75 cents for 100 euros, respectively. The result doesn't significantly change for different redemption yield and coupon rate.

Actual and estimated prices can mainly differ because bonds within the same rating category are not homogeneous. Moreover, there are other possible reasons. First, credit rating are revised infrequently and often with one lag. Second, corporate bonds could be mispriced. Finally the magnitude of fitted errors strongly suggest the use of the "observed redemption yield spread".

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[24]We consider the following rating categories: AA, A and BBB.

[25]The euro government bonds considered here are those belong to the IBOOX Euro government bond Index.

10 Appendix B

Under the assumption that $\boldsymbol{\beta_i} = \boldsymbol{\beta}$, $\forall i$, equation (9) becomes:

$$y_{it} = \boldsymbol{\alpha}_{\boldsymbol{i}}^{'}\boldsymbol{d_t} + \boldsymbol{\beta}^{'}\boldsymbol{x_{it}} + \boldsymbol{\gamma}_{\boldsymbol{i}}^{'}\boldsymbol{f_t} + \epsilon_{it} \;\; i = 1\ldots, I, t = 1\ldots, T \tag{17}$$

Stacking the time series observations for i yields:

$$\boldsymbol{y_i} = \boldsymbol{D}\boldsymbol{\alpha_i} + \boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{F}\boldsymbol{\gamma_i} + \boldsymbol{\epsilon_i} \;\; i = 1\ldots, I \tag{18}$$

where

$$\begin{aligned}
\boldsymbol{y_i} &= (y_{i1}, y_{i2}, \ldots, y_{iT})^{'} && (T \times 1)\\
\boldsymbol{X_i} &= (\boldsymbol{x_{i1}}, \boldsymbol{x_{i2}}, \ldots, \boldsymbol{x_{iT}})^{'} && (T \times K)\\
\boldsymbol{D} &= (\boldsymbol{d_1}, \boldsymbol{d_2}, \ldots, \boldsymbol{d_T})^{'} && (T \times M)\\
\boldsymbol{F} &= (\boldsymbol{f_1}, \boldsymbol{f_2}, \ldots, \boldsymbol{f_T})^{'} && (T \times I)\\
\boldsymbol{\epsilon_i} &= (\epsilon_{i1}, \epsilon_{i2}, \ldots, \epsilon_{iT})^{'} && (T \times 1)
\end{aligned}$$

We first obtain the consistent CCEP estimator of equation (12) and then we estimate $\boldsymbol{\alpha_i}$ in the following OLS regression:

$$\boldsymbol{y_i} - \boldsymbol{X}_i\hat{\boldsymbol{\beta}}_{\boldsymbol{P}} = \boldsymbol{D}\boldsymbol{\alpha_i} + \boldsymbol{\nu_i} \tag{19}$$

where ν_{it} are idiosyncratic errors.

$$\hat{\boldsymbol{\alpha}}_{\boldsymbol{i}} = (\boldsymbol{D}^{'}\boldsymbol{D})^{-1}\boldsymbol{D}^{'}(\boldsymbol{y_i} - \boldsymbol{X}_i\hat{\boldsymbol{\beta}}_{\boldsymbol{P}}) \tag{20}$$

$$\hat{\boldsymbol{\alpha}}_{\boldsymbol{i}} = \boldsymbol{\alpha_i} + (\boldsymbol{D}^{'}\boldsymbol{D})^{-1}(\boldsymbol{D}^{'}\boldsymbol{X}_i\boldsymbol{\beta} + \boldsymbol{D}^{'}\boldsymbol{F}\boldsymbol{\gamma_i} + \boldsymbol{D}^{'}\boldsymbol{\epsilon_i} - \boldsymbol{D}^{'}\boldsymbol{X}_i\hat{\boldsymbol{\beta}}_{\boldsymbol{P}}) \tag{21}$$

We assume that:

1. $$E[\boldsymbol{d_t}\boldsymbol{d_t}^{'}] = \boldsymbol{Q_d} \;\; finite \;\; positive \;\; definite \;\; matrix \tag{22}$$

2. $$rank(E[\boldsymbol{d_t}\boldsymbol{d_t}^{'}]) = M \tag{23}$$

3. $$E[\boldsymbol{d_t}\boldsymbol{x_{it}}^{'}] = \boldsymbol{Q_{dx_i}} \;\; finite \;\; matrix \tag{24}$$

4. $$E[\epsilon_{it}|\boldsymbol{d_t}] = 0 \;\; \forall i, t \tag{25}$$

5. $$E[\boldsymbol{f_t}\boldsymbol{d_t}^{'}] = \boldsymbol{0}, \;\; \forall t. \tag{26}$$

Under assumptions 1-5 and given that $\hat{\boldsymbol{\beta}}_{\boldsymbol{P}}$ is a consistent estimator of $\boldsymbol{\beta}_{\boldsymbol{P}}$, then $\hat{\boldsymbol{\alpha}}_{\boldsymbol{i}} \xrightarrow{p} \boldsymbol{\alpha}_{\boldsymbol{i}}$ as $T \to \infty$ for $i = 1, \ldots, I$.

When $\boldsymbol{\alpha}_i = \boldsymbol{\alpha}$ for $\forall i$, the pooled OLS estimator of $\boldsymbol{\alpha}$ is given by:

$$\hat{\boldsymbol{\alpha}} = (\boldsymbol{G}_{\boldsymbol{D}}^{'}\boldsymbol{G}_{\boldsymbol{D}})^{-1}\boldsymbol{G}_{\boldsymbol{D}}^{'}(\boldsymbol{y} - \boldsymbol{X}\hat{\boldsymbol{\beta}}_{\boldsymbol{P}}) \tag{27}$$

where

$$\begin{aligned} \boldsymbol{G}_{\boldsymbol{D}} &= \boldsymbol{\iota}_{\boldsymbol{I}} \otimes \boldsymbol{D} \qquad (TI \times M) \\ \boldsymbol{X} &= (\boldsymbol{X}_{\boldsymbol{1}}^{'}, \boldsymbol{X}_{\boldsymbol{2}}^{'}, \ldots, \boldsymbol{X}_{\boldsymbol{I}}^{'})^{'} \qquad (TI \times K) \\ \boldsymbol{y} &= (\boldsymbol{y}_{\boldsymbol{1}}^{'}, \boldsymbol{y}_{\boldsymbol{2}}^{'}, \ldots, \boldsymbol{y}_{\boldsymbol{I}}^{'})^{'} \qquad (TI \times 1) \end{aligned}$$

where $\boldsymbol{y}$ is the $(TI \times 1)$ vector of observations over y_{it} and $\boldsymbol{\iota}_{\boldsymbol{I}}$ is the unit vector of size I. We note that:

$$\begin{aligned} (\boldsymbol{G}_{\boldsymbol{D}}^{'}\boldsymbol{G}_{\boldsymbol{D}}) &= IT\frac{\sum_{t=1}^{T}\boldsymbol{d}_{\boldsymbol{t}}\boldsymbol{d}_{\boldsymbol{t}}^{'}}{T} \\ (\boldsymbol{D}^{'}\boldsymbol{F}) &= IT\frac{\sum_{t=1}^{T}\boldsymbol{d}_{\boldsymbol{t}}\boldsymbol{f}_{\boldsymbol{t}}^{'}}{T} \\ (\boldsymbol{D}^{'}\boldsymbol{\epsilon}) &= IT\frac{\sum_{i=1}^{I}\sum_{t=1}^{T}\boldsymbol{d}_{\boldsymbol{t}}\epsilon_{it}}{IT} \end{aligned}$$

where $\boldsymbol{\epsilon} = (\boldsymbol{\epsilon}_{\boldsymbol{1}}^{'}, \boldsymbol{\epsilon}_{\boldsymbol{2}}^{'}, \ldots, \boldsymbol{\epsilon}_{\boldsymbol{I}}^{'})^{'}$.

Under assumptions 1-5 and given that $\hat{\boldsymbol{\beta}}_{\boldsymbol{P}} \xrightarrow{p} \boldsymbol{\beta}$, then $\hat{\boldsymbol{\alpha}} \xrightarrow{p} \boldsymbol{\alpha}$ as I and $T \to \infty$.

11 Appendix C

In section 6 the estimation procedure of individual and observed and unobserved common factors effects is based on the estimate of the latter by principal components. In this section, we provide some simulation evidence that this procedure produces consistent estimates of the unobserved factors.
We assume the following data generating process (DGP):

$$y_{it} = \alpha_{i1} + \alpha_2 d_{2t} + \beta_1 x_{1it} + \beta_2 x_{2it} + \gamma_i f_t + \epsilon_{it} \tag{28}$$

$$x_{1it} = a_{11} + a_{21} d_{2t} + \gamma_1 f_t + v_{1it} \tag{29}$$

$$x_{2it} = a_{12} + a_{22} d_{2t} + \gamma_2 f_t + v_{2it} \tag{30}$$

for $i = 1, \ldots, I$, and $t = 1, \ldots, T$. This DGP considers only two individual specific components, x_{1it} and x_{2it}, two observed common factors, d_{1t} and d_{2t}, and one unobserved common factor f_t, with $E[f_t d_{2t}] = 0, \ \forall t$. The parameters

$$A = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix}$$

and

$$\Gamma = \begin{bmatrix} \gamma_1 \\ \gamma_2 \end{bmatrix}$$

are generated as $IIDN(\mathbf{0}, 0.5 \times \mathbf{I}_4)$, and $IIDN(\mathbf{0}, 0.5 \times \mathbf{I}_2)$ and are not changed across replications. $\boldsymbol{\beta} = [\beta_1, \beta_2] = [0.5, 1.5]$, $\alpha_2 = 0.5$, $\gamma_i = IIDN(1, 0.2)$. $\alpha_{i1} = IIDN(1, 1)$ are treated as fixed effects. The common factors and the individual specific errors are generated as independent stationary AR(1) processes with zero means and unit variances:

$$\begin{aligned} d_{1t} &= 1 \\ d_{2t} &= \rho_d d_{2,t-1} + v_{dt}, \quad t = -49, \ldots 1, \ldots, T. \\ v_{dt} &\sim IIDN(0, 1 - \rho_d^2), \quad \rho_d = 0.5, \quad d_{2,-50} = 0 \end{aligned}$$

$$\begin{aligned} f_t &= \rho_f f_{t-1} + v_{ft}, \quad t = -49, \ldots 1, \ldots, T. \\ v_{ft} &\sim IIDN(0, 1 - \rho_f^2), \quad \rho_f = 0.5, \quad f_{-50} = 0 \end{aligned}$$

$$\begin{aligned} v_{jit} &= \rho_{v_{ij}} v_{ji,t-1} + \nu_{ijt}, \quad t = -49, \ldots 1, \ldots, T. \\ \nu_{ijt} &\sim IIDN(0, 1 - \rho_{v_{ij}}^2), \quad v_{ji,-50} = 0 \ \ j = 1, 2 \end{aligned}$$

and

$$\rho_{v_{ij}} \sim IIDU\,(0.05, 0.95)\,, \quad j = 1, 2$$

The errors of y_{it} are generated as stationary AR(1) processes:

$$\begin{aligned} \epsilon_{it} &= \rho_{i\epsilon}\epsilon_{i,t-1} + \sigma_i(1 - \rho_{i\epsilon}^2)^{1/2}\zeta_{it} \quad \text{for} \quad i = 1, \ldots, I \\ \rho_{i\epsilon} &\sim IIDU\,(0.05, 0.95) \\ \sigma_i^2 &\sim IIDU\,(0.5, 1.5) \\ \zeta_{it} &\sim IIDN\,(0, 1) \end{aligned}$$

After having generated the data according to the DGP described above, first, we compute the CCEP estimator of $\boldsymbol{\beta}$ in (28) and the resulting residuals, as computed in (15), second, we select the number of principal components, extracted from the estimated covariance matrix of residuals, according to the Bai and Ng (2002)'s information criteria. These will be the factor estimates. In order to show that $\widehat{f}_t$ represents a consistent estimator of f_t we compute the correlation coefficient between $\{\hat{f}_t\}_{t=1}^T$ and $\{f_t\}_{t=1}^T$ for each Monte Carlo simulation. Table 1 reports the average correlation coefficient over 1000 repetitions for combinations of $T = 20, 50, 100$, and $I = 10, 30, 100$. The results suggest that the factor estimates are highly correlated with the unobserved factor. This seems to confirm the results in Bai (2003), obtained in a different context, that is as $\sqrt{T}/I \to 0$ the estimation error in the factor estimates is negligible.

Table 1: **Average correlation coefficients between $\{\hat{f}_t\}_{t=1}^T$ and $\{f_t\}_{t=1}^T$.**

	I=30	I=100	I=500
T=10	0.9965	0.9980	0.9989
T=30	0.9970	0.9984	0.9991
T=100	0.9959	0.9979	0.9989

Table 2: **Price Estimation Error based on Extended Nelson-Siegel method**

	LEHMAN BROTHERS	SOCIETE TEL FRANCAIS
Coupon	5.47	4.375
Settlement date	31-Aug-05	31-Aug-05
Redemption date	31-Jul-07	12-Nov-10
Redemption value	100	100
Rating	A	A
Observed redemption yield	3.11%	2.99%
Observed price	104.50583	106.32241
Estimated price	104.19048	105.56467
Price error	32	76

We estimate the price error for two corporate bonds included in the IBOXX index. The price error is expressed in cents for 100 euros.

Table 3: **Summary Statistics**

		Mean	Std Dev	Min	Max
Credit spread change	*our sample*	-1.58	22.61	-492.20	465.70
	full sample	0.26	44.02	-740.20	2529.80
Coupon (%)	*our sample*	5.55	0.74	3.50	7.25
	full sample	5.37	0.92	2.13	9.75
Years to maturity	*our sample*	5.21	2.28	0.94	14.07
	full sample	5.66	3.45	0.92	29.94
Equity Volatility		1.98%	0.62%	0.00%	6.59%
Equity Excess Return		-0.10%	0.36%	-1.95%	1.27%

Table 3 reports summary statistics on the corporate bonds both in our sample and for all the nonputable and noncallable corporate bonds included in the IBOXX index. The credit spread changes are measured in basis points.

Table 4: **Sample composition for rating and sector**

Panel A		
Rating	% of our sample	% of the full sample
AAA	1.80%	14.99%
AA+	0.37%	15.00%
AA	3.35%	15.25%
AA-	13.37%	5.29%
A+	16.35%	12.46%
A	12.88%	1.39%
A-	19.81%	5.42%
BBB+	14.58%	12.02%
BBB	12.87%	5.50%
BBB-	4.63%	12.67%
Panel B		
Industrial Sector	% of sample	% of the full sample
Financials	38.16%	37.92%
Industrials	49.76%	50.80%
Utilities	12.08%	11.28%

Table 4 reports summary statistics on the corporate bonds both in our sample and for all the nonputable and noncallable corporate bonds included in the IBOXX index.

Table 5: **Summary Statistics**

Panel A		
Industry	% of sample	% of the full sample
Automobiles	9.18%	10.60%
Banks	27.29%	23.66%
Basic-Resources	0.97%	1.31%
Chemicals	1.73%	2.15%
Construction	1.45%	2.38%
Cyclical-Goods & Services	0.97%	1.18%
Energy	2.42%	2.84%
Financial-Services	7.98%	11.45%
Food & Beverage	1.93%	2.19%
Health-Care	1.45%	0.89%
Industrial-Goods & Services	6.73%	6.95%
Insurance	2.90%	2.81%
Media	2.42%	2.10%
Retail	6.84%	6.77%
Telecommunications	13.53%	11.19%
Travel & Leisure	0.16%	0.25%
Utilities	12.08%	11.28%
Panel B		
Maturity Bucket	% of sample	% of the full sample
Short (1-4 years)	35.53%	34.84%
Medium (4-10 years)	62.08%	60.06%
Long (+10 years)	2.39%	5.10%

Table 5 reports summary statistics on the corporate bonds both in our sample and for all the nonputable and the noncallable corporate bonds included in the IBOXX index.

Table 6: **Cross-section dependence**

Panel A

% PC_1 for y	44.53%
% PC_2 for y	17.92%

Panel B

	average correlation	avg absolute correlation
Delta credit spread	0.4047	0.4102
OLS residuals	0.3553	0.3484
Fixed Effects residuals	0.12	0.2795
CD stat	12.65	
	(0.00)	

Table 6 reports the proportion of delta credit spread variability explained by the j-th principal component, PC_j, the average and the average absolute cross-section correlation for delta credit spread and estimation residuals. CD Stat is the Pesaran Cross-Section Dependence Statistic. P-value appears in parentheses.

Table 7: **Predicted effects of the included regressors**

Individual specific regressors	Predicted sign	Remarks
Beginning of month credit spread	-	
Average of daily excess return over preceding 180 days	-	
Standard Deviation of daily excess return over preceding 180 days	+	
Rating	+	We assign a value to each rating. From 10 (AAA) to 1 (BBB-)
A Rating		dummy variable
BBB Rating		dummy variable
Medium Maturity (from 3 to 6 years)		dummy variable
Long Maturity (above 6 years)		dummy variable
Delta credit spread for rating	+	
Delta credit spread for sector	+	
Common factors		
5-year delta swap spread	+	
10 year German government benchmark monthly variation (mv)	-	
German government curve slope mv	-	
German government curve convexity mv		
mv in upgraded Euro corporate bonds	-	
mv in downgraded Euro corporate bonds	+	
Morgan Stanley USA monthly return	-	

Table 7 reports the expected sign of the included regressors on the credit spread changes.

Table 8: **Regression Results**

	Pooling		Issue fixed effects	
Specification	1	2	3	4
Constant	1.35	0.15		
	(1.45)	(0.15)		
Beginning of month credit spread	-0.07	-0.08	-0.12	-0.12
	(-16.88)	(-16.11)	(-20.02)	(-19.31)
Average of daily excess return over preceding 180 days	-123.39	-126.47	-802.08	-856.61
	(-1.82)	(-1.83)	(-4.66)	(-4.89)
Standard Deviation of daily excess return over preceding 180 days	47.80	28.87	205.41	220.83
	(1.16)	(0.68)	(2.11)	(2.22)
A rating		1.54		-1.11
		(2.25)		(-0.58)
BBB rating		3.33		-6.80
		(3.93)		(-2.75)
Medium Term	0.94	1.35	3.98	3.18
	(1.82)	(2.52)	(3.97)	(3.09)
Long Term	1.04	1.80	7.87	7.29
	(0.63)	(1.07)	(2.25)	(2.04)
Delta credit spread for rating	0.69		0.67	
	(30.30)		(28.65)	
Delta credit spread for sector		0.67		0.64
		(25.00)		(23.53)
5 years Swap Spread monthly variation	5.44	6.32	3.48	4.52
	(1.26)	(1.44)	(0.80)	(1.02)
10 year German government benchmark monthly variation	6.82	7.10	6.62	6.46
	(2.53)	(2.59)	(2.44)	(2.34)
German government curve slope monthly variation	-4.04	-4.00	-1.86	-2.73
	(-1.28)	(-1.22)	(-0.58)	(-0.82)
German government curve convexity monthly variation	-18.87	-19.08	-24.04	-20.80
	(-1.53)	(-1.52)	(-1.94)	(-1.65)
monthly variation in upgraded euro corporate bonds	0.03	-0.11	-0.35	-0.17
	(0.08)	(-0.26)	(-0.85)	(-0.40)
monthly variation in downgraded euro corporate bonds	0.72	0.72	0.97	0.81
	(3.97)	(3.84)	(5.22)	(4.24)
Morgan Stanley USA monthly return	-29.16	-28.24	-25.12	-25.40
	(-4.54)	(-4.25)	(-3.90)	(-3.80)
Number of Issuers	207.00	207.00	207.00	207.00
Number of observations	6831.00	6831.00	6831.00	6831.00
R^2	0.22	0.19	0.23	0.21
F	146.822 (0.00)	108.512 (0.00)	156.481 (0.00)	115.785 (0.00)

Table 8 reports the regression results for a pooling OLS model (specifications 1 and 2) and a FE model (specifications 3 and 4). T-statistics appear in parentheses for the parameter estimates and p-value appear in parentheses for the test statistics.

Table 9: **Information criteria for common factors**

# of factors	IC_{p1}	IC_{p2}	PC_{p1}	PC_{p2}
1	4.62	4.62	90.97	90.97
2	4.72	4.73	91.28	91.28
3	4.83	4.84	91.59	91.59
4	4.94	4.94	91.89	91.90
5	5.05	5.05	92.20	92.21
6	5.16	5.16	92.51	92.52
7	5.26	5.27	92.81	92.83
8	5.37	5.38	93.12	93.14

Table 9 reports the information criteria of Bai and Ng (2002) for detecting the number of common factors in a factor model.

Table 10: **Regression Results**

	1	2	3	4
Beginning of month credit spread	-0.15	-0.15	-0.147704	-0.147535
	(-22.78)	(-22.75)	-(22.54)	-(22.49)
Average daily stock excess return (preceding 180 days)	-556.26	-543.00	-562.59	-547.29
	(-3.23)	(-3.15)	-(3.25)	-(3.15)
Standard Deviation of daily stock excess return over preceding 180 days			27.49	17.04
			(0.28)	(0.17)
Delta credit spread for rating	0.60	0.58	0.60	0.58
	(19.32)	(16.22)	(19.15)	(16.18)
Delta credit spread for sector		0.07		0.07
		(1.37)		
5 years Swap Spread monthly variation	-8.04	-11.15	-8.03	-10.79
	(-1.69)	(-2.16)	-(1.66)	-(2.06)
10 year German government benchmark monthly variation	3.47	4.75	3.47	4.61
	(1.46)	(1.89)	(1.45)	(1.82)
German government curve slope monthly variation	-8.22	-11.37	-8.41	-11.15
	(-2.07)	(-2.56)	-(2.10)	-(2.49)
monthly variation in upgraded euro corporate bonds	-0.87	-0.75	-0.85	-0.75
	(-2.17)	(-1.84)	-(2.10)	-(1.82)
monthly variation in downgraded euro corporate bonds	1.89	1.76	1.87	1.76
	(9.74)	(8.45)	(9.59)	(8.38)
Morgan Stanley USA monthly return	-40.88	-35.01	-40.48	-35.37
	(-6.40)	(-4.75)	-(6.32)	-(4.77)
Estimated factor, $\hat{f}_1$	0.02	0.02	0.02	0.02
	(11.14)	(11.12)	(10.96)	(10.37)
Number of Issuers	207	207	207	207
Number of observations	6831	6831	6831	6831
R^2	0.255	0.255	0.254	0.255
F	123.56 (0.00)	117.09 (0.00)	116.87 (0.00)	111.07 (0.00)
Partial R^2 Observed factors ($\boldsymbol{d}_t$)	0.02			
Partial R^2 Individual Specific Regressors ($\boldsymbol{x}_{it}$)	0.19			
Partial R^2 Estimated Common Factor ($\widehat{\boldsymbol{f}}_t$)	0.02			
F-statistic for equality of dummy variables :	1.14 (0.08)	1.14 (0.09)	1.13 (0.09)	1.12 (0.11)
Hausman Chi-Squared Specification Test	115.18 (0.00)	114.71 (0.00)	113.64 (0.00)	113.02 (0.00)

Table 10 reports the regression results for four fixed effect panel data models when we include the estimated common factor. We include fixed effects for each issuer. t statistics for parameter estimates and p-value for tests appear in parentheses.

Table 11: **Relation between the estimated factor and the price variance**

	All Bonds	Aggr. Bond Index
Constant	-89.08	2.79
	(2.02)	(0.09)
Price variance	56.76	266.60
	(2.05)	(1.80)

Table 11 reports OLS regression results for $\hat{f}_t = \alpha + \beta\sigma^2_{it}$ where σ^2_{it} is the price variance of bond i at time t and $\hat{f}_t$ is the estimated systematic factor. The price variance is computed on a six month rolling windows. The first column reports the average OLS parameters and t statistics over the regressions for each bond. The second column reports the estimated parameters and the t statistics for the aggregate index.

Table 12: **Average Partial Correlation of delta credit spreads with the estimated factor**

Rating	average partial correlation
AAA	0.3
AA	0.33
A	0.39
BBB	0.47

Table 12 reports the average correlation of delta credit spreads with the estimated factor, controlling for the explanatory variables contained in Table 10.

Figure 1: Euro Government Bonds. Market prices and estimated prices

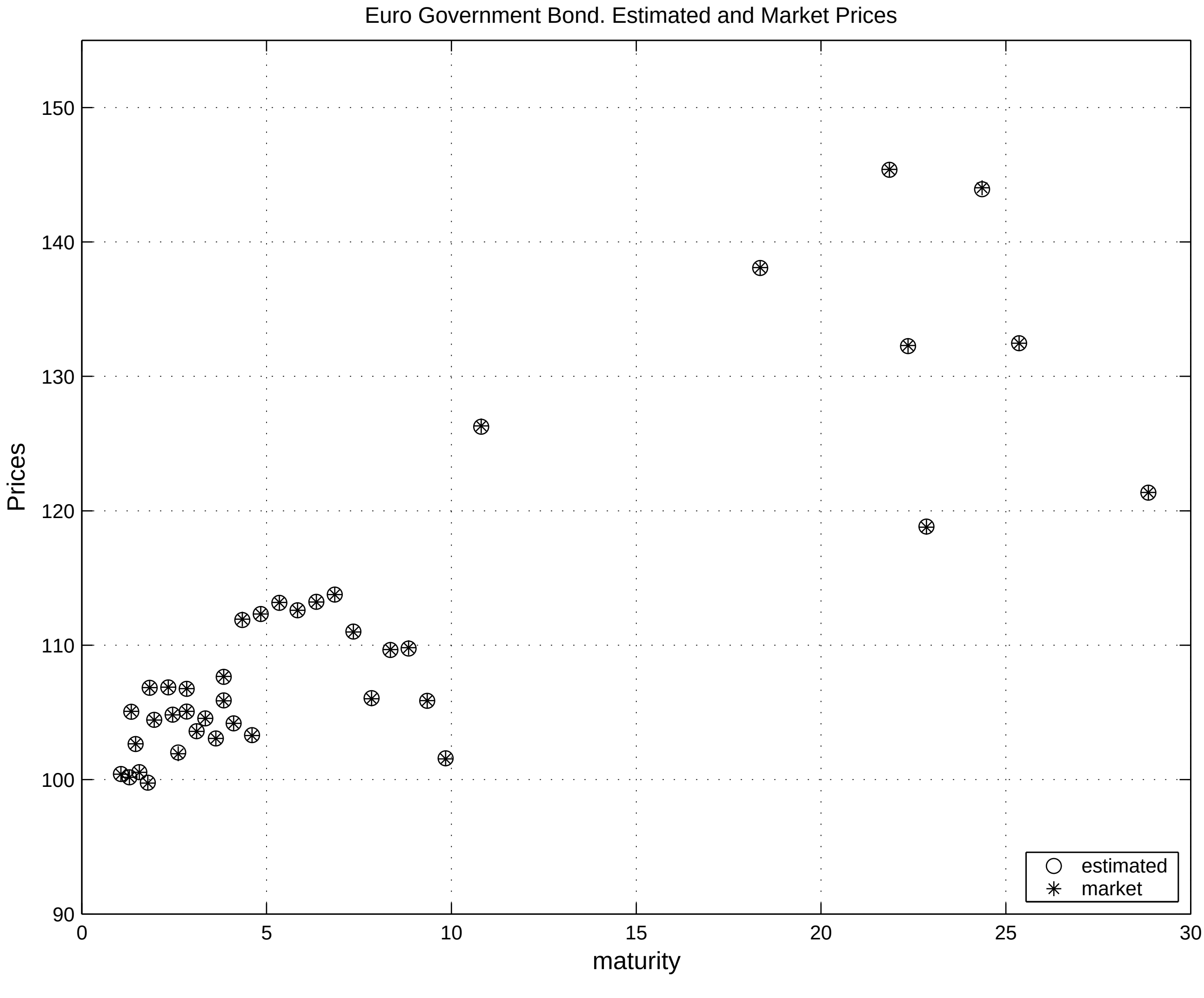

Figure 2: Euro Corporate Bonds. Market prices and estimated prices for A rated bonds