FACULTEIT ECONOMIE EN BEDRIJFSWETENSCHAPPEN

The relative informational efficiency of the European corporate bond and stock markets.

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Abstract

In this research, the relationship between European corporate bonds and stocks is examined. The informational efficiency of both bond and stock markets relative to each other is evaluated based upon which market leads the other in incorporating information about the firm. The analysis is conducted by employing a panel vector autoregression (VAR) on corporate bond returns and the corresponding stock returns from 159 firms over a 15 year time period. Results suggest that a correlation is present where stocks lead bonds. This correlation is stronger in high-yield bonds compared to investment grade bonds. This implies that the stock market incorporates firm news more efficiently and that high-yield bonds react more to firm news.

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Introduction

The predictability of returns of financial assets have long been of interest to investors and have been the subject of a great deal of research. However, the research on this topic has mainly focussed on the stock market and the predictability of returns in this market. Yet, over the past years, as authorities are working on making the bond market more accessible through improving transparency, this market has gained more consideration. The increasingly transparent information in this market makes it more accessible for research. With the increase in studies about return predictability of bonds, a body of research has emerged about the correlation between stocks and corporate bonds and their assumed ability to predict each other's returns.

Even though most of the past research has focussed on the USA market, this paper will consider the European bond markets. USA authorities have made larger strides towards increasing the transparency in the corporate bond market. The most prominent example of the increased transparency is the introduction of TRACE (Trade Reporting And Compliance Engine) by FINRA. TRACE is a system that facilitates the mandatory reporting of all over-the-counter trades in the secondary fixed income markets (finra, 2018). As the European markets have not yet introduced or generalised such systems, the transparency is expected to be lower. An expected result of this lower transparency is that information is less easily distributed within these markets and thus these markets have a higher probability of slow integration of new information.

Both stocks and bonds are issued by the same firm and as so, they reflect the same firm value and are expected to react to the same information about the firm. Previous research has suggested that both markets are not equally informationally efficient, if this is the case, one market would lead the lagging market in information. This lead-lag relationship could be useful in predicting the returns of the lagging market. Investors would be able to buy or sell assets in the lagging market based upon the returns of other assets by the same firm in the leading market. One could argue that the bond market should be more informationally efficient because a larger concentration of institutional investors occupy this market compared to many retail investors in the stock market. On the other hand, many argue that the stock market should be more informationally efficient because this market gets more attention of analysts and as so, information is spread at a faster rate throughout this market.

Previous research has been inconclusive about the presence and direction of a cross-serial relationship. In the situation a cross-serial relationship is present, some have found a relationship were stocks lead bonds and others have found a relationship where bonds lead stocks or even no relationship at all. However in either case, this relationship, if one could irrefutably be established, could lead to a significant trading strategy. Additionally, research suggest that the relationship between bonds and stocks is stronger for high-yield bonds as they resemble closer to equity. High yield bonds are defined by Euronext (2017) as follows: 'Based on the two main credit rating agencies, high-yield bonds carry a rating below 'BBB' from S&P, and below 'BAA' from Moody's. Bonds with ratings at or above these levels are considered investment grade.' Firms issuing high-yield bonds are supposed to be closer to default and therefore the bonds react more to news about the firm's assets whereas investment grade bonds are not threatened by default and react closer to changes in interest rates.

This research utilizes daily data to examine if a relationship is present in the European markets by conducting a panel Vector Autoregression (VAR) on corporate bond and stock returns. Results identify a relationship between stock and bond returns where stocks lead bonds up until two days. This suggest that the European corporate bond market is in fact less informationally efficient. Further, results also show that the relationship is significantly different for investment grade and high-yield bonds where the effect is strongest for high-yield bond, indicating that high-yield bonds returns are closer related to the corresponding stock returns.

The first section of this paper will discuss the existing literature and will develop the overall research questions and hypotheses. Following, the second part will explain the data collection and explain the methodology used. The third part will display and discuss the results. Lastly the fourth section will conclude and summarize.

1 Literature review

1.1 Existing literature

This research will focus on the relationship between returns in the stock and bond market. Merton (1974) established that a relationship between both should exist because they are both claims on the value of the firm's assets. He stated that equity can be described as a put option on the firm's assets and that debt can be described as a combination of investing in a risk-free asset and shorting a put in the company. As both stocks and corporate bonds depend on the same underlying assets, this would mean that they react to the same information. On the one hand, if information is released about the mean value of the firm, both stocks and bonds should react in the same way to this information. Thus information about the mean value of the firm should evoke a positive correlation. On the other hand, information about the volatility of a firms assets should affect stock and bonds in opposite ways. Increased asset volatility has a positive effect on stock returns and a negative effect on bond returns. If stock and bond markets are equally informationally efficient, the observed correlation between both will be contemporaneous. If however both markets are not equally informationally efficient, a cross-serial correlation is observed. In the case of a cross-serial correlation, the returns on the lagging market should be predictable based upon the returns in the leading market. Based upon these insights, a body of research has developed looking at the correlation between the stock and bond market returns.

The research about the correlation and lead-lag relationship between stocks and bonds was initiated by Kwan (1996), he used weekly bond and stock data over a 14 year period and looked at the correlation on a firm-level, which was a first at the time. His research shows that stock returns and yield changes are contemporaneously correlated and that current yield changes are cross-serially correlated with lagged stock returns. However current stock returns do not seem to be correlated with lagged yield changes. Furthermore he shows that highly rated bonds are closely correlated with riskless interest rates and uncorrelated with the firms stock returns, while the opposite is true for speculative-grade bonds. Besides the correlation, Kwan also shows that the dominant information driving the correlation is information about the mean value of the firm's assets, as the correlation between stock returns and yield changes in negative. Expanding on Kwan's (1996) research, Downing et al. (2009) test for the same correlation based on hourly and daily data over a period of 1 year and 2 months. In line with Kwan (1996) they also find that returns on low-rated non-convertible bonds are correlated with lagged stock returns while high-rated bonds are primarily correlated with treasury bonds. However for convertible bonds they find that all rating classes are predictable. Hong et al. (2012) come to the same conclusion as Kwan (1996) and Downing et al. (2009) that stocks and bonds are contemporaneously correlated and stock returns lead bond returns with this effect being stronger for high-yield bonds. Hong et al's (2012) results also show a strong non-linear structure in the serial dependence between stock and bond returns. The results of Hong et al. (2012) are on an aggregate level as their data is comprised from indices whereas Kwan (1996) and Downing et al. (2009) look at the correlation on a firm-level. Zhang and Wu (2014) find the same results for high-yield bonds, these are results based upon 22 years of high-yield bond data. Additionally, they also showed that this lead-lag relationship is stronger in bear markets compared to bull markets.

Few studies have examined the European corporate bond market. These include Norden and Weber (2009) who studied the co-movements between the stock market, the corporate bond, stock and CDS markets in the USA and Europe. They find that stock returns lead bond spread changes with a negative relationship, however their research mainly focusses on the relationship with CDS spread changes. Their study also shows significant differences in results for the USA market compared to the European market. A further study about the European bond market compared to the stock market was done by Tolikas (2016), he did a study about the newly created ORB (Order book for Retail Bonds) market on the London stock exchange. Tolikas (2016) finds that stock returns have predictive power over bond returns for investment grade as well as high-yield bonds. He concludes that the bond market is relatively more informationally efficient in all rating categories excluding not rated bonds. This differs from the research about the USA market in the range of predictability. The research about the USA market mainly finds predictability in high-yield bond returns and not for investment grade bond returns. Furthermore, Tolikas (2017) also did a study on the USA bond and stock market and his results from this research, show that, like the ORB market, stock returns lead bond returns on a daily level for all rating categories except for Aaa and Ca-D rated bonds. In other words, all rating categories other than the safest and the least safe category are cross-serially correlated. Besides Tolikas, Cao et al. (2017) also looked at the relationship between bond and stock returns outside of the USA market, more specifically in Canada. They consider monthly stock and bond data over a period of 27 years. For the contemporaneous relationship between stocks and bonds, they find that the information is mainly about the mean value of the firm's assets, similar to previous research on this topic. In addition to this, they discover a different pattern in the cross-serial relationship between stocks and bonds. Up until 2007, stocks and bonds follow the lead-lag relationship described by Kwan (1996), Downing et al (2009) and others, were stock returns lead bond returns. However, it appears that the financial crisis initiated an intensified information relationship between stocks and bonds, from this point on information flows between stocks and bond could be observed in both directions. This relationship was not captured by either Hong et al. (2012) or Tolikas (2017) who also included the 2008 financial crisis in their sample. Demirovic et al. (2017) researched the nature of the correlation between stocks and bonds. They find, as did Kwan (1996) and others, that the correlation is positive and thus driven by changes in the mean value of the firms' assets. Furthermore, they find that this correlation is driven by credit risk. The closer companies are to default, the greater the correlation between stocks and bonds. This is in line with other studies which concluded that high-yield bond returns are more predictable. Additionally they find that, in times of high market risk, the correlation is close to non-existent. In this case, the correlation seems to be driven by market-wide risk factors rather than firm-specific risk factors.

Unlike the results found by Kwan (1996), Downing et al. (2009) and others, Hotchkiss and Ronen (2002) find no causal relationship between stock and bond returns based on their research on the 20 most active high-yield bonds over 1 year on an hourly basis. They, however, do find a contemporaneous relationship between bond and stock returns. From this they conclude that information is distributed equally efficiently in both markets. Their results conflict directly those found by Kwan (1996). Bittlingmayer and Moser (2014) also find a different relationship from the one described by Kwan (1996). In their research about the predictive value of bonds over stocks, with monthly intervals. They find that high-yield bond returns lead stock returns in monthly intervals. Bittlingmayer and Moser's (2014) findings show an opposite picture to what Kwan (1996) found.

There is no clear consensus in the literature about the correlation between the stock and bond markets. Even among those researchers proving the correlation in the same direction, there is still a discussion about the extent of the correlation. This could be as a result of different data collection, Kwan (1996) works with dealer quotes, on the other hand Hong et al. (2012) work with transaction prices as to avoid matrix pricing and stale quotes. Another source of irregularities in the results could be the time frame and scope of the different studies. Hotchkiss and Ronen (2002) only look at data over 1 year where Kwan (1996) looks at a time period of 14 years. Furthermore, there also is a difference in the frequency of the data, this ranges from monthly to hourly data. Even though all of these reasons could explain discrepancies in the results, Ronen and Zhou (2013) propose different reasons for the contradicting results. In their research, Ronen and Zhou (2013) suggest that when accounting for dynamic liquidity, trade size and timing effects, the lead-lag relationship between stock and bond returns, observed by Kwan (1996), Downing et al. (2009)

and others vanishes. They argue that the changing liquidity of bonds, the impact of institutional trades and overnight transactions in the bond market have been neglected in previous research. Moreover they state that these factors explain the previously observed lead-lag relationship and the discrepancies between different studies. In line with Ronen and Zhou (2013), Tsai (2014) examines the impact of institutional sized bond trades. She finds that there is a difference between the bonds preferred by retail and institutional investors. Furthermore they find that institutional bond returns are less autocorrelated while being more cross-correlated with stock returns. When they control for dynamic liquidity, off-exchange trades and institutional sized trades in their sample they find that stock returns are a better predictor for bond returns than the other way around. However, when only considering institutional sized trades in speculative firms, they find that the predictive role of bond returns in regards to stock returns becomes more important.

Both Zhang and Wu (2014) and Tolikas (2017) take a look at the profitability of a trading strategy based upon the insights from their research. Zhang and Wu (2014) compare forecasting performance based on the lead-lag relationship with forecasting performance based upon the sample mean. They find that the forecasting model based upon the lead-lag relationship has a superior forecasting performance. Additionally, they find that the forecasting performance is greater in a bear market because the threat of default increases in bear markets. Tolikas (2017) goes one step further than just examining if the lead-lag relationship can contribute to a superior forecasting performance, he looks at the possibility of the relationship being used for a profitable trading strategy. He finds that a significant strategy can be generated from the lead-lag relationship, however the transaction costs would probably outweigh the possible profits to be made. For this reason, it is probably only profitable for the lowest rated bonds as the lead time gives the investor enough time to end a position in a default-bound bond.

Next to research about the general correlation between bond and stock markets, there has also been more specific research around earnings announcement and the relationship between the stock and bond market around these announcements. Hotchkiss and Ronen (2002) find that, in line with their findings about the informational efficiency of stock and bond markets, stocks as well as bonds incorporate the information from earnings announcements relatively quick. On the other hand, Omri (2017) finds in his research that the price reaction of bonds to earnings announcements can predict the price reaction of stocks to this earnings announcement and that this effect is more distinct for speculative grade bonds. He additionally finds that the informational value of a bonds reaction is greater for the most liquid bonds compared to the less liquid bonds. These findings contradict the results from Kwans (1996) research.

Next to research about the relationship around earnings announcements, there has also been a body of research about momentum spillover from stocks to bonds. Gebhardt et al. (2005) conduct test on the momentum spill over effect between stocks and bonds. In their tests they find that a stock-lead-bond relationship exists, more specifically that past six months momentum winners in the stock market can predict the bonds with higher returns for the subsequent period. They find the cause of this momentum spillover to be that both stocks and bonds underreact to firm information in past stock returns, however stocks adjust to the information more quickly. Their research lead to the conclusion that the stock market is more informationally efficient. Haesen et al. (2017) also examined the momentum spillover effect from stocks to bonds, they show that the momentum spillover effect as shown by Gebhardt et al. (2005) also exists for high-yield bonds. The momentum spillover effect as shown by Gebhardt et al. (2005) and Haesen et al. (2017) indicates that the stock market is more efficient than the bond market, both for investment grade and high-yield bonds and, as so, stock returns should lead bond returns. However, compared to studies about the correlation between both returns, the studies about momentum spillover looks at a different time frame. Gebhardt et al. (2005) look at a 6 month holding period and the effect after one and six months. Heasen et al. (2017) use data of a monthly frequency.

The research up until this point has mostly focussed on the USA market, with the exception of Norden and Weber (2009), Tolikas (2016) and Cao et al. (2017). The European market has been largely neglected in the research about this topic, probably because a lack of transparency in the European bond market compared to the USA market. However it is not possible to expand the conclusions from the USA market to the rest of the world. Yang et al. (2009) show in their research of government bonds throughout 150 years and covering the USA and UK market that the stock-bond correlations have substantially different patterns in the USA and UK over business cycles. Different effects between stocks and bonds in USA compared to Europe have also been shown in Norden and Weber (2009). As so, this research will examine the possible relationship on the European market.

1.2 Research question and hypotheses

1.2.1 Research question

1. Does a correlation between European corporate bonds and the underlying stocks exist and in which direction?

2. Does this correlation differ between investment grade and high-yield bonds?

The research up until now has focussed mainly on the USA market. Yang et al. (2009) show that USA and UK stock-bond correlations react differently on market conditions. This might imply that this difference persists for the wider European market. Previous research has suggested that high-yield bonds hold a stronger correlation with stocks because of their higher default risk. Investment-grade bonds do not have a high risk of default and for this will not react as much to information about the value of the firm but more to changes in interest rates. This might suggest that a difference in the correlation of investment grade and high-yield bonds with their corresponding stocks exist.

1.2.2 Hypotheses

Hypothesis 1: A correlation exist between European high-yield corporate bonds and stocks.

Based on the previous research in this domain, a correlation between stocks and bonds is expected. Since both are claims on the same underlying assets, they should both react to changes in the value of these assets.

Hypothesis 2: The correlation is a cross-serial correlation from stocks to bonds.

As the European bond market is not yet as transparent as its USA counterpart, it is expected that the European high-yield corporate bond market is less informationally efficient than the European stock market. The stock market is the subject of much more financial analysis and as so, the information about (expected) movements should be extensive.

Hypothesis 3: The correlation is strongest for the high-yield bonds.

Investment grade bonds are regarded as safer and as so should react less to news about the firm. Higher rated bonds are expected to be closely related to risk free returns. High-yield bonds however are closer to default and the reaction to firm news is therefore expected to be more explicit.

2 Data and methodology

2.1 Data

2.1.1 Bond returns

The first dependent variable used in this analysis are daily returns on European corporate bonds (Rbond). Daily returns are used based on the findings of Bessembinder et al. (2009), they studied the empirical methods to analyse abnormal bond returns and find that tests using daily data are more powerful compared to monthly data. Daily returns are calculated from the total return index, retrieved from Thomson Reuters Eikon Datastream. Returns are calculated as following: $R = (RI_t - RI_{t-1})/RI_{t-1}$. Data is collected for all bond exchange in the European Union over a time period of fifteen years, starting on January 1st 2003 until December 31st 2017. Investment grade as well as high-yield bonds will be included in the sample and a dummy will be added to identify both categories. The definition of high-yield bonds is taken from Euronext (2017): 'Based on the two main credit rating agencies, high-yield bonds carry a rating below 'BBB' from S&P, and below 'BAA' from Moody's. Bonds with ratings at or above these levels are considered investment grade.' The rating assigned to bonds in the sample is based upon Moody's rating. A few filters were then applied to this raw data, firstly, only those bonds issued by companies with publicly traded equity were kept in the sample. Furthermore, only fixed rate bonds without any imbedded options will be kept in the sample. The European Central bank (2017) defines a fixed rate bond as: 'A financial instrument for which the coupon is fixed throughout the life of the instrument.' This is done to avoid a bias in the results due to differences between bonds. Lastly, only euro denominated bonds were used to avoid an exchange rate bias. Most firms in the sample issued multiple bonds, to obtain a correct representation of the firm value the bonds will be aggregated on the firm level with the issue amount as weights.

2.1.2 Stock returns

The second dependent variable are the stock returns corresponding to the bond returns already obtained (Rstock). Bond returns are matched to the underlying stock returns which are also obtained from Thomson Reuters Eikon Datastream.

2.1.3 Descriptive statistics

In Table 1, the descriptive statistics for the bonds are shown. Firstly, it is possible to see that the most of the bonds are investment grade, 491 of 592 bonds with a rating of Aaa until Baa3. 101 of the bonds are high-yield. These 592 bonds are distributed among 159 companies. Furthermore, in all classes the standard deviation is extremely high, indicating highly diverse issue amounts.

2.2 Methodology

Firstly, an initial inspection for correlation between the variables will be performed by looking at the correlation between stock and bond returns and the autocorrelation of the stock and bond returns. The autocorrelation is inspected as the bond and stock returns will also be regressed against their own lags.

	Rating	Count	Amount issued	
			Mean	Standard deviation
Investment grade bond	Aaa	1	550 000.0	NA
	Aa1	1	125 000.0	NA
	Aa2	2	750 000.0	353 553.4
	Aa3	11	881 818.2	348 764.1
	A1	36	721 111.1	379 945.7
	A2	57	765 114.0	739 80.3
	A3	74	804 483.1	426 469.4
	Baa1	174	681 773.2	350 772.9
	Baa2	97	547 355.7	276 459.5
	Baa3	38	603 947.4	215 020.9
High-yield bond	Ba1	42	667 261.9	273 219.7
	Ba2	14	628 571.4	251 697.5
	Ba3	18	421 009.0	251 700.8
	B1	7	928 571.4	345 032.8
	B2	2	472 500.0	215 667.6
	B3	10	363 580.0	140 672.7
	Caa1	7	780 000.0	350 713.6
	C	1	114 212.3	NA

Table 1: descriptive statistics for the bonds used in the analysis

The contemporaneous returns will be inspected through a panel regression. For this regression, fixed and random effects will be tested to assess if they should be included in the model. As both investment grade and high-yield bond are included in the sample, each regression will be performed in three versions. Once with the full sample, once with only the investment grade bonds and once with only the high-yield bonds. After these different estimations have been performed, an F-test will be administered to test if the results from the investment grade and high-yield bonds are significantly different. The 2 equations used for these estimations are equations 1 and 2, each will be performed on the three samples.

$$Rbond_i = \alpha + \beta_1 Rstock_i + \varepsilon_i \qquad (1)$$

$$Rstock_i = \alpha + \beta_1 Rbond_i + \varepsilon_i \qquad (2)$$

After the test for a contemporaneous correlation, the cross-sectional correlation will be tested. A panel vector autoregression (VAR) is performed to study the cross-sectional relationship between the stock and bond returns in depth. The lag order selection criteria that will be used is one of Andrews and Lu's moment selection criteria (2001), namely their adaptation of the Akaiki information criteria (MAIC). Earlier studies like Downing et al. (2009), Hong et al. (2012), Tolikas (2016) (2017) and others have used a vector autoregression method to capture the lead-lag relationship between stock and bond returns. However Ronen and Zhou (2013) suggest in their research that this might not be the best choice to find the relationship between both. They argue that a bivariate vector autoregression simply shows if stocks (bonds) lead bonds (stocks), however, they neglect to include the investors ability to react to this lead-lag relationship. This research strategy therefore disregards the economic value of the results. However, Ronen and Zhou do not offer an alternative to the vector autoregression method and as so, the panel vector autoregression will be used. The economic feasibility of a trading strategy based upon these results will be discussed separately.

Regarding the VAR estimation, a model will be estimated where the bond (stock) returns will be regressed against the lagged stock and bond returns. This model is estimated to identify the relationship between the bond and stock returns. Equation 3 will be used in the estimation.

$$y_{i,t} = \sum_{i=1}^{k} y_{i,t-k} + u_i + v_t + \varepsilon_{it} \quad (3)$$

Where y_i is a (1x2) vector of the dependent variables, bond and stock returns. Individual fixed effects are used to capture the differences originating from different bond exchanges and are represented by u_i. Furthermore, time fixed effects, v_t, are employed. A forward orthogonal deviation is applied in order to fulfil the assumption of serially uncorrelated errors. The panel VAR, like the panel regression, will as well be performed for the full sample and the two subsamples. The estimation will be performed by using Stata's pvar package, based upon the research of Abrigo and Love (2016). This package performs a panel VAR with a GMM estimation.

After the panel VAR is estimated, a second determination of predicting value of one variable over the other is performed in the form of a Granger causality test. The Granger causality test shows if there is a bivariate causality between the stock and bond returns. If one variable Granger causes the other, this indicates that this variable precedes the other and as so this market should be more informationally efficient. The null hypothesis says that stock returns do not Granger cause bond returns and bond returns do not granger cause stock returns. Equations 4 and 5 are used for the Granger causality test.

$$Rbond_t = \sum_{i=1}^{n} \beta_{1i} Rstock_{t-i} + \sum_{i=j}^{n} \beta_{2j} Rbond_{t-j} + u_t \quad (4)$$

$$Rstock_t = \sum_{i=1}^{n} \beta_{1i} Rbond_{t-i} + \sum_{i=j}^{n} \beta_{2j} Rstock_{t-j} + u_t \quad (5)$$

In the event that a significant correlation has been identified by the previous tests, the economic significance of these results should be evaluated. This can be assessed by testing if a significant trading strategy can be devised based upon these insights. A trading strategy is constructed in the following manner, assuming that the correlation found is a stock-lead-bond relationship, if the relationship found is in the other way, this strategy will be reversed. The stocks will be divided into portfolios based upon rating, in the case the results are significantly different between both groups. For each stock portfolio, stocks will be divided based upon their performance compared to the portfolio performance, one group for the outperformers and one for the underperformers. In the case a positive (negative) correlation was found, bond portfolios will be constructed in which a long (short) position will be taken for those bonds related to an outperforming stock and a short (long) position will be taken for those bonds corresponding to an underperforming stock. After the portfolios are established, they will be held and revaluated after a holding period corresponding to the predetermined amount of lags. The returns earned from this position will be evaluated against the transaction costs involved in order to determine if this strategy actually has a net profit.

3 Results

3.1 Contemporaneous correlation

An initial check for a contemporaneous correlation is to look at the correlation table. The correlation between stock and bond returns are displayed in table 2, this gives an initial idea of the correlation between both returns. The results show that a correlation between both exists however it is very small. This result gives a small support to hypothesis 1, as the correlation identified is weak.

	Rbond	Rstock
Rbond	1.0000	-
Rstock	0.0055	1.0000

Table 2: correlation between stock and bond returns

3.1.1 Contemporaneous regression

For a more in depth look at the contemporaneous correlation, a panel regression is performed. This regression is estimated six times, like said before, for three different samples and with 2 different dependent variables. To test if the results are significantly different between the two different subsamples, investment grade and high-yield bonds, an F-test is performed. For the estimation where bond returns are the dependent variable, the null hypothesis that the results of both subsamples are not significantly different is accepted, with a p-value of 0.1247 (with F(2, 41312) = 2.08). However, when the stock returns are the dependent variable the null hypothesis is rejected with a p-value of 0.000 (with F(2, 1661892) = 155.55).

The estimations are examined for fixed and random effects, by performing a redundant fixed effects test and a Hausman test. The first estimation requires fixed effects while the second can be estimated using a pooled OLS. The results of these estimations are presented in table 3. For all samples, except the high-yield sample, the R^2 is 0, which implies that the stock (bond) returns do not have any effect on the bond (stock) returns. However for the full sample, the stock (bond) returns are significant which implies that a correlation exists however this has no effect. For the high-yield sample, an extremely small effect is registered. This is in line with hypothesis three which states that the correlation is strongest for the high-yield bonds. These results imply that European bond markets and stock markets are not equally informationally efficient and thus information is assimilated faster in one of these markets.

	Dependent	R^2	Constant	Rbond	Rstock
Complete sample	Rbond	0.000	0.0002378***	-	0.0049694***
	Rstock	0.000	0.0004256***	0.0062914***	-
Investment grade sample	Rbond	0.000	0.0002422***	-	0.0035276
	Rstock	0.000	0.0004497***	0.0035536	-
High-yield sample	Rbond	0.0009	0.0002217***	-	0.010258***
	Rstock	0.0009	0.0003145***	0.0920427***	-

Table 3: contemporaneous regression results

3.2 Cross-sectional correlation

As the returns will also be examined against their own lagged returns, it might be interesting to first take a look at the autocorrelations. To examine if the past returns of the bond or stocks could be useful in the prediction of future returns, the autocorrelation is examined. The results from the test for autocorrelation are presented in table 4. The stock returns show significant autocorrelation for all but the first lag. Bond returns on the other hand show no significant autocorrelation for any lag.

Rstock			Rbond		
Lags	Chi²	p-value	Lags	Chi²	p-value
1-1	2.056	0.1516	1-1	1.560	0.2117
1-2	15.527	0.0004	1-2	3.631	0.1628
1-3	15.758	0.0013	1-3	3.668	0.2996
1-4	25.167	0.0000	1-4	7.223	0.1246
1-5	64.213	0.0000	1-5	7.509	0.1854
1-6	73.874	0.0000	1-6	7.819	0.2517
1-7	78.943	0.0000	1-7	8.164	0.3184
1-8	78.944	0.0000	1-8	8.187	0.4154
1-9	79.560	0.0000	1-9	8.209	0.5132
1-10	79.785	0.0000	1-10	9.151	0.5178

Table 4: autocorrelation test for returns of stock or bond

3.2.1 Lag order selection

In order to perform any of the determinative tests for a cross-sectional correlation, the ideal lag order has to be selected. The lag order selection criteria obtained from Stata are reported in table 5. The ideal lag order is selected based on the adapted Akaiki information criteria (MAIC). From the statistics displayed in table 5, the fifth lag order appears to be the ideal lag order and 5 lags will therefore be used in the panel VAR.

Lag	CD*	MBIC**	MAIC**	MQIC**
1	0.0035771	-308.6902	59.79057	-48.52248
2	0.0328428	-291.0569	36.48155	-59.79672
3	0.2532915	-261.0498	25.54634	-58.69714
4	0.25753	-217.567	28.08686	-44.12185
5	0.2287219	-223.5273	-18.81576	-78.98968
6	0.2771804	-173.003	-9.233732	-57.37287
7	0.2935838	-135.8743	-13.04735	-49.1517
8	0.3105538	-90.46443	-8.5759802	-32.64937
9	0.320134	-42.5383	-1.595983	-13.63077
10	0.328827	-	-	-

* coefficient of determination

** model selection criteria developed by Andrews and Lu (2001)

Table 5: lag order selection criteria for the determinative tests

3.2.2 Panel Vector Autoregression model

To test if there is a significant difference between the results of the estimation for the subsample for investment grade bonds and high-yield bonds, a Chi²-test is executed. The results of the Chi²-test to test for the equality of coefficient shows that the results from the subsamples, investment grade bonds and high-yield bonds, are significantly different. The null hypothesis which states that the coefficients of both subsamples are equal is rejected with a p-value of 0.000 (with $Chi^2(3) = 461.35$). This result agrees the third hypothesis, which implies a difference between investment grade and high-yield bonds in their correlation with stock returns.

The results of the panel VAR estimations are represented in table 6. The first and second lag of the stock returns have a significant effect on the current bond returns, as expected following hypothesis 2. However the effect is strongest in the high-yield bonds. The stronger effect in high-yield bonds is consistent with hypothesis 3. The fourth lag of stock returns also has a significant effect on bond returns however only at the 90% level. These results imply that, as expected, that stock returns lead bond returns and that the stock market is more informationally efficient. Moreover, as the effect is larger for high-yield bonds, this suggest that high-yield bond returns are, in fact, closer related to the stocks of a company than investment grade bonds. The full sample and investment grade bond returns are also correlated with their own third and fourth lag, the high-yield bonds are correlated with their first lag. This indicates that the effect of firm news in high-yield bond takes up to two days to be fully integrated in the price. These correlations were unexpected following the autocorrelation test which showed no autocorrelation for bond returns.

The stock returns show no correlation with the lagged bond returns. This is in line with the second hypothesis which assumed the correlation to be one where stocks lead bonds. Lagged stock returns however do show a significant effect on current stock returns. The full sample stock returns show to be correlated with the first, second and fifth lagged stock returns. The first and fifth lagged correlation seem to be originating in the investment grade sample and the second lagged correlation in the high-yield sample.

All estimations where further tested if they satisfied the stability condition. For all estimations the eigenvalues lay within the unit circle and as so all estimations are stable.

	Complete sample		Investment grade subsample		High-yield subsample	
	Rbond	Rstock	Rbond	Rstock	Rbond	Rstock
Rbond L1	-0.0783345	-0.0020459	-0.0878173	-0.0014854	0.0216235*	-0.001789
Rbond L2	-0.1018037	0.0007053	-0.0931221	0.0003212	-0.3393354	0.193153
Rbond L3	0.5083587**	-0.0062852	0.5228947**	-0.006901	-0.3393354	0.0132494
Rbond L4	0.119087*	0.0062999	0.1303159*	0.0052118	-0.100662	0.0353737
Rbond L5	0.08018	-0.0072111	0.0770208	-0.0073082	0.0034371	0.0026725
Rstock L1	0.0167764**	-0.0120266*	0.0153261*	-0.056594*	0.0221124***	0.0015318
Rstock L2	0.0098733***	-0.0115434*	0.0089984**	-0.0082246	0.018239**	-0.0247767**
Rstock L3	0.0041859	0.0036891	0.0068364	-0.0050395	0.010081	0.0008287
Rstock L4	-0.0088444	0.0013359	-0.0088615	0.0010988	0.0104694*	-0.0004574
Rstock L5	0.0510618	-0.0131051**	0.0664099	-0.0135493**	0.0051381	-0.01418

* significant at 90% level, ** significant at 95% level, *** significant at 99% level

Table 6: coefficients and significance levels for the panel VAR estimations

3.2.3 Granger causality test

Following the panel VAR, a Granger causality test is performed for all three subsamples. The results of the Granger-causality test are presented in table 7. Consistent with the hypothesis 2, the Granger causality test determines that the stock returns Granger cause bond returns however bond returns do not Granger cause stock returns. This is true for all samples. This result is also consistent with the results from the panel VAR.

		Chi²	df	P-value
Complete sample	Rbond does not granger cause Rstock	7.205	5	0.206
	Rstock does not granger cause Rbond	25.758	5	0.000
Investment grade subsample	Rbond does not granger cause Rstock IG	7.403	5	0.192
	Rstock does not granger cause Rbond IG	16.719	5	0.005
High yield subsample	Rbond does not granger cause Rstock HY	1.672	5	0.892
	Rstock does not granger cause Rbond HY	56.48	5	0.000

Table 7: Granger causality test

3.3 Trading strategy

A trading strategy is tested in order to predict bond returns based on stock returns. This is tested because a correlation as well as Granger causality was found where stock returns lead bond returns. The trading strategy is not tested for stock returns as no correlation is discovered and bond returns also do not Granger cause stock returns.

The portfolios are established based upon rating class, investment grade or high-yield bonds, as the F-test showed results for both subsamples to be significantly different from each other. As the relationship found between the bond returns and the lagged stock returns is positive, a long position will be taken into those bond corresponding to stocks which outperform the portfolio and a short position in those corresponding to stocks which underperform the portfolio. For the bond returns, the two day returns is taken as the panel VAR estimation is significant up until the second lag.

When testing this trading strategy, the total portfolio returns for the investment grade sample are € 0.14823, € 0.02536 and € 0.50671 for the start of January, February and March respectively. For the high-yield sample, the total portfolio return are € 0.10709, € 0.05727 and € 0.02621, for the same periods. Overall, these returns are positive however extremely low and will not outweigh the transaction costs endured to perform trades for all these bonds. As Tolikas (2017) also noted in his research and test for a possible trading strategy, a profitable trading strategy is probably not possible, however it might be possible to react to default-bound bonds and avoid a complete loss.

4 Conclusion

The aim of this research is to examine the relationship between corporate bonds on the European bond exchanges and the corresponding stocks. The informational efficiency of these two markets is investigated to determine if one market's returns could be predicted based on the other's returns. In case, one market is more informationally efficient thus a cross-sectional correlation exists, this market's returns might be used to predict behaviour in the other market. The relationship is researched as the correlation from stock to bonds as well as from bonds to stock, both the contemporaneous as well as the cross-sectional correlation is examined. A contemporaneous correlation implies an equal informational efficiency between both markets where a cross-sectional relationship indicates the leading market as more informationally efficient.

Existing literature mainly focusses on the USA market and in general the European markets have been largely neglected in previous research. Previous research on this topic has presented conflicting results with results indicating a cross-sectional correlation, a correlation in both directions or none at all. The hypotheses adopted in this research are firstly, that a correlation exists between stock and bond returns. Furthermore, that the correlation is cross-sectional from stocks to bonds and finally that this correlation is more pronounced in high-yield bonds than in investment grade bonds.

The results of this research showed a very weak contemporaneous relationship between stock and bonds returns which only held some explanatory power for the high-yield subsample. This indicates little to no equal informational efficiency between both markets. A cross-sectional correlation is identified where stock returns lead bond returns, however no correlation was found in the opposite direction. This shows that the European corporate bond is less informationally efficient than the stock market. This means that information about a firm is distributed faster and more efficient throughout the stock market, the bond market on the other hand is less efficient and it takes more time before information about the firms value is fully integrated into bond prices. Furthermore, the correlation found where stocks lead bonds is stronger for the high-yield subsample. This indicates that high-yield bonds, as expected, are closer related to stocks. This was expected because investment grade bonds are considered to be relatively safe and concerns about the cash flow are low. High-yield bonds, on the contrary, are closer to default and the reaction to firm news will therefore be stronger. Lastly a trading strategy based upon these results is attempted. Despite the fact that a significant correlation is identified, a profitable trading strategy is not. The return before transaction costs is barely positive and will disappear entirely if transaction costs are taken into account.

Even though a correlation is revealed, this might not give a realistic image of the situation. Ronen and Zhou (2013) suggest in their research that some control variables should be added. They argue in their research that when dynamic liquidity, trade size and timing effects are taken into account, the lead-lag relationship, identified in this paper as well as in others, would disappear. Due to the non-transparent European bond exchanges, information about trade size and volume was not available from Eikon Datastream. When further steps are taken to improve the transparency on the European bond exchanges, this line of research might be further explored to improve the understanding of the relationship between both markets.

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Press announcement

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For immediate release

Stock returns predict bond returns

Results from a recent master thesis presented at KULeuven university show that the stocks from a firm incorporate information faster than the bonds from the same firm. As stocks incorporate new information about the firm faster than bonds, the stock's behaviour could be used to predict the reaction of bonds to the same news.

Information incorporation

The results from this master thesis show a relationship exists between today's bond returns and the stock returns from yesterday and two days ago. This implies that stocks react faster and more efficient to new information about the firm compared to bonds from that same firm. The relationship between stocks and bonds is found to be stronger for high-yield bonds, which are rated lower, than for investment grade bonds. The relationship between high-yield bonds and stocks is stronger because these bonds are more likely to go into default. As their cash flow is less certain, the reaction to news about the firm is stronger, more similar to the reaction in stocks. Even though a relationship between both was found, it is quite small, stock return movement is not able to explain all of the bond return movement.

Trading strategy

Nonetheless a relationship was found, a profitable trading strategy cannot be established based on this. When testing the trading strategy, a very small profit was made however this profit will not be enough to cover the transaction costs associated with the necessary trades. The stock returns do not seem to explain enough of the bond movements to get accurate enough predictions for a profitable trading strategy. Even though the results cannot be used to build a profitable trading strategy, they might be used to detect bonds which are about to go into default and avoid a complete loss. The results of this research is based on information from 159 firms over a 15 year time period.

---END OF MESSAGE--

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