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The Informational Efficiency of the Norwegian Corporate Bond Market

An empirical analysis of predictability in cross-market returns between stocks and corporate bonds in Norway

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NORWEGIAN SCHOOL OF ECONOMICS

Preface

This thesis marks the end of our MSc in Economics and Business Administration at the Norwegian School of Economics.

In our work with the thesis, we have taken the opportunity to learn more about the Norwegian market for corporate bonds. Intrigued by a guest lecture on bond valuation and market signals, held by Thomas Eitzen, Chief Analyst of Fixed Income at SEB, we examine the relative informational efficiency of corporate bonds in Norway. Furthermore, as previous research on the Norwegian corporate bond market is scarce, our topic is of interest to both researchers and practitioners.

We would like to thank our supervisor, Aksel Mjøs, for the valuable guidance and feedback we have received during our work with the thesis. Further, we are grateful to Hannah Marie Holm at Nordic Bond Pricing and Per Marius Pettersen at Stamdata. They have taken the time to both provide and answer questions concerning the datasets used in our analysis. Lastly, we would like to thank Johannes Kolberg at Børsprosjektet at NHH for help with the OBI database.

Abstract

This paper examines the relative informational efficiency of the Norwegian corporate bond market. To overcome problems with infrequent trading, we supplement transaction data for bonds and stocks with bond price estimates, and employ a VAR model to determine predictability in cross-market returns. In periods where news about common factors are more prominent, we find evidence of stocks leading bonds. In contrast, during periods of increased investor awareness, firm-specific news typically dominates, and related bonds and stocks exhibit equal informational efficiency. These findings suggest that the type of new information revealed might determine whether bondholders choose to enter the market.

Contents

1. Introduction

Following the 2014 collapse in oil prices, multiple oil-related firms saw the market value of their securities plummet at the Oslo Stock Exchange (OSE). Amongst these was Seadrill, once the world's largest offshore drilling operator. At the time of the collapse, the firm had their stock, as well as one of their issued bonds, listed at the OSE. While both types of securities experienced a dramatic fall in the subsequent period, the bond seemed to be lagging the stock by a large margin. The firm ultimately filed for bankruptcy in the fall of 2017. In retrospect, one could question whether bondholders grasped the impact on the firm of the news released over the period, or even looked at the stock price.

Investors in both stocks and bonds hold claims on the same corporate assets. Financial theory suggests that, in efficient capital markets, new information about the future cash flow from assets should be reflected in both security types simultaneously. However, multiple studies challenge the validity of the efficient market hypothesis. In particular, they find predictive power in past returns of securities both intra-market and cross-market. This paper examines the properties of the Norwegian corporate bond market and elaborates on the relationship between pricing of bonds and stocks in Norway. More specifically, we address the following two research questions: (1) Do corporate bonds tend to lead or lag their associated stock in incorporating new information into the pricing? (2) What drives predictability in cross-market returns between corporate bonds and their associated stock?

Differences in informational efficiency between the stock and bond markets, where one market could predict the other, is obviously of interest to all investors in Norwegian securities. Existing literature based on US data reveals an opaque relationship between the price movements of stocks and corporate bonds, with conflicting results across several studies. This paper gives insight into when differences in informational efficiency appear and can help explain the inconsistencies in previous studies. As the first analysis of its kind conducted on Norwegian data (to our knowledge) this paper also contributes to the understanding of the unique properties of the Norwegian corporate bond market.

Previous research on the Norwegian corporate bond market is scarce. While recent years have seen increased trading activity, and subsequently made it more conceivable to conduct meaningful empirical analysis, the majority of listed corporate bonds trade infrequently. To overcome the problem of infrequent trading in this study, a dataset with bond price estimates is obtained from Nordic Bond Pricing (NBP). NBP is a provider of daily price estimates for bonds, established in 2013 as a joint venture between the Norwegian Fund and Asset Management Association and Nordic Trustee. The use of bond price estimates allows us to greatly expand the number of bond-stock pairs in our sample, as well as remove noise usually present in transaction data. However, considerations must be taken when we analyse informational efficiency. If investors are unable to trade at the estimated bond prices, the actual lead-lag relationship between bonds and stocks may deviate from our results.

In line with previous studies, we employ a bivariate vector-autoregressive model (VAR) to assess the predictability in cross-market returns, both on portfolio and security level. We conduct the analysis using daily bond price estimates, and supplement with available transaction data in periods of heightened trading activity, as well as for the most actively traded bonds. To evaluate the results, we apply two test statistics: the Granger causality test and the sum test. Furthermore, to examine the effect of common factors, we evaluate sensitivity in our results to market and interest rate risk and add the returns on the OSEBX index and the 3-year Norwegian government bond as control variables.

First, our results show that the behaviour of corporate bonds depends on the associated credit risk, as measured by the bonds' credit rating. While high yield bonds behave more like equity, investment grade bonds are primarily sensitive to changes in the interest rate. This also affects the relationship between bond and stock returns. Using daily returns for the entire analysis period, we find some evidence of a stock lead in lower rated bonds. Noticeably, there are cross-sectional differences in our sample, and predictability appears to increase with credit risk. Of the predictable bonds, a significant proportion is issued by firms that experienced financial distress during our analysis period.

Second, evidence of a stock lead disappears when we examine periods of heightened trading activity and investor awareness. Around earnings announcements, our results indicate that corporate bonds are just as informationally efficient as their associated stock. These findings suggest that in periods where news about common factors are more prominent, as represented by the volatile oil price during our analysis period, stocks are leading bonds. In contrast, during periods of increased investor awareness, firm-specific news typically dominates, and we see an improvement in the relative informational efficiency of corporate bonds. The type of new information revealed might determine whether bondholders choose to enter the market, which helps explain why we get different results depending on what period we analyse, as well as the conflicting results in previous studies.

The rest of the paper is organised as follows: section 2 presents relevant background and literature for our analysis, including the empirical method we apply; section 3 elaborates on the stock and corporate bond data; therein the datasets, adjustments and descriptive statistics; section 4 provides the empirical analysis and our discussion of the relative informational efficiency of corporate bonds; and, lastly, section 5 summarises the results and concludes the paper.

2. Background and literature

In this section, we present relevant background and literature for the analysis. First, we review and discuss previous studies on relative informational efficiency in stocks and corporate bonds. Second, as previous studies show ambiguous results, we address why differences in informational efficiency between stocks and bonds of the same issuer might occur. Third, we examine relevant characteristics of the Norwegian security markets, and highlight key differences from the US market. Lastly, we present the empirical method used in the analysis.

2.1. Informational efficiency in stocks and corporate bonds

Investors in stocks and bonds issued by a firm hold claims on the future cash flow from the firm's assets. As shown by Merton (1974), stocks can be expressed as a call option on the value of a firm's assets, and corporate bonds as a portfolio of risk free debt and a short position in a put option on the same assets. Thus, a change in either the mean value or volatility of assets affects the value of both security types. An increase in the mean value has a positive impact on both stocks and bonds, while an increase in volatility has a positive impact on stocks, and a negative impact on bonds.

In efficient capital markets, new information about the mean value or volatility of assets should be reflected in security prices instantaneously (see Fama (1970)). As noted by Kwan (1996), the relationship between price movements in stocks and bonds depends on the type of information revealed. If news about the mean value of assets are most frequent, stock and bond returns should exhibit positive correlation. On the other hand, if news about the volatility of assets are most frequent, stock and bond returns should exhibit negative correlation.

Early studies on the field find that returns in the two security types are positively and contemporaneously correlated and conclude that firm-specific news on average reveal information about the mean value of assets (see Cornell and Green (1991), Kwan (1996) and Hotchkiss and Ronen (2002)). Recent studies substantiate these results but emphasise the difference between investment grade and high yield issues. In particular, they find that the contemporaneous correlation is considerably stronger between stocks and high yield bonds. Downing et al. (2009) and Hong et al. (2012) attribute these findings to differences in credit risk. While the cash flow of investment grade bonds is relatively stable, high yield bonds, like stocks, are more sensitive to firm-specific news due to a higher probability of default.

Multiple studies challenge the validity of the efficient market hypothesis and find predictive power in past returns both intra-market and cross-market[1]. Informational efficiency in the markets for stocks and corporate bonds determines how fast prices react to new information about the mean value or volatility of assets. If one market is more efficient than the other, cross-market returns should exhibit predictive power, establishing a lead-lag relationship between the two types of securities.

Previous research on the lead-lag relationship between stocks and corporate bonds provides ambiguous results. Using weekly dealer quotes, Kwan (1996) finds that stocks lead bonds in all but the AAA-rated issues, with no significant relationship the other way. Similarly, Downing et al. (2009) find that stock returns predict the returns of high yield bonds on a day-to-day level and intra-day level. However, no such relationship is found for investment grade issues. An opposing view is found in Hotchkiss and Ronen (2002). They study the same return horizons as Downing et al. (2009) but fail to establish a lead-lag relationship between the two security types. The conflicting results have been attributed to sample differences. While Kwan (1996) relies on weekly dealer quotes, Hotchkiss and Ronen (2002) and Downing et al. (2009) use high frequency transaction data.

Recent papers try to overcome limitations in the previous studies. Hong et al. (2012) address several methodological issues and find that stock market returns hold predictive power over the returns of bonds across all rating categories. While the notion that stocks lead investment grade bonds contrasts the results of Downing et al. (2009), their results

[1] Recognised examples include the momentum effect (Jegadeesh and Titman (1993)) and the slow diffusion of new information in the stock market (Hong and Stein (1999)).

suggest that the lead-lag relationship is considerably stronger in high yield issues. In comparison, Ronen and Zhou (2013) find that stock leads disappear when institutional trade dominance and other bond trading features are accounted for. Based on their result, they argue that the markets for stocks and corporate bonds are equally informationally efficient. Lastly, Bittlingmayer and Moser (2014) use monthly observations to study the informational role of past bond returns. They find a partial lead in high yield bond returns on future stock prices, with negative returns being correlated with a future price decline in the associated stock.

2.2. Why do some markets lag?

In the aforementioned research, the presence of a lead-lag relationship has been attributed to the activity of informed traders, market characteristics and behavioural finance. Informed traders, both insiders and professionals, take a position in the market that allows them to make a return on their information (see Grossman and Stiglitz (1980)). Their decision to trade in one particular market depends on differences in transaction costs, insider-trading regulations and exposure to news.

Informed trader activity is closely related to different investor types in the stock and bond markets. As noted by Schultz (2001), trading in the corporate bond market is primarily institutional. A dominance of institutional investors has several important implications with regards to informational efficiency. First, Hendershott et al. (2015) find that institutional trading predicts firm-specific news. Compared to retail investors, institutions possess greater resources that allow them to obtain and process relevant information. Second, trading activity in the corporate bond market is significantly lower than that of other financial assets. As bonds are fixed-income securities with a finite maturity, institutions often rely on buy and hold strategies, where bonds are incorporated into portfolios and held to maturity. Alexander et al. (2000) summarise anecdotal evidence of this behaviour. Lastly, transaction costs differ substantially between retail-sized and institutional-sized trades. In line with previous studies, Edwards et al. (2007) find transaction costs in the corporate bond market to decrease significantly with trade size.

Further, the concentration of financial intermediates differs between the stock market and the market for corporate bonds. Financial analysts provide valuable information about expected future returns to stock- and bondholders. Womack (1996) and Barber et al. (2001) find significant post-recommendation stock returns in line with analyst forecasts, while de Franco et al. (2009) find similar return patterns in the corporate bond market. In addition, bond market reactions are substantially stronger following recommendations from bond analysts, compared to recommendations from stock analysts. As analyst coverage of stocks greatly exceeds that of corporate bonds, the informational role of financial intermediates is relevant in the assessment of informational efficiency.

Later studies look to behavioural finance to explain findings of predictability in past returns. As shown by Hong and Stein (1999), if investors are able to process only a subset of the available information, there will be an initial underreaction and price drift in securities. Research on the US stock market supports this notion. Cohen and Frazzini (2008) show that investors fail to recognise information about future returns across economically linked firms, such as customer-supplier links, while DellaVigna and Pollet (2009) find substantial post-earnings drift after Friday announcements when investor inattention is more likely. Further, several studies show that investor sentiment affects prices. A topic of particular interest is the reaction to positive and negative news. Chan (2003) and Hou (2007) examine information diffusion in stock prices and find that underreactions are stronger following negative news.

2.3. Characteristics of the Norwegian bond market

Most studies of informational efficiency in corporate bond pricing utilise US market data. In the following, we highlight relevant features of the Norwegian bond market, as well as key differences from the US bond market.

Not surprisingly, the Norwegian bond market is considerably smaller than the US and the largest European bond markets in terms of size. At the end of 2016, total outstanding bond volume in the Norwegian market summed to USD 206 billion, less than one percent of the corresponding US volume. Corporate bonds amounted to approximately 2/3 of total volume, of which $\frac{3}{4}$ was issued by financial institutions, as shown by Ødegaard (2017).

While research on the Norwegian bond market is scarce, Ødegaard (2017) provides a detailed analysis of market features in a recent working paper. Of particular interest to our analysis, is his study of activity and trading costs at the OSE and Nordic ABM. First, he finds a noticeable increase in trading activity in corporate bonds[2] over the last years. This trend is present in both financial and non-financial issues. While the former is due to trading in covered bonds, activity in non-financial issues is related to the increased use of bonds instead of bank loans for debt financing of Norwegian firms. However, the majority of listed corporate bonds trade infrequently, with less than ten registered trading days a year. Second, he finds that trading costs in the Norwegian market are lower for corporate bonds than for stocks. This contrasts the US market. As shown by Edwards et al. (2007), in the US, trading costs in corporate bonds typically exceed that of stocks.

The results reported in Ødegaard (2017) have important implications for our study of informational efficiency in the Norwegian corporate bond market. First, infrequent trading in Norwegian corporate bonds makes statistical inference based on transaction data difficult. Second, transaction costs are relevant for informed traders in their choice of market and might affect investor preferences. Thus, when comparing our results to previous studies, differences in transaction costs should be considered.

Another important characteristic with implications for our analysis, is the exposure to common factors in the Norwegian economy and security markets, particularly the oil price[3]. Energy firms account for approximately 1/3 of total stock market value at the OSE[4] and represent a significant issuer of corporate bonds in Norway. The influence of energy firms is illustrated in Panel A in Figure 2.1, which makes our sample sensitive to changes in the oil price. The two indices are clearly positively correlated, and support findings in Gjerde and Sættem (1999) and Næs et al. (2009). Both studies find that changes in the oil price affect expected corporate cash flows across a broad range of

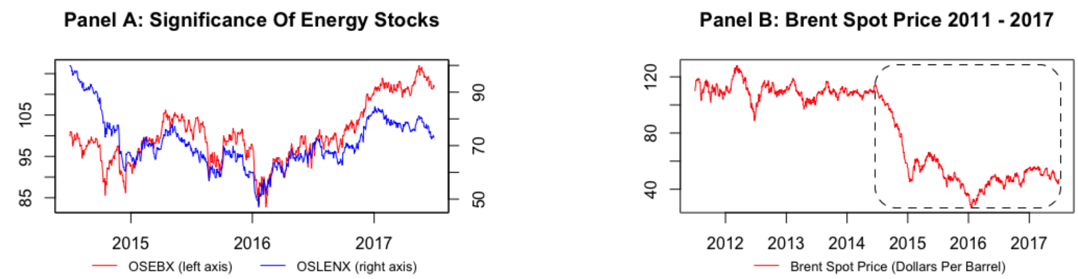
[2]Corporate bonds include all non-governmental bonds, herein covered bonds.

[3]Gjerde and Sættem (1999), Næs et al. (2009) and Bjørnland (2009) explore this topic in more detail.

[4]As per 01.12.2014. Retrieved from Oslo Børs.

sectors in the Norwegian economy. Panel B graphs the Brent oil price during our three-year sample period. Generally, the period is characterised by increased volatility and a collapse in oil prices[5]. This has important implications for our analysis.

Figure 2.1 – Oil price sensitivity in the Norwegian security markets.



Note: Figure 2.1 illustrates the significance of energy stocks at the OSE. Panel A displays the pairwise movement of the Oslo Børs Benchmark Index (OSEBX) and the Oslo Energy Index (OSLENX) from 01.07.2014 to 30.06.2017. Both indices have been normalised to 100 at 01.07.2014. Panel B displays the development in the Brent Spot Price from 01.07.2011 to 01.07.2017. The dashed figure marks our sample period. Sources: Oslo Børs and the U.S. Energy Information Administration.

First, information about the oil price is publicly available to all investors. As changes in the oil price affect future cash flows from corporate assets, shocks should be reflected in security prices immediately. If one market generally reacts faster to changes in the oil price, increased volatility would lead to predictability in cross-market returns. Previous studies focus solely on stock market returns and find that stocks react sluggishly to changes in the oil price (see e.g. Driesprong et al. (2008) and Bjørnland (2009)).

Second, the collapse in oil prices has affected the financial position of firms within the oil-related sector, many of which have experienced financial distress during our sample period. Downing et al. (2009) find increased predictability in cross-market returns for firms in financial distress. They argue that firms in financial distress disclose news of sufficient importance to trigger trading in both stocks and bonds, regardless of transaction costs. Most corporate bonds trade infrequently. Thus, increased trading activity in periods of financial distress reveals the true informational efficiency of corporate bonds.

[5]Table A.1 in Appendix A displays summary statistics for the Brent Spot Price.

2.4. Empirical method

Following previous studies, we employ a bivariate vector-autoregressive model (VAR) to determine predictability in cross-market returns (see e.g. Downing et al. (2009) and Ronen and Zhou (2013)):

$$z_t = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=1}^{L} \beta_{S,i} R_{S,t-i} + \epsilon_t \tag{1}$$

where $z_t = [R_{B,t}, R_{S,t}]$, $R_{B,t}$ is the daily return on a bond (bond portfolio) and $R_{S,t}$ is the daily return on the associated stock (stock portfolio)[6]. The lag length, L, is set to 5 days, guided by the Akaike Information Criterion (AIC) and previous research. Our results are not sensitive to the choice of lags. We employ White-corrected standard errors, to account for heteroscedasticity in the error terms.

In order to examine predictability in cross-market returns, we entertain the idea of Granger causality[7]. To determine whether stocks (bonds) Granger cause bonds (stocks), an F-test is conducted on cross-market coefficients from the estimated VAR model, with the null hypothesis that they are all statistically equal to zero. A rejection of the null indicates that past returns in stocks (bonds) contain information about current returns in bonds (stocks). As advocated by Downing et al. (2009), we also conduct an F-test of whether the sum of estimated cross-market coefficients is equal to zero. This test provides additional insight when the Granger causality test is rejected based on a small subset of the estimated coefficients. A simultaneous rejection of both tests enhances the indication of a lead-lag relationship.

When we use transaction data, a few important methodological issues must be addressed. First, we impose stricter trading activity criteria for bonds to be part of the analysis. As transaction data for most Norwegian corporate bonds are negligible, stricter activity

[6]We also estimate the VAR model using weekly returns and find qualitatively similar results. These results are reported in Appendix B.

[7]Stock (bond) returns are said to Granger cause bond (stock) returns, if past stock (bond) returns provide statistically significant information about current bond (stock) returns, when past bond (stock) returns are accounted for.

criteria are necessary to draw meaningful inference from our results. For included issues, a zero return is assumed on trading days where no trade occurred. Second, for all but the initial analysis using the most actively traded bonds, the VAR model is estimated using a pooled OLS. The pooled model allows us to increase the number of observations, while standard errors are clustered on firm level, to account for correlation between bonds issued by the same firm.

To validate our analysis of predictability in cross-market returns, we examine the effects of changes in the market and interest rate risk on our results. Market risk is measured using the OSEBX index, and interest rate risk using the 3-year Norwegian government bond[8]. To conduct our analysis, we first estimate the following regression, as specified in Cornell and Green (1991):

$$r_{B,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{OSEBX,i} R_{OSEBX,t-i} + \epsilon_t \tag{2}$$

where $r_{B,t}$ is the daily return on a portfolio of bonds, $R_{T,t-i}$ is the daily return on the 3-year Norwegian government bond and $R_{OSEBX,t-i}$ is the daily return on the OSEBX index. While this specification allows us to study bond return sensitivity to common factors, firm-specific news are excluded. To align our discussion of sensitivity to that of informational efficiency, we include stock portfolio returns in the above equation. More specifically, we follow Hotchkiss and Ronen (2002) and Downing et al. (2009), and estimate:

$$r_{B,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{S,i} R_{S,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{OSEBX,i} R_{OSEBX,t-i} + \epsilon_t \tag{3}$$

where $R_{S,t-i}$ is the daily return on the associated stock portfolio. While market risk is reflected in both OSEBX returns and stock portfolio returns, we would expect the latter to be significant if bond returns are sensitive to firm-specific news. As in the

[8]Represents the maturity closest to the average of our sample. It is a synthetic three-year yield calculated by weighting two government bonds with shorter and longer residual maturity, respectively. Data and definition retrieved from Norges Bank.

VAR model, the choice of lag length, L, is set to 5 days in both equations. Finally, consistent with previous studies, we employ standard errors robust to heteroscedasticity and autocorrelation in the error terms using the Generalized Method of Moments, as proposed by Hansen (1982)[9].

[9] We get qualitatively similar results using OLS with heteroscedasticity robust standard errors.

3. Data description

This section describes the data used in our analysis. First, we introduce the primary data sources: Oslo Børs Informasjon (OBI), Nordic Bond Pricing (NBP) and Stamdata. Second, selection criteria and necessary adjustments to fit our analytical purposes are presented. Lastly, we provide and discuss descriptive statistics.

3.1. Data sources

Transaction data is obtained from OBI[1]. The OBI database contains information about trading in stocks and bonds listed on the OSE and the Nordic ABM. For our analysis, OBI provides daily closing prices and turnover in stocks, as well as closing prices and trading volume in bonds. In order to calculate daily returns in stocks, the closing prices obtained from OBI are adjusted for non-trade days and stock splits. No such adjustments are available for bonds, and transaction data is scarce due to infrequent trading.

To overcome the problem of infrequent trading, a dataset with corporate bond price estimates is obtained from NBP[2]. NBP is a provider of daily price estimates for bonds, established in 2013 as a joint venture between the Norwegian Fund and Asset Management Association and Nordic Trustee. As an independent third party, NBP collects and utilises information from a wide array of sources to deliver reliable estimates. This includes credit spreads, bid-ask quotes and transaction data from relevant market participants (e.g. banks and brokerage houses), as well as market events and news.

There are two advantages in using price estimates in our analysis. First, price estimates allow us to greatly expand our data sample. Only a handful of Norwegian corporate bonds trade frequently enough to make statistical inference based on transaction data. In comparison, NBP provides daily price estimates for more than 3000 bonds in the

[1] See http://mora.rente.nhh.no/borsprosjektet/

[2] See http://nordicbondpricing.no/

Nordic markets. Second, price estimates remove noise usually present in transaction data. In closing prices from OBI, failure to control for differences between retail-sized and institutional-sized trades, as well as mixed observations of bid and ask prices, might give inconsistent bond returns[3]. This is not the case with price estimates from NBP. As the dataset obtained from NBP reports mid-prices, bond returns are unaffected by transaction costs.

However, there is one apparent disadvantage in using price estimates; they do not necessarily reflect the prices investors are able to trade on in the market. While NBP is able to update their estimates when firm-specific news is released, it is plausible that low liquidity in corporate bonds prevents investors from reacting to the same information.

To summarise, the use of corporate bond price estimates is well suited to examine the structural relationship between stocks and bonds, as described in Merton (1974). However, considerations must be taken when analysing informational efficiency. In particular, bond price estimates allow us to generalise our findings due to a larger sample and remove noise. Both are important to determine the impact of firm-specific news on asset prices. If, on the other hand, investors are unable to trade at the estimated bond prices, the actual lead-lag relationship between stocks and bonds could deviate from our results.

To expand our analysis, we combine data from OBI and NBP with the Stamdata database[4]. Stamdata is a Nordic Trustee subsidiary that provides reference data for Nordic debt securities. These data are used to calculate descriptive statistics, as well as to stratify our sample into portfolios based on credit rating and sector.

3.2. Sample criteria and adjustments

Our sample is based on price and reference data for 783 corporate bonds in the period from 01.07.2014 to 30.06.2017. The bonds are selected based on several criteria: the bonds must be issued at 30.03.2017 at the latest, and mature at 30.09.2014 at the earliest; the

[3]Ronen and Zhou (2013) find that evidence of stock leads disappear when institutional dominance is accounted for.

[4]See https://nordictrustee.com/stamdata1

bonds must be listed on either the OSE or the Nordic ABM; the bonds must be issued in NOK; the bonds cannot contain equity-like features; and lastly, the bonds need a single, constituent stock traded at the OSE.

The first criterion guarantees a minimum of three months of daily observations to make statistical inference. The second allows us to garner transaction data from the OBI database and supplement the bond price estimates obtained from NBP. The third removes currency effects due to changes in the exchange rate. The fourth removes bonds with equity-like features, such as convertible debt. As noted by Kwan (1996), these bonds behave more like equity in the presence of news and might exhibit a different stock-bond relationship than straight bonds, obscuring our results. The final criterion allows us to obtain stock prices from the OBI database, which is essential to compare cross-market returns.

In order to carry out a meaningful analysis, some adjustments and calculations are necessary. First, we include a trading activity criterion. As noted earlier, trading activity in the Norwegian corporate bond market is limited. While the use of bond price estimates allows us to expand our sample, we demand at least one trade in included bonds during our sample period. This criterion secures a minimum of trading activity, as well as transaction data from the OBI database. Of the initially selected bonds, only 277 traded in the three-year period from 01.07.2014 to 30.06.2017. This gives us an analysis sample of 277 bonds in total, issued by 63 different firms[5].

Second, we calculate individual daily security returns. For each of the 63 firms in our sample, individual daily stock returns are calculated using closing prices from the OBI database. To get consistent results, the prices obtained from OBI are adjusted for non-trade days and stock splits. Generally, OBI assumes a zero return on days without registered trades. No adjustments are made for dividend payments.

For the primary analysis, bond returns are calculated from the price estimates provided by NBP. These estimates are clean price, and do not include accrued interest. As we are interested in the correlation between cross-market returns due to changes in firm

[5]For characteristics of the full bond sample, see Table A.2 in Appendix A.

fundamentals, accrued interest is omitted from the analysis. In addition, bond returns are calculated from actual transaction data obtained from OBI. These returns provide additional insight and are useful to evaluate the validity of using price estimates in our analysis. To calculate bond returns from transaction data, we use the last observed trade on-exchange each day. No price information is available for bond trades after market close. Following Hotchkiss and Ronen (2002) and Downing et al. (2009), a zero return is assumed for trading days without any registered trades.

Third, following previous studies, we use reference data from Stamdata to construct equally weighted bond portfolios stratified by credit rating and sector (see e.g. Kwan (1996) and Downing et al. (2009)). This allows us to study subgroups of bonds with similar characteristics. We categorise the bonds into two rating groups: investment grade issues (BBB and up) and high yield issues (below BBB); and seven sectors: finance, industry, oil & gas, real estate, seafood, shipping and other non-financials. To compare cross-market returns, we construct equally weighted stock portfolios corresponding to the bonds present in each bond portfolio. If one firm is the issuer of multiple bonds in a portfolio, the firm's stock receives increased weight in the stock portfolio.

It is important to note that Stamdata only provides the current credit rating and sector for outstanding bonds, and the last observed rating and sector for matured bonds. Thus, the groups are static over our sample period. This is a simplification. Changes in financial outlook affect issuer and bond ratings, even though the use of investment grade and high yield rating categories only, limits the effect of these rating migrations. In comparison, the sector a firm operates within is more static in nature.

Lastly, we obtain information about daily trade volume from the OBI database. As no information is available for intra-day transactions, trading volume is useful to examine trading activity, and accentuates daily differences. OBI reports two measures of bond trading volume: official volume and non-official volume. In our analysis, only the former is utilised. Official volume includes auto-matched trades, uncrossed trades and regular trades off-exchange (over-the-counter).

3.3. Descriptive statistics

Table 3.1 displays summary statistics for the 277 bonds in our analysis sample. Approximately 1/3 falls within the high yield category, and 2/3 within the investment grade category. There are 63 different bond issuers in the sample, indicating that some firms have multiple bonds outstanding. In particular, this applies to investment grade issuers. In the investment grade (high yield) category, 177 (100) bonds are split between 22 (41) firms. On average, investment grade issues in our sample are larger, have longer maturity and trade less frequently, than their high yield counterparts.

The average investment grade (high yield) issue in our sample is NOK 1 876 million (NOK 739 million). Much of this difference is due to highly rated covered bonds issued by financial institutions. The average remaining time to maturity for the analysis sample is approximately 3 years, with investment grade (high yield) bonds slightly above (below). This is short compared to previous studies on US data and might impact our results. In particular, it is natural to assume that bond issues with a longer remaining time to maturity are more sensitive to news about firm fundamentals, all else equal. Finally, included bonds trade on average 50 days during our three-year period, with high yield bonds as the most active at 82 days. This substantiates previous findings of scarce trading activity in the Norwegian corporate bond market. As noted by Ødegaard (2017), trading activity in investment grade issues is driven by the inclusion of covered bonds.

Credit rating is more or less homogeneous within each sector. Finance and real estate are mostly investment grade bonds, while oil & gas, seafood and shipping make up the high yield bonds. The exceptions are industry and other non-financials, where both rating categories are well represented. As shown in Table 3.1, bonds issued by financial institutions dominate the investment grade category, and account for approximately 2/3 of the issues. Similarly, the oil & gas sector is the primary issuer of high yield bonds and constitutes $\frac{1}{2}$ of the high yield category. When excluding covered bonds, differences in issue size and time to maturity across sectors are limited. The only notable difference is trading activity. In general, bonds within the typical high yield sectors trade more

Table 3.1 – Characteristics of bonds. Analysis sample.

Portfolio	Number of bonds		Number of firms		Rating (%)		Volume (mNOK)		Age	YTM	Number of
	#	%	#	%	HY	IG	Outstanding	Issue size	Mean	Mean	trading days
Full	277		63		36.10	63.90	255,376.00	1,465.76	3.40	3.09	49.78
HY	100	36.10	41	65.08	100.00	0.00	41,458.67	739.41	2.87	2.58	81.86
IG	177	63.90	22	34.92	0.00	100.00	213,917.33	1,876.12	3.70	3.38	31.66
Finance	116	41.88	11	17.46	0.00	100.00	181,422.33	2,476.20	4.37	3.22	39.47
Industry	24	8.66	9	14.29	54.17	45.83	14,413.00	844.83	2.61	3.41	72.88
Oil & gas	48	17.33	19	30.16	100.00	0.00	17,118.67	718.49	2.84	2.66	82.06
Real estate	40	14.44	6	9.52	10.00	90.00	19,295.00	729.86	2.12	3.07	18.73
Seafood	5	1.81	4	6.35	100.00	0.00	2,750.00	630.00	2.45	2.64	77.60
Shipping	23	8.30	6	9.52	100.00	0.00	12,402.00	829.02	3.24	2.86	78.30
Other	21	7.58	8	12.70	33.33	66.67	7,975.00	675.00	3.09	3.46	27.90

Note: Table 3.1 contains descriptive information about the 277 listed bonds (OSE or Nordic ABM) from the full sample where trading activity is recorded during our sample period. This includes all bonds with at least one official trade. "Rating (%)" shows the respective fractions of high yield and investment grade bonds within each category, in percentage points. "Volume (mNOK)" shows the total outstanding volume (as of 30.10.2017), as well as the mean original issue size, within each category. "Age" shows the mean age, while "YTM" shows the mean remaining time to maturity. Bond characteristics are obtained from Stamdata. The average number of trading days is compiled from OBI.

frequently. Thus, to a large degree, each sector portfolio displays similar characteristics to the corresponding rating portfolio.

Table 3.2 displays summary statistics for individual bond and stock returns, where bond returns are calculated using NBP price estimates. As expected, due to the short return horizon, the mean daily returns are close to zero for both security types, with oil & gas and seafood as noticeable exceptions. Further, it should be noted that investment grade bonds have outperformed high yield bonds over our sample period, driven by the negative returns in oil-related securities following the collapse in oil prices. Finally, high yield bonds and their associated stocks exhibit the highest volatility, consistent with greater risk in these securities.

Table 3.2 – Descriptive statistics of daily returns of bonds and stocks.

Portfolio	Bonds (B)		Stocks (S)			
	Mean %	St.Dev. %	Mean %	St.Dev. %	$\rho_{B,S}$	$\rho_{B,T}$
Full	-0.014	0.735	0.011	3.732	0.002	-0.124
HY	-0.035	1.202	-0.076	5.763	0.052	0.028
IG	-0.001	0.096	0.062	1.618	-0.026	-0.210
Finance	-0.001	0.096	0.058	1.614	-0.038	-0.201
Industry	-0.002	0.202	0.034	2.373	-0.005	-0.142
Oil & gas	-0.067	1.637	-0.218	7.311	0.068	0.037
Real estate	-0.000	0.084	0.071	1.473	0.017	-0.175
Seafood	-0.002	0.098	0.121	1.904	0.001	0.014
Shipping	-0.009	0.695	0.081	4.732	0.063	0.018
Other	-0.001	0.115	0.071	2.127	-0.008	-0.146

Note: Table 3.2 displays summary statistics for the bonds and associated stocks in the analysis sample. Individual daily bond returns are calculated using price estimates obtained from Nordic Bond Pricing. Individual daily stock returns are calculated using generic prices obtained from OBI. OBI's generic price equals the last stock trade each day. If no trade has occurred, the previous closing price is utilised before a best guess. The columns "$\rho_{B,S}$" and "$\rho_{B,T}$" display the average contemporaneous correlation between the daily returns on bonds, their associated stocks and the 3-year Norwegian government bond, respectively.

Table 3.2 also reports correlations between returns. There are several things to note about the figures, and we begin with bonds and their associated stocks. For the full sample, on average, the daily contemporaneous correlation is close to zero. However, there are significant differences between rating categories. We find that the correlation coefficient for high yield bonds, on average, is positive, and stronger than for investment grade bonds. This result is substantiated by the findings for each sector. In particular, the two dominating high yield sectors, oil & gas and shipping, exhibit the strongest positive contemporaneous correlation, while results for the remaining sectors are more ambiguous.

To a large degree, these findings are consistent with previous studies, and align well with the results reported by Downing et al. (2009). Their sample is the most similar to ours, and the only noticeable difference is a slightly lower magnitude in our estimated coefficients. One likely explanation stands out. Following the intuition provided by Kwan (1996), the correlation between cross-market returns depends on whether news convey information about the mean value or about the volatility of assets. As the reported correlation coefficients reflect the net effect of both, a larger share of news about volatility in assets would skew the results downwards. In the oil-dependent Norwegian economy, it is plausible that both types of news have been prominent, due to the volatility and collapse in oil prices during our sample period.

Overall, our findings are consistent with the insight provided by Merton (1974), that lower rated bond issues are more similar in market behaviour to stocks, than higher rated issues. This result is substantiated by the contemporaneous correlation between daily bond returns and the 3-year Norwegian government bond. While investment grade bonds, on average, display a strong negative correlation, the average correlation coefficient for high yield bonds is close to zero. As investment grade bonds in general have more stable cash flows and a longer time to maturity, a higher sensitivity to changes in the interest rate is expected.

4. Empirical analysis: Predictability in cross-market returns

In this section, we introduce our empirical analysis of cross-market returns in the Norwegian security markets. To overcome the problem of scarce transaction data for Norwegian corporate bonds, the analysis is conducted using both transaction data and price estimates obtained from NBP. The main objective of this section is to determine whether past returns in stocks (bonds) hold predictive power over current returns in bonds (stocks).

The section is organised into three parts. First, we conduct a preliminary analysis, and draw insight from the six most actively traded bonds in our sample. Second, we expand the analysis of predictability in cross-market returns to the full sample, relying on price estimates from NBP and periods of heightened trading activity. Finally, to examine the validity of our results, we include additional control variables and assess the use of NBP price estimates in our analysis.

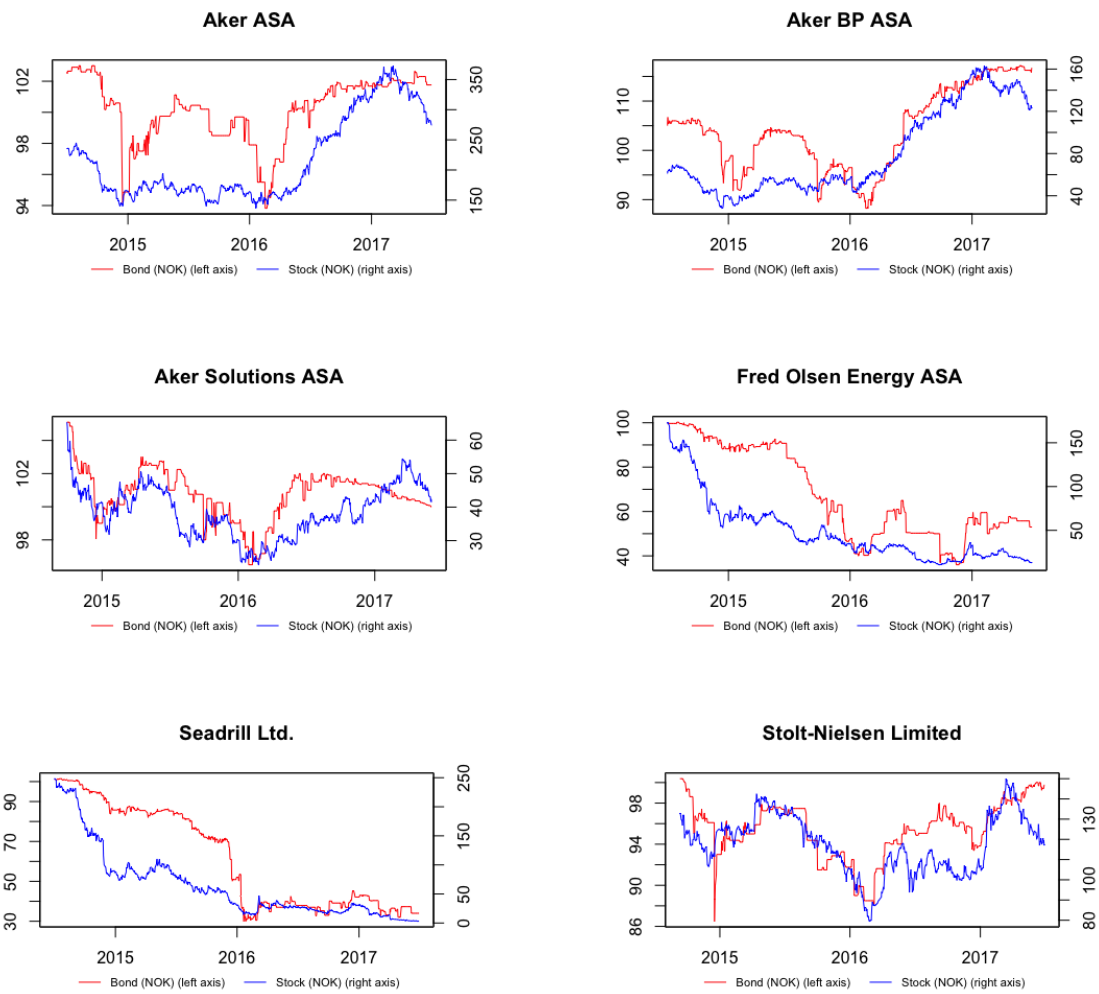
4.1. Most actively traded bonds

We begin our analysis with insights from the most actively traded bonds in our sample. A small subset of bonds provides an initial understanding of the relationship between stock and bond returns, while a higher trading frequency allows us to use transaction data in the analysis. After a short presentation of the included bonds, we estimate the VAR model described in equation (1), and compare results using transaction data and NBP price estimates.

To get meaningful results when we estimate the VAR model using transaction data on security level, we limit the initial analysis to the six most actively traded bond-stock pairs. The full analysis sample includes 277 bonds with registered trading activity in the OBI database. Of these, only six bonds are registered with more than 200 trading days during our sample period. Noticeably, all are high yield issues within the sectors industry, oil &

gas and shipping, and the issues trade, on average, every third day. Figure 4.1 shows the pairwise movement of security prices for the included bonds and their associated stocks.

Figure 4.1 – Bond and stock price. Most active bonds.



Note: Figure 4.1 displays the pairwise movement of six bonds and their associated stocks during the sample period. The included pairs represent the most actively traded bonds (number of trading days > 200): NO0010680309 (Aker ASA), NO0010684145 (Aker BP ASA), NO0010647431 (Aker Solutions ASA), NO0010704125 (Fred Olsen Energy ASA), NO0010673148 (Seadrill Ltd.) and NO0010705551 (Stolt-Nielsen Limited). Based on Stamdata's classification, all six bonds have "High Yield" grade. Bond prices are plotted against the left vertical axis. Stock prices are plotted against the right vertical axis.

While similar price movements indicate a joint reaction to new information, the graphs provide limited insight into predictability in cross-market returns. However, there are conspicuous exceptions, as evident for Fred Olsen Energy and Seadrill. Both firms experienced a dramatic fall in security prices during 2015/2016, with bonds lagging stocks by a large margin. One could question whether bondholders grasped the impact of the news released over the period, or even looked at the stock price. Next, we elaborate on these findings and turn to a more formal analysis of predictability in cross-market returns.

Table 4.1 – Daily bond and stock returns. Actively traded bonds.

Bond		Observed trades		NBP estimates			
		Sum	Granger	Sum	Granger	Trading days	N
Aker						206	749
	Stock lead	0.367	0.352	0.140	0.364		
	Bond lead	0.171	0.146	0.019**	0.023**		
Aker BP						346	749
	Stock lead	0.000***	0.003***	0.001***	0.045**		
	Bond lead	0.222	0.001***	0.127	0.000***		
Aker Solutions						264	667
	Stock lead	0.009***	0.059*	0.012**	0.053*		
	Bond lead	0.022**	0.323	0.395	0.907		
Fred Olsen Energy						247	749
	Stock lead	0.000***	0.001***	0.003***	0.019**		
	Bond lead	0.164	0.182	0.011**	0.104		
Seadrill						319	749
	Stock lead	0.001***	0.002***	0.006***	0.041**		
	Bond lead	0.376	0.451	0.458	0.240		
Stolt-Nielsen						223	698
	Stock lead	0.141	0.631	0.024**	0.230		
	Bond lead	0.640	0.433	0.568	0.791		

Note: Table 4.1 reports the results of hypothesis tests on coefficient estimates from the following vector-autoregressive model on the most actively traded bonds (number of trades $>$ 200) in our sample and their associated stock:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. The lag-length L is set to five days. "Stock lead" ("Bond lead") refers to tests on the estimated coefficients of lagged stock (bond) returns with bond (stock) returns as the dependent variable. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of the five cross-market coefficients is equal to zero. "Granger" gives the F-statistic and p-value for the null hypothesis that all five of the cross-market coefficients are equal to zero. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively. "Observed trades" reports results from the model run with bond trading prices obtained from OBI. The number of observed trading days for each bond is reported in "Trading days". On days where no trades occurred, the last observed price is utilised. "NBP estimates" reports results from the model run with bond estimates obtained from Nordic Bond Pricing.

Table 4.1 summarises the results from estimating the VAR model described in equation (1) on each of the six bond-stock pairs presented in Figure 4.1. As we are primarily interested in cross-market predictability in returns and the validity of using price estimates, only the p-values of the sum test and the Granger causality test are reported[1]. We begin with results obtained using transaction data. Noticeably, all three bonds within the oil & gas sector show strong evidence of stocks leading bonds, with no significant effect the

[1]See Table A.3 and A.4 in Appendix A for estimated coefficients using transaction data and price estimates, respectively.

other way[2]. More specifically, for the bonds issued by Aker BP, Fred Olsen Energy and Seadrill, we reject the null of both predictability tests on lagged stock returns at the 1 % significance level. Similarly, some evidence of a stock lead is found in the bond issued by Aker Solutions, where stocks are found to Granger cause bonds at the 10 % significance level. In the two last bonds, issued by Aker and Stolt-Nielsen, no significant effect is found either way.

The results obtained using NBP bond price estimates are qualitatively similar to those found using transaction data. The only difference is evidence of the bond issued by Aker leading stocks, when estimates from NBP are utilised. However, this bond is the least traded of the included bonds, with registered trading days close to every fourth day during our sample period. Due to our assumption of a zero return on trading days where no trade occurred, this might weaken similarities between the two approaches. Overall, the results reported in Table 4.1 support the use of price estimates in our analysis.

Three additional comments should be made about the above findings. First, while cross-sectional differences appear, we find evidence of stocks leading bonds in issues with lower credit rating. This is consistent with the results reported in Kwan (1996) and Downing et al. (2009). The effect is especially apparent in bonds issued by firms within the oil & gas sector, which indicates that bonds might react more sluggishly to common factors, such as changes in the oil price. Second, both Fred Olsen Energy and Seadrill have experienced financial distress during our sample period and show indications of a stock lead. Consistent with our findings, Downing et al. (2009) argue that periods of financial distress induce increased trading activity in securities, which in turn reveal the relative informational efficiency across markets. As a final note, Hotchkiss and Ronen (2002) find no evidence of a lead-lag relationship using 20 of the most actively traded US high yield bonds. While this result contrasts our findings, the bonds in their sample exhibit a considerably higher trading frequency, with trades registered on 95 % of the days.

[2]Estimated coefficients for Aker BP show evidence of bonds Granger causing stocks. However, the sum test is not significant.

4.2. Is there a lead-lag relationship between stock and bond returns?

The above insights set the stage for our analysis of predictability in cross-market returns on the full analysis sample. To date, studies of the lead-lag relationship between stocks and bonds have been conducted on US market data, which provide ambiguous results. However, the Norwegian corporate bond market differs from the US corporate bond market in several ways. A smaller market size, infrequent trading and increased oil-exposure might all affect results.

In the following, we present and discuss the results from estimating the VAR model described in equation (1) using bond price estimates from NBP, as well as transaction data from periods of heightened trading activity. First, we conduct the analysis on portfolio level, stratified by credit rating and sector, mainly as a means of comparison to earlier studies. Second, we utilise the cross-sectional differences in our sample, and apply the same analysis on the individual security level. This allows us to develop a deeper understanding of the relationship between stock and bond returns. Lastly, we entertain the notion that trading frequency should be higher in periods of firm-specific news and examine predictability in cross-market returns around earnings announcements.

4.2.1 Portfolio level analysis

We begin our analysis using the returns of portfolios stratified by credit rating and sector. This allows us to compare our results to those of previous studies and expand on the initial overview of the lead-lag relationship between cross-market returns. The results are displayed in Table 4.2 and 4.3, where estimates of the VAR model described in equation (1), as well as tests of predictability, are presented.

Table 4.2 – Daily bond and stock portfolio returns (credit rating).

	Lagged bond returns					Lagged stock returns								
	β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	Sum	Granger	$R2$	$R2+$
HY														
Bonds	0.214***	0.130***	0.109**	0.071	0.050	0.018***	0.001	0.002	-0.003	0.005	4.930**	2.270**	0.175	0.194
	(3.421)	(2.605)	(2.372)	(1.146)	(1.058)	(2.931)	(0.354)	(0.445)	(-0.626)	(1.125)	(0.027)	(0.046)		
Stocks	1.341*	-0.767**	0.390	-0.421	-0.044	0.073*	-0.031	0.054	-0.004	0.009	0.530	1.700	0.008	0.042
	(1.783)	(-2.203)	(0.904)	(-1.067)	(-0.126)	(1.658)	(-0.907)	(1.397)	(-0.108)	(0.292)	(0.466)	(0.133)		
IG														
Bonds	0.149***	0.021	0.048	-0.019	0.036	0.003	0.002	0.002	0.002	0.006***	7.590***	2.410**	0.024	0.040
	(3.214)	(0.478)	(1.057)	(-0.436)	(0.773)	(1.241)	(0.815)	(1.055)	(0.737)	(3.000)	(0.006)	(0.035)		
Stocks	-1.019	-0.382	-0.281	0.466	0.003	0.002	-0.037	0.055	-0.041	-0.015	0.710	0.570	0.007	0.012
	(-1.359)	(-0.535)	(-0.387)	(0.691)	(0.005)	(0.032)	(-0.735)	(1.171)	(-0.902)	(-0.312)	(0.399)	(0.727)		

Note: Table 4.2 reports the results from the following vector-autoregressive model:

$$z_t = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=1}^{L} \beta_{S,i} R_{S,t-i} + \epsilon_t$$

where $z_t = [R_{B,t}, R_{S,t}]$, $R_{B,t}$ is the daily return on an equally-weighted portfolio of bonds with the indicated rating and $R_{S,t}$ is the daily return on the associated stock portfolio. The lag-length L is set to five days. Robust t-statistics are shown beneath the coefficient estimates. “Sum” gives the F-statistic and p-value for the null hypothesis that the sum of the five cross-market coefficients is equal to zero. “Granger” gives the F-statistic and p-value for the null hypothesis that all five of the cross-market coefficients are equal to zero. "$R2$" gives the adjusted-$R2$ statistic for a regression including lagged own-market returns only, while "$R2+$" gives the adjusted-$R2$ statistic for the regression shown. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

For credit rating portfolios, a stock lead appears to be present in both high yield and investment grade bonds, with no significant effect the other way. In both cases, we find evidence that stocks Granger cause bonds at the 5 % significance level. The indication that past cross-market returns contain useful information for current bond returns, is substantiated by the simultaneous rejection of the sum test at the 5 % and 1 % significance level, respectively. For the high yield portfolio, the Granger test seems to recognise the significant coefficient of the first lagged stock return. Similarly, for the investment grade portfolio, the significant coefficient of the last lagged stock return seems to be decisive. Note, however, that the magnitude of the estimated coefficients for the investment grade portfolio is below that of the lower rated counterpart. The sum test is rejected due to consistent positive estimates.

Overall, our results align well with the findings in Kwan (1996) and Downing et al. (2009). Both studies apply the portfolio approach, and find evidence that stocks lead corporate bonds. This effect is particularly strong in lower rated bond issues. It should be noted that US market data allows these studies to segment their samples into accurate credit rating categories. In comparison, we are limited to segmentation into investment grade and high yield portfolios, in which the former consists of bonds with ratings from BBB (e.g. Yara International ASA) to AAA (e.g. DNB Boligkreditt AS). This might help explain our findings of a stock lead in investment grade issues. In particular, Kwan (1996) find that stocks lead bonds in all but the AAA-rated issues, and Downing et al. (2009) find some evidence of stocks Granger causing BBB-rated bonds.

For the sector portfolios, the results are more ambiguous. First, we find indications of a stock lead in industry and finance, where stocks Granger cause bonds at the 1 % and 5 % significance level, respectively. Similar, but weaker, results are evident for shipping, as well as for the mixed portfolio of other non-financials. In all four portfolios, the sum test is rejected. Second, we find indications of a bond lead in seafood. Here, statistically significant test statistics at the 1 % significance level are found in both the Granger causality test and the sum test. Note that some evidence is found for a bond lead in industry. While the Granger causality test is rejected at the 1 % significance level, the sum test fails to reject the null, due to large variations in the estimated coefficients

Table 4.3 – Daily bond and stock portfolio returns (sector).

	Lagged bond returns					Lagged stock returns								
	β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	Sum	Granger	$R2$	$R2+$
Finance														
Bonds	0.172***	-0.003	0.074*	-0.044	0.031	0.003	0.002	0.002	0.000	0.005***	7.190***	2.460**	0.030	0.045
	(3.562)	(-0.080)	(1.708)	(-1.043)	(0.686)	(1.308)	(0.995)	(1.034)	(0.232)	(3.027)	(0.008)	(0.032)		
Stocks	-1.646*	-1.072	-0.063	0.284	-0.281	0.008	-0.024	0.026	-0.014	-0.018	2.610	1.290	0.002	0.011
	(-1.877)	(-1.253)	(-0.077)	(0.359)	(-0.303)	(0.151)	(-0.496)	(0.583)	(-0.331)	(-0.344)	(0.106)	(0.268)		
Industry														
Bonds	0.331***	0.121*	0.003	0.041	0.077*	0.008**	0.003	0.006	0.003	0.005*	14.440***	3.870***	0.210	0.239
	(4.175)	(1.847)	(0.040)	(0.851)	(1.669)	(2.536)	(0.866)	(1.334)	(1.172)	(1.748)	(0.000)	(0.002)		
Stocks	1.007	-1.865	0.708	-2.008***	0.460	0.060	-0.063	0.045	-0.034	0.035	2.160	3.210***	0.006	0.033
	(1.246)	(-1.595)	(0.840)	(-2.725)	(0.636)	(1.316)	(-1.345)	(1.081)	(-0.812)	(0.870)	(0.143)	(0.007)		
Oil & gas														
Bonds	0.161***	0.134***	0.105***	0.099	0.053	0.012	-0.001	-0.004	-0.005	0.004	0.220	0.900	0.128	0.135
	(2.732)	(2.673)	(2.658)	(1.189)	(1.115)	(1.589)	(-0.197)	(-0.651)	(-0.722)	(1.030)	(0.636)	(0.479)		
Stocks	1.493	-0.389	-0.022	-0.026	0.094	0.030	-0.020	0.030	0.020	0.002	2.140	0.970	0.003	0.050
	(1.539)	(-1.423)	(-0.063)	(-0.065)	(0.265)	(0.864)	(-0.835)	(0.674)	(0.709)	(0.080)	(0.144)	(0.436)		
Real estate														
Bonds	0.069	0.073	0.029	0.037	0.030	0.002	0.002	0.002	0.001	-0.002	1.620	1.020	0.016	0.024
	(1.517)	(1.452)	(0.537)	(0.804)	(0.471)	(0.921)	(1.536)	(1.302)	(0.505)	(-1.114)	(0.203)	(0.403)		
Stocks	-1.518	1.586*	-0.893	0.946	-0.001	-0.134***	-0.001	0.027	0.013	-0.001	0.000	1.190	0.020	0.031
	(-1.467)	(1.663)	(-0.924)	(0.916)	(-0.001)	(-2.974)	(-0.017)	(0.701)	(0.339)	(-0.023)	(0.951)	(0.311)		
Seafood														
Bonds	0.234***	0.051	0.039	-0.001	0.074	0.004**	0.002	0.000	0.001	0.003*	5.790**	1.460	0.077	0.096
	(3.120)	(1.172)	(0.570)	(-0.040)	(1.646)	(2.208)	(1.107)	(-0.040)	(0.796)	(1.718)	(0.016)	(0.199)		
Stocks	-0.941	-2.509**	-2.153**	-0.691	0.423	-0.044	0.011	-0.021	-0.026	-0.019	14.700***	5.750***	0.004	0.029
	(-1.083)	(-2.332)	(-2.452)	(-0.626)	(0.474)	(-0.966)	(0.242)	(-0.507)	(-0.667)	(-0.517)	(0.000)	(0.000)		
Shipping														
Bonds	0.350**	-0.080	0.018	0.003	0.033	0.026**	0.006	0.013**	0.007	0.003	6.830***	2.190*	0.200	0.251
	(2.094)	(-1.338)	(0.667)	(0.097)	(1.288)	(2.168)	(0.840)	(2.086)	(1.180)	(0.982)	(0.009)	(0.054)		
Stocks	-0.155	-0.220	-0.680**	0.241	0.259	0.028	0.080*	0.047	0.033	-0.077**	0.760	1.130	0.010	0.017
	(-0.437)	(-0.674)	(-2.111)	(0.936)	(0.639)	(0.673)	(1.769)	(0.672)	(0.684)	(-1.991)	(0.383)	(0.345)		
Other														
Bonds	0.111***	0.061*	0.017	-0.026	0.139***	0.002	0.001	0.001	0.002	0.003**	6.500**	1.870*	0.039	0.050
	(3.003)	(1.648)	(0.426)	(-0.723)	(2.979)	(1.426)	(0.614)	(1.098)	(0.634)	(2.243)	(0.011)	(0.097)		
Stocks	0.210	1.197	-0.686	-0.708	1.035	-0.006	-0.036	0.028	-0.041	-0.064*	0.270	0.860	0.009	0.013
	(0.177)	(1.410)	(-0.715)	(-0.688)	(1.185)	(-0.136)	(-0.974)	(0.659)	(-1.266)	(-1.659)	(0.602)	(0.511)		

Note: Table 4.3 reports the results from the following vector-autoregressive model:

$$z_t = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=1}^{L} \beta_{S,i} R_{S,t-i} + \epsilon_t$$

where $z_t = [R_{B,t}, R_{S,t}]$, $R_{B,t}$ is the daily return on an equally-weighted portfolio of bonds within the indicated sector and $R_{S,t}$ is the daily return on the associated stock portfolio. The lag-length L is set to five days. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of the five cross-market coefficients is equal to zero. "Granger" gives the F-statistic and p-value for the null hypothesis that all five of the cross-market coefficients are equal to zero. "$R2$" gives the adjusted-$R2$ statistic for a regression including lagged own-market returns only, while "$R2+$" gives the adjusted-$R2$ statistic for the regression shown. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

of lagged bond returns.

Given the credit rating composition of each sector portfolio, these results indicate cross-sectional differences within rating groups. Finance, industry and shipping are the only sectors that show consistent results with their associated credit rating portfolio. Noticeable is the lack of any lead-lag relationship in oil & gas, which makes up approximately half of the high yield bonds in our sample. A plausible explanation for the deviations is sector-specific properties. To illustrate, the performance of oil-related securities is naturally correlated to oil prices, information that is easily obtained by investors. While previous studies find that stocks react sluggishly to changes in the oil price, it is also likely that increased volatility and collapse in oil prices during our sample period affect investor awareness in both markets. In both cases, a lead-lag relationship between bond and stock returns would become less apparent, consistent with our findings of stronger contemporaneous correlation in the oil & gas sector. While this intuition contrasts our findings for the most actively traded bonds, it is likely that portfolio aggregation obscures cross-sectional differences between individual bond-stock pairs.

Finally, we observe that adding lagged cross-market returns provides a slight boost in the adjusted-$R2$ statistic for all estimated regressions. To this end, it is interesting to note the informational differences in lagged returns of the individual portfolios, cross-market returns excluded. For the high yield bond portfolio, own past returns are significant at the 1 % significance level for the first two lags, and the 5 % significance level for the third. The adjusted-$R2$ statistic including only lagged bond returns is 0.175. In comparison, for the investment grade bond portfolio, only the first lag is statistically significant, and the adjusted-$R2$ statistic is 0.024. Little information is contained in own past returns for stocks. These returns are consistent with estimates for the sector portfolios and indicate a slower information diffusion in high yield bonds.

4.2.2 Security level analysis

In order to elaborate on the results found on portfolio level, we turn to a more detailed analysis of cross-market predictability on security level. We are particularly interested in cross-sectional differences in our sample, as evident from the incongruity between the credit rating portfolios and some of their associated sector portfolios. In the following, we first present results from estimating the VAR model described in equation (1) on each individual bond-stock pair. Then, where a lead-lag relationship is present, we discuss relevant properties of the predictable securities.

In the interest of brevity, we omit the estimated coefficients and standard errors from the security level regressions, and report summary statistics only[3]. Consistent with previous studies, the results show substantial cross-sectional differences in our sample. Table 4.4 summarises the results from our predictability tests. We report the proportion of bond-stock pairs within each category that rejects the null of the Granger causality test (column Granger), as well as pairs that reject the null of the Granger causality test and the sum test simultaneously (column Granger+). The null hypotheses are rejected at the 5 % significance level.

For stock leads, Table 4.4 portrays a sharp distinction between low and high rated bond issues. In the high yield category, we find evidence of a stock lead in 18.00 % of the included bonds. In comparison, 0.56 % of the bonds in the investment grade category reject the null of both predictability tests simultaneously. These results indicate that past stock returns contain useful information about future returns in high yield bonds, but little, if any, information about future returns in investment grade bonds. This conclusion is substantiated by findings in the sector categories. In particular, we find that bonds in sectors characterised by a relatively higher credit risk more often display evidence of a stock lead. In the oil & gas sector, 29.17 % of the issued bonds reject the null of both predictability tests simultaneously, followed by shipping and industry with 8.70 % and 8.33 % rejection, respectively.

There are two noticeable findings in the above results. First, bond return predictability appears to be increasing with credit risk, a notion that is substantiated by examining the issuing firms of predictable bonds in our sample. Six out of eleven issuers experienced financial distress during our sample period, with many also having their debt restructured

[3]See Table A.5 in Appendix A for mean estimated coefficients and standard deviations in results.

Table 4.4 – Security level hypothesis test results (%).

Portfolio	Stock lead		Bond lead		Two-way lead-lag	
	Granger	Granger+	Granger	Granger+	Granger	Granger+
HY	19.00	18.00	12.00	5.00	2.00	1.00
IG	3.95	0.56	10.17	5.08	0.56	0.00
Finance	2.59	0.00	7.76	2.59	0.00	0.00
Industry	8.33	8.33	12.50	4.17	0.00	0.00
Oil & gas	29.17	29.17	8.33	2.08	2.08	0.00
Real estate	7.50	2.50	20.00	15.00	2.50	0.00
Seafood	0.00	0.00	20.00	20.00	20.00	20.00
Shipping	8.70	8.70	8.70	0.00	0.00	0.00
Other	9.52	0.00	14.29	9.52	0.00	0.00

Note: Table 4.4 reports the results of hypothesis tests on the security-level coefficient estimates for the vector-autoregressive model:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. The lag-length L is set to five days. The statistic "Granger" gives the proportion of bonds (stocks) for which the F-statistic of the null hypothesis that all the estimated coefficients of lagged stock (bond) returns equals 0 is statistically significant at the 95% level. The statistic "Granger +" gives the proportion of bonds (stocks) for which (1) the F-statistic of the null hypothesis that all the estimated coefficients of lagged stock (bond) returns equals 0, and (2) the F-statistic of the null hypothesis that the sum of the estimated coefficients of lagged stock (bond) returns equals 0, is statistically significant at the 95% level.

or refinanced[4]. Thus, financial distress seems to highlight cross-market differences in informational efficiency. This result supports the findings in our analysis of the most actively traded bonds, as well as those in Downing et al. (2009). They argue that firm-specific news in periods of financial distress induces increased trading activity in both stocks and bonds. In an otherwise illiquid market, increased trading activity helps reveal the relative informational inefficiency of corporate bonds.

Second, we find seemingly conflicting results between the portfolio and security level analysis. Noticeable is the high proportion of bonds within the oil & gas sector that shows evidence of a stock lead. Additionally, not a single bond within the finance sector shows similar evidence. While these results contradict our previous findings, they substantiate

[4]The six issuers are I.M. Skaugen SE, DOF ASA, Siem Offshore Inc., Seadrill Ltd, BW Offshore Limited and Fred Olsen Energy ASA.

our discussion of blurred results on portfolio level, due to the aggregation of individual securities. To illustrate, for bonds within the oil & gas sector, the mean estimated coefficient of the first lagged stock return is 0.012, with a standard deviation of 0.025. This indicates that individual bond issues in the oil & gas sector exhibit both positive and negative coefficients of significant magnitude to reject the null of no stock lead. In comparison, for bonds within the finance sector, the estimated mean coefficients are closer to zero, with lower standard deviations.

Further, Table 4.4 portrays information of bond leads in our sample. We find evidence of bonds leading stocks in eight out of nine categories, with noticeable variation across sectors. In one end, for the seafood and real estate sectors, the proportion of the bonds that simultaneously reject the null of both predictability tests are 20.00 %[5] and 15.00 %, respectively. In the other end, bonds within the shipping sector show no signs of leading their associated stocks. We also note the lack of a bond lead pattern in terms of credit rating. In the high yield category, we find evidence of a bond lead in 5.00 % of the included bonds. Similar results are found within the investment grade category, where 5.08 % of the included bonds reject the null of both predictability tests simultaneously. This notion is further confirmed by summary statistics for bonds within finance and oil & gas, the sectors representing the risk extremities in our sample. In the finance sector, the proportion of bonds that show evidence of a bond lead is 2.59 %, while the same number is 2.08 % in the oil & gas sector.

Three comments should be made about the above results. First, the bond leads in our sample cannot be explained by differences in credit risk. This is consistent with Downing et al. (2009), who find no clear connection between credit ratings and bond leads. Second, Ronen and Zhou (2013) argue that investors prefer to trade in one, or a few, of the issuer's outstanding bonds following firm-specific news. This is consistent with our findings of a few bonds leading stocks across multiple categories. While differences in informational efficiency between the outstanding bonds of a firm are likely, it is beyond our study to quantify this effect. Lastly, Downing et al. (2009) find a considerably higher

[5] Considering the small amount of bonds in this sector, 5, we do not place too much emphasis on this result.

proportion of predictable bonds in their sample, with more than half of the high yield bonds being Granger caused by their associated stocks. Results using weekly returns indicate the presence of cross-sectional differences in information diffusion across bonds in our sample[6]. Weak evidence of a stock lead when we apply a longer return horizon, suggests that some bonds take longer to reflect information that affects both markets. If this characteristic is less prominent in the US market, cross-sectional differences in information diffusion across bonds help explain the relatively low rejection proportion in Table 4.4.

To summarise, the aggregation of stocks and bonds into portfolios helps generalise our results. However, important information of interest to investors, such as drivers of predictability and individual differences, becomes blurred.

4.2.3 Informational efficiency around earnings announcements

In the following, we use transaction data to examine informational efficiency around earnings announcements. As announcements contain firm-specific information of interest to investors, increased awareness might affect predictability in cross-market returns and induce increased trading activity in securities. We begin with a short presentation of trading activity around the announcement date. Second, we estimate the return model described in equation (1) using both transaction data and NBP bond price estimates. We end with a discussion and comparison of our results to previous studies.

If earnings announcements reveal new information of interest to the market, we expect to observe increased trading activity in both bonds and stocks following the announcement date. We formalise this notion in Table 4.5, which summarises volume and trading statistics around earnings announcements in our sample. The reported numbers show a noticeable difference in daily trading activity, especially on the first trading day following an announcement. In both security types, daily average trading volume nearly doubles on the post-announcement day, and a slightly higher trading frequency in bonds indicates activity in less frequently traded issues.

[6] Appendix B summarises these results.

Table 4.5 – Trading activity on information and non-information days.

	Eday		Eday+		Non-Eperiod	
	Mean	Median	Mean	Median	Mean	Median
Firm level:						
Average bond volume (mNOK)	18.482	2.076	10.036	1.858	8.277	1.847
Average stock volume (mNOK)	64.908	8.636	38.224	6.080	32.609	4.629
Bond level:						
Average volume (mNOK)	5.514	0.143	3.592	0.983	2.827	0.982
Trading day frequency	0.121	0.067	0.098	0.077	0.091	0.070

Note: Table 4.5 summarises corporate bond trading activity during earnings announcement days and non-earnings announcement days. On firm level, for stocks and bonds, the table reports average and median trading volume on the trading day following an announcement ("Eday"), the five trading days preceding and following an announcement ("Eday+") and non-earnings days ("Non-Eperiod"). On bond level, the table reports average and median trading volume and trading day frequency on the trading day following an announcement ("Eday"), the five trading days preceding and following an announcement ("Eday+") and non-earnings days ("Non-Eperiod"). "Trading day frequency" is defined as the proportion of days where at least one trade occurred, for each period respectively. The time and date of each earnings announcement is retrieved from newsweb.no. If no information is found on newsweb.no, the respective days are treated as non-earnings days. Bond and stock volumes are retrieved from OBI.

These findings have important implications for our analysis. First, if otherwise infrequently traded bonds become more active around earnings announcements, we are able to make meaningful inference using transaction data from a larger number of ISIN. Second, evidence of increased activity in both bonds and stocks indicates higher investor awareness around earnings announcements. If both markets react to the released news simultaneously, we expect previous findings of cross-market predictability to disappear. This notion is substantiated by a considerably higher trading activity on the post-announcement day.

To examine informational efficiency, we estimate the VAR model described in equation (1) using pooled OLS. Results are displayed in Table 4.6. In the initial analysis, we limit the number of earnings announcement periods included, and calculate the bond returns using transaction data. To make meaningful inference, a minimum of five registered trading days in the ten-day interval around the announcement is required. This criterion limits our sample to 53 earnings announcement periods, split between 30 bonds issued by 16 firms.

Table 4.6 – Daily bond and stock returns in earnings announcement periods.

Panel A: Transaction prices.

		Lagged bond returns					Lagged stock returns							
Grade		β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	N	Sum	Granger
HY												230		
	Bonds	-0.029	-0.008	-0.285***	-0.027	-0.059	0.005	0.015	0.014	-0.021	-0.024		0.250	3.890**
		(-0.700)	(-0.350)	(-11.160)	(-1.060)	(-0.710)	(0.340)	(1.180)	(1.090)	(-1.590)	(-1.070)		(0.623)	(0.020)
	Stocks	0.262	0.040	-0.095	0.073	-0.044	0.097	0.167*	0.079	-0.098	0.035		0.170	4.100**
		(0.730)	(0.410)	(-0.860)	(0.820)	(-0.300)	(1.410)	(2.120)	0.930)	(-1.670)	(0.500)		(0.684)	(0.017)
IG												35		
	Bonds	0.047	-0.281**	0.468***	0.530***	-0.349	-0.005	-0.006	-0.007	-0.010	-0.005		0.820	0.430
		(0.250)	(-2.130)	(3.040)	(4.160)	(-1.610)	(-0.850)	(-0.610)	(-0.880)	(-1.200)	(-0.460)		(0.374)	(0.826)
	Stocks	3.787	4.795***	3.564	-3.013	-7.321**	-0.144	-0.578**	-0.281	-0.042	0.030		0.610	2.950**
		(1.000)	(2.920)	(1.350)	(-1.370)	(-2.200)	(-0.620)	(-2.500)	(-1.340)	(-0.140)	(0.120)		(0.441)	(0.033)

Panel B: NBP price estimates.

		Lagged bond returns					Lagged stock returns							
Grade		β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	N	Sum	Granger
HY												230		
	Bonds	0.392**	0.008	-0.051	0.013	-0.076**	0.014	-0.001	-0.003	-0.001	-0.004		0.320	0.590
		(2.860)	(0.100)	(-1.250)	(0.230)	(-2.900)	(0.880)	(-0.170)	(-1.400)	(-0.150)	(-0.410)		(0.583)	(0.711)
	Stocks	0.388	0.696*	-0.055	-0.204	0.047	0.106	0.171**	0.065	-0.100	0.047		0.930	4.030**
		(0.610)	(1.790)	(-0.350)	(-1.160)	(0.280)	(1.510)	(2.220)	(0.780)	(-1.720)	(0.660)		(0.351)	(0.018)
IG												35		
	Bonds	0.321***	-0.517***	-0.129	0.426***	0.322***	-0.005	-0.001	-0.005	0.007*	-0.001		0.070	1.630
		(2.860)	(-3.320)	(-1.240)	(4.430)	(3.250)	(-0.800)	(-0.140)	(-1.080)	(1.730)	(-0.130)		(0.790)	(0.192)
	Stocks	-3.011	-1.478	4.995	0.494	-4.025*	-0.038	-0.589**	-0.293	0.021	-0.160		1.400	5.400***
		(-0.740)	(-0.410)	(1.460)	(0.130)	(-2.000)	(-0.180)	(-2.470)	(-1.280)	(0.070)	(-0.630)		(0.248)	(0.002)

Panel C: NBP price estimates. All earnings announcement periods.

		Lagged bond returns					Lagged stock returns							
Grade		β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	N	Sum	Granger
HY												4745		
	Bonds	0.279***	-0.036	0.071*	-0.002	-0.008	0.003	-0.001	0.003	0.008	0.003		1.090	0.330
		(4.630)	(-0.620)	(1.770)	(-0.100)	(-0.410)	(0.420)	(-0.140)	(0.480)	(0.990)	(0.410)		(0.303)	(0.890)
	Stocks	0.047	0.269*	0.143	0.334	-0.150	0.005	0.007	0.064**	-0.020	0.016		4.790**	4.300***
		(0.370)	(1.800)	(0.700)	(1.430)	(-1.330)	(0.210)	(0.220)	(2.130)	(-0.710)	(0.500)		(0.035)	(0.003)
IG												7720		
	Bonds	0.177***	-0.019	0.091*	-0.049	0.033	0.000	0.002**	0.001*	0.002***	0.003***		7.350**	3.980**
		(4.890)	(-0.570)	(1.920)	(-1.320)	(0.990)	(0.440)	(2.450)	(1.840)	(2.860)	(3.000)		(0.014)	(0.011)
	Stocks	-0.882**	-0.205	0.210	0.671*	-1.140	-0.044	-0.064***	-0.017	0.051	0.063		2.760	2.620*
		(-2.690)	(-0.400)	(0.290)	(1.750)	(-1.360)	(-1.470)	(-4.200)	(-0.440)	(0.830)	(1.040)		(0.112)	(0.056)

Note: Table 4.6 reports the results from the following vector-autoregressive model, using pooled OLS:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. For an earnings announcement period to be included, the bond must have traded a minimum of five days in the ten-day trading day interval around the announcement. On trading days without registered trades, a zero yield is assumed. The High Yield category is clustered on firm level, to account for correlation between bonds issued by the same firm (15 firms in total). Since the Investment Grade category only includes one firm (DNB ASA), White-corrected standard errors have been utilised instead. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of cross-market coefficients is equal to zero. "Granger" gives the F-statistic and p-value for the null hypothesis that cross-market coefficients are equal to zero. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Panel A reports regression results using transaction data. Noticeably, previous findings of stocks leading bonds weaken around earnings announcements, and a slight reversal of roles is observed. In the high yield category, we find some evidence of a two-way lead-lag relationship in cross-market returns. For both stock and bond returns, we reject the null of the Granger causality test at the 5 % significance level but fail to reject the null of the sum test. In the investment grade category, we find similar indications of a bond lead, with bonds Granger causing stocks at the 5 % significance level. No significant effect is found the other way.

We find qualitatively similar results when using price estimates from NBP. First, in Panel B, we limit our sample to the earnings announcements included initially. While the slight indication of bonds leading stocks persists, all evidence of a stock lead disappears. Second, in Panel C, we use all earnings announcements in our sample. For high yield bonds, reported results boost evidence of a bond lead, with the null hypothesis of the Granger causality test and sum test rejected at the 1 % and 5 % significance level, respectively. Somewhat surprising, for investment grade bonds, a reversal is found when utilising the entire sample. More specifically, we find evidence of stocks leading bonds, with no significant effect the other way. A possible explanation for this lack of consistency in higher rated issues, is the initial trading activity criterion. Observations in Panel A and B are limited to a small sample of bonds issued by DNB, making statistical inference difficult.

The above results align well with similar studies using US market data. In their sample of actively traded high yield bonds, Hotchkiss and Ronen (2002) find that information contained in earnings announcements is quickly incorporated into both stock and bond prices. However, on an intra-day basis, stock prices take slightly longer to fully reflect released news. Similarly, Ronen and Zhou (2013) show that evidence of stocks leading bonds tend to disappear around earning announcements, when bond trading features are accounted for. They address institutional dominance, overnight trading and shifting liquidity in bonds, and find comparable efficiency between an issuer's stock and the bond that attracts the highest concentration of institutional trades following the announcement.

While the results reported in Table 4.6 contradict our previous findings, bond market features might explain the reversal of cross-market predictability around earnings announcements. First, as noted by Hendershott et al. (2015), institutional trading predicts firm-specific news. The combination of institutional dominance and lower transaction costs in the Norwegian bond market makes it likely that informed traders use corporate bonds to exploit new information. Second, as noted by Ronen and Zhou (2013), investors prefer to trade in one, or a few, of the issuer's outstanding bonds following firm-specific news. In Panel A and B, the sample is limited to actively traded bonds, which might explain findings of comparable efficiency in both markets. Third, studies of behavioural finance show that stocks react sluggishly to negative news (see Chan (2003) and Hou (2007)). Thus, whether the included earnings announcements reveal positive or negative news could affect the relative informational efficiency between the two markets.

Overall, in periods of heightened investor awareness and activity, we observe a noticeably different pattern in terms of the relative informational efficiency between stocks and corporate bonds. Previous stock-lead indications weaken and are in some cases replaced by bond-leads. Whether these findings are due to a slower reaction in bonds to common factors, rather than firm-specific news, remains to be determined. The next part will elaborate on this notion.

4.3. Validation of results

In the final part of our analysis, we address two critical questions in our assessment of predictability in cross-market returns. First, to examine the effect of common factors, we explore the underlying characteristics of bond returns in our sample more thoroughly. In particular, we evaluate sensitivity in our results to market and interest rate risk. Second, to validate the use of price estimates in our analysis, we utilise all consecutive bond trades in our sample, and rely solely on transaction data to examine the relationship between bond and stock returns.

4.3.1 Sensitivity of bond returns to market and interest risk

The findings so far show conflicting results for predictability in cross-market returns. In contrast to our findings over the full sample period, a different pattern of relative informational efficiency between bonds and stocks emerges around earnings announcements. In the following, we address the issue of common factors, and examine sensitivity of bond returns to market and interest rate risk. We use portfolio level returns and estimate the return models described in equation (2) and (3), respectively. Market risk is measured using the OSEBX index, and interest rate risk using the 3-year Norwegian government bond. Before results are reported and discussed, we provide a short overview over expected findings.

The intuition provided by Merton (1974) suggests that credit risk should affect our results. For high rated bonds, cash flows are expected to be relatively stable, with little or no sensitivity to firm-specific news. As these bonds also portray longer maturities and lower coupon rates, they are primarily expected to be sensitive to changes in the interest rate. In comparison, lower rated bonds are closer to default, and firm-specific news become more important. Combined with a lower duration, these bonds are expected to be less sensitive to changes in the interest rate and behave more like equity. This intuition is consistent with the results found in our discussion of contemporaneous correlation.

Regression results from the sensitivity analysis are displayed below, where estimates of equation (2) and (3) are reported in Table 4.7 and 4.8, respectively. Following previous studies, we only report the sum of the estimated coefficients for each variable. p-values of the F-test that the sum of estimated coefficients, contemporaneously and lagged, are equal to zero are included in parentheses.

Table 4.7 – Bond return sensitivity.

Portfolio	$\sum_{i=1}^{L} \beta_{B,i}$	$\sum_{i=0}^{L} \beta_{T,i}$	$\sum_{i=0}^{L} \beta_{OSEBX,i}$
HY	0.581 (0.000)	0.003 (0.691)	0.090 (0.000)
IG	0.292 (0.002)	-0.005 (0.000)	-0.003 (0.342)
Finance	0.238 (0.010)	-0.006 (0.000)	-0.003 (0.417)
Industry	0.621 (0.000)	0.005 (0.192)	0.034 (0.000)
Oil & gas	0.538 (0.000)	0.002 (0.856)	0.139 (0.000)
Real estate	0.351 (0.000)	-0.002 (0.019)	-0.002 (0.490)
Seafood	0.375 (0.000)	0.002 (0.180)	0.016 (0.016)
Shipping	0.472 (0.000)	-0.001 (0.914)	0.051 (0.000)
Other	0.399 (0.000)	-0.002 (0.092)	0.001 (0.742)

Note: Table 4.7 reports the results from the following regression model:

$$r_{B,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{OSEBX,i} R_{OSEBX,t-i} + \epsilon_t,$$

where $r_{B,t}$ is the daily return on an equally-weighted portfolio of bonds within the indicated credit rating or sector, $R_{T,t-i}$ is the contemporaneous and lagged daily return on the 3-year Norwegian government bond, and $R_{OSEBX,t-i}$ is the contemporaneous and lagged daily return on the OSEBX index. The lag-length L is set to five days. The table displays the sum of the estimated coefficients, with the p-value of the null hypothesis that each sum is statistically equal to zero in parenthesis.

True to our expectations, lower rated bonds appear to be more sensitive to market returns. As Table 4.7 shows, the high yield portfolio exhibits a positive and significant relationship with contemporaneously and lagged OSEBX returns. No significant relationship is found between the high yield portfolio and the 3-year Norwegian government bond. Lower rated sector portfolios show similar behaviour and provide additional support to these findings. The industry, oil & gas, seafood and shipping portfolios are all sensitive to market returns; neither rejects the null of the sum test for the returns of the 3-year Norwegian government bond. On the other hand, higher rated portfolios appear more sensitive to movements in the interest rate. The investment grade portfolio, as well as the higher rated sector portfolios finance and real estate, exhibit negative and significant relationships with contemporaneously and lagged returns of the 3-year Norwegian government bond. Neither is sensitive to market returns.

In order to relate the above results to our discussion of relative informational efficiency, we include cross-market returns in our regression. While systematic risk is reflected in both the OSEBX returns and the stock portfolio returns, we expect the latter to be significant if bond returns are sensitive to firm-specific news. These results are reported in Table 4.8.

Table 4.8 – Bond return sensitivity. Including stock portfolio returns.

Portfolio	$\sum_{i=1}^{L} \beta_{B,i}$	$\sum_{i=0}^{L} \beta_{S,i}$	$\sum_{i=0}^{L} \beta_{T,i}$	$\sum_{i=0}^{L} \beta_{OSEBX,i}$
HY	0.587 (0.000)	0.000 (0.996)	0.003 (0.627)	0.087 (0.002)
IG	0.285 (0.002)	0.010 (0.087)	-0.005 (0.000)	-0.009 (0.042)
Finance	0.239 (0.010)	0.004 (0.445)	-0.006 (0.000)	-0.005 (0.227)
Industry	0.615 (0.000)	0.009 (0.231)	0.005 (0.207)	0.023 (0.052)
Oil & gas	0.560 (0.000)	-0.018 (0.179)	0.002 (0.854)	0.161 (0.000)
Real estate	0.346 (0.000)	0.004 (0.209)	-0.002 (0.020)	-0.004 (0.213)
Seafood	0.396 (0.000)	0.009 (0.008)	0.003 (0.108)	0.011 (0.081)
Shipping	0.353 (0.000)	0.097 (0.001)	-0.002 (0.797)	-0.017 (0.464)
Other	0.379 (0.000)	0.009 (0.030)	-0.002 (0.134)	-0.006 (0.245)

Note: Table 4.8 reports the results from the following regression model:

$$r_{B,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{S,i} R_{S,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{OSEBX,i} R_{OSEBX,t-i} + \epsilon_t,$$

where $r_{B,t}$ is the daily return on an equally-weighted portfolio of bonds within the indicated credit rating or sector, $R_{S,t-i}$ is the contemporaneous and lagged daily return on the associated stock portfolio, $R_{T,t-i}$ is the contemporaneous and lagged daily return on the 3-year Norwegian government bond, and $R_{OSEBX,t-i}$ is the contemporaneous and lagged daily return on the OSEBX index. The lag-length L is set to five days. The table displays the sum of the estimated coefficients, with the p-value of the null hypothesis that each sum is statistically equal to zero in parenthesis.

There are several noticeable findings in the estimated regression coefficients. For the high yield portfolio, inclusion of contemporaneously and lagged stock portfolio returns provides little new information. Somewhat surprising, we fail to reject the null hypothesis of the sum test for estimated coefficients on stock portfolio returns. Consistent with the results portrayed in Table 4.7, the sum of the estimated coefficients on the OSEBX returns is significant and equal in magnitude. However, regressions on sector portfolio returns show variations in sensitivity across the lower rated bonds. In particular, a clear distinction is evident between the two dominant high yield sectors oil & gas and shipping. For the oil & gas portfolio, adding contemporaneously and lagged stock portfolio returns boosts evidence of market sensitivity, with the sum of the estimated coefficients on the OSEBX returns going from 0.139 to 0.161. The opposite is true for the shipping portfolio. Here, all evidence of market sensitivity disappears, and is replaced by a strongly significant relationship with the underlying stocks. As portrayed in Table 4.8, the sum of estimated coefficients on the stock portfolio returns is 0.097.

The above results provide additional insight into the dynamics of cross-market returns in our sample. First, sluggish response to common factors, rather than firm-specific news, appears to cause the stock lead in lower rated bonds, as indicated in our previous analysis. Due to the large proportion of oil-related securities, high yield bonds exhibit a substantial systematic risk component. As shown by Bjørnland (2009), the Norwegian stock market reacts to changes in the oil price. Similarly, changes in the oil price affect the value of oil-related bonds, as the oil price portrays important information about future cash flows from the issuing firms. Thus, considering the collapse and volatility in oil prices over our sample period, sensitivity to the OSEBX index return is expected. Noticeable is the lack of significance on stock portfolio returns for high yield and oil & gas portfolios. Overall, this suggests that our previous findings of a stock lead follow from a slower reaction in corporate bonds to common factors, such as changes in the oil price.

Second, bond return sensitivity to common factors and firm-specific news varies across the lower rated sectors. For the shipping and seafood portfolios, the sum of estimated coefficients on stock portfolio returns is significant at the 1 % level. No evidence of market sensitivity is found. This contrasts our findings for oil & gas. Using 20 of the most actively traded US high yield bonds, Hotchkiss and Ronen (2002) find sensitivity to firm-specific news only in the bonds closest to default (B+ and below). This notion aligns well with our discussion of stock leads in periods of financial distress. However, it cannot alone explain the variations in sensitivity between sector portfolios, as the majority of bonds issued by financially distressed firms are found within the oil & gas sector. Two other explanations are more likely: First, sectors react differently to common factors. To illustrate, shipping firms experience a reduction in costs with lower oil prices but might suffer from lower activity and demand. Second, the magnitude of firm-specific news during our sample period varies across sectors.

For the investment grade portfolio, the inclusion of contemporaneously and lagged stock portfolio returns provides additional information about the sensitivity to market and firm-specific risks. As evident from Table 4.8, the sum of estimated coefficients on the OSEBX returns drops from -0.003 to -0.009 and is significant at the 5 % significance level. However, this result lacks support in the higher rated sector portfolios. Neither finance nor real estate exhibit sensitivity to market returns. Further, between the investment grade portfolio and returns on the underlying stock portfolio, a positive relationship is evident at the 10 % significance level. In the finance portfolio, no such relationship is evident. These findings should be considered when evaluating stock leads found in the previous analysis. The sum of estimated coefficients on returns of the 3-year Norwegian government bond shows similar significance and magnitude as in Table 4.7 across all portfolios.

Overall, we derive two conclusions from the results reported in Table 4.7 and 4.8. First, when we account for market risk, cross-market sensitivity in bond returns diminishes. This result supports previous indications of bonds lagging stocks due to a slower reaction to common factors, rather than firm-specific news. Second, consistent with the intuition provided by Merton (1974), lower rated bond portfolios behave more like equity, while higher rated bond portfolios are primarily sensitive to changes in the interest rate. Similar studies on US market data show ambiguous results, however (see Hotchkiss and Ronen (2002) and Downing et al. (2009)).

4.3.2 Informational efficiency in periods of consecutive trading days

As a final assessment of our findings, we examine all bonds with consecutive trading days in our sample. This approach allows us to rely solely on transaction data and use the full sample of observed cross-market returns to evaluate our use of price estimates in the analysis. First, we address bond return sensitivity, and look at contemporaneously and lagged cross-correlations. Second, we use the sample of consecutive trading days to estimate the VAR model described in equation (1). Lastly, we re-estimate the model using NBP price estimates to assess the validity of our findings.

Table 4.9 – Cross-correlation. Observations with consecutive trades.

		HY		IG	
		$R_{B,t}$	$R_{S,t}$	$R_{B,t}$	$R_{S,t}$
t	$R_{B,t}$	-	0.118***	-	-0.048
	$R_{S,t}$	0.118***	-	-0.048	-
	$R_{T,t}$	0.020	0.073***	-0.107***	0.043
	$R_{OSEBX,t}$	0.025	0.370***	0.016	0.123***
$t-1$	$R_{B,t-1}$	-0.195***	-0.050	-0.250***	-0.088
	$R_{S,t-1}$	0.191***	0.021	0.090	-0.076*
	$R_{T,t-1}$	0.018	-0.052**	0.081	0.034
	$R_{OSEBX,t-1}$	0.130***	0.132***	0.228***	-0.080*

Note: Table 4.9 reports cross-correlations between the daily returns on bonds (R_B), their associated stocks (R_S), the 3-year Norwegian government bond (R_T) and the OSEBX index (R_{OSEBX}). The sample is based on observed trades for bonds in OBI. Contemporaneous correlations utilise all observations where a bond trades on two consecutive days (HY: N=2041, IG: N=692). Lagged correlations utilise all observations where a bond trades on three consecutive days (HY: N=711, IG: N=158). $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Table 4.9 displays cross-correlations between corporate bond returns and returns on the associated stock, the OSEBX index and the 3-year Norwegian government bond. Contemporaneous (lagged) correlations utilise all observations with two (three) or more consecutive bond trade days. In the high yield category, the correlation coefficients indicate a noticeable equity component in bonds, with no sensitivity to changes in the interest rate. In particular, we find significant and positive relationships between bond returns and contemporaneous and lagged returns on the associated stock. In the investment grade category, this relationship remains insignificant, but bond returns are negatively related to the contemporaneous returns of the 3-year Norwegian government bond. Noticeably, for both categories, we find a negative relationship with own lagged returns, which could indicate a slight price reversion in bonds. Finally, both high yield and investment grade issues appear to be sensitive to market risk, as evident from significant and positive correlation coefficients on the lagged OSEBX returns.

Overall, the results reported in Table 4.9 are consistent with our previous findings. Lower rated bond issues behave more like equity, while higher rated issues are more sensitive to changes in the interest rate. However, a few considerations should be made when interpreting the reported correlation coefficients. First, noise present in transaction data might bias our results, as we are unable to control for transaction costs. Second, infrequent trading limits our sample of bonds with three consecutive trading days.

To test the validity of using price estimates, we estimate the model described in equation (1) using pooled OLS, with clusters on firm level to account for correlation between bonds issued by the same firm. In order to utilise the entire sample of registered bond trades, we are limited to lag lengths of one and two, respectively. The results are reported in Table 4.10. In Panel A (Panel B), all pairwise observations where a bond trade occurred on three (four) consecutive trading days are included.

Panel B shows some evidence of a two-way lead-lag relationship in cross-market returns. In the high yield category, for both stock and bond returns, we reject the null of the Granger causality test at the 1 % significance level but fail to reject the null of the sum test. In the investment grade category, we find evidence of bonds leading stocks, with the null of the Granger causality test and the sum test rejected at the 1 % and 5 % significance level, respectively. No significant effect is found the other way. However, reported results in Panel A indicate that these findings must be treated with caution, due to scarce transaction data. Contrarily to the results reported in Panel B, for high yield bonds, no evidence of a lead-lag relationship is evident when the return model is estimated using one lag.

While the above findings are somewhat inconsistent with results from our portfolio and security level analysis, we highlight one possible explanation. Given that new information induces increased trading activity in securities, it is natural to assume that a significant proportion of the consecutive bond trading days in our sample follow the release of firm-

Table 4.10 – Daily bond and stock returns. Registered trading days using transaction data.

Panel A: Observations with bond trades on three consecutive trading days.

		Lagged bond returns		Lagged stock returns				
Grade		β_1	β_2	S_1	S_2	N	Sum	Granger
HY						711		
	Bonds	-0.215		0.095*				
		(-1.010)		(1.820)				
	Stocks	-0.108		0.015				
		(-0.710)		(0.300)				
IG						158		
	Bonds	-0.320		0.011				
		(-0.890)		(1.260)				
	Stocks	-1.009***		0.010				
		(-3.200)		(0.160)				

Panel B: Observations with bond trades on four consecutive trading days.

		Lagged bond returns		Lagged stock returns				
Grade		β_1	β_2	S_1	S_2	N	Sum	Granger
HY						292		
	Bonds	-0.110	0.439***	0.135**	-0.131***		0.010	6.110***
		(-0.530)	(3.270)	(2.230)	(-3.430)		(0.913)	(0.009)
	Stocks	-0.004	0.317**	0.024	-0.107		1.050	7.500***
		(-0.020)	(2.670)	(0.350)	(-1.610)		(0.319)	(0.004)
IG						44		
	Bonds	0.123**	0.095**	0.018	0.001		2.940	2.260
		(3.140)	(3.980)	(1.280)	(0.140)		(0.162)	(0.221)
	Stocks	-5.019***	2.879***	0.504**	0.163		10.110**	49.090***
		(-9.670)	(4.810)	(3.820)	(1.550)		(0.034)	(0.002)

Note: Table 4.10 reports the results from the following vector-autoregressive model, using pooled OLS:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. In Panel A (Panel B), all pairwise observations where a bond trade occurred on three (four) consecutive days are included. Both models are clustered on firm level, to account for correlation between bonds issued by the same firm. Panel A (Panel B) includes 31 (21) High Yield-firms and 13 (5) Investment Grade-firms. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of cross-market coefficients is equal to zero. "Granger" gives the F-statistic and p-value for the null hypothesis that all cross-market coefficients are equal to zero. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Table 4.11 – Daily bond and stock returns. Registered trading days using NBP price estimates.

Panel A: Observations with bond trades on three consecutive trading days.

		Lagged bond returns		Lagged stock returns				
Grade		β_1	β_2	S_1	S_2	N	Sum	Granger
HY						711		
	Bonds	0.423***		0.031				
		(5.240)		(1.100)				
	Stocks	0.477		-0.010				
		(1.610)		(-0.230)				
IG						158		
	Bonds	0.535***		0.001				
		(13.540)		(0.240)				
	Stocks	0.543		-0.001				
		(-0.860)		(-0.010)				

Panel B: Observations with bond trades on four consecutive trading days.

		Lagged bond returns		Lagged stock returns				
Grade		β_1	β_2	S_1	S_2	N	Sum	Granger
HY						292		
	Bonds	0.436***	0.150***	0.022	-0.020		0.000	1.990
		(2.940)	(3.850)	(0.500)	(-1.360)		(0.981)	(0.162)
	Stocks	0.052	0.354	-0.010	-0.092		2.640	4.710**
		(0.110)	(1.250)	(-0.170)	(-1.700)		(0.120)	(0.021)
IG						44		
	Bonds	0.990***	-0.255	-0.012	-0.003		2.260	9.890**
		(4.640)	-1.730)	(-1.050)	(-1.390)		(0.207)	(0.028)
	Stocks	0.451	-3.802*	0.358*	0.124		19.330**	61.960***
		(0.190)	(-2.190)	(2.360)	(1.530)		(0.012)	(0.001)

Note: Table 4.11 reports the results from the following vector-autoregressive model, using pooled OLS:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. In Panel A (Panel B), all pairwise observations where a bond trade occurred on three (four) consecutive days are included. Both models are clustered on firm level, to account for correlation between bonds issued by the same firm. Panel A (Panel B) includes 31 (21) High Yield-firms and 13 (5) Investment Grade-firms. Robust t-statistics are shown beneath the coefficient estimates. “Sum” gives the F-statistic and p-value for the null hypothesis that the sum of cross-market coefficients is equal to zero. “Granger” gives the F-statistic and p-value for the null hypothesis that all cross-market coefficients are equal to zero. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

specific news. If so, we would expect a weakened stock lead due to increased investor awareness and bond market features, as outlined in our discussion of informational efficiency around earnings announcements.

Finally, when we re-estimate the model using price estimates from NBP, we get somewhat similar results. These are reported in Table 4.11. For both high yield and investment grade issues, we find evidence of bonds Granger causing stocks at the 5 % and 1 % significance level, respectively. However, in contrast to our analysis using observed trades, indications of a stock lead are found in the higher rated bonds. While this discrepancy is likely to follow from market noise, scarce transaction data complicates inference, and causality must be treated with caution.

Overall, consistent with our analysis of informational efficiency around earnings announcements, the above results indicate that the relative informational efficiency of corporate bonds tends to improve in periods of firm-specific news. Further, qualitatively similar results using transaction data and NBP price estimates support the use of estimates in our primary analysis. Even though minor discrepancies arise, no red flags are apparent.

5. Conclusion

This paper examines the properties of the Norwegian bond market and elaborates on the relationship between corporate bonds and stocks in Norway. In particular, we address the following two research questions: (1) Do corporate bonds tend to lead or lag their associated stock in incorporating new information into the pricing? (2) What drives predictability in cross-market returns between corporate bonds and their associated stock? To answer these questions, we rely on daily bond price estimates and transaction data for bonds and stocks from 01.07.2014 to 30.06.2017. Using a VAR model, we show how stocks and corporate bonds behave relative to one another and provide insight into how and when differences in informational efficiency appear.

First, we observe that high yield bonds behave more like equity than investment grade bonds. In our analysis sample, lower rated bonds exhibit sensitivity to returns on their associated stock, the OSEBX index, or both. The same bonds show no evidence of sensitivity to the 3-year Norwegian government bond. Higher rated bonds, on the other hand, display a different behaviour. These bonds are highly sensitive to changes in the interest rate and react less to changes in equity returns. The observed results are intuitive, as lower rated bonds have a higher probability of default, and consistent with previous research in the US bond market.

Second, our results indicate that bond predictability increases with credit risk. In a period characterised by increased volatility and collapse in oil prices, the majority of the predictable bonds in our sample are issued by firms within the oil & gas sector. Interestingly, we also note that six out of the eleven issuers with predictable bonds experienced financial distress during the analysis period, as evidenced by restructuring and refinancing of debt. As first proposed by Downing et al. (2009), financial distress seems to highlight cross-market differences in informational efficiency.

Third, in periods of heightened investor awareness and trading activity, we observe a change in the relative informational efficiency of corporate bonds. Around earnings announcements, previous indications of stocks leading bonds weaken, and are in some cases reversed, with bonds leading stocks. Considering that the Norwegian bond market is characterised by institutional investors and low transaction costs, the observed reversal is likely an effect of informed traders using corporate bonds to exploit new information. While this particular analysis suffers from few observations, the results are strengthened by their consistency with previous research.

Overall, our findings indicate that the answers to our research questions are intertwined. The results suggest that in periods where common factors are more prominent, as represented by the volatile oil price, stocks lead bonds. The Norwegian bond market appears to react sluggishly to new information about macroeconomic factors. In contrast, in periods of increased investor awareness, firm-specific news typically dominates, and we observe an improvement in the relative informational efficiency of Norwegian corporate bonds. The type of new information revealed might determine whether bondholders choose to enter the market, which helps explain why we get different results depending on what period we analyse, as well as the conflicting results in previous studies.

However, when assessing our results, we have to bear in mind the limitations of our datasets. First, scarce transaction data, due to infrequent trading in Norwegian corporate bonds, limits statistical inference and makes it difficult to draw a finite conclusion. In our analysis, we try to overcome this problem through the use of daily bond price estimates obtained from NBP. While the comparison of results was indeed positive, with qualitatively similar results using available transaction data and price estimates, differences occurred. Second, lack of available information about rating migrations and the size of bond trades limits the accuracy of our analysis. In particular, we are unable to assess whether the reported results apply to institutional and retail investors alike.

To summarise, our paper provides additional insight into the scarcely researched Norwegian bond market. Differences in informational efficiency between stocks and corporate bonds, and when they typically occur, are important to bear in mind for practitioners and policy makers alike. However, as evident from our limitations, additional research is needed on the topic. If trading activity in the Norwegian bond market continues to increase, more transaction data could provide interesting possibilities for researchers.

Based on our results and previous research on US market data, future research should address: what is the effect of bond market characteristics (e.g. overnight trades and institutional trades) on informational efficiency in Norway; and why does the informational efficiency of Norwegian corporate bonds appear to be contingent on the type of information revealed? One topic of interest is the behaviour of institutional bondholders in concentrated markets, such as the Norwegian, to determine whether they actively choose not to trade on new information about common factors to avoid price movements and a loss on their position.

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Appendices

This section describes supplementary material used in our analysis. First, we present additional tables not included in the above sections, then, we provide a brief overview of our results using weekly return data.

A. Additional tables

Appendix A presents additional tables used in our analysis. This includes: first, summary statistics for the Brent Spot Price; second, summary statistics for the full sample of 783 bonds; third, regression statistics from estimating the VAR model described in equation (1) on the six most actively traded bonds using both transaction data and NBP price estimates; and, lastly, mean coefficients from estimating the VAR model described in equation (1) on each individual bond-stock pair.

Table A.1 – Brent Spot Price. Summary statistics.

	01.07.2011-30.06.2014	01.07.2014-30.06.2017
Mean price (Dollars Per Barrel)	110.080	55.461
Volatility (Dollars Per Barrel)	5.871	17.881
Minimum (Dollars Per Barrel)	88.690	26.010
Maximum (Dollars Per Barrel)	128.140	110.840
Period development (Dollars Per Barrel)	1.210	-63.760
Mean daily change (%)	0.010	-0.080
Mean daily volatility (%)	1.290	2.420

Note: Table A.1 reports summary statistics for the Brent Spot Price in two periods; (1) the three years preceding our analysis period and (2) the analysis period. "Period development" shows the difference between the first observation and the last observation, exposing period trends. "Mean daily change" shows the average daily oil price change in percentage points, while "Mean daily volatility" shows the average daily volatility in percentage points. Data is retrieved from the U.S. Energy Information Administration.

Table A.2 – Characteristics of bonds. Full sample.

Portfolio	Number of bonds		Number of firms		Rating (%)		Volume (mNOK)		Age	YTM	Number of
	#	%	#	%	HY	IG	Outstanding	Issue size	Mean	Mean	trading days
Full	783		84		15.07	84.93	412,766.50	896.67	2.99	2.88	17.61
HY	118	15.07	45	53.57	100.00	0.00	41,667.17	679.79	2.94	2.36	69.37
IG	665	84.93	39	46.43	0.00	100.00	371,099.33	935.10	2.99	2.97	8.43
Finance	597	76.25	26	30.95	0.00	100.00	333,554.33	957.38	3.06	2.83	7.67
Industry	26	3.32	10	11.90	53.85	46.15	15,513.00	824.08	2.49	3.72	67.27
Oil & gas	59	7.54	21	25.00	96.61	3.39	20,118.67	689.84	2.91	2.72	66.76
Real estate	43	5.49	6	7.14	13.95	86.05	19,545.00	655.12	2.08	3.11	17.42
Seafood	7	0.89	5	5.95	100.00	0.00	2,750.00	614.29	2.34	2.12	55.43
Shipping	27	3.45	7	8.33	100.00	0.00	12,510.00	760.32	3.44	2.72	66.70
Other	24	3.07	9	10.71	29.17	70.83	8,775.00	640.63	3.04	3.66	24.42

Note: Table A.2 contains descriptive information about the 783 listed bonds (OSE or Nordic ABM) issued by the 84 firms with a publicly traded stock on the OSE during our sample period. "Rating (%)" shows the respective fractions of high yield and investment grade bonds within each category, in percentage points. "Volume (mNOK)" shows the total outstanding volume (as of 30.10.2017), as well as the mean original issue size, within each category. "Age" shows the mean age, while "YTM" shows the mean remaining time to maturity. Bond characteristics are obtained from Stamdata. The average number of trading days is compiled from OBI.

Table A.3 – Daily bond and stock returns using transaction data. Actively traded bonds.

	Lagged bond returns					Lagged stock returns					
	β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	N
Aker											749
Bonds	-0.011	-0.025	-0.070	0.016	-0.017	-0.005	0.008	0.005	-0.009	0.014	
	(-0.160)	(-1.020)	(-1.640)	(0.260)	(-0.420)	(-0.590)	(1.080)	(0.570)	(-1.330)	(1.450)	
Stocks	-0.014	0.192	-0.675*	-0.359	-0.020	0.049	-0.017	-0.017	-0.038	0.076*	
	(-0.060)	(0.880)	(-1.780)	(-1.530)	(-0.120)	(1.190)	(-0.410)	(-0.450)	(-1.030)	(1.870)	
Aker BP											749
Bonds	-0.088	-0.022	-0.048**	0.013	0.012	0.019*	0.031***	0.015	0.012	0.028***	
	(-1.720)	(-0.530)	(-2.020)	(0.390)	(0.510)	(1.670)	(2.900)	(1.530)	(1.030)	(2.660)	
Stocks	0.434***	-0.172	-0.184	-0.336*	-0.372*	0.093*	-0.059	-0.062*	0.011	0.073*	
	(3.060)	(-1.100)	(-1.030)	(-1.670)	(-1.940)	(1.840)	(-1.540)	(-1.660)	(0.250)	(1.810)	
Aker Solutions											667
Bonds	-0.086**	-0.046	-0.140**	-0.001	-0.012	-0.003	0.011**	0.007	0.010**	0.001	
	(-2.100)	(-0.960)	(-2.490)	(-0.020)	(-0.350)	(-0.610)	(2.370)	(1.600)	(2.120)	(0.250)	
Stocks	-0.445	-0.689	-0.311	-0.466	-0.807	-0.011	-0.006	-0.041	-0.014	0.037	
	(-1.210)	(-1.500)	(-0.620)	(-1.080)	(-1.450)	(-0.240)	(-0.130)	(-0.950)	(-0.330)	(1.140)	
Fred Olsen Energy											749
Bonds	0.005	-0.051	0.040	0.001	-0.037	0.050***	0.051***	0.048***	0.002	0.033	
	(0.130)	-0.870)	(0.690)	(0.040)	(-1.050)	(3.080)	(2.610)	(2.800)	(0.170)	(1.570)	
Stocks	0.041	-0.039	0.166**	0.043	0.050	-0.036	-0.024	0.038	0.043	0.079*	
	(0.570)	(-0.460)	(2.490)	(0.530)	(0.630)	(-0.840)	(-0.490)	(0.980)	(1.090)	(1.670)	
Seadrill											749
Bonds	-0.155**	0.024	-0.096	-0.037	-0.043	0.102***	-0.014	0.074**	0.013	0.030	
	(-2.040)	(0.620)	(-1.430)	(-0.860)	(-0.820)	(3.270)	(-0.610)	(2.540)	(0.570)	(1.430)	
Stocks	-0.112	0.193*	0.115	0.041	0.040	0.070	-0.057	-0.077	0.049	-0.015	
	(-1.000)	(1.770)	(0.780)	(0.350)	(0.240)	(0.760)	(-1.060)	(-1.480)	(1.170)	(-0.280)	
Stolt-Nielsen											698
Bonds	-0.103	-0.085*	-0.084*	-0.118*	-0.022	0.016	0.009	-0.005	0.013	0.003	
	(-1.560)	(-1.850)	(-1.950)	(-1.870)	(-0.720)	(1.550)	(1.000)	(-0.560)	(1.050)	(0.290)	
Stocks	-0.124	0.071	-0.040	-0.168*	0.089	-0.015	0.029	-0.045	0.003	-0.043	
	(-0.670)	(0.440)	(-0.310)	(-1.940)	(0.680)	(-0.290)	(0.600)	(-0.960)	(0.080)	(-0.950)	

Note: Table A.3 reports the results from the following vector-autoregressive model, using transaction data to calculate bond returns:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. The lag-length L is set to five days. Robust t-statistics are shown beneath the coefficient estimates. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Table A.4 – Daily bond and stock returns using NBP price estimates. Actively traded bonds.

	Lagged bond returns					Lagged stock returns					
	β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5	N
Aker											749
Bonds	0.229*	0.181***	-0.114	0.004	0.058	-0.002	0.003	0.009	0.001	0.003	
	(1.800)	(2.750)	(-1.180)	(0.080)	(1.450)	(-0.440)	(0.930)	(1.320)	(0.220)	(0.650)	
Stocks	0.071	-0.671	-0.348	-0.786**	-0.255	0.038	-0.022	-0.027	-0.030	0.080**	
	(0.190)	(-0.790)	(-1.130)	(-2.430)	(-0.730)	(0.950)	(-0.540)	(-0.720)	(-0.820)	(1.970)	
Aker BP											749
Bonds	0.076**	-0.011	0.030	0.026	0.057*	0.015*	0.019**	0.016**	0.016*	0.004	
	(2.000)	(-0.370)	0.810)	(1.090)	(1.670)	(1.860)	(2.350)	(2.330)	(1.720)	(0.520)	
Stocks	0.588***	-0.248	-0.128	-0.542*	-0.501**	0.088*	-0.062	-0.062	0.005	0.070*	
	(2.980)	(-0.980)	(-0.590)	(-1.930)	(-2.120)	(1.680)	(-1.610)	(-1.640)	(0.120)	(1.730)	
Aker Solutions											667
Bonds	0.125**	0.058	-0.042	0.059**	-0.013	0.001	0.002	0.001	0.004**	0.003	
	(2.170)	(1.590)	(-1.000)	(2.060)	(-0.200)	(0.380)	(0.870)	(0.630)	(2.470)	(1.610)	
Stocks	-0.158	-0.205	-0.278	-0.926	-0.281	-0.007	-0.003	-0.039	-0.021	0.029	
	(-0.160)	(-0.170)	(-0.230)	(-1.040)	(-0.230)	(-0.160)	(-0.060)	(-0.920)	(-0.490)	(0.860)	
Fred Olsen Energy											749
Bonds	0.118*	0.082*	0.044	0.017	-0.005	0.028*	0.030***	0.019*	0.023**	0.014	
	(1.850)	(1.780)	(1.000)	(0.660)	(-0.210)	(1.780)	(3.080)	(1.710)	(1.990)	(1.300)	
Stocks	0.150*	0.045	0.039	0.024	0.201**	-0.045	-0.031	0.028	0.038	0.073	
	(1.740)	(0.460)	(0.500)	(0.270)	(2.110)	(-1.030)	(-0.640)	(0.720)	(0.980)	(1.580)	
Seadrill											749
Bonds	0.230**	-0.013	0.034	-0.030	0.110	0.044**	0.000	0.032*	0.015*	0.013	
	(2.490)	(-0.290)	(0.560)	(-0.680)	(1.610)	(2.180)	(0.030)	(1.920)	(1.770)	(1.460)	
Stocks	0.309*	-0.057	0.247	0.103	-0.238	0.054	-0.074	-0.065	0.023	-0.001	
	(1.890)	(-0.230)	(1.120)	(0.390)	(-0.950)	(0.570)	(-1.600)	(-1.250)	(0.510)	(-0.020)	
Stolt-Nielsen											698
Bonds	0.111*	-0.008	-0.067	-0.013	-0.008	0.014	0.012**	-0.003	0.008	0.009	
	(1.750)	(-0.130)	(-0.740)	(-0.370)	(-0.150)	(1.540)	(2.210)	(-0.460)	(0.970)	(1.470)	
Stocks	-0.219	-0.004	0.105	-0.206	0.060	-0.018	0.032	-0.044	-0.002	-0.041	
	(-0.780)	(-0.020)	(0.360)	(-1.440)	(0.350)	(-0.350)	(0.680)	(-0.930)	(-0.040)	(-0.910)	

Note: Table A.3 reports the results from the following vector-autoregressive model, using NBP price estimates to calculate bond returns:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. The lag-length L is set to five days. Robust t-statistics are shown beneath the coefficient estimates. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Table A.5 – Security level mean coefficients.

	Lagged bond returns					Lagged stock returns				
	β_1	β_2	β_3	β_4	β_5	S_1	S_2	S_3	S_4	S_5
HY	0.110	0.036	0.012	0.026	0.035	0.008	0.004	0.005	0.004	0.002
	(0.104)	(0.082)	(0.079)	(0.075)	(0.069)	(0.020)	(0.008)	(0.011)	(0.011)	(0.011)
IG	0.049	-0.003	0.022	-0.012	0.110	0.000	0.001	0.000	0.000	0.001
	(0.112)	(0.114)	(0.087)	(0.131)	(0.125)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)
Finance	0.062	-0.009	0.036	0.013	0.085	0.001	0.000	0.000	0.000	0.001
	(0.099)	(0.081)	(0.077)	(0.084)	(0.098)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)
Industry	0.109	0.054	0.021	0.004	0.071	0.002	0.002	0.002	0.002	0.002
	(0.118)	(0.060)	(0.088)	(0.071)	(0.101)	(0.005)	(0.004)	(0.004)	(0.003)	(0.005)
Oil & gas	0.120	0.049	0.012	0.023	0.033	0.012	0.005	0.007	0.007	0.003
	(0.082)	(0.093)	(0.077)	(0.059)	(0.072)	(0.025)	(0.011)	(0.015)	(0.015)	(0.015)
Real estate	0.014	-0.009	-0.022	-0.073	0.159	0.001	0.001	0.000	0.001	-0.001
	(0.150)	(0.190)	(0.113)	(0.221)	(0.176)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
Seafood	0.013	0.046	-0.015	0.013	0.047	0.003	0.003	-0.001	0.000	0.002
	(0.144)	(0.081)	(0.108)	(0.093)	(0.043)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Shipping	0.106	0.001	0.011	0.060	0.038	0.007	0.003	0.003	0.003	0.002
	(0.127)	(0.071)	(0.069)	(0.092)	(0.069)	(0.016)	(0.006)	(0.005)	(0.004)	(0.004)
Other	0.052	0.025	0.023	-0.032	0.115	0.000	0.003	0.002	0.000	0.000
	(0.077)	(0.067)	(0.057)	(0.081)	(0.120)	(0.003)	(0.008)	(0.008)	(0.002)	(0.006)

Note: Table A.5 summarises the results from estimating the following regression model on each individual bond-stock pair in our sample:

$$R_{B,j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $R_{B,j,t}$ is the daily return on bond j and $R_{S,j,t}$ is the daily return on stock j issued by the same firm. The lag-length L is set to five days. The table reports the mean estimated coefficients from the regressions, while standard deviations in results are shown in parentheses below.

B. Supplementary analysis: Weekly returns

Appendix B provides a brief overview of our results using weekly returns. Weekly lags allow us to examine whether the related securities take longer to incorporate new information, at intervals not captured by daily observations. Due to scarce transaction data, this analysis is limited to bond returns calculated using bond price estimates obtained from NBP.

To assess the lead-lag relationship between stocks and corporate bonds, we estimate the VAR model described in equation (1), both on portfolio and security level. These results are reported in Table B.1, B.2 and B.3. Further, to examine sensitivity of bond returns to market and interest risk, we estimate the return models described in equation (2) and (3). These results are reported in Table B.4 and B.5. Before results are reported, we outline our main findings.

As evident from the tables below, we find qualitatively similar results using daily and weekly returns, with weak evidence of stocks leading bonds. This suggests the presence of cross-sectional differences in information diffusion across bonds in our sample[1]. Noticeably, we observe a shift from predictable bonds within the oil & gas sector (daily), to predictable bonds within the shipping sector (weekly). No overlap in predictable bonds is found. Consistent with our findings using daily observations, we observe that high yield bonds are sensitive to returns on their associated stock and the OSEBX index, while investment grade bonds are more sensitive to changes in the interest rate.

[1] One possible reason can be derived from Ronen and Zhou (2013). They suggest that investors prefer to trade in one, or a few, of the issuer's outstanding bonds following firm-specific news. If remaining bonds incorporate the same information more gradually, this might explain findings of cross-sectional differences in our sample.

Table B.1 – Weekly bond and stock portfolio returns (credit rating).

	Lagged bond returns				Lagged stock returns					
	β_1	β_2	β_3	β_4	S_1	S_2	S_3	S_4	Sum	Granger
HY										
Bonds	0.170	0.151	0.143*	-0.043	0.028	0.024*	0.041	0.003	6.063**	2.057*
	(1.586)	(1.259)	(1.786)	(-0.603)	(1.619)	(1.748)	(1.539)	(0.212)	(0.015)	(0.090)
Stocks	-0.325	-0.493	0.651	-0.457	0.118	0.052	0.151	0.050	0.835	1.257
	(-0.528)	(-0.912)	(1.329)	(-1.474)	(1.394)	(0.775)	(1.038)	(0.515)	(0.363)	(0.290)
IG										
Bonds	0.112	0.120	-0.037	0.063	0.014**	-0.002	-0.004	0.009	2.357	1.656
	(1.207)	(1.318)	(-0.373)	(0.655)	(2.317)	(-0.241)	(-0.613)	(1.412)	(0.127)	(0.164)
Stocks	-0.865	-0.208	2.342*	-0.371	0.126	-0.002	-0.077	0.093	0.188	0.998
	(-0.718)	(-0.180)	(1.939)	(-0.300)	(1.380)	(-0.024)	(-0.995)	(1.213)	(0.665)	(0.411)

Note: Table B.1 reports the results from the following vector-autoregressive model:

$$z_t = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=1}^{L} \beta_{S,i} R_{S,t-i} + \epsilon_t$$

where $z_t = [R_{B,t}, R_{S,t}]$, $R_{B,t}$ is the weekly return on an equally-weighted portfolio of bonds with the indicated rating and $R_{S,t}$ is the weekly return on the associated stock portfolio. The lag-length L is set to four weeks. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of the four cross-market coefficients is equal to zero. "Granger" gives the F-statistic and p-value for the null hypothesis that all four of the cross-market coefficients are equal to zero. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Table B.2 – Weekly bond and stock portfolio returns (sector).

	Lagged bond returns				Lagged stock returns					
	β_1	β_2	β_3	β_4	S_1	S_2	S_3	S_4	Sum	Granger
Finance										
Bonds	0.103	0.093	-0.038	0.062	0.010**	-0.004	-0.004	0.005	0.648	1.568
	(1.105)	(1.025)	(-0.374)	(0.602)	(2.143)	(-0.765)	(-0.682)	(0.878)	(0.422)	(0.186)
Stocks	-1.325	-0.983	2.318	-0.219	0.115	-0.015	-0.046	0.167*	0.006	0.812
	(-0.854)	(-0.644)	(1.495)	(-0.142)	(1.443)	(-0.171)	(-0.584)	(1.947)	(0.940)	(0.520)
Industry										
Bonds	0.243*	-0.004	0.210***	-0.088	0.038***	0.010	0.014	-0.002	7.708***	3.885***
	(1.685)	(-0.032)	(2.947)	(-1.193)	(3.726)	(1.090)	(1.067)	(-0.282)	(0.006)	(0.005)
Stocks	-1.278*	-0.096	1.362	-1.765**	0.177*	0.112	-0.161*	0.145*	1.661	2.254*
	(-1.901)	(-0.148)	(1.452)	(-2.127)	(1.895)	(1.344)	(-1.736)	(1.714)	(0.200)	(0.066)
Oil & gas										
Bonds	0.250**	0.125	0.194*	-0.082	0.006	0.024*	0.016	0.004	3.092*	1.375
	(2.560)	(1.440)	(1.789)	(-1.150)	(0.395)	(1.690)	(1.448)	(0.367)	(0.081)	(0.246)
Stocks	0.516	-0.422	0.397	-0.552	0.089	-0.025	0.159	0.008	0.009	1.170
	(0.867)	(-0.925)	(0.589)	(-1.205)	(0.887)	(-0.446)	(1.145)	(0.098)	(0.923)	(0.327)
Real estate										
Bonds	0.170	0.137	-0.034	0.071	-0.000	0.007	0.002	0.000	0.963	0.513
	(1.652)	(1.490)	(-0.346)	(0.860)	(-0.063)	(1.310)	(0.541)	(0.056)	(0.328)	(0.726)
Stocks	0.452	0.685	0.001	1.158	0.042	0.096	-0.062	0.013	1.165	0.361
	(0.275)	(0.369)	(0.001)	(0.672)	(0.527)	(1.194)	(-0.624)	(0.142)	(0.282)	(0.836)
Seafood										
Bonds	0.253***	0.104	0.194	0.019	0.012***	-0.008*	-0.002	-0.007	0.608	2.778**
	(3.520)	(1.157)	(1.524)	(0.259)	(2.872)	(-1.688)	(-0.711)	(-1.649)	(0.437)	(0.029)
Stocks	-4.680**	-1.041	2.156	-2.278	-0.089	-0.059	0.019	-0.093	7.429***	3.878***
	(-2.571)	(-0.514)	(1.224)	(-1.508)	(-0.930)	(-0.804)	(0.229)	(-1.125)	(0.007)	(0.005)
Shipping										
Bonds	-0.188	-0.030	-0.060	-0.044	0.076	0.034	0.018	0.021	3.614*	3.294**
	(-0.928)	(-0.522)	(-0.852)	(-0.746)	(1.355)	(1.626)	(1.409)	(1.498)	(0.059)	(0.013)
Stocks	-1.433*	-0.563	0.608	0.111	0.220	0.259**	-0.088	-0.095	1.638	1.870
	(-1.760)	(-1.201)	(1.553)	(0.329)	(0.950)	(2.157)	(-1.037)	(-1.080)	(0.203)	(0.119)
Other										
Bonds	0.122	0.127	0.067	-0.080	0.009***	0.004	0.005	0.006	13.244***	4.663***
	(1.431)	(1.480)	(0.768)	(-1.035)	(2.778)	(1.083)	(0.926)	(1.326)	(0.000)	(0.001)
Stocks	-3.021	0.647	2.097	-1.244	0.048	0.213	-0.038	-0.120*	0.433	0.741
	(-1.403)	(0.289)	(0.866)	(-0.652)	(0.622)	(1.555)	(-0.376)	(-1.764)	(0.512)	(0.565)

Note: Table B.2 reports the results from the following vector-autoregressive model:

$$z_t = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=1}^{L} \beta_{S,i} R_{S,t-i} + \epsilon_t$$

where $z_t = [R_{B,t}, R_{S,t}]$, $R_{B,t}$ is the weekly return on an equally-weighted portfolio of bonds within the indicated sector and $R_{S,t}$ is the weekly return on the associated stock portfolio. The lag-length L is set to four weeks. Robust t-statistics are shown beneath the coefficient estimates. "Sum" gives the F-statistic and p-value for the null hypothesis that the sum of the four cross-market coefficients is equal to zero. "Granger" gives the F-statistic and p-value for the null hypothesis that all four of the cross-market coefficients are equal to zero. $*$, $**$ and $***$ represent significance at the 10%, 5% and 1% level, respectively.

Table B.3 – Security level hypothesis test results (%). Weekly.

Portfolio	Stock lead		Bond lead		Two-way lead-lag	
	Granger	Granger+	Granger	Granger+	Granger	Granger+
HY	16.00	15.00	19.00	10.00	4.00	2.00
IG	7.51	1.73	10.98	2.89	0.00	0.00
Finance	4.35	0.87	9.57	0.87	0.00	0.00
Industry	8.33	8.33	41.67	20.83	0.00	0.00
Oil & gas	10.42	10.42	20.83	10.42	4.17	0.00
Real estate	16.22	2.70	10.81	5.41	0.00	0.00
Seafood	20.00	0.00	20.00	20.00	0.00	0.00
Shipping	26.09	26.09	0.00	0.00	0.00	0.00
Other	19.05	14.29	9.52	4.76	9.52	9.52

Note: Table B.3 reports the results of hypothesis tests on the security-level coefficient estimates for the vector-autoregressive model:

$$z_{j,t} = \alpha_j + \sum_{i=1}^{L} \beta_{B,i,j} R_{B,j,t-i} + \sum_{i=1}^{L} \beta_{S,i,j} R_{S,j,t-i} + \epsilon_{j,t}$$

where $z_{j,t} = [R_{B,j,t}, R_{S,j,t}]$, $R_{B,j,t}$ is the weekly return on bond j and $R_{S,j,t}$ is the weekly return on stock j issued by the same firm. The lag-length L is set to four weeks. The statistic "Granger" gives the proportion of bonds (stocks) for which the F-statistic of the null hypothesis that all the estimated coefficients of lagged stock (bond) returns equals 0 is statistically significant at the 95% level. The statistic "Granger +" gives the proportion of bonds (stocks) for which (1) the F-statistic of the null hypothesis that all the estimated coefficients of lagged stock (bond) returns equals 0, and (2) the F-statistic of the null hypothesis that the sum of the estimated coefficients of lagged stock (bond) returns equals 0, is statistically significant at the 95% level.

Table B.4 – Weekly bond return sensitivity.

Portfolio	$\sum_{i=1}^{L} \beta_{B,i}$	$\sum_{i=0}^{L} \beta_{T,i}$	$\sum_{i=0}^{L} \beta_{OSEBX,i}$
HY	0.552 (0.000)	0.006 (0.732)	0.233 (0.000)
IG	0.329 (0.017)	-0.007 (0.000)	0.008 (0.441)
Finance	0.214 (0.123)	-0.009 (0.000)	0.005 (0.603)
Industry	0.422 (0.006)	0.002 (0.789)	0.121 (0.000)
Oil & gas	0.523 (0.000)	0.022 (0.241)	0.321 (0.000)
Real estate	0.513 (0.000)	-0.002 (0.226)	0.013 (0.171)
Seafood	0.441 (0.000)	0.004 (0.101)	0.064 (0.000)
Shipping	0.113 (0.088)	-0.021 (0.235)	0.214 (0.001)
Other	0.423 (0.001)	-0.003 (0.149)	0.021 (0.045)

Note: Table B.4 reports the results from the following regression model:

$$r_{B,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{OSEBX,i} R_{OSEBX,t-i} + \epsilon_t,$$

where $r_{B,t}$ is the weekly return on an equally-weighted portfolio of bonds within the indicated credit rating or sector, $R_{T,t-i}$ is the contemporaneous and lagged weekly return on the 3-year Norwegian government bond, and $R_{OSEBX,t-i}$ is the contemporaneous and lagged weekly return on the OSEBX index. The lag-length L is set to four weeks. The table displays the sum of the estimated coefficients, with the p-value of the null hypothesis that each sum is statistically equal to zero in parenthesis.

Table B.5 – Weekly bond return sensitivity. Including stock portfolio returns.

Portfolio	$\sum_{i=1}^{L} \beta_{B,i}$	$\sum_{i=0}^{L} \beta_{S,i}$	$\sum_{i=0}^{L} \beta_{T,i}$	$\sum_{i=0}^{L} \beta_{OSEBX,i}$
HY	0.467 (0.001)	0.098 (0.005)	0.006 (0.704)	0.110 (0.111)
IG	0.281 (0.037)	0.013 (0.376)	-0.008 (0.000)	0.001 (0.949)
Finance	0.209 (0.126)	0.002 (0.834)	-0.009 (0.000)	0.005 (0.630)
Industry	0.412 (0.012)	0.020 (0.323)	0.003 (0.660)	0.097 (0.005)
Oil & gas	0.491 (0.000)	0.053 (0.013)	0.022 (0.222)	0.229 (0.016)
Real estate	0.490 (0.000)	0.011 (0.112)	-0.001 (0.438)	0.006 (0.581)
Seafood	0.453 (0.000)	-0.010 (0.247)	0.002 (0.460)	0.067 (0.000)
Shipping	-0.121 (0.288)	0.250 (0.000)	-0.021 (0.191)	0.007 (0.901)
Other	0.399 (0.007)	0.019 (0.007)	-0.002 (0.412)	0.004 (0.744)

Note: Table B.5 reports the results from the following regression model:

$$r_{B,t} = \alpha + \sum_{i=1}^{L} \beta_{B,i} R_{B,t-i} + \sum_{i=0}^{L} \beta_{S,i} R_{S,t-i} + \sum_{i=0}^{L} \beta_{T,i} R_{T,t-i} + \sum_{i=0}^{L} \beta_{OSEBX,i} R_{OSEBX,t-i} + \epsilon_t,$$

where $r_{B,t}$ is the weekly return on an equally-weighted portfolio of bonds within the indicated credit rating or sector, $R_{S,t-i}$ is the contemporaneous and lagged weekly return on the associated stock portfolio , $R_{T,t-i}$ is the contemporaneous and lagged weekly return on the 3-year Norwegian government bond, and $R_{OSEBX,t-i}$ is the contemporaneous and lagged weekly return on the OSEBX index. The lag-length L is set to four weeks. The table displays the sum of the estimated coefficients, with the p-value of the null hypothesis that each sum is statistically equal to zero in parenthesis.