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A joint analysis of country and industry factors in European stock and corporate bond returns

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PREFACE AND ACKNOWLEDGEMENTS

If you have ever taken a standard econometrics class, the phrase "Garbage in is garbage out" will undoubtedly be familiar to you. For those who have not, it means that no matter how sophisticated your econometric model is, the quality of the results coming out of it cannot be better than the quality of the data that went in. It is this simple phrase that motivated me to deliver a high-quality data set for the econometric analysis of this thesis. The data collection process however turned out to be extremely challenging and became the crux of this research. I spent many hours behind financial data terminals finding the right data, and again many hours behind my own computer filtering out the "garbage data" and aligning data from different collection sources. In the end my persistence paid off and I managed to construct the desired data set (see Appendix A). Thereafter, I was challenged to get a full understanding of the Heston and Rouwenhorst (1994) model, the main method I apply in this thesis. This motivated me to write a comprehensive note on this model, which is presented in Appendix B. I am proud of the final result.

For sure, this thesis would not have been completed without the support and encouragement of several people. I would like to thank my supervisors, Prof. Dr. Mary Pieterse-Bloem and Zhaowen Qian (PhD student) of the Erasmus School of Economics, for their comments and guidance, their patience, and their continuing enthusiasm for this work. I would also like to thank them for allowing me to work with their unique data set of European corporate bonds. Last but foremost, I must express my very profound gratitude to my loving family for their unfailing believe in my ability to succeed and for maintaining a positive attitude, even when faced with difficult circumstances.

Joost Coenraad Keij

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ABSTRACT

In this thesis I provide a joint analysis of the relative importance of country and industry factors in European stock and corporate bond returns for the period April 1999 to January 2013. Using a unique data set of stock and corporate bonds that are linked at the firm level, I find that stock returns are mainly driven by industry factors, while country factors dominate industry factors in corporate bond returns. However, after the start of the global financial crisis, country factors appear to become at least as important as industry factors in stock returns, while the relative significance of country factors in corporate bond returns seems to lower due to a rising importance of industry factors. Moreover, my findings show that both country and industry factors should be included in a stock diversification strategy to obtain optimal performance in terms of mean-variance efficiency. In contrast, a diversification strategy across countries only already appears to be mean-variance efficient for corporate bonds.

Keywords: Corporate bonds and stocks; Portfolio diversification; Country and industry factors; EMU; Financial integration

JEL classifications: F36, G11, G15

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CHAPTER 1 Introduction

The relative importance of country and industry factors in returns is well researched for both the European stock and corporate bond markets separately. One might expect that the results from these separate studies exhibit similar patterns for two reasons. First and foremost, because according to the theory of financial integration decreasing country versus industry factors are expected over time in European asset returns, especially after the start of the Economic and Monetary Union (EMU) in January 1999 (Baele et al., 2004). Second, because the used stock and corporate bond samples are linked, in some part, at the firm level. In theory, since the stocks and corporate bonds that are issued by the same firms are different claims to the same firms' assets and underlying operating cash flows, their return components should be related to varying degrees (Merton, 1974).

The existing corporate bond and stock studies tell different stories regarding the relative importance of country and industry factors, however. Contrary to the expectation of the theory of financial integration, country factors dominate industry factors overall in European corporate bond returns over the 22 years from 1991 to 2013 without a trend towards greater integration (e.g. Pieterse-Bloem, 2011; Pieterse-Bloem and Mahieu, 2013; Pieterse-Bloem et al., 2016, 2017). A similar domination of country factors is only observed in European stock returns until around the start of the EMU (Heston and Rouwenhorst, 1994, 1995; Rouwenhorst, 1999; Ferreira and Ferreira, 2006). Thereafter, industry factors have begun to play an increasingly larger role than country factors in the European stock market, as expected under progressing financial integration (e.g. Flavin, 2004; Moerman, 2008; Eiling et al., 2006; Chou et al., 2014). To get a better understanding why the European corporate bond market offers such a distinct and different perspective on the relative importance of country and industry factors compared to the stock market, the returns from both markets should be jointly analyzed, something that, to my knowledge, has not yet been done in this area of the finance literature.

In this study I do so by investigating two samples of European stocks and corporate bonds that are issued by the same firms. I thus use the aforementioned notion that stocks and corporate bonds are linked at the firm level and expect to find more similar patterns in the country and industry factors extracted from the returns of the matched stocks and corporate bonds. Unlike for the US, where the study of the link between the returns of stocks and corporate bonds of the same firm is not uncommon (e.g. Gebhardt et al., 2005; van Zundert and Driessen, 2017), similar studies for Europe are missing. This is probably due to the fact that North American stock and corporate bond data can be matched directly by financial security identification codes with firm unique characters, i.e. CUSIP codes, while for Europe such overlapping identifiers are absent. I overcome this impediment by linking stocks and corporate bonds based on issuers' names and manage to match 3441 corporate bond return series to 379 stock return series covering the period from April 1999 to January 2013.

My contribution to this area of research is not to describe a new method to examine the relative performance of country and industry factors in asset returns, but rather to build on previous analyses conducted for corporate bond and stock markets. In particular, I follow a methodology similar to the one employed in Pieterse-Bloem and Mahieu (2013), which consists of two prevailing approaches to investigate whether the stock and corporate bond returns are driven by country or industry factors. The first approach is the method of Heston and Rouwenhorst (1994) which decomposes sets of stock or corporate bond returns into pure country and industry factors. The importance of the separate factors can then be defined by looking at the extent to which they explain return variation. The second approach examines the diversification opportunities contained in country- and industry-based investment strategies directly in a mean-variance performance framework. I use spanning tests to determine whether the mean-variance performance of portfolios consisting of either country or industry indices can be improved by adding indices from the opposite set, and efficiency tests to determine whether the maximum Sharpe ratios of the two sets of country- and industry-based portfolios are statistically different from each other.

In contrast to the expectation, the findings of this thesis show that even firm level linked European stock and corporate bond data provide very distinct views on the relative importance of country and industry factors in returns. According to the results of the Heston and Rouwenhorst (1994) methodology industry factors dominate country factors in the matched stock returns overall, while country factors are far more important than industry factors in the matched corporate bond returns. Furthermore, the results of the spanning and efficiency tests for the matched stocks show overall that neither a country- nor an industry-based investment strategy does outperform the other and that both a country and an industry-based portfolio can be improved by adding indices from the opposite set. In contrast, the results of the spanning and efficiency tests for the matched corporate bonds suggest that a country-based portfolio outperforms an industry-based portfolio in terms of mean-variance efficiency overall.

The rest of this study is organized as follows. Chapter 2 discusses the existing literature related to my study. In Chapter 3 the matched samples of stocks and corporate bonds are presented. Chapter 4 describes the methodologies applied. The empirical results are contained in Chapter 5. Finally, Chapter 6 summarizes and concludes the study.

CHAPTER 2 Literature review

My study relates and contributes to two streams of literature. The first stream of related studies is about the relative importance of country and industry factors in European portfolio diversification. The second stream concerns the relationship between the returns of stocks and corporate bonds of the same firm. This chapter reviews the most relevant studies from both strands of literature in the context of this study.

2.1 Country and industry factors in stock and corporate bond returns

The application of methods that adequately decompose a set of asset returns into pure country and industry factors is generally considered to begin with the influential paper of Heston and Rouwenhorst (1994). These authors investigate whether European stock portfolio diversification benefits more from picking pure country or industry stocks. Their applied methodology is made up of restricted cross-sectional weighted (ordinary) least squares regressions of individual firms' stock returns on a set of country and industry dummy variables for each time period. The restrictions are imposed such that the coefficient estimates of the dummy variables can be interpreted as factors that give the pure return associated with the country or the industry they belong to in excess of the total value-(equally-)weighted market index return. The importance of each country and industry factor is then calculated by the time series variance of the corresponding coefficient estimates over fixed or rolling time windows of arbitrary length.

An advantage of the decomposition methodology of Heston and Rouwenhorst (1994) is that it produces powerful and intuitive results. In their case, that in the European stock market in the period from 1978 to 1992, country factors play a bigger role in stock returns than industry factors. For instance, the average variance of the country factors is almost four times higher than the average variance of the industry factors over the entire sample period. Moreover, Heston and Rouwenhorst (1994) find that diversification across industries within a single country only reduces portfolio variance to 38% of the average stock variance, while diversification across countries within a single industry reduces the portfolio variance to 20%. Based on these results, they conclude that country diversification is a much more effective instrument to reduce portfolio risk than industry diversification.

An important hypothesis raised in the follow-up study of Heston and Rouwenhorst (1995) states that country factors are likely to be less significant for explaining the relative performance of countries that are more homogeneous. From this hypothesis it would be expected that country factors in European asset returns diminish in anticipation of and following the start of the EMU in January 1999, as the financial markets of the participating countries become increasingly integrated. Most of the subsequent studies that build on the decomposition methodology of Heston and Rouwenhorst (1994) test this expectation. So does Rouwenhorst (1999). He re-investigates the initial result for stocks in Heston and Rouwenhorst (1994) for the same set of European countries and industries, but for the later period from 1993 to 1998. His conclusion is that, despite the convergence of European interest rates and the European-wide harmonization of fiscal and monetary policies in anticipation of the start of the EMU, no evidence exists that country factors loose relative importance in European stock returns.

However, the next studies that apply the decomposition methodology of Heston and Rouwenhorst (1994) and that concentrate solely on the European stock market state that the conclusion of Rouwenhorst (1999) is too quick and that his findings already indicate signs of a shift toward more prominent industry factors. Examples are Galati and Tsatsaronis (2003), Flavin (2004) and Ferreira and Ferreira (2006), who all examine stock returns from EMU members for the periods 1990 to 2000, 1995 to 2002 and 1975 to 2001, respectively. Both Galati and Tsatsaronis (2003) and Flavin (2004) observe that industry factors start to outweigh the impact of country factors in the few months before the formal start of the EMU. Moreover, they conclude that the importance of industry factors is increasing since then, outrunning that of the country factors, which remains constant. The results of Ferreira and Ferreira (2006) confirm that industry factors become increasingly important relative to country factors in the late 1990s. However, the authors do not yet find a dominant role for industry factors two years after the introduction of the EMU, but conclude that the importance of country and industry factors is similar in magnitude. Further analysis of both Flavin (2004) and Ferreira and Ferreira (2006) reveals that the change in the relative importance of country and industry factors is also to be found in a sample of European (non-EMU) countries. Therefore, the reversal in the relative importance of these factors can be regarded as a European-wide development.

The first study that translates the results from the Heston and Rouwenhorst (1994) methodology of stock to corporate bond returns is Varotto (2003). His data set contains credit risk induced returns of corporate bonds from nine countries, including five from Europe, and covers the period from 1993 to 1998. In line with the results for stock returns from the same period, he finds that country factors dominate industry factors in corporate bond returns. Pieterse-Bloem and Mahieu (2013) are the first to use the traditional model of Heston and Rouwenhorst (1994) to examine the impact of the EMU on the roles of country and industry factors in the cross-section of European corporate bonds. Their analysis of European corporate bond returns between 1991 and 2008 shows, contrary to the findings in the studies for stock returns, that the dominance of country factors increases significantly from before to after the start of the EMU. While country factors dominate industry factors in the Pre-EMU era by a factor of 1.6, they do so by a factor of 6.4 in the Post-EMU era. This result gives the impression that the corporate bond market provides a different perspective on financial integration in Europe compared to the stock market.

It is tempting to conclude from the results of the literature discussed so far that an industry diversification strategy performs better than a country diversification strategy for European stocks in the Post-EMU period and that for European corporate bonds the reverse is true. Yet, one should be careful not to draw such strong inferences from Heston and Rouwenhorst (1994) model-based analyses for two reasons. First, because the assumptions of fixed and constant (zero or one) country and industry factor loadings underlying the Heston and Rouwenhorst (1994) model might bias the estimation of the country and industry factors. Second, because the essence of the Heston and Rouwenhorst (1994) decomposition methodology is to determine the extent to which country and industry factors explain return variation, and not to compare industry- and country-based portfolio performance. Motivated by this recognition, Eiling et al. (2006) and Moerman (2008) adopt a different methodology, one based on mean-variance analysis, to directly evaluate the risk-return properties of country- and industry-based stock portfolios. First, three mean-variance efficient frontiers are constructed: one based on country indices alone, one based on industry indices alone, and one based on country and industry indices combined. Next, so-called spanning and efficiency tests are performed to determine whether the optimal country and industry portfolios on the frontiers have statistically different mean-variance characteristics. More specifically, spanning tests show whether the efficient frontiers from given sets of either country or industry indices can be improved by adding the indices from the opposite set, whereas efficiency tests show whether the maximum Sharpe ratios of the two sets of optimal country- and industry-based portfolios are significantly different from each other.

Moerman (2008) uses return series of country and industry indices from all EMU-participating countries (except Luxembourg) covering the period from 1995 to 2004. By applying spanning tests, he finds that diversification over industries results in more efficient portfolios than diversification over countries. This result becomes even more pronounced when he examines the two sub-samples for the Pre- and Post-EMU periods. The conclusions are somewhat mixed in the Pre-EMU sample, but the Post-EMU period provides strong evidence that diversifying over industries result in a much better performance than diversifying over countries. This is in accordance with the previously discussed results of Galati and Tsatsaronis (2003) and Flavin (2004) showing a reversal toward prominent industry factors in stock returns after the introduction of the EMU. Eiling et al. (2006) perform similar spanning tests and also efficiency tests on returns of country and industry indices from the same EMU-member countries as in Moerman (2008), but covering the period from 1990 to 2003. The results of their spanning tests show, in contrast to Moerman's 2008 findings, equal mean-variance efficiency of country- and industry-based portfolios over the whole sample period, as well as over both Pre- and Post-EMU periods. The maximum Sharpe ratios of industry-based portfolio sets are found to be higher than those of country-based portfolio sets over the full sample. However, the differences are statistically insignificant according to the efficiency tests. Overall, the results of Eiling et al. (2006) are consistent with Ferreira and Ferreira (2006) showing that country-based strategies provide better risk-return trade-offs in the 1990s, while industry-based portfolios perform as well as country-based portfolios in the Post-EMU period.

Pieterse-Bloem and Mahieu (2013) are the first to apply spanning and efficiency tests on country and industry indices constructed from individual European corporate bond returns. They find that in the Pre-EMU period both country- and industry-based strategies yield mean-variance inefficient portfolios, meaning that the mean-variance performance of both types of portfolios can be improved by adding indices from the opposite set. In the Post-EMU period country- and industry-based portfolios are found to be both efficient in a mean-variance setting. They observe that country-based portfolios always have a higher maximum Sharpe ratio than industry-based portfolios, albeit never statistically different. The authors comment, however, that it seems true that over the longer run country-based corporate bond strategies are rewarded with better risk-adjusted returns than industry-based strategies. This latter is in line with their results for the Heston and Rouwenhorst (1994) decomposition methodology, as discussed above.

Despite the extensive literature documenting a shift toward more prominent industry factors governing European stock returns in the advent of the EMU, there are not many studies that investigate whether this phenomenon persists during the period of the global financial crisis and the European sovereign debt crisis. Scarce examples are Chou et al. (2014) and Artiach et al. (2018), whose samples cover the periods of 1992 to 2011 and 1974 to 2013, respectively. Both studies are restricted to the European stock market and find, by applying the Heston and Rouwenhorst (1994) methodology [1], that country factors regain strength and become at least as important as industry factors during the crisis period (the period after 2008). According to Chou et al. (2014) a large proportion of this increase in importance of country factors is driven by the peripheral-EMU countries, i.e. countries with the weakest macroeconomic fundamentals (Portugal, Italy, Ireland, Greece and Spain). For core-EMU countries (Germany, France, the Netherlands, Belgium, Austria and Finland) they show that industry factors remain important but have become less so dominant due to the rising significance of country factors. Chou et al. (2014) also apply spanning tests and find that, during the crisis period, the traditional country-based investment strategy may gain more diversification benefits compared with the industry-based strategy. This result corroborates their finding from the Heston and Rouwenhorst (1994) model that country factors regain strength relative to industry factors during the crisis period. The findings of the spanning tests also confirm that the peripheral-EMU countries are the major contributor to the increase in importance of country factors.

Pieterse-Bloem et al. (2016, 2017) extend the corporate bond sample compiled by Pieterse-Bloem and Mahieu (2013) from 2008 to 2013 to examine the effect of the global financial crisis and the European

[1] It should be noted that Artiach et al. (2018) use a two-step approach to obtain country and industry factor loadings that are different across stocks. In the first step they use the Heston and Rouwenhorst (1994) model to estimate time series of country and industry factors. Then in the second step the factors are standardized and used as exogenous variables at the firm level to obtain a stock's sensitivities to them.

sovereign debt crisis on the relative importance of country and industry factors in European corporate bond returns as well. Similarly to the results for stock returns, they find, by applying the methodology of Heston and Rouwenhorst (1994), an increase in importance of country relative to industry factors in corporate bond returns from the Pre-crisis period (1991 to half 2007) to the crisis period (half 2007 to 2013). However, this relative increase is not particularly driven by peripheral-EMU countries, unlike in the case of stocks returns, but mainly results from the overall decrease of the significance of industry factors during the crisis period. Noteworthy is that the largest drop in industry factor importance is found with respect to the financial industry. Given that the source of the crisis lies within the financial industry, one would rather expect a more important role for the financial industry factor in explaining return variation in the crisis period. A possible explanation that Pieterse-Bloem et al. (2016) give for this unexpected result is that not the financial industry, but the government institutions industry is the transmission channel for the crisis in Europe, as European governments bailed out several financial institutions in the course of the crisis. This idea is supported by their observation of an exclusive increase in industry factor importance with respect to the government institutions industry in the crisis period. By performing rolling spanning and efficiency tests, Pieterse-Bloem et al. (2017) evaluate the mean-variance performance of country- and industry-based corporate bond portfolios over time, including the crisis period. The results show that, despite the fact that country factors explain more return variation than industry factors on average, a combined country and industry allocation is needed to obtain mean-variance efficient portfolios, especially during a highly volatile period such as the period of the global financial crisis.

2.2 The stock and corporate bond return relationship at the firm level

Merton (1974) was the first to establish a theoretical framework for understanding the relationship between stock and corporate bond returns at the firm level. The framework is based on option pricing and builds on the firm value being the only state variable that connects prices of different claims (e.g. stocks and corporate bonds) to the same firm's assets. It demonstrates that the price of a corporate bond is related to that of a risk-free loan minus the value of a put option written on the firm's assets [2] and that the price of a stock equals the value of a call option written on the firm's assets instead. This option characterization of stocks and corporate bonds shows that whether the individual stock and corporate bond return relation will be positive or negative depends on the type of firm-specific information that becomes available over time. If the information is about the mean value of the firm's assets, then the stock and corporate bond prices move in the same direction.[3] But, if the information is about the volatility of the firm's assets, then the stock and corporate bond prices move in the opposite direction.[4] Most empirical studies that examine the return relationship of stocks and corporate bonds draw upon these insights from what is called Merton's structural model.

The earliest studies that investigate firm-level stock and corporate bond data to do so in an event study setting. The basic idea of these studies is to assess and compare the impact of (the announcement of) a specific corporate event on a firm's stock and corporate bond price. Particular attention is usually devoted to corporate events in which agency conflicts between stock- and corporate bondholders occur. These agency conflicts arise when the firm is involved in events which have different consequences for stock and corporate bond values. From the perspective of Merton's framework, these are events that affect the volatility of a firm's assets. Unexpected dividend payments and stock buybacks are classic

[2] In other words, the bondholder has a short position in a put option written on the firm's assets.

[3] Recall here that the values of a long position in a call option and a short position in a put option are affected in the same direction by a change in the current price of the underlying asset.

[4] Recall here that the value of a long (short) position in a call (put) option generally increases (decreases) with the volatility level of the underlying asset.

examples of such events for which corporate bondholders pay the price and from which stockholders benefit. Consistent with the theory, studies find, on average, abnormal positive stock returns and negative corporate bond returns during the announcement periods of both these events (Kalay, 1982; Woolridge, 1983; Maxwell and Stephens, 2003). Similar opposite movements of stock and corporate bond returns are also observed in other events associated with agency conflicts, such as mergers and acquisitions (Bessembinder et al., 2008; Bhanot et al., 2010), and corporate spin-offs (Maxwell and Rao, 2003).

The use of firm-level stock and corporate bond panel data seems to begin with the pioneering study of Kwan (1996). He investigates both the contemporaneous correlation and the cross-serial correlation between individual stocks and corporate bonds issued by the same firm. His results show that weekly US stock returns and corporate bond yield changes are negatively contemporaneously correlated. Since corporate bond yields and returns move in opposite directions, this finding implies a positive contemporaneous correlation between stock and corporate bond returns. As stated by Kwan (1996), it indicates that the firm-specific information driving stocks and corporate bonds is mainly related to the mean value of the firms' assets, rather than to the volatility of the firms' assets. Moreover, along with being contemporaneously correlated, Kwan (1996) shows that current corporate bond yield changes are significantly correlated with the lagged stock returns from the same firm. However, he also finds that current stock returns are not related to lagged corporate bond yield changes. Based on these findings, Kwan (1996) concludes that individual stock prices tend to lead corporate bond prices in incorporating common firm-specific information and hence that the stock market tends to be more informationally efficient than the corporate bond market.[5] A final interesting observation from Kwan (1996) is that high-grade corporate bonds are driven mostly by risk-free interest rates and are uncorrelated with the stocks from the same firm, while low-grade corporate bonds are highly correlated with the stocks from the same firm, but are unresponsive to risk-free interest rates. Hence, it appears that high-grade corporate bonds resemble risk-free (Treasury) bonds more than risky bonds and that low-grade corporate bonds behave like stocks.

Collin-Dufresn et al. (2001) use both aggregate and firm-specific factors, including individual firms' stock returns, to explain the variation in monthly yield spreads of individual US corporate bonds. They find that the firm-specific factors that are suggested by the traditional structural model of Merton (1974) appear less important than the aggregate factors in determining the yield spread changes. Moreover, they observe that the changes in yield spreads are, to a great extent, driven by factors not related to the stock market. According to Collin-Dufresn et al. (2001), this can be naturally explained by the segmentation of stock and corporate bond markets. They argue that if markets are segmented and different investors[6] trade in stocks and corporate bonds, then returns in those markets could be driven by independent demand and supply shocks in both markets. Yet, the difficulty in this case is to explain why stock and corporate bonds do not respond to the same aggregate factors because of market segmentation.

Campbell and Taksler (2003) link monthly US corporate bond data with stock data to investigate the influence of a firm's stock volatility on the yield spread of its corporate bond. Their results show that the volatility has a large explanatory power for variation in the yield spreads, even larger than would be expected from the structural model of Merton (1974). In their study an individual firm level investigation is preferable above an aggregate market/index level, so they argue, to avoid a potential composition effect which might blur the relationship between stock returns and corporate bond yields (returns). According to them a composition effect exists if corporate bonds are issued by different firms rather than those that dominate stock indices.

[5] There are two reasons why the stock market might be more informationally efficient than the corporate bond market. First, on average, much more attention is paid by analysts and media to stocks than to corporate bonds of the same firm. Second, stocks are in general more actively traded than corporate bonds and investors with private information might therefore prefer to trade in the stock market where they can take advantage of less informed investors. Under this scenario, stock prices should incorporate firm-specific information quicker than corporate bond prices (Ronen and Zhou, 2013).

[6] The corporate bond market contains less individual investors than the stock market. The corporate bond market tends to be dominated by institutional entities (Ronen and Zhou, 2013).

Gebhardt et al. (2005) note that the corporate bond market presents an opportunity for out-of-sample evaluation of behavioral anomalies observed in the stock market, especially because the two markets are linked at the firm level. Moreover, they argue that the corporate bond market can provide potential clues as to the sources of these anomalies due to the differences in the investor clientele and the information environment between the stock and corporate bonds markets. Their paper focuses on the momentum anomaly, and in particular, investigates whether there is an interaction between momentum in the returns of stocks and corporate bonds. To this end, they match monthly US corporate bond returns with stock returns of the same firms. Their results show that firms that recently outperformed in the stock market tend to subsequently outperform in the high grade corporate bond market. They call this phenomenon 'momentum spillover' from stocks to corporate bonds of the same firm. As in Kwan (1996), these results indicate that high grade corporate bond prices underreact to firm-specific information that was already reflected in past stock prices. Another and recent study that examines the momentum spillover from stocks to corporate bonds is Haesen et al. (2017). They show that the spillover effect is also present for low grade corporate bonds.

Schaefer and Strebulaev (2008) employ Merton's structural model to predict hedge ratios (i.e. return sensitivities) of corporate bonds against stocks of the same firm. Using data on matched monthly US stock and corporate bond returns, they find that these predicted hedge ratios are not statistically different from the stock-bond sensitivities obtained from the return data. Bao and Hou (2013), who examine similar hedge ratios using also monthly US stock and corporate bond returns of the same firms, show that corporate bonds that are later in their firms' maturity structure have higher empirical hedge ratios. Both Schaefer and Strebulaev (2008) and Bao and Hou (2013) show that the hedge ratios are larger for firms with greater credit risk.

By applying an approach which is built on the structural-form framework of Merton, Campello et al. (2008) compute firm-specific expected stock returns from individual US monthly corporate bond yield spreads, and use these returns to test asset pricing factors. They find that the market, size and book-to-market factors are significantly priced in the cross-section of the expected stock returns. However, the momentum factor does not seem to be a priced risk factor. Van Zundert and Driessen (2017) follow the approach of Campello et al. (2008), but instead of testing asset pricing factors, they analyze the cross-sectional relation between the corporate bond-implied expected stock returns and monthly firm-specific average realized stock returns for the US market. Their results are rather surprising, as a negative relation is found, suggesting that stock and corporate bond markets are not integrated and that there is relative mispricing between stocks and corporate bonds.

Choi and Kim (2018) investigate whether the stock and corporate bond markets are integrated by looking at the extent to which well-known stock market anomalies are also priced in the corporate bond market. In their empirical analyses, they use monthly US stock and corporate bond returns of the same firms and focus mainly on pricing factors suggested by structural models a la Merton (1974). These are factors related to asset growth, investment-to-assets, gross profitability, and net issuance anomalies. Their findings show that profitability and net issuance anomalies do not appear in corporate bond returns. Asset growth and investment-to-assets are significantly priced in the cross section of corporate bond returns, but the associated risk premia are inconsistent with risk premia implied by stock returns. Consequently, Choi and Kim (2018) conclude that the stock and corporate bond markets are not integrated with respect to the considered factors.

CHAPTER 3 Data

For my empirical analyses, I use corporate bond data provided by Pieterse-Bloem et al. (2016) and stock data from (Thomson Reuters) Datastream. I match the corporate bond data with the stock data based on issuers' names, while taking corporate events, such as mergers and acquisitions, into account. See Appendix A for all the details regarding the data collection and the matching procedure. Only common-ordinary stocks and fixed rate bullet corporate bonds are included in the samples. Moreover, a single stock can have multiple corporate bonds associated.

Outright (holding-period) returns for individual stocks and corporate bonds are computed in US Dollars from end-of-month total return indices.[7] Excess returns are calculated as the outright returns from the stocks and corporate bonds in excess of the risk-free interest rate (proxied by the 1-month US Dollar deposit rate from Datastream). I refer to the market value of a stock or corporate bond as its total amount outstanding in the market. For a stock the market value is equal to the current stock price (in US dollars) times the number of outstanding stocks. For a corporate bond the market value is equal to the initial amount issued (in US dollars).

Finally, I have two, matched unbalanced data sets of 379 stock and 3441 corporate bond monthly return series covering the period from April 1999 to January 2013.[8] The whole sample period is divided into two sub-periods: the Pre-crisis (Post-EMU) period from April 1999 to July 2007 and the Post-crisis period from August 2007 to January 2013. Each stock and corporate bond is assigned to one out of eight European countries and to one out of six industries, based on the classification system of Bloomberg. Out of the eight countries, four are core-EMU countries (Belgium/Luxembourg (BL), France (FR), Germany (GE) and the Netherlands (NE)), two are peripheral EMU countries (Italy (IT) and Spain (SP)), and the remaining are non-EMU countries (Sweden (SW) and the United Kingdom (UK)). The six industries that are represented are Financials & Funds (FF), Consumer (CO), Communications & Technology (CT), Basic materials & Energy (BE), Industrials (IN) and Utilities (UT).

Tables 1 and 2 respectively show how the stocks and corporate bonds are distributed over the different countries and industries. It can be observed from Panels A and B in both tables that most firms that issue both stocks and corporate bonds come from the UK or are related to the financial industry. By comparing Panels B in both tables, it becomes apparent that in the financial industry more corporate bonds per firm are issued relative to the other industries. Therefore, the proportions of stocks among the other industries are larger than their proportions of corporate bonds, while the reverse is true for the financial industry. However, the dominance of the financial industry in the corporate bond sample is somewhat reduced on a value-weighted basis (Panel D of Table 2), implying that financial firms issue corporate bonds with relatively low notional value. In contrast, the corporate bonds from Sweden seem to have relatively high notional amounts.

Panels C and D in both tables indicate that each country has at least one stock and bond in each industry, except for the utility industry in the Netherlands and Sweden. Utilities are listed firms in some countries but state-owned in others, which precludes them from appearing in each country. Furthermore, Panels C and D show that the dominant role of the financial industry is present in each country for both the stock and corporate bond sample. France, Germany and UK are also more concentrated in the consumer industry in the stock as well as in the corporate bond sample. Overall, I conclude that there are sufficient diversification opportunities in the matched samples.

[7] For the return calculation, total return indices are preferred above prices since they not only track price movements, but also dividends for stocks and coupon payments for corporate bonds. They therefore provide a more accurate representation of the securities' performance.

[8] Note that in Section A.3 of Appendix A it is stated that 391 stocks are matched with 3739 bonds over the period from January 1991 to January 2013. Due to data coverage limitations in the earliest parts of the stock and bond samples, only the months from April 1999 to January 2013 are used in the analyses.

Table 1: Country and industry composition of stock sample

Panel A: By country (number and percent of total)			
Belgium/Luxembourg	BL	23	6.07%
France	FR	74	19.53%
Germany	GE	62	16.36%
Italy	IT	44	11.61%
Netherlands	NE	15	3.96%
Spain	SP	19	5.01%
Sweden	SW	25	6.60%
United Kingdom	UK	117	30.87%
Total	379		

Panel B: By industry (number and percent of total)			
Financials & Funds	FF	119	31.40%
Consumer	CO	99	26.12%
Communications & Technology	CT	38	10.03%
Basic materials & Energy	BE	38	10.03%
Industrials	IN	48	12.66%
Utilities	UT	37	9.76%
Total	379		

Panel C: Number of stocks by country and industry

	FF	CO	CT	BE	IN	UT	Total
Belgium/Luxembourg	6	5	3	3	2	4	23
France	13	25	10	8	13	5	74
Germany	20	19	3	6	11	3	62
Italy	23	6	3	2	3	7	44
Netherlands	5	2	3	3	2	-	15
Spain	8	2	1	1	2	5	19
Sweden	9	6	2	3	5	-	25
United Kingdom	35	34	13	12	10	13	117
Total	119	99	38	38	48	37	379

Panel D: Average weights in the total value-weighted market

	FF	CO	CT	BE	IN	UT	Total
Belgium/Luxembourg	1.29	0.07	0.17	0.17	0.01	0.34	2.05
France	4.81	6.14	3.24	3.92	2.00	2.86	22.98
Germany	3.88	4.22	1.68	1.35	1.43	1.65	14.22
Italy	3.84	0.32	0.61	2.19	0.05	1.13	8.13
Netherlands	1.57	0.46	0.77	1.33	0.92	-	5.05
Spain	2.54	0.07	1.42	0.39	0.24	1.06	5.72
Sweden	1.82	0.28	1.39	0.06	0.50	-	4.04
United Kingdom	13.11	8.96	7.20	5.21	1.11	2.23	37.81
Total	32.85	20.53	16.48	14.61	6.27	9.27	100.00

Notes: Panels A and B give for each country and industry, the number of stocks included in the matched stock sample and as a percentage of the total number of stocks. Panel C gives for each country by industry the number of stocks included in the matched stock sample. Panel D gives for each country by industry the average weight of the stocks in the total value-weighted market over the matched stock sample. Percentages do not add up to precisely 100.00 due to rounding.

Table 2: Country and industry composition of corporate bond sample

Panel A: By country (number and percent of total)			
Belgium/Luxembourg	BL	124	3.60%
France	FR	739	21.48%
Germany	GE	775	22.52%
Italy	IT	388	11.28%
Netherlands	NE	188	5.46%
Spain	SP	91	2.64%
Sweden	SW	309	8.98%
United Kingdom	UK	827	24.03%
Total	3441		

Panel B: By industry (number and percent of total)			
Financials & Funds	FF	2051	59.60%
Consumer	CO	516	15.00%
Communications & Technology	CT	261	7.59%
Basic materials & Energy	BE	136	3.95%
Industrials	IN	180	5.23%
Utilities	UT	297	8.63%
Total	3441		

Panel C: Number of corporate bonds by country and industry

	FF	CO	CT	BE	IN	UT	Total
Belgium/Luxembourg	86	6	7	6	7	12	124
France	300	179	68	31	74	87	739
Germany	570	106	25	25	21	28	775
Italy	294	17	26	14	3	34	388
Netherlands	119	14	31	14	10	-	188
Spain	54	3	10	4	7	13	91
Sweden	166	56	38	14	35	-	309
United Kingdom	462	135	56	28	23	123	827
Total	2051	516	261	136	180	297	3441

Panel D: Average weights in the total value-weighted market

	FF	CO	CT	BE	IN	UT	Total
Belgium/Luxembourg	0.65	0.06	0.15	0.16	0.02	0.53	1.57
France	4.65	5.26	3.87	0.63	2.18	4.32	20.92
Germany	7.47	3.35	1.54	0.83	0.60	1.77	15.56
Italy	5.11	0.75	1.91	0.76	0.04	1.39	9.97
Netherlands	1.98	0.35	1.36	0.40	0.27	-	4.36
Spain	0.92	0.05	0.48	0.31	0.31	0.69	2.75
Sweden	16.40	0.21	0.52	0.03	0.15	-	17.30
United Kingdom	12.82	5.26	3.84	0.81	0.94	3.89	27.57
Total	50.00	15.29	13.67	3.93	4.51	12.59	100.00

Notes: Panels A and B give for each country and industry, the number of corporate bonds included in the matched bond sample and as a percentage of the total number of bonds. Panel C gives for each country by industry the number of bonds included in the matched bond sample. Panel D gives for each country by industry the average weight of the bonds in the total value-weighted market over the matched bond sample. Percentages do not add up to precisely 100.00 due to rounding.

My empirical analyses require actual country and industry return indices. These are created from the individual matched stock and corporate bond return series separately. Concretely, stock (corporate bond) returns are equally and value weighted based on their country and industry classifications. See Section B.1 in Appendix B for the exact details regarding the construction of the actual indices.

Tables 3 and 4 list the descriptive statistics of the stock and corporate bond indices, respectively. Panel A in Table 3 shows that there are substantial differences across country stock indices both in terms of mean returns and standard deviations. Judging from both equally- and value-weighted return statistics, Spain and Sweden are among the best-performing countries, while Belgium, Italy and the Netherlands are the lowest performers. As a trade-off for the higher returns, the standard deviations of Spain and Sweden are relatively high. The UK is by far the least volatile country. From Panel B in Table 3 it can be seen that the performance of the industry stock indices is as divided as the country performance. The worst-performing is the Communications & Technology industry, followed by the Financials & Funds industry. The Financials & Funds industry is extremely volatile relative to the other industries. The highest mean return seems to be found in the Basic materials & Energy index. The correlation matrices in Table 3 indicate that the cross-industry correlations appear to be lower than the cross-country correlations.

Panels A and B in Table 4 show that the performance and volatility of country and industry corporate bond indices are more uniform than those of their stock equivalents. Moreover, the mean returns and standard deviations of the corporate bond indices are on average considerably lower than what is observed for the stock indices. The cross-correlations of the corporate bond indices appear to be closer to unity than those of the stock indices. These observations are in line with well-documented stylized facts on stock and corporate bond returns. As opposed to the between stock index correlations, the correlations between industry corporate bond indices seem to be higher than the cross-correlations of the country corporate bond indices. This implies that for corporate bonds diversification benefits are expected to be larger among countries than among industries, while for stocks the reverse is expected. Based on both the equally- and value-weighted return statistics, the best-performing country corporate bond indices are the UK and France and the above-average performing industries are Communications & Technology and Utilities. Low-performing countries are Belgium, Germany and the Netherlands, and Financials & Funds among the industries.

Table 3: Summary performance statistics of stock indices

Panel A: By country													
Country	EW return		VW return		Correlation matrix								
	Mean	St. dev.	Mean	St. dev.	BL	FR	GE	IT	NE	SP	SW	UK	Total
BL	0.642	6.994	0.179	7.978	1	0.798	0.661	0.803	0.765	0.643	0.716	0.819	0.848
FR	0.859	7.010	0.514	6.625	0.850	1	0.840	0.856	0.874	0.818	0.793	0.862	0.964
GE	0.873	7.509	0.736	7.884	0.833	0.913	1	0.735	0.787	0.707	0.760	0.735	0.870
IT	0.231	7.456	0.313	7.111	0.803	0.855	0.817	1	0.775	0.782	0.715	0.802	0.883
NE	0.342	7.547	0.308	7.110	0.780	0.898	0.854	0.805	1	0.749	0.809	0.791	0.888
SP	1.135	7.647	0.868	7.847	0.681	0.794	0.739	0.812	0.772	1	0.685	0.741	0.836
SW	1.097	7.834	0.789	8.030	0.748	0.863	0.838	0.743	0.838	0.682	1	0.771	0.840
UK	0.753	5.735	0.389	5.206	0.824	0.861	0.827	0.784	0.816	0.701	0.803	1	0.942
Total	0.743	6.379	0.441	5.946	0.886	0.963	0.935	0.890	0.911	0.818	0.879	0.941	1
Panel B: By industry													
Industry	EW return		VW return		Correlation matrix								
	Mean	St. dev.	Mean	St. dev.	FF	CO	CT	BE	IN	UT	Total		
FF	0.497	8.393	0.356	8.406	1	0.758	0.604	0.713	0.809	0.750	0.940		
CO	0.874	6.001	0.603	5.233	0.874	1	0.463	0.723	0.697	0.714	0.829		
CT	0.270	7.574	0.145	7.033	0.667	0.628	1	0.490	0.675	0.472	0.759		
BE	1.293	6.774	1.005	6.251	0.812	0.887	0.585	1	0.648	0.723	0.823		
IN	1.050	7.258	1.060	7.477	0.856	0.903	0.719	0.843	1	0.637	0.862		
UT	0.859	5.087	0.576	5.546	0.746	0.746	0.470	0.721	0.679	1	0.805		
Total	0.743	6.379	0.441	5.946	0.963	0.948	0.754	0.893	0.931	0.794	1		

Notes: Panel A (B) summarizes the mean and the standard deviation of the actual equally-weighted (EW) and the value-weighted (VW) monthly stock index returns by country (industry). All returns are in US dollars and expressed in percent per month. In the correlation matrices, the coefficients above the diagonal refer to the value-weighted returns and below the diagonal are between the equally-weighted returns.

Table 4: Summary performance statistics of corporate bond indices

Panel A: By country													
Country	EW return		VW return		Correlation matrix								
	Mean	St. dev.	Mean	St. dev.	BL	FR	GE	IT	NE	SP	SW	UK	Total
BL	0.322	3.089	0.311	3.126	1	0.955	0.967	0.939	0.957	0.924	0.890	0.862	0.954
FR	0.445	2.989	0.455	3.064	0.965	1	0.978	0.960	0.969	0.935	0.895	0.897	0.978
GE	0.381	3.008	0.374	3.080	0.977	0.978	1	0.949	0.969	0.926	0.921	0.883	0.980
IT	0.400	3.049	0.388	3.101	0.939	0.965	0.948	1	0.942	0.940	0.873	0.850	0.952
NE	0.384	2.908	0.388	2.961	0.970	0.975	0.976	0.942	1	0.932	0.913	0.880	0.969
SP	0.429	2.939	0.434	3.043	0.911	0.930	0.908	0.941	0.919	1	0.870	0.823	0.928
SW	0.386	3.246	0.412	3.297	0.941	0.917	0.942	0.893	0.934	0.875	1	0.788	0.937
UK	0.528	2.655	0.495	2.706	0.800	0.853	0.832	0.807	0.825	0.770	0.751	1	0.933
Total	0.441	2.768	0.427	2.876	0.949	0.979	0.975	0.948	0.963	0.909	0.915	0.923	1

Panel B: By industry											
Industry	EW return		VW return		Correlation matrix						
	Mean	St. dev.	Mean	St. dev.	FF	CO	CT	BE	IN	UT	Total
FF	0.395	2.875	0.396	3.000	1	0.939	0.938	0.970	0.930	0.909	0.986
CO	0.447	2.712	0.401	2.833	0.958	1	0.966	0.973	0.983	0.965	0.976
CT	0.507	2.787	0.479	2.921	0.948	0.973	1	0.960	0.963	0.959	0.974
BE	0.407	2.949	0.396	2.979	0.983	0.968	0.943	1	0.962	0.934	0.985
IN	0.468	2.911	0.435	2.982	0.952	0.980	0.965	0.962	1	0.969	0.970
UT	0.513	2.850	0.467	2.948	0.912	0.953	0.964	0.902	0.945	1	0.956
Total	0.441	2.768	0.427	2.876	0.990	0.984	0.978	0.980	0.975	0.954	1

Notes: Panel A (B) summarizes the mean and the standard deviation of the actual equally-weighted (EW) and the value-weighted (VW) monthly corporate bond index returns by country (industry). All returns are in US dollars and expressed in percent per month. In the correlation matrices, the coefficients above the diagonal refer to the value-weighted returns and below the diagonal are between the equally-weighted returns.

CHAPTER 4 Methodology

This chapter introduces the two methodologies I adopt to study the relative importance of country and industry factors in the matched stock and corporate bond returns. The methods are similar to the ones used by Pieterse-Bloem and Mahieu (2013) and for comparison reasons I stay close to their notation. Note that Appendix B contains a comprehensive overview (including full derivations) of the Heston and Rouwenhorst (1994) methodology.[9] A summary of this overview is given in this chapter.

4.1 Heston and Rouwenhorst (1994) methodology

Heston and Rouwenhorst (1994) describe an intuitively appealing dummy variable regression framework that I follow to decompose the constructed equally- and value-weighted stock or corporate bond country and industry indices into global, country and industry components. The starting point is the following cross-sectional regression model for the return of stock or corporate bond i ($i = 1, \ldots, N$) that belongs to exactly one industry j ($j = 1, \ldots, J$) and one country k ($k = 1, \ldots, K$):

$$R_i = \alpha + \sum_{j=1}^{J} \phi_j I_{i,j} + \sum_{k=1}^{K} \psi_k C_{i,k} + \epsilon_i, \tag{1}$$

where $I_{i,j}$ ($C_{i,k}$) is a dummy variable indicating whether the stock or corporate bond is assigned to industry j (country k) or not. The parameters α, ϕ_j and ψ_k respectively are a base level of return, the industry effect and the country effect, and ϵ_i is a security-specific random error term. The relationship in 1 can, however, for a given month t ($t = 1, \ldots, T$) in the sample, not be estimated by least squares in its current form because it is unidentified, due to perfect multicollinearity (dummy variable trap). Heston and Rouwenhorst (1994) solve this problem by imposing the following two identifying restrictions on the parameters of the industry and country effects:

$$\sum_{j=1}^{J} w_j \phi_j = 0 \tag{2a}$$

$$\sum_{k=1}^{K} v_k \psi_k = 0, \tag{2b}$$

where w_j (v_k) denotes the value weight of industry j (country k) in the actual total (i.e. European) value-weighted market. By doing so, Heston and Rouwenhorst (1994) force the least-squares estimate of α in Model 1 to be equal to the actual total value-weighted market index, as is shown in Equation B.15 in Appendix B. The parameter estimates $\hat{\alpha}$, $\hat{\phi}_j$ ($j = 1, \ldots, J$) and $\hat{\psi}_k$ ($k = 1, \ldots, K$) are obtained by weighted least squares in Model 1, with weights equal to the market values of the stocks or corporate bonds.

Equation B.16 then shows that the actual value-weighted index of industry j, R_j^{vw}, can be decomposed into a component equal to the actual value-weighted total market index, $\hat{\alpha}$, a pure industry effect, $\hat{\phi}_j$, and a component representing the overall country effects for industry j, $\sum_{k=1}^{K} \hat{\psi}_k \sum_{i=1}^{N} p_{i,j} C_{i,k}$:

$$R_j^{vw} = \hat{\alpha} + \hat{\phi}_j + \sum_{k=1}^{K} \hat{\psi}_k \sum_{i=1}^{N} p_{i,j} C_{i,k}, \tag{3}$$

where $p_{i,j}$ denotes the value weight of stock or corporate bond i in industry j. Likewise, Equation B.17

[9] To the extent of my knowledge, such an extensive overview of the Heston and Rouwenhorst (1994) model is not available in the literature.

shows that the actual value-weighted index of country k, R_k^{vw}, can be decomposed into a component equal to the actual value-weighted total market index, $\hat{\alpha}$, a component representing the overall industry effect for country k, $\sum_{j=1}^{J} \hat{\phi}_j \sum_{i=1}^{N} p_{i,k} I_{i,j}$, and a pure country effect, $\hat{\psi}_k$:

$$R_k^{vw} = \hat{\alpha} + \sum_{j=1}^{J} \hat{\phi}_j \sum_{i=1}^{N} p_{i,k} I_{i,j} + \hat{\psi}_k, \tag{4}$$

where $p_{i,k}$ denotes the value weight of stock or corporate bond i in country k. In order to decompose the actual equally-weighted industry and country indices, Heston and Rouwenhorst (1994) assume that each stock or corporate bond i has the same market value equal to one. Under this assumption, a value-weighted index coincides with a corresponding equally-weighted index. The estimate $\hat{\alpha}$ in Model 1 then becomes equal to the actual equally-weighted total market index. Furthermore, a decomposition of the actual equally-weighted index of industry j can now be obtained from Equation 3 as

$$R_j^{ew} = \hat{\alpha} + \hat{\phi}_j + \sum_{k=1}^{K} \hat{\psi}_k \sum_{i} \frac{1}{n_j} C_{i,k}, \tag{5}$$

where the i-summation is taken over the stocks or corporate bonds from industry j only and n_j stands for the number of stocks or corporate bonds in industry j. Similarly, a decomposition of the actual equally-weighted index of country k can be obtained from Equation 4 as

$$R_k^{ew} = \hat{\alpha} + \sum_{j=1}^{J} \hat{\phi}_j \sum_{i} \frac{1}{m_k} I_{i,j} + \hat{\psi}_k, \tag{6}$$

where the i-summation is taken over the stocks or corporate bonds from country k only and m_k stands for the number of stocks or corporate bonds in country k. Finally, Appendix B explains that the expressions $\hat{\alpha} + \hat{\phi}_j$ and $\hat{\alpha} + \hat{\psi}_k$ can be interpreted as (the least squares estimates of) pure (equally- or value-weighted) industry and county indices, respectively. The pure industry indices have the same country composition as the total market index and are thus corrected for country effects, while the pure country indices have the same industry distribution as the total market index and are therefore adjusted for industry effects.

The cross-sectional regression in 1 can be performed for every time period $t = 1, \ldots, T$, providing me time series of the estimated industry and country effects/factors and time series of the estimated pure (value- or equally-weighted) industry and country indices. These pure indices can be used to examine the underlying sources of variation in the actual (value- or equally-weighted) industry and country indices.

4.2 Mean–variance spanning and efficiency tests

The second methodology I consider is based on mean-variance analysis and has the aim to directly evaluate the risk-return properties of country- and industry-based stock and corporate bond portfolios. The perspective of a US-based mean-variance investor is taken who optimizes his portfolio of either European stock or corporate bond country and industry indices. First, both for the stock and corporate bond indices three mean-variance efficient frontiers are constructed: one based on country indices alone, one based on industry indices alone, and one based on country and industry indices combined. Then, following Pieterse-Bloem and Mahieu (2013), I perform spanning and efficiency tests to determine whether the optimal country and industry portfolios on the frontiers have statistically different mean-variance characteristics.

Concretely, spanning tests tell me whether adding country (industry) indices affects the frontier constructed from industry (country) indices alone. If the null hypothesis that the frontier constructed from industry (country) indices alone coincides with the frontier of the combined indices cannot be rejected, I can say that the set of industry indices spans the set of country and industry indices together. In that case investing only in the industry (country) indices is sufficient to yield the optimal risk-return trade-off. Efficiency tests compare the performance of country- versus industry-based portfolios by means of their maximum attainable Sharpe ratios. In these tests the null hypothesis states that the difference between the maximum Sharpe ratios of both portfolio sets is zero. If this null hypothesis cannot be rejected then the optimal country and industry portfolios are said to be equally mean-variance efficient.

Test statistics for the spanning and efficiency tests are obtained from estimates of regressions of country index returns on industry index returns and vice versa. I refer to Appendix A in Pieterse-Bloem and Mahieu (2013) for a complete description of how to perform the spanning and efficiency tests using regression analysis. It should be noted that outright returns are used for the spanning tests and excess returns for the efficiency tests. Moreover, short sale constraints are not considered in these tests. In this study I perform the tests for the actual country and industry indices as well as for the pure country and industry indices obtained from the Heston and Rouwenhorst (1994) methodology. I also implement what is called 'exclusive' spanning and efficiency tests, where the overlapping stocks or corporate bonds are excluded from the intersection between particular country and industry indices (see also Appendix A in Pieterse-Bloem and Mahieu (2013)). In this way it can be examined whether the results of the spanning and efficiency tests are robust to the exclusion of covariance-inducing common components among country and industry indices.

CHAPTER 5 Results

5.1 Results of Heston and Rouwenhorst (1994) methodology

It follows from Equation 3 (5) that the excess return of an actual value-weighted (equally-weighted) industry index over the total (i.e. European) market can be decomposed into a pure industry effect and a weighted average of country effects. Likewise, Equation 4 (6) shows that an excess actual value-weighted (equally-weighted) country index return is equal to a pure country effect and a weighted average of industry effects. Tables 5 and 6 provide the results of this decomposition over the full sample period of April 1999 to January 2013 for the stock and corporate bond indices, respectively. The importance of each country and industry effect/factor[10] is determined by the time series variance of the corresponding coefficient estimates. The results in Tables 5 and 6 can be compared and used to recognize distinct and overlapping patterns in the country and industry factors extracted from the matched stock and corporate bond returns.

Tables 5 and 6 clearly show different results regarding the relative importance of country and industry factors in the matched stock and corporate bond returns. Table 5 shows that the variance of pure industry effects outweighs that of the pure country effects on average by a factor of 1.2 for both the equally- (= 11.306/9.343) and value-weighted (= 13.674/11.156) stock indices. On the contrary, from Table 6 it can be seen that the variance of pure country effects is on average larger than that of the pure industry effects by a factor of 3.5 for the equally-weighted corporate bond indices (= 0.926/0.266) and by a factor of 3 for the value-weighted corporate bond indices (= 0.816/0.268). These results are, however, in accordance with findings from previous work on either stocks or corporate bonds, showing that industry factors dominate country factors in stock returns during the Post-EMU period, while country effects prevail over industry effects in corporate bond returns. Consequently, industry effects in country stock indices are generally larger than country effects in industry stock indices and, conversely, industry effects in country corporate bond indices are on average lower than country effects in industry corporate bond indices. Industry effects account for about 10 to 15.5% of excess country stock index returns and only for about 4 to 6% of excess country corporate bond index returns. They are most prominent for both the stock and corporate bond indices of Spain, which is rather concentrated in the Finance & Funds industry. Country effects account only for about 4% of excess industry stock index returns and for as many as 17 to 32% of excess industry corporate bond index returns. They are most prevalent for both the stock and corporate bond indices of the Industrials and Utilities industries. The variances of the pure country effects in both the stock and corporate bond returns seem to be largest for Spain and Sweden and low for France. The Consumer industry factor in both the stock and corporate bond returns appears to have a relatively low variance.

Tables 7 and 8 present the results of the decomposition of the excess value-weighted stock and corporate bond country and industry indices, respectively, over the period before and after the start of the global financial crisis in July 2007. These results can be compared with each other and with those in Tables 5 and 6. The most important finding from Table 7 is that country factors become at least as or even more important than industry factors in stock returns from the Pre- to the Post-crisis period. So while the factor by which industry effects dominate country effects in stock returns during the Pre-crisis period is equal to 1.4 (= 14.713/10.457), it deteriorates to just below 1 (= 12.008/12.316) during the Post-crisis period. Over the two subperiods, industry factors in stock returns have become less important in absolute terms, but also have become less so dominant due to the increasing significance of country factors. On the contrary, Table 6 shows that industry factors gain strength relative to country factors in the matched corporate bond returns from the Pre- to the Post-crisis period. Country effects dominate

[10]Note that I use the terms 'effects' and 'factors' interchangeably.

Table 5: Decomposition of excess actual stock indices

Panel A: Country indices								
	EW indices:				VW indices:			
	Pure country effect		Sum of industry effects		Pure country effect		Sum of industry effects	
Country	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
BL	10.412	0.987	1.821	0.173	16.681	0.899	2.942	0.159
FR	3.926	1.049	0.403	0.108	3.664	1.100	0.689	0.207
GE	7.514	1.005	0.611	0.082	13.479	0.847	1.168	0.073
IT	10.715	0.923	1.280	0.110	9.898	0.880	2.077	0.185
NE	8.742	0.878	0.869	0.087	9.590	0.888	1.874	0.174
SP	16.277	0.840	2.190	0.113	15.582	0.822	3.490	0.184
SW	12.325	0.867	1.480	0.104	15.970	0.814	4.116	0.210
UK	4.831	1.020	0.156	0.033	4.384	1.063	0.197	0.048
Average	9.343	0.946	1.101	0.101	11.156	0.914	2.069	0.155
Panel B: Industry indices								
	EW indices:				VW indices:			
	Pure industry effect		Sum of country effects		Pure industry effect		Sum of country effects	
Industry	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
FF	8.629	1.074	0.308	0.038	13.097	1.087	0.209	0.017
CO	3.821	0.932	0.243	0.059	10.231	0.915	0.320	0.029
CT	24.875	0.987	0.281	0.011	20.938	0.981	0.388	0.018
BE	9.035	0.958	0.311	0.033	13.192	0.994	0.743	0.056
IN	7.215	1.007	0.333	0.046	11.671	0.797	1.548	0.106
UT	14.261	0.947	0.526	0.035	12.913	0.993	0.644	0.050
Average	11.306	0.984	0.334	0.037	13.674	0.961	0.642	0.046

Notes: This table provides the variance of the components of the equally-weighted (EW) and value-weighted (VW) country (Panel A) and industry (Panel B) stock index returns in excess of the total stock market index (i.e. the European market index). The ratio gives the ratio of the variance of that component to the variance of the index return in excess of the total market index.

Table 6: Decomposition of excess actual corporate bond indices

Panel A: Country indices								
	EW indices:				VW indices:			
	Pure country effect		Sum of industry effects		Pure country effect		Sum of industry effects	
Country	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
BL	0.917	0.946	0.055	0.057	0.977	1.087	0.067	0.075
FR	0.412	1.021	0.027	0.067	0.351	0.838	0.037	0.089
GE	0.370	0.791	0.056	0.119	0.292	0.743	0.052	0.131
IT	0.918	0.963	0.017	0.017	0.856	0.949	0.033	0.037
NE	0.579	0.950	0.010	0.017	0.507	0.950	0.012	0.022
SP	1.494	0.994	0.055	0.037	1.210	0.945	0.102	0.079
SW	1.685	0.957	0.015	0.009	1.305	0.947	0.039	0.028
UK	1.033	0.903	0.010	0.009	1.029	0.955	0.008	0.007
Average	0.926	0.940	0.031	0.041	0.816	0.927	0.044	0.059
Panel B: Industry indices								
	EW indices:				VW indices:			
	Pure industry effect		Sum of country effects		Pure industry effect		Sum of country effects	
Industry	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
FF	0.118	0.670	0.025	0.141	0.162	0.629	0.070	0.271
CO	0.184	0.752	0.071	0.289	0.179	0.457	0.176	0.450
CT	0.278	0.833	0.016	0.048	0.279	0.646	0.095	0.220
BE	0.284	0.775	0.049	0.133	0.269	0.983	0.122	0.447
IN	0.278	0.655	0.108	0.255	0.272	0.525	0.193	0.372
UT	0.455	0.615	0.129	0.175	0.447	0.596	0.148	0.197
Average	0.266	0.717	0.066	0.174	0.268	0.639	0.134	0.326

Notes: This table provides the variance of the components of the equally-weighted (EW) and value-weighted (VW) country (Panel A) and industry (Panel B) corporate bond index returns in excess of the total corporate bond market index (i.e. the European market index). The ratio gives the ratio of the variance of that component to the variance of the index return in excess of the total market index.

industry effects in corporate bond returns before the crisis by a factor of 3.5 (= 0.831/0.235), but they do so after the crisis only by a factor of 2.5 (= 0.799/0.321). This relative strengthening of industry effects in the corporate bond returns is primarily caused by an increase in the absolute significance of the industry effects themselves. Country factors in corporate bond returns are overall about equally important in the Pre- and Post-crisis periods.

Similar shifts in importance of specific country or industry factors can be observed between the results for the stocks and corporate bonds over the periods before and after the start of the crisis. For example, the factors of Belgium/Luxembourg, Spain and the UK in both the stock and corporate bond returns have their variances increased from the Pre- to the Post-crisis period, while the variances of the other country factors are decreasing (with the exception of the variance of the Germany factor in the corporate bond returns). Moreover, the largest increase in variance of pure industry effects from the Pre- to the Post-crisis period occurs, both in stock and corporate bond returns, with respect to the Financial & Funds industry. This result is in line with the fact that the financial industry is the source of the global financial crisis. The largest drop in variances of pure industry factors in both stock and corporate bond returns is found with respect to the Communications & Technology industry. This might reflect the role the communication and technology firms played in the dot-com bubble and its aftermath, which took place during the Pre-crisis period. Especially because the factors corresponding to the Communications & Technology industry were the most and second most important among, respectively, the stock and corporate bond industry factors in the Pre-crisis period. In contrast, the corporate bond factor for the Communications & Technology industry have become the least important over the Post-crisis period.

5.2 Results of spanning and efficiency tests

Tables 9 (10) and 11 (12) present the results of the spanning and efficiency tests applied on the actual (pure) country and industry indices of stocks and corporate bonds, respectively. In the four tables, H_0: spanning K (J) gives the test statistic for the null hypothesis that country (industry) indices are spanned by industry (country) indices and H_0: efficiency gives the test statistic for the null hypothesis that the maximum attainable Sharpe ratios of the sets of mean-variance optimal country and industry portfolios are equal. Test statistics in bold exceed the critical values at the 5% significance level and indicate rejection of the null hypothesis. A rejection of the null hypothesis implies that country-based stock or corporate bond portfolios statistically differ from industry-based stock or corporate bond portfolios with regard to mean-variance performance over the specified period. The tests are performed for the complete indices and the indices excluding overlapping components. The difference in Sharpe ratio is consequently derived as the industry-based maximum Sharpe ratio minus the country-based maximum Sharpe ratio.

One can see from Tables 9 and 10 that, based on the full sample period, neither actual country nor pure country stock indices are spanned by actual or pure industry stock indices, and vice versa (both for complete indices and indices excluding overlapping components). In other words, for stocks neither a country nor an industry diversification strategy seems mean-variance optimal over the full period. However, when splitting the full period in Pre- and Post-crisis periods, there is some little evidence that industry-based portfolios outperform country-based portfolios in the Pre-crisis period: the null hypothesis that equally-weighted actual stock country indices are spanned by equally-weighted actual stock industry indices is not rejected. Yet, this evidence is far from conclusive, since all other spanning tests are always rejected for this period. In the Post-crisis period again all spanning tests are rejected. The maximum attainable Sharpe ratio is for each type of index and for each (sub)period always higher for the set of country stock portfolios than for the set of industry stock portfolios, but the difference is never significant. In summary, both spanning and efficiency tests suggest that neither a country- nor an industry-based portfolio does outperform the other and that both are mean-variance inefficient.

Table 7: Decomposition of excess actual stock indices, Pre- and Post-crisis

Panel A: Country indices								
	April 1999-July 2007				August 2007-January 2013			
	Pure country effect		Sum of industry effects		Pure country effect		Sum of industry effects	
Country	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
BL	12.443	0.859	3.693	0.255	23.290	0.951	1.669	0.068
FR	4.057	0.992	0.780	0.191	3.092	1.403	0.560	0.254
GE	14.755	0.920	1.202	0.075	11.732	0.735	1.123	0.070
IT	11.229	0.878	2.080	0.163	7.828	0.900	2.082	0.239
NE	11.543	0.948	1.863	0.153	6.737	0.764	1.917	0.217
SP	10.946	0.793	1.574	0.114	22.714	0.845	6.456	0.240
SW	16.168	0.733	5.455	0.247	15.901	0.987	2.104	0.131
UK	2.515	0.935	0.060	0.022	7.233	1.145	0.410	0.065
Average	10.457	0.882	2.088	0.152	12.316	0.966	2.040	0.161

Panel B: Industry indices								
	April 1999-July 2007				August 2007-January 2013			
	Pure industry effect		Sum of country effects		Pure industry effect		Sum of country effects	
Industry	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
FF	6.766	1.061	0.157	0.025	22.703	1.100	0.290	0.014
CO	9.761	0.934	0.305	0.029	10.985	0.892	0.346	0.028
CT	26.210	0.983	0.172	0.007	12.953	0.985	0.710	0.054
BE	14.672	0.946	0.299	0.019	10.983	1.096	1.391	0.139
IN	15.453	0.790	2.050	0.105	5.965	0.831	0.803	0.112
UT	15.414	1.019	0.719	0.048	8.458	0.919	0.539	0.059
Average	14.713	0.955	0.617	0.039	12.008	0.971	0.680	0.068

Notes: This table provides the variance of the components of the value-weighted country (Panel A) and industry (Panel B) stock index returns in excess of the total stock market index (i.e. the European market index) for April 1999 to July 2007 (Pre-crisis period) and for August 2007 to January 2013 (Post-crisis period). The ratio gives the ratio of the variance of that component to the variance of the index return in excess of the total market index.

Table 8: Decomposition of excess actual corporate bond indices, Pre- and Post-crisis

Panel A: Country indices								
	April 1999-July 2007				August 2007-January 2013			
	Pure country effect		Sum of industry effects		Pure country effect		Sum of industry effects	
Country	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
BL	0.875	1.194	0.060	0.081	1.130	0.981	0.079	0.069
FR	0.497	0.804	0.033	0.053	0.129	1.104	0.045	0.387
GE	0.263	0.985	0.006	0.023	0.335	0.579	0.121	0.208
IT	1.041	0.991	0.023	0.022	0.583	0.850	0.049	0.072
NE	0.620	0.972	0.008	0.013	0.342	0.895	0.018	0.046
SP	0.906	1.189	0.048	0.064	1.687	0.810	0.184	0.088
SW	1.472	0.880	0.026	0.015	1.066	1.127	0.059	0.063
UK	0.969	0.946	0.005	0.005	1.123	0.967	0.013	0.011
Average	0.831	0.995	0.026	0.034	0.799	0.914	0.071	0.118
Panel B: Industry indices								
	April 1999-July 2007				August 2007-January 2013			
	Pure industry effect		Sum of country effects		Pure industry effect		Sum of country effects	
Industry	Variance	Ratio	Variance	Ratio	Variance	Ratio	Variance	Ratio
FF	0.028	0.177	0.086	0.553	0.369	0.886	0.045	0.109
CO	0.130	0.277	0.258	0.549	0.256	0.924	0.055	0.197
CT	0.390	0.660	0.141	0.238	0.114	0.580	0.027	0.137
BE	0.196	0.979	0.157	0.788	0.384	0.990	0.069	0.178
IN	0.251	0.446	0.261	0.463	0.309	0.673	0.092	0.201
UT	0.418	0.463	0.218	0.241	0.497	0.943	0.044	0.084
Average	0.235	0.500	0.187	0.472	0.321	0.833	0.055	0.151

Notes: This table provides the variance of the components of the value-weighted country (Panel A) and industry (Panel B) corporate bond index returns in excess of the total corporate bond market index (i.e. the European market index) for April 1999 to July 2007 (Pre-crisis period) and for August 2007 to January 2013 (Post-crisis period). The ratio gives the ratio of the variance of that component to the variance of the index return in excess of the total market index.

The first thing that jumps out from Tables 11 and 12 is that the null hypotheses of the spanning tests for corporate bond indices are far more often not rejected than those of the spanning tests for stock indices. Moreover, it appears that the results of the spanning tests for the pure corporate bond indices, which are corrected for either country or industry effects, and/or for the indices excluding overlapping components are different from, but more conclusive regarding out-performance than, those of the spanning tests for the actual and complete corporate bond indices. According to the spanning tests for the actual and complete corporate bond indices, country corporate bond indices are spanned by industry corporate bond indices in the Pre-crisis period, and vice versa. In other words, it is equally efficient to invest in country corporate bond indices or in industry corporate bond indices only in the Pre-crisis period. In the Post-crisis period, however, the spanning tests for the actual and complete corporate bond indices are all four rejected, implying that neither a corporate bond diversification by country nor by industry seems mean-variance optimal. Although the latter two results regarding mean-variance efficiency are different in both subperiods, they are not conclusive whether a country- or industry-based corporate bond portfolio does outperform the other or not (also not for the full period). The results of the spanning tests for the pure corporate bond indices and/or for the indices excluding overlapping components clearly show, however, that a country-based corporate bond portfolio outperforms an industry-based corporate bond portfolio in terms of mean-variance efficiency in the Post-crisis period as well as over the full sample period. For these types of indices, either equally- or value-weighted, and for these two periods, the null hypothesis that country corporate bond indices are spanned by industry corporate bond indices is always rejected, while the null hypothesis that industry corporate bond indices are spanned by country corporate bond indices is never rejected. Similar to the results for stocks, the maximum attainable Sharpe ratio is for each type of index and for each (sub)period always higher for the set of country corporate bond portfolios than for the set of industry corporate bond portfolios, albeit never significantly according to the efficiency tests. In brief, the results of the spanning tests for the corporate bond indices indicate that in the Pre-crisis period both a country and an industry allocation of corporate bonds is mean-variance optimal, but that in the Post-crisis period a country diversification is superior to an industry diversification. Based on the full sample period, a country-based corporate bond portfolio also appears to outperform an industry-based corporate bond portfolio.

Table 9: Spanning and efficiency of actual country and industry indices of stocks

Country and industry indices from:	Critical value	Full period 4/1999–1/2013		Pre-crisis 4/1999–7/2007		Post-crisis 8/2007–1/2013	
		EW	VW	EW	VW	EW	VW
I. Outright stock returns							
H_0: spanning K	26.30	**49.72**	**102.03**	25.69	**68.49**	**52.18**	**50.24**
H_0: spanning J	21.03	**229.75**	**190.67**	**45.02**	**75.82**	**238.60**	**90.16**
Excl. overlapping components							
H_0: spanning K	26.30	**80.60**	**112.48**	**49.12**	**101.52**	**51.35**	**48.48**
H_0: spanning J	21.03	**211.33**	**186.09**	**72.13**	**97.61**	**153.48**	**101.89**
II. Excess stock returns							
H_0: efficiency	3.841	0.016	0.002	0.019	0.032	0.043	0.008
Difference in Sharpe ratio		-0.128	-0.050	-0.139	-0.180	-0.207	-0.088
Excl. overlapping components							
H_0: efficiency	3.841	0.019	0.003	0.034	0.012	0.031	0.004
Difference in Sharpe ratio		-0.138	-0.054	-0.183	-0.108	-0.177	-0.066

Notes: This table provides the results of the spanning and efficiency tests applied on the actual equally- (EW) and value-weighted (VW) country and industry indices obtained from outright or excess stock returns for the periods indicated in the column headings. H_0: spanning K (J) gives the test statistic for the null hypothesis that country (industry) indices are spanned by industry (country) indices. H_0: efficiency gives the test statistic for the null hypothesis that the maximum attainable Sharpe ratios of the sets of mean-variance optimal country and industry portfolios are equal. The test statistics of the spanning and efficiency tests are compared with the critical values at the 5% significance level. Test statistics in bold exceed the critical values. The tests are performed for the complete indices and the indices excluding overlapping components. The difference in Sharpe ratio is consequently calculated as the industry-based maximum Sharpe ratio minus the country-based maximum Sharpe ratio.

Table 10: Spanning and efficiency of pure country and industry indices of stocks

Country and industry indices from:	Critical value	Full period 4/1999–1/2013		Pre-crisis 4/1999–7/2007		Post-crisis 8/2007–1/2013	
		EW	VW	EW	VW	EW	VW
I. Outright stock returns							
H_0: spanning K	26.30	**70.639**	**111.79**	**33.40**	**83.72**	**64.71**	**52.73**
H_0: spanning J	21.03	**225.72**	**159.23**	**69.36**	**76.81**	**166.15**	**108.17**
Excl. overlapping components							
H_0: spanning K	26.30	**80.57**	**131.54**	**46.66**	**123.89**	**54.97**	**50.11**
H_0: spanning J	21.03	**201.63**	**168.90**	**77.29**	**98.93**	**142.69**	**104.09**
II. Excess stock returns							
H_0: efficiency	3.841	0.009	0.002	0.015	0.025	0.146	0.001
Difference in Sharpe ratio		-0.097	-0.042	-0.121	-0.158	-0.383	-0.028
Excl. overlapping components							
H_0: efficiency	3.841	0.013	0.002	0.020	0.012	0.037	0.001
Difference in Sharpe ratio		-0.113	-0.047	-0.140	-0.109	-0.192	-0.035

Notes: This table provides the results of the spanning and efficiency tests applied on the pure equally- (EW) and value-weighted (VW) country and industry indices obtained from outright or excess stock returns for the periods indicated in the column headings. H_0: spanning K (J) gives the test statistic for the null hypothesis that country (industry) indices are spanned by industry (country) indices. H_0: efficiency gives the test statistic for the null hypothesis that the maximum attainable Sharpe ratios of the sets of mean-variance optimal country and industry portfolios are equal. The test statistics of the spanning and efficiency tests are compared with the critical values at the 5% significance level. Test statistics in bold exceed the critical values. The tests are performed for the complete indices and the indices excluding overlapping components. The difference in Sharpe ratio is consequently calculated as the industry-based maximum Sharpe ratio minus the country-based maximum Sharpe ratio.

Table 11: Spanning and efficiency of actual country and industry indices of corporate bonds

Country and industry indices from:	Critical value	Full period 4/1999–1/2013		Pre-crisis 4/1999–7/2007		Post-crisis 8/2007–1/2013	
		EW	VW	EW	VW	EW	VW
I. Outright corporate bond returns							
H_0: spanning K	26.30	25.02	**40.13**	9.12	15.78	**36.33**	**47.52**
H_0: spanning J	21.03	14.49	18.68	6.79	10.03	**21.83**	**21.14**
Excl. overlapping components							
H_0: spanning K	26.30	**49.03**	**59.94**	15.15	23.10	**38.08**	**55.67**
H_0: spanning J	21.03	15.45	11.90	7.08	8.04	13.49	11.43
II. Excess corporate bond returns							
H_0: efficiency	3.841	0.001	0.006	0.004	0.009	0.115	0.737
Difference in Sharpe ratio		-0.034	-0.077	-0.061	-0.096	-0.339	-0.859
Excl. overlapping components							
H_0: efficiency	3.841	0.001	0.003	0.002	0.005	0.073	0.125
Difference in Sharpe ratio		-0.037	-0.053	-0.048	-0.069	-0.270	-0.353

Notes: This table provides the results of the spanning and efficiency tests applied on the actual equally- (EW) and value-weighted (VW) country and industry indices obtained from outright or excess corporate bond returns for the periods indicated in the column headings. H_0: spanning K (J) gives the test statistic for the null hypothesis that country (industry) indices are spanned by industry (country) indices. H_0: efficiency gives the test statistic for the null hypothesis that the maximum attainable Sharpe ratios of the sets of mean-variance optimal country and industry portfolios are equal. The test statistics of the spanning and efficiency tests are compared with the critical values at the 5% significance level. Test statistics in bold exceed the critical values. The tests are performed for the complete indices and the indices excluding overlapping components. The difference in Sharpe ratio is consequently calculated as the industry-based maximum Sharpe ratio minus the country-based maximum Sharpe ratio.

Table 12: Spanning and efficiency of pure country and industry indices of corporate bonds

Country and industry indices from:	Critical value	Full period 4/1999–1/2013		Pre-crisis 4/1999–7/2007		Post-crisis 8/2007–1/2013	
		EW	VW	EW	VW	EW	VW
I. Outright corporate bond returns							
H_0: spanning K	26.30	**33.94**	**36.94**	8.12	12.61	**43.14**	**47.42**
H_0: spanning J	21.03	19.42	14.36	7.22	8.28	20.55	18.68
Excl. overlapping components							
H_0: spanning K	26.30	**54.39**	**57.26**	12.47	15.08	**46.76**	**63.22**
H_0: spanning J	21.03	19.69	11.95	8.34	9.40	16.17	14.92
II. Excess corporate bond returns							
H_0: efficiency	3.841	0.001	0.002	0.019	0.001	0.314	0.236
Difference in Sharpe ratio		-0.027	-0.039	-0.138	-0.024	-0.560	-0.486
Excl. overlapping components							
H_0: efficiency	3.841	0.001	0.001	0.005	0.001	0.071	0.106
Difference in Sharpe ratio		-0.031	-0.036	-0.069	-0.035	-0.267	-0.326

Notes: This table provides the results of the spanning and efficiency tests applied on the pure equally- (EW) and value-weighted (VW) country and industry indices obtained from outright or excess corporate bond returns for the periods indicated in the column headings. H_0: spanning K (J) gives the test statistic for the null hypothesis that country (industry) indices are spanned by industry (country) indices. H_0: efficiency gives the test statistic for the null hypothesis that the maximum attainable Sharpe ratios of the sets of mean-variance optimal country and industry portfolios are equal. The test statistics of the spanning and efficiency tests are compared with the critical values at the 5% significance level. Test statistics in bold exceed the critical values. The tests are performed for the complete indices and the indices excluding overlapping components. The difference in Sharpe ratio is consequently calculated as the industry-based maximum Sharpe ratio minus the country-based maximum Sharpe ratio.

CHAPTER 6 Conclusion

In this thesis I jointly analyze the relative importance of country and industry factors as determinants of European stock and corporate bond returns over the period from April 1999 to January 2013. I do so by examining two samples of stocks and corporate bonds that are linked at the firm level. Despite previous studies on either stocks or corporate bonds telling different stories regarding the relative importance of country and industry factors in stock and corporate bond returns, I expect to find more similar patterns in the country and industry factors extracted from the returns of the stocks and corporate bonds of the same firm, because in theory their return components should be related to a varying degree. The results of two prevailing approaches to investigate whether the stock and corporate bond returns are driven by country or industry factors, namely the method of Heston and Rouwenhorst (1994) and spanning and efficiency tests, are compared between the matched stock and corporate bond samples.

The main results of this thesis show, contrary to my expectation, that even firm level linked European stock and corporate bond samples offer very distinct perspectives on the relative importance of country and industry factors in returns. The results of the Heston and Rouwenhorst (1994) methodology indicate that industry factors dominate country factors in the matched stock returns overall, while country factors are far more important than industry factors in the matched corporate bond returns. Moreover, after the global financial crisis in 2008, country factors are shown to regain strength and become at least as important as industry factors in the matched stock returns, while the significance of country factors in the matched corporate bond returns seems to lower due to the rising importance of industry factors. The results of the spanning and efficiency tests for the matched stocks show that neither a country- nor an industry-based portfolio does outperform the other and that both are mean-variance inefficient, both during the Pre- and Post-crisis periods, as well as over the full sample period. In contrast, the results of the spanning and efficiency tests for the matched corporate bonds suggest that both a country- and an industry-based portfolio are mean-variance efficient in the Pre-crisis period, and that a country-based portfolio outperforms an industry-based portfolio in terms of mean-variance efficiency in the Post-crisis period and over the full sample period.

The conclusion that can be made from the results is that there is no sample composition effect that is causing the different patterns in the relative importance of country and industry factors in stock and corporate bond returns. With this I mean that the different results from previous studies on the relative importance of country and industry factors in either stock or corporate bond returns cannot be explained by the fact that they use stock and corporate bond data from different firms. It is now naturally to say that the reason of the different results lies in that stock and corporate bond markets have contrasting natures and play different roles in the economy. I leave the broader and fuller investigation of this insight for future research.

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APPENDIX A Details regarding the data collection

The objective is to match as many European corporate bond return series from the data set of Pieterse-Bloem et al. (2016) as possible with return series of the same firms' stocks. To this end, the challenge is to merge data from two well-known, but independent data providers: Bloomberg, which is the main data source for the corporate bond data set of Pieterse-Bloem et al. (2016); and Thomson Reuters Datastream (Datastream), which is the most comprehensive database available to have stored historical data on European stocks. The main complication in this regard is the absence of a financial security identification code with firm unique characters for European corporate bonds and stocks, making direct matching of European corporate bond and stock data from the two different databases impossible.[11] As solution, I propose to collect as many data on European stocks that were traded within the sample period of the corporate bond data set as possible from Datastream and subsequently match the bonds with the stocks based on issuers' names.

Despite the intuitive appeal of this matching approach, its application is not trivial for three reasons. First, Bloomberg and Datastream may use alternate names to represent the same underlying firms. The matching should therefore be robust to a variety of discrepancies between bond and stock issuers' names from the two databases, including spelling variations, abbreviations, omissions and additions. Second, many corporate bonds from the data set of Pieterse-Bloem et al. (2016) are issued by parent firms through unlisted subsidiaries that operate as finance vehicles. Ignoring these bonds from the matching process with the reason that they cannot be directly linked to a corresponding stock would not make sense. The most obvious would be to match these bonds with the stocks of the parent firms as ultimate guarantors of the bond payments. However, to do this correctly, information about the hierarchical structures of the firms concerned is required, which can only be obtained by the time-consuming task of manually consulting individual firm profiles maintained in various financial databases. Third, matched pairs of bonds and stocks should be followed through time to validate their correctness over time. Initially correct matches can become incorrect over time due to corporate events, such as mergers, acquisitions and bankruptcies, that cause stocks to be delisted or former bond guarantors to be replaced by new ones. In such cases, it should be examined whether the bonds concerned can be rematched to other stocks after the time their initial stock matches become incorrect. However, following the matched pairs of bonds and stocks through time while making possible corrections in line with corporate history is easier said than done due to the large amount of manual work involved in finding and processing the appropriate corporate information from various financial databases, newswires and internet searches.

The following sections in this Appendix further detail the matching approach and the difficulties encountered in its application. First, Section A.1 summarizes the structure of the corporate bond data set as provided by Pieterse-Bloem et al. (2016) and discusses the types of bond issuers' names used in the matching process. Then, Section A.2 describes how a full sample of European stocks is extracted from Datastream and which methods are applied to cleanse and prepare the stock data for the matching process and the econometric analysis. Finally, Section A.3 gives a detailed breakdown of the steps involved in the matching process.

[11] In contrast, North American corporate bond and stock data can be matched directly by using CUSIP codes. A CUSIP is a North America only financial security identification code that has nine characters out of which the first six uniquely identifies the issuer of the security. North American corporate bonds and stocks issued by the same firms should thus have the first six characters of their CUSIPs in common.

A.1 Full corporate bond sample

Pieterse-Bloem et al. (2016) provide representative data for the European corporate bond market.[12] Their data set consists of 8,446 (fixed rate, bullet) corporate bonds which are all registered in Bloomberg's fixed income database with their own ISIN. Holding-period returns, converted into US dollars and in excess of the risk-free rate (proxied by the 1-month US dollar deposit rate), are available at the monthly frequency for each bond and cover the period from January 1991 to January 2013. Pieterse-Bloem et al. (2016) choose this sample period so as to have data for approximately the same length of period prior to the launch of the EMU, after the launch of the EMU up to the start of the financial crisis, and following the start of financial crisis. Since the bonds are issued and mature at different dates throughout the sample period, the set of bond return series is unbalanced.

Apart from the return series, the following descriptive information of the bonds is provided: the short name of the bond issuer, the amount issued in US dollars, and the country and industry allocation of the bond issuer. The country and industry allocations are based on the classification system of Bloomberg, and are designed such that each bond is assigned to one out of eight European countries and to one out of seven industries. Out of the eight countries, four are core-EMU countries (Belgium/Luxembourg (BL), France (FR), Germany (GE) and the Netherlands (NL)), two are peripheral EMU countries (Italy (IT) and Spain (SP)), and the remaining are non-EMU countries (Sweden (SW) and the United Kingdom (UK)).[13] The seven industries that are represented are Financials & Funds (FF), Government Institutions (GI), Consumer (CO), Communications & Technology (CT), Basic materials & Energy (BE), Industrials (IN) and Utilities (UT). The bonds that are issued by parent firms through subsidiaries that operate as finance vehicles are allocated to the countries and industries of the corresponding parent firms, even though the issuing subsidiaries might be based in different countries (often for tax reasons) and have their businesses described as 'financial services'. These bonds are thus treated as if they were directly issued by the parent firms themselves, enabling me to match their returns with the stock returns of the parent firms later on. The bonds that are allocated to the government institutions industry are ignored during the matching process, since government institutions do not have stocks listed on an exchange.

My approach by which the bond return series are matched with return series of the same firms' stocks requires the availability of accurate issuers' names in order to succeed. The bond issuers' names provided in the data set of Pieterse-Bloem et al. (2016) are, however, limited to a certain number of characters and therefore often shortened by abbreviations and/or omissions. An example is the name corresponding to a bond issued by the French firm Casino Guichard-Perrachon SA. According to the data set of Pieterse-Bloem et al. (2016), the short name of the issuer is "ETAB ECON CASINO GUICH-P". Such a name is insufficiently accurate to efficiently identify the stock corresponding to this bond in Datastream and is, in terms of accuracy, illustrative for many other short names in the data set. Fortunately, Bloomberg offers variables that provide the full name of a bond issuer. I opt to use the name of the bond issuer according to its official legal filings and retrieve this variable for all bonds from a Bloomberg Terminal.[14] These full bond issuers' names meet the desired level of accuracy in the sense that they do not contain abbreviations and/or omissions that hinder the identification of the bonds' underlying firms. In the case of the example, the full name of the bond issuer becomes "Casino Guichard-Perrachon".

Bloomberg's standard is, however, to update the bond issuers' names in conjunction with corporate events and, accordingly, to provide the current names available. The short and full issuers' names

[12] I refer to Chapter 4 in Pieterse-Bloem (2011) for more details regarding the original sources of the bond data and the methods applied to cleanse and prepare the bond data for the econometric analysis. Pieterse-Bloem et al. (2016) extend the data set of Pieterse-Bloem (2011) with almost five more years of bond data following the same data cleansing methods.

[13] Belgium and Luxembourg are treated as a single country in the analysis, due to data availability reasons. Italy and Spain are referred to as peripheral countries due to their lower creditworthiness relative to the core-EMU countries during the sample period.

[14] The variable symbol to extract a bond issuer's name according to its legal filings from a Bloomberg Terminal is DY648.

therefore actually represent the names of the bond guarantors at the time the names were retrieved, and not necessarily the names of the initial bond issuers. The true initial name of a bond issuer is returned only if the bond issuer was not subjected to name changes after the issuance of the bond. An example of a bond whose issuer's name changed during the bond's life is the bond initially issued by the listed UK firm Great Universal Stores PLC in 1999, with a maturity date in 2009. After a regular name change to GUS PLC in 2001, the firm was demerged into two separate listed firms, Home Retail Group and Experian Finance PLC, in 2006. From then, the remaining bond payments were guaranteed by Experian, the listed parent firm of Experian Finance PLC. Since the bond data were retrieved after the demerger date of GUS PLC, both the short and full issuer's name represent the name of the bond guarantor, Experian Finance PLC, and not the name of the initial bond issuer, Great Universal Stores PLC. This example illustrates that bond returns may become only partially or even falsely matched with stock returns over time when only the short and full issuers' names are considered as bond-specific information during the matching process: if the stocks of Experian became listed at or after the date of the demerger of GUS PLC, then only the bond returns from after the date of the initial public offering of Experian's stock would become correctly matched with the stock returns of Experian, while the earlier bond returns cannot become matched with the stock returns of GUS PLC, as they should, due to the lack of information regarding the bond's history of guarantors; if the stocks of Experian were already listed before the date of the demerger of GUS PLC, then the earlier bond returns would even become incorrectly matched with the stock returns of Experian. In order to prevent this from happening, the matching approach requires some additional name data capable of capturing the name changes of the bonds' issuers and subsequent guarantors over time. Bloomberg once again helps in finding this information: it offers a variable that lists the previous firm names associated with a bond issuer.[15] I also extract this variable for all bonds from a Bloomberg Terminal. For the bond from the last example, Bloomberg returns that the name of its initial issuer is 'Great Universal Stores PLC' and that this name is later changed to 'GUS PLC'. The current short and full issuers' names and the previous names combined thus indicate, as desired, the order in which the bonds should be matched with stocks over time. The exact dates when to potentially rematch bonds with other stocks due to corporate events can be based on corporate information from various financial databases, newswires and internet searches.

A.2 Full stock sample

The following describes how Datastream is used to collect as many monthly holding period returns as possible on common-ordinary stocks that are from the same countries as the ones considered in the bonds' country allocation and that traded within the sample period of the bond data set. First, the filter function of the Datastream Navigator is employed to construct, for each country under consideration, a list of all active and delisted securities that are categorized as equities.[16] Each list contains the Datastream codes, which uniquely identify securities in Datastream's database, of all the equities that are part of the list. The Datastream codes from the lists are then put together and used to download the Datastream variables as defined in Table A.1 for all the selected equities.

For each equity, historic total return indices and market values are extracted for the same sample period as the bond data with a monthly frequency. For the return calculation, total return indices are preferred above equity prices since they not only track price movements, but also dividends. They therefore provide a more accurate representation of an equity's performance. The equities for which no total return index data are available within the sample period are dropped from the sample. Datastream's practice is to repeat the last valid total return index value after an equity is delisted. To detect and remove

[15]The variable symbol to extract a list of the previous firm names associated with a bond issuer from a Bloomberg Terminal is DT345.

[16]Delisted equities are maintained in the sample to avoid a survivorship bias.

the resulting padded data points, I delete, following Ince and Porter (2006), all monthly observations from the end of the sample period to the first repeating total return index value.[17] The default for Datastream is to give total return indices and market values in local currencies. As this study is from the perspective of an US-based investor, the total return indices and market values are converted into US dollars using end-of-month exchange rates of the various local currencies versus the US dollar.[18] Monthly holding period returns are calculated from the converted total return indices.

The equities are assigned to countries and industries according to Datastream's classification, which is consistent with FTSE Russell's Classification Benchmark. I require each equity's country and industry to be clearly identified by the Datastream variables GEOG and INDM, respectively, in order to be included in the final sample.[19] Moreover, I only keep the equities that are listed on the major exchanges of the countries they are allocated to, to increase the clarity of the equities' country allocation and to have the analysis not impacted by inaccurate equity data from small exchanges.[20] The industries that are represented are Oil and Gas (OG), Basic Materials (BM), Industrials (IN), Consumer Goods (CG), Health Care (HC), Consumer Services (CS), Telecommunications (TEL), Utilities (UT), Financials (FI), and Technology (TEC). Since Datastream and Bloomberg each apply a different (competing) system for classifying firms into industries, the equities' and the bonds' industry allocation cannot be exactly harmonized.

My analysis is restricted to common-ordinary stocks. However, among the equities retrieved, several non-common equities and duplicates are present. I therefore next conduct an extensive screening process, based on four filters formulated by Ince and Porter (2006) and Griffin et al. (2010), to detect and eliminate these equities from the final sample. In the first filter, equities for which the Datastream variable TYPE is not equal to 'EQ' are excluded due to their non-common equity features.[21] The second filter removes duplicated equities, resulting from cross-listings and multi-class equity structures, by requiring the Datastream variables MAJOR and PQ01 to be respectively equal to 'Y' and 'P' for each equity. In the third filter, equities that are allocated to the sector codes for investment vehicles according to the Datastream variable INDM are dropped.[22] The fourth filter deletes equities for which the Datastream variable NAME contains keywords or phrases that indicate that the security is non-common equity. This last filter is based on the fact that Datastream tracks equity-type information mainly by adding text to the equity's name field. Griffin et al. (2010) provide a comprehensive overview of standard keywords and phrases to distinguish non-common from common equities, which I use while screening the name fields of the equities.[23] After the completion of the screening process, a sample of 5961 common-ordinary stocks remains, which is, in my belief, virtually clean of non-common equities and duplicates.

[17] I realize that a small number of valid repeating total return index values may be lost at the end of the sample.

[18] The currency conversion is performed using Datastream's currency converter. The total return indices are converted with nine decimal places, using the Datastream function *DPL#(X(RI)~U$,9)*, such that the monthly holding period returns of the equities are not impacted by rounding errors.

[19] Note that the country filters applied in the Datastream Navigator are also based on the Datastream variable GEOG.

[20] The major stock exchange is defined as the one with the highest number of listed equities. Only for Germany multiple domestic exchanges are considered, namely the exchanges in Frankfurt, Stuttgart, Berlin, Düsseldorf, Hamburg, Hanover, and Munich.

[21] More specifically, equities that Datastream classifies as american depositary receipts, closed-end funds, exchange-traded fund, profit participation certificates, global depositary receipts, non-voting depository receipts, preference shares, and warrants are excluded.

[22] More specifically, equities that are allocated to the following sectors are excluded: Real Estate Investment Trusts, Equity Investment Instruments, Nonequity Investment Instruments.

[23] Tables B.1 and B.2 in Griffin et al. (2010) lists most keywords and phrases that Datastream adds to the variable NAME to indicate that a security is non-common equity. To these lists I add the following keywords: "REG", "REGD", "REGULATION S", "(REGS)" (sale of these equities is restricted); "(DI)" (depository interests); "Limited Data", "LTD DATA" (the equity data is inaccurate according to Datastream); "AFV" in Belgium (these equities have preferential dividends or tax incentives); "RSP", "RNC" in Italy (these equities have non-voting provisions); "SDB" in Sweden (Swedish depository receipts).

Table A.1: Datastream Variable Definitions

Variable name	Variable Mnemonic	Static or Time-series	Description
Name	NAME	S	The name of the equity as stored on Datastream's databases
Firm name	WC06001	S	The legal name of the firm corresponding to the equity as reported in the annual report
Previous name	PNAME	S	The previous name of the equity (the previous value of NAME)
Date of last name change	DNMC	S	The date when PNAME changed to NAME
Geography group code	GEOG	S	The home country of the equity
Industry group code	INDM	S	The industry classification of the equity
Type of security	TYPE	S	The type of the security requested
Major security flag	MAJOR	S	For firms with more than one equity, this variable indicates which of the securities is the most significant in terms of market value and liquidity of the primary quotation of that security
Quote indicator	PQ1	S	This variable indicates whether a quote is primary or secondary
Exchange code	EXMNEM	S	The exchange where the equity is listed
Total return index	RI	T	Theoretical growth in value of a equity holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity at the closing price applicable on the ex-dividend date
Market value	MV	T	The stock price multiplied by the number of common stocks in issue

Notes: This table provides the definitions of the Datastream variables used in this study. Variable names, mnemonics and descriptions are from Datastream. The third column indicates whether the variable is static (S) or a time-series (T).

To facilitate the matching of the bonds with the stocks, I retrieve the Datastream variable WC06001 for all stocks, which represents, similar to the full bond issuer's name, the legal name of the stock issuer as reported in the annual report. Also similar to the full bond issuer's name, this variable is updated in conjunction with corporate events, in particular regular corporate name changes, mergers and demergers. It therefore actually returns the name of the firm currently corresponding to the stock. Special care is required regarding the firm names underlying the stocks involved in mergers and demergers. After the merger of two listed firms, it is common practice for Datastream to extend the stock data series of one of the two firms involved with new stock data from the newly created firm and to accordingly set the corresponding Datastream variable WC06001 to the name of the newly created firm. Meanwhile, the stock data series of the other firm is declared dead. An example is the merger of the French firms Banque Nationale de Paris (BNP) and Paribas into BNP Paribas. Datastream uses two separate series to store the stock data of the three firms: one for Paribas and one for BNP and BNP Paribas combined. The merger date determines both the split point that divides the stock data belonging to BNP from those belonging to BNP Paribas and the end point of the stock data series of Paribas. Analogously, after the demerger of a listed firm into two newly created and listed firms, Datastream extends the stock data series of the demerged firm with new stock data from one of the two newly created firms. The corresponding Datastream variable WC06001 is accordingly set to the name of the relevant newly created firm and a new stock data series is started for the other newly created firm. The demerger of GUS PLC into Home Retail Group and Experian Finance PLC, as discussed in Section A.1, can again serve as an example. Datastream uses two separate series to store the stock data of the three firms: one for Experian and one for GUS PLC and Home Retail Group combined. The demerger date determines both the split point that divides the stock data belonging to GUS PLC from those belonging to Home Retail Group and the starting point of the stock data series of Experian. Since the matching process requires the exact knowledge of which firms underlie a stock data series in order to prevent bond returns to become only partially or even falsely matched with stock returns over time, the Datastream variable WC06001 has to be supplemented with extra information about its previous name values. Datastream offers the variables PNAME and DNMC, which respectively represent the previous name related to a stock data series and the corresponding date when the name change took place. These variables are helpful, but not sufficient for the matching process, since they are limited to the most recent previous name, while more than two firms may underlie a stock data series. To recover all previous firm names underlying a stock data series, I make use of the comprehensive mergers and acquisitions (M&As) database of Thomson One. From this database I retrieve a list of all M&As involving firms from the countries under consideration that occurred during the sample period of this study. The list contains for each M&A deal, the effective M&A dates and the original names at the time of the deals of the firms involved. Since Thomson One is, like Datastream, supplied by Thomson Reuters, it provides Datastream codes for the stocks corresponding to the listed firms involved in M&As. Then, via the Datastream codes, the M&A information can be linked to the stock data series, which in turn allows me to determine the underlying firms of the stock data series over time, on a series-by-series basis.

A.3 Matching of stock and corporate bond data

Bloomberg and Datastream could represent the name of the same firm in different ways, e.g. due to spelling variations, abbreviations, omissions and additions. For example, the German firm K+S AG is represented by Bloomberg as 'K+S Aktiengesellschaft', while Datastream uses the name 'K&S AG'. Therefore, the task of the first step of the matching process is to identify all pairs of approximately matching bond and stock issuers' names that represent the same firms. To this end, I make use of an efficient lookup method based on textual similarity developed by Arasu et al. (2011) and called the Fuzzy

Lookup.[24] The matching of textual data by the Fuzzy Lookup is designed to be robust to a variety of errors including spelling variations, abbreviations and omissions and additions, and is therefore very suitable for my purpose. At the core of the Fuzzy Lookup is a similarity function that given both a bond and stock issuer's name returns a number between zero and one quantifying their similarity, a one indicating an exact match. In total I perform four Fuzzy Lookups to match (previous) bond issuers' names with (previous) stock issuers' names. The first Fuzzy Lookup is set up such that each combination of current bond and current stock issuer's name is considered and that for each current bond issuer's name the corresponding current stock issuer's name with the greatest similarity rate is provided. Based on the first lookup results, I determine a candidate list of paired bonds and stocks that are most certainly issued by the same firms. Recall that I treat bonds issued by unlisted subsidiary firms as if they were directly issued by the parent firms themselves and match them accordingly with the stocks of the parent firms. Similarly, I perform a second, third, and fourth Fuzzy Lookup, where I try to respectively match the so far unmatched current bond issuers' names with the previous stock issuers' names, the so far unmatched previous bond issuers' names with the current stock issuers' names, and the so far unmatched previous bond issuers' names with the previous stock issuers' names. The potential bond and stock matches following from these last Fuzzy Lookups are also added to the candidate list of paired bonds and stocks. Finally, as a last resort, the still unmatched bonds are manually checked if they can be matched with stocks. In this way I manage to find the corresponding stocks for several bonds that are issued by subsidiary firms whose names are in so far different from their parent firms' names that they could not be linked to the parent firms' names (and thus stocks) by means of the Fuzzy Lookups. For example, I manage to match a bond issued by the UK firm St. Michael Finance PLC, which operates as a wholly owned finance vehicle of the Marks & Spencer Group, with the stock of the Marks & Spencer Group. I also add the potential bond and stock matches resulting from the manual searches to the candidate list of paired bonds and stocks.

The candidate bond and stock matches may, however, not be completely correct over time because of the different impact mergers, acquisitions, bankruptcies and other delisting events have on the underlying firms of both the bond and stock data series. In the second step of the matching process I therefore follow the candidate matches through time and I subsequently distinguish straight matches from matches that need to be manually adjusted in conjunction with corporate events. I define a straight match as a bond and stock match whose corresponding and overlapping bond and stock returns automatically have the same underlying firm(s) over time. I require a straight matched bond and stock to have at least one overlapping return, otherwise the match is discarded. An example of a straight matched bond is the bond initially issued by Banque Nationale de Paris (BNP) in September 1995 and maturing in September 2005, with BNP Paribas as bond guarantor since May 2000 after the merger of BNP and Paribas. Matching on name with the Fuzzy Lookup leads to a match with the stock of BNP Paribas. As explained in Section A.2, the stock data series of BNP Paribas contain the older stock data of BNP. The straight matching of the data series of this bond with the data series of the stock of BNP Paribas therefore automatically takes into account the merger.

In the third step of the matching process the candidate matches that need manual adjustments in conjunction with corporate events are specifically considered. Two types of manual adjustments can be distinguished. First, some already-matched bonds are manually linked to a second stock in order to take into account mergers, demergers, and acquisitions. Second, some series of matched and overlapping bond and stock returns are truncated from below or above to prevent some of the bond and stock returns to be falsely matched. An example of the first type is given by the matching of the bond initially issued by Paribas in August 1997 and maturing in August 2007, with BNP Paribas as bond guarantor since May

[24]The Fuzzy Lookup is available as an add-in for Microsoft Excel.

2000 after the merger of BNP and Paribas. Matching on name with the Fuzzy Lookup leads to a match with the stock of BNP Paribas. However, as explained in Section A.2, the stock data of BNP Paribas and Paribas are both stored in separate series. Therefore, the match of this bond is manually adjusted such that from issuance its data series are linked to the stock data series of Paribas till the merger, and thereafter to the stock data series of BNP Paribas. In this case the stock of Paribas is regarded as the 'second' match of the bond, since the bond was already matched to the stock of BNP Paribas by means of the Fuzzy Lookup. An example of the second type of manual adjustments is given by the matching of the bond initially issued by the unlisted UK firm National & Provincial Building Society in May 1992 and maturing in May 1997, with the listed UK firm Abbey National as bond guarantor since August 1996 after a full take-over. Matching on name with the Fuzzy Lookup leads to a match with the stock of Abbey National. Although the stock of Abbey National was already listed before the issuance of the bond by the National & Provincial Building Society, only the bond data after the take-over are allowed to be matched with the stock data of Abbey National. Therefore the match of this bond is manually adjusted such that the bond data before the take-over remain unmatched and that the bond data after the take-over are matched with the stock data of Abbey National.

In order to be included in the final sample of bond and stock matches, I require the matches to meet the following three criteria. First, in the case the bond is issued by a subsidiary firm, I require the subsidiary firm to be directly or indirectly wholly owned (over time) by the parent firm whose stock is matched with the bond. Note that I try to match a bond issued by a subsidiary firm with the stock of the closest listed parent firm above the subsidiary firm in the corporate hierarchy. Second, the country allocations of the matched bonds and stocks must agree (over time). Third, the industry allocations of the straight matched bonds and stocks must approximately agree (over time). This last criterion is not that strictly maintained, since it is rather subjective due to the differences in the industry allocations of the bonds and stocks. Still, it provides a last check whether the matched bonds and stocks are truly issued by the same firms. After the completion of the matching process, 3739 bond return series are (partially) linked to 391 stock return series.

APPENDIX B Heston and Rouwenhorst (1994) model explained

B.1 Basic notation and construction of indices

Suppose I have, similar to Heston and Rouwenhorst (1994) and Pieterse-Bloem and Mahieu (2013), an unbalanced data set of holding-period return series and corresponding market value series[25] of securities of the same type (e.g. common stocks or corporate bonds), that are measured at a certain frequency (e.g. monthly) for the periods $t = 1, \dots, T$, and that are converted into a common currency. Then suppose securities $i = 1, \dots, N$ have a holding-period return R_i and a market value MV_i available for a particular period t, where R_i is determined at the end of the period and MV_i at the beginning of the period.[26] The actual equally- and value-weighted total market indices for a particular period t, denoted by R_M^{ew} and R_M^{vw} respectively, can then be derived as follows:

$$R_M^{ew} = \frac{1}{N}\sum_{i=1}^{N} R_i \tag{B.1}$$

$$R_M^{vw} = \frac{1}{\sum_{i=1}^{N} MV_i}\sum_{i=1}^{N} MV_i R_i. \tag{B.2}$$

Each security i is related to exactly one industry $j = 1, \dots, J$ and one country $k = 1, \dots, K$. Let $I_{i,j}$ and $C_{i,k}$ be dummy variables defined as

$$I_{i,j} = \begin{cases} 1, & \text{if security } i \text{ belongs to industry } j \\ 0, & \text{otherwise} \end{cases}$$

and

$$C_{i,k} = \begin{cases} 1, & \text{if security } i \text{ belongs to country } k \\ 0, & \text{otherwise.} \end{cases}$$

Now I can introduce the following expressions that are valid for a particular period t:

$$n_j = \sum_{i=1}^{N} I_{i,j} \qquad \text{(number of securities in industry } j\text{)}$$

$$m_k = \sum_{i=1}^{N} C_{i,k} \qquad \text{(number of securities in country } k\text{)}$$

$$w_j = \frac{\sum_{i=1}^{N} MV_i I_{i,j}}{\sum_{i=1}^{N} MV_i} \qquad \text{(value weight of industry } j \text{ in the total value-weighted market)}$$

[25] As stated in Chapter 3, I refer to the market value of a security as its total amount outstanding in the market. For a stock the market value is equal to the current stock price times the number of outstanding stocks. For a corporate bond the market value is equal to the amount issued.

[26] Note that I omit the time index t for notational convenience. Obviously, variables such as the number of available securities, N, can have different values over the different time periods t.

$$v_k = \frac{\sum_{i=1}^{N} MV_i C_{i,k}}{\sum_{i=1}^{N} MV_i} \qquad \text{(value weight of country } k \text{ in the total value-weighted market)}$$

and

$$p_{i,j} = \begin{cases} \frac{MV_i}{w_j \sum_{i=1}^{N} MV_i}, & \text{if security } i \text{ belongs to industry } j \\ 0, & \text{otherwise} \end{cases}$$

$$p_{i,k} = \begin{cases} \frac{MV_i}{v_k \sum_{i=1}^{N} MV_i}, & \text{if security } i \text{ belongs to country } k \\ 0, & \text{otherwise,} \end{cases}$$

where $p_{i,j}$ $(p_{i,k})$ denotes the value weight of security i in industry j (country k). Notice that the weights sum to one, e.g. $\sum_{j=1}^{J} w_j = \sum_{k=1}^{K} v_k = \sum_{i=1}^{N} p_{i,j} = \sum_{i=1}^{N} p_{i,k} = 1$, and are each non-negative by construction.

The actual equally- and value-weighted indices of the industries and countries under consideration for a particular period t can now be determined as follows:

$$R_j^{ew} = \frac{1}{n_j} \sum_{i=1}^{N} R_i I_{i,j} \tag{B.3}$$

$$R_k^{ew} = \frac{1}{m_k} \sum_{i=1}^{N} R_i C_{i,k} \tag{B.4}$$

$$R_j^{vw} = \sum_{i=1}^{N} p_{i,j} R_i \tag{B.5}$$

$$R_k^{vw} = \sum_{i=1}^{N} p_{i,k} R_i, \tag{B.6}$$

where R_j^{ew} (R_k^{ew}) and R_j^{vw} (R_k^{vw}) respectively denote the actual equally- and value-weighted indices of industry j (country k). The construction of the indices in B.1 through B.6 can be repeated for every period $t = 1, \ldots, T$, giving me time series of the indices.

B.2 Decomposition model of Heston and Rouwenhorst (1994)

Heston and Rouwenhorst (1994) describe a linear regression approach to decompose the equally- and value-weighted industry and country indices given in Specifications B.3 through B.6 into global, country and industry components. The starting point of their approach is the following cross-sectional model for the holding-period return of the ith security that belongs to industry j and country k:

$$R_i = \alpha + \phi_j + \psi_k + \epsilon_i, \tag{B.7}$$

where the unknown but non-stochastic parameters α, ϕ_j and ψ_k respectively are a base level of return in a particular period t, the industry effect and the country effect, and ϵ_i is a security-specific random error term. Specification B.7 allows for independent influences of industry and country effects, but excludes any interaction between these effects. Using the dummy variables $I_{i,j}$ and $C_{i,k}$ as known and fixed regressors, Heston and Rouwenhorst (1994) rewrite Model B.7 in a linear regression form as

$$R_i = \alpha + \sum_{j=1}^{J} \phi_j I_{i,j} + \sum_{k=1}^{K} \psi_k C_{i,k} + \epsilon_i. \tag{B.8}$$

They assume that the security-specific error terms have a zero mean, e.g. $E\left[\epsilon_i\right] = 0$ for all i, have finite but different variances, e.g. $E\left[\epsilon_i^2\right] = \sigma_i^2 \in (0, \infty)$ for all i, and are uncorrelated across securities, e.g. $E\left[\epsilon_i \epsilon_h\right] = 0$ for all $i \neq h$. For the heteroskedasticity they postulate the following model:

$$\sigma_i^2 = \frac{\sigma^2}{MV_i}, \tag{B.9}$$

where the market value MV_i is known and positive for each security i and the non-stochastic parameter σ^2 is unknown. In this case Model B.8 can be transformed to a model with homoscedastic security-specific error terms by multiplying the equation by $\sqrt{MV_i}$. Let $\epsilon_i^* = \sqrt{MV_i}\epsilon_i$, then the following transformed model is obtained:

$$\sqrt{MV_i} R_i = \sqrt{MV_i}\alpha + \sum_{j=1}^{J} \phi_j \left(\sqrt{MV_i} I_{i,j}\right) + \sum_{k=1}^{K} \psi_k \left(\sqrt{MV_i} C_{i,k}\right) + \epsilon_i^*. \tag{B.10}$$

Indeed, it holds that the security-specific error terms ϵ_i^*, $i = 1, \ldots, N$, now have equal variances of $E\left[\epsilon_i^{*2}\right] = MV_i E\left[\epsilon_i^2\right] = \sigma^2$. They still have a zero mean, e.g. $E\left[\epsilon_i^*\right] = \sqrt{MV_i} E\left[\epsilon_i\right] = 0$ for all i, and are still uncorrelated across securities, e.g. $E\left[\epsilon_i^* \epsilon_h^*\right] = \sqrt{MV_i}\sqrt{MV_h} E\left[\epsilon_i \epsilon_h\right] = 0$ for all $i \neq h$.

The relationship in B.10 can, however, not be estimated by ordinary least squares in its current form because it is unidentified, due to perfect multicollinearity. The sum of the J transformed industry dummy variables for each security i as well as the sum of the K transformed country dummy variables are equal to the variable that is attached to the parameter α, e.g. $\sum_{j=1}^{J} \sqrt{MV_i} I_{i,j} = \sum_{k=1}^{K} \sqrt{MV_i} C_{i,k} = \sqrt{MV_i}$. Heston and Rouwenhorst (1994) solve this problem by imposing the following two identifying restrictions on the parameters of the industry and country effects for a particular period t:

$$\sum_{j=1}^{J} w_j \phi_j = 0 \tag{B.11a}$$

$$\sum_{k=1}^{K} v_k \psi_k = 0, \tag{B.11b}$$

where w_j (v_k) still denotes the known value weight of industry j (country k) in the total value-weighted market. By doing so, Heston and Rouwenhorst (1994) force the ordinary least squares estimate of α in B.10 to be equal to the actual value-weighted total market index given in Specification B.2, as will be shown below. The restrictions in B.11 thus imply that the actual value-weighted total market index, which is the equivalent of the average security in the data set, has neither industry nor country effects. Consequentially, the industry and country effects are measured relative to the actual value-weighted total market index.[27]

In order to estimate the parameters in regression Equation B.10 subjected to the restrictions in B.11a

[27]See Suits (1984) and Kennedy (1986) for a discussion about interpreting dummy variable estimates as deviations from average behavior.

and B.11b, I first rewrite the restrictions as

$$0 = \sum_{j=1}^{J} w_j\phi_j = \sum_{j=1}^{J-1} w_j\phi_j + w_J\phi_J \Leftrightarrow \phi_J = -\sum_{j=1}^{J-1}\phi_j\frac{w_j}{w_J} \tag{B.12a}$$

$$0 = \sum_{k=1}^{K} v_k\psi_k = \sum_{k=1}^{K-1} v_k\psi_k + v_K\psi_K \Leftrightarrow \psi_K = -\sum_{k=1}^{K-1}\psi_k\frac{v_k}{v_K}, \tag{B.12b}$$

using the last industry J and the last country K as arbitrary benchmark. Then I substitute the rewritten restrictions into regression Equation B.10 and get the following unrestricted regression model which ignores the parameters ϕ_J and ψ_K:

$$\begin{aligned}
\sqrt{MV_i}R_i &= \sqrt{MV_i}\alpha + \sum_{j=1}^{J-1}\phi_j\left(\sqrt{MV_i}I_{i,j}\right) - \left(\sum_{j=1}^{J-1}\phi_j\frac{w_j}{w_J}\right)\left(\sqrt{MV_i}I_{i,J}\right) \\
&\quad + \sum_{k=1}^{K-1}\psi_k\left(\sqrt{MV_i}C_{i,k}\right) - \left(\sum_{k=1}^{K-1}\psi_k\frac{v_k}{v_K}\right)\left(\sqrt{MV_i}C_{i,K}\right) + \epsilon_i^* \\
&= \sqrt{MV_i}\alpha + \sum_{j=1}^{J-1}\phi_j\left(\sqrt{MV_i}\left(I_{i,j} - \frac{w_j}{w_J}I_{i,J}\right)\right) \\
&\quad + \sum_{k=1}^{K-1}\psi_k\left(\sqrt{MV_i}\left(C_{i,k} - \frac{v_k}{v_K}C_{i,K}\right)\right) + \epsilon_i^* \\
&= \sqrt{MV_i}\alpha + \sum_{j=1}^{J-1}\phi_j\left(\sqrt{MV_i}Y_{i,j}\right) + \sum_{k=1}^{K-1}\psi_k\left(\sqrt{MV_i}Z_{i,k}\right) + \epsilon_i^*,
\end{aligned} \tag{B.13}$$

where $Y_{i,j} = \left(I_{i,j} - \frac{w_j}{w_J}I_{i,J}\right)$ and $Z_{i,k} = \left(C_{i,k} - \frac{v_k}{v_K}C_{i,K}\right)$. Let $\sqrt{MV_i}x_i$ be the known regressor vector for the ith security in this unrestricted regression model, where $x_i = [1, Y_{i,1}, \ldots, Y_{i,J-1}, Z_{i,1}, \ldots, Z_{i,K-1}]'$, and let $\beta = [\alpha, \phi_1, \ldots, \phi_{J-1}, \psi_1, \ldots, \psi_{K-1}]'$ be the corresponding vector of unknown parameters. The formula for the ordinary least squares estimator of β is then given by:

$$\hat{\beta} = [\hat{\alpha}, \hat{\phi}_1, \ldots, \hat{\phi}_{J-1}, \hat{\psi}_1, \ldots, \hat{\psi}_{K-1}]' = \left(\sum_{i=1}^{N} MV_i x_i x_i'\right)^{-1}\left(\sum_{i=1}^{N} MV_i x_i R_i\right).$$

Notice that securities with bigger market values (and thus smaller variances) have a larger weight in determining the estimate $\hat{\beta}$ relative to securities with smaller market values (and thus bigger variances). Essentially, the same estimator is obtained by weighted least squares in Model B.13 after it is transformed back by dividing the (last) equation by $\sqrt{MV_i}$. In this case the weights are obviously the market values of the securities.

Estimates for ϕ_J and ψ_K follow from the restrictions in B.12a and B.12b and are given as

$$\hat{\phi}_J = -\sum_{j=1}^{J-1}\hat{\phi}_j\frac{w_j}{w_J}$$

and

$$\hat{\psi}_K = -\sum_{k=1}^{K-1}\hat{\psi}_k\frac{v_k}{v_K}.$$

The estimated Model B.13, including $\hat{\phi}_J$ and $\hat{\psi}_K$, can then be written as

$$\begin{aligned}\sqrt{MV_i}R_i &= \sqrt{MV_i}\hat{\alpha} + \sum_{j=1}^{J-1}\hat{\phi}_j\left(\sqrt{MV_i}Y_{i,j}\right) + \sum_{k=1}^{K-1}\hat{\psi}_k\left(\sqrt{MV_i}Z_{i,k}\right) + e_i^* \\ &= \sqrt{MV_i}\hat{\alpha} + \sum_{j=1}^{J}\hat{\phi}_j\left(\sqrt{MV_i}I_{i,j}\right) + \sum_{k=1}^{K}\hat{\psi}_k\left(\sqrt{MV_i}C_{i,k}\right) + e_i^*,\end{aligned} \tag{B.14}$$

where e_i^* is a security-specific residual. Next, it can be shown that the estimate $\hat{\alpha}$ indeed equals the actual value-weighted total market index, R_M^{vw}, by substituting the last equality of B.14 into Specification B.2:

$$\begin{aligned}R_M^{vw} &= \frac{1}{\sum\limits_{i=1}^{N} MV_i}\sum_{i=1}^{N} MV_i R_i \\ &= \frac{1}{\sum\limits_{i=1}^{N} MV_i}\sum_{i=1}^{N}\sqrt{MV_i}\sqrt{MV_i}R_i \\ &= \frac{1}{\sum\limits_{i=1}^{N} MV_i}\sum_{i=1}^{N} MV_i\hat{\alpha} + \frac{1}{\sum\limits_{i=1}^{N} MV_i}\sum_{i=1}^{N}\sum_{j=1}^{J}\hat{\phi}_j(MV_i I_{i,j}) \\ &\quad + \frac{1}{\sum\limits_{i=1}^{N} MV_i}\sum_{i=1}^{N}\sum_{k=1}^{K}\hat{\psi}_k(MV_i C_{i,k}) + \frac{1}{\sum\limits_{i=1}^{N} MV_i}\sum_{i=1}^{N}\sqrt{MV_i}e_i^* \\ &= \hat{\alpha} + \sum_{j=1}^{J}\hat{\phi}_j\frac{\sum\limits_{i=1}^{N} MV_i I_{i,j}}{\sum\limits_{i=1}^{N} MV_i} + \sum_{k=1}^{K}\hat{\psi}_k\frac{\sum\limits_{i=1}^{N} MV_i C_{i,k}}{\sum\limits_{i=1}^{N} MV_i} \\ &= \hat{\alpha} + \sum_{j=1}^{J}\hat{\phi}_j w_j + \sum_{k=1}^{K}\hat{\psi}_k v_k \\ &= \hat{\alpha},\end{aligned} \tag{B.15}$$

where I use in the third equality that $\sum\limits_{i=1}^{N}\sqrt{MV_i}e_i^* = 0$, because of the least squares property that the vector of residuals is orthogonal to the vector of values taken by the regressor variable that is attached to $\hat{\alpha}$ in B.14, and in the fifth equality I use that $\sum\limits_{j=1}^{J}\hat{\phi}_j w_j = \sum\limits_{k=1}^{K}\hat{\psi}_k v_k = 0$ because of the imposed restrictions given in B.11.

By substituting the last equality of B.14 into Specification B.5, the actual value-weighted index of industry j, R_j^{vw}, can be decomposed into a component equal to the actual value-weighted total market index, $\hat{\alpha}$, a pure industry effect, $\hat{\phi}_j$, and a component representing the overall country effect for industry j, $\sum\limits_{k=1}^{K}\hat{\psi}_k\sum\limits_{i=1}^{N} p_{i,j}C_{i,k}$:

$$
\begin{aligned}
R_j^{vw} &= \sum_{i=1}^{N} p_{i,j} R_i \\
&= \sum_{i=1}^{N} \frac{I_{i,j}}{w_j \sum\limits_{i=1}^{N} MV_i} MV_i R_i \\
&= \sum_{i=1}^{N} \frac{I_{i,j}}{w_j \sum\limits_{i=1}^{N} MV_i} \sqrt{MV_i}\sqrt{MV_i} R_i \\
&= \sum_{i=1}^{N} \frac{I_{i,j}}{w_j \sum\limits_{i=1}^{N} MV_i} MV_i \hat{\alpha} + \sum_{i=1}^{N} \frac{I_{i,j}}{w_j \sum\limits_{i=1}^{N} MV_i} \sum_{j=1}^{J} \hat{\phi}_j \left(MV_i I_{i,j}\right) \\
&\quad + \sum_{i=1}^{N} \frac{I_{i,j}}{w_j \sum\limits_{i=1}^{N} MV_i} \sum_{k=1}^{K} \hat{\psi}_k \left(MV_i C_{i,k}\right) + \frac{1}{w_j \sum\limits_{i=1}^{N} MV_i} \sum_{i=1}^{N} \sqrt{MV_i} I_{i,j} e_i^* \\
&= \frac{w_j \sum\limits_{i=1}^{N} MV_i}{w_j \sum\limits_{i=1}^{N} MV_i} \hat{\alpha} + \sum_{i=1}^{N} \frac{I_{i,j} MV_i}{w_j \sum\limits_{i=1}^{N} MV_i} \sum_{j=1}^{J} \hat{\phi}_j I_{i,j} + \sum_{i=1}^{N} \frac{I_{i,j} MV_i}{w_j \sum\limits_{i=1}^{N} MV_i} \sum_{k=1}^{K} \hat{\psi}_k C_{i,k} \\
&= \hat{\alpha} + \sum_{i=1}^{N} p_{i,j} \sum_{j=1}^{J} \hat{\phi}_j I_{i,j} + \sum_{i=1}^{N} p_{i,j} \sum_{k=1}^{K} \hat{\psi}_k C_{i,k} \\
&= \hat{\alpha} + \hat{\phi}_j + \sum_{k=1}^{K} \hat{\psi}_k \sum_{i=1}^{N} p_{i,j} C_{i,k},
\end{aligned}
\tag{B.16}
$$

where I use in the first and fifth equality that $p_{i,j} = \frac{MV_i I_{i,j}}{w_j \sum_{i=1}^{N} MV_i}$, and in the fourth equality that $\sum_{i=1}^{N} I_{i,j} MV_i = w_j \sum_{i=1}^{N} MV_i$ and that $\sum_{i=1}^{N} \sqrt{MV_i} I_{i,j} e_i^* = 0$, because of the least squares property that the vector of residuals is orthogonal to the vector of values taken by the regressor variable that is attached to $\hat{\phi}_j$ in B.14. Because (1) each security i is allocated to only one industry, (2) $p_{i,j}$ is zero if security i is not allocated to industry j and (3) $\sum_i p_{i,j} = 1$, where the i-summation is taken over the securities allocated to industry j only, it holds that $\sum_{i=1}^{N} p_{i,j} \sum_{j=1}^{J} \hat{\phi}_j I_{i,j} = \hat{\phi}_j \sum_i p_{i,j} = \hat{\phi}_j$ in the sixth equality. Notice that the term $\sum_{i=1}^{N} p_{i,j} C_{i,k}$ in the last equality represents the value weight of country k in the actual value-weighted index of industry j. The overall country effect for industry j is thus measured as the weighted sum of the K country effects. Now, consider the case that the actual value-weighted index of industry j has the same geographical distribution as the actual value-weighted total market index, that is, $\sum_{i=1}^{N} p_{i,j} C_{i,k} = v_k$ for $k = 1, \ldots, K$. Since the actual value-weighted total market index is free of country effects by definition (because of the restriction in B.11b), the same holds for the the actual value-weighted index of industry j in this case. Consequently, the component measuring the overall country effect of industry j in the last equality of B.16 vanishes, e.g. $\sum_{k=1}^{K} \hat{\psi}_k \sum_{i=1}^{N} p_{i,j} C_{i,k} = \sum_{k=1}^{K} \hat{\psi}_k v_k = 0$, and it can be inferred that the remaining expression, $\hat{\alpha} + \hat{\phi}_j$, can be interpreted as (the least squares estimate of) the pure value-weighted index of industry j, which is corrected for country composition and thus country effects. From this interpretation it follows that the pure industry effect, $\hat{\phi}_j$, alone is measuring how well each country in industry j performs relative to the average security from that country. The component representing the overall country effect of industry j captures the part of R_j^{vw} that can be attributed to the difference between the geographical distribution of the actual value-weighted index of industry j and the geographical distribution of the actual value-weighted total market index. If the actual value-weighted index of industry j consists of proportionally more securities from countries that outperform (underperform) the total market than the actual value-weighted total market index itself, then the overall country effect for industry j will, ceteris paribus, be positive (negative).

Similarly, by substituting the last equality of B.14 into Specification B.6, the actual value-weighted index of country k, R_k^{vw}, can be decomposed into a component equal to the actual value-weighted total market index, $\hat{\alpha}$, a component representing the overall industry effect for country k, $\sum_{j=1}^{J} \hat{\phi}_j \sum_{i=1}^{N} p_{i,k} I_{i,j}$, and a pure country effect, $\hat{\psi}_k$:

$$
\begin{aligned}
R_k^{vw} &= \sum_{i=1}^{N} p_{i,k} R_i \\
&= \sum_{i=1}^{N} \frac{C_{i,k}}{v_k \sum_{i=1}^{N} MV_i} MV_i R_i \\
&= \sum_{i=1}^{N} \frac{C_{i,k}}{v_k \sum_{i=1}^{N} MV_i} \sqrt{MV_i}\sqrt{MV_i} R_i \\
&= \sum_{i=1}^{N} \frac{C_{i,k}}{v_k \sum_{i=1}^{N} MV_i} MV_i \hat{\alpha} + \sum_{i=1}^{N} \frac{C_{i,k}}{v_k \sum_{i=1}^{N} MV_i} \sum_{j=1}^{J} \hat{\phi}_j \left(MV_i I_{i,j}\right) \\
&\quad + \sum_{i=1}^{N} \frac{C_{i,k}}{v_k \sum_{i=1}^{N} MV_i} \sum_{k=1}^{K} \hat{\psi}_k \left(MV_i C_{i,k}\right) + \frac{1}{v_k \sum_{i=1}^{N} MV_i} \sum_{i=1}^{N} \sqrt{MV_i} C_{i,k} e_i^* \\
&= \frac{v_k \sum_{i=1}^{N} MV_i}{v_k \sum_{i=1}^{N} MV_i} \hat{\alpha} + \sum_{i=1}^{N} \frac{C_{i,k} MV_i}{v_k \sum_{i=1}^{N} MV_i} \sum_{j=1}^{J} \hat{\phi}_j I_{i,j} + \sum_{i=1}^{N} \frac{C_{i,k} MV_i}{v_k \sum_{i=1}^{N} MV_i} \sum_{k=1}^{K} \hat{\psi}_k C_{i,k} \\
&= \hat{\alpha} + \sum_{i=1}^{N} p_{i,k} \sum_{j=1}^{J} \hat{\phi}_j I_{i,j} + \sum_{i=1}^{N} p_{i,k} \sum_{k=1}^{K} \hat{\psi}_k C_{i,k} \\
&= \hat{\alpha} + \sum_{j=1}^{J} \hat{\phi}_j \sum_{i=1}^{N} p_{i,k} I_{i,j} + \hat{\psi}_k,
\end{aligned} \tag{B.17}
$$

where I use in the first and fifth equality that $p_{i,k} = \frac{MV_i C_{i,k}}{v_k \sum_{i=1}^{N} MV_i}$, and in the fourth equality that $\sum_{i=1}^{N} C_{i,k} MV_i = v_k \sum_{i=1}^{N} MV_i$ and that $\sum_{i=1}^{N} \sqrt{MV_i} C_{i,k} e_i^* = 0$, because of the least squares property that the vector of residuals is orthogonal to the vector of values taken by the regressor variable that is attached to $\hat{\psi}_k$ in B.14. Because (1) each security i is allocated to only one country, (2) $p_{i,k}$ is zero if security i is not allocated to country k and (3) $\sum_i p_{i,k} = 1$, where the i-summation is taken over the securities from country k only, it holds that $\sum_{i=1}^{N} p_{i,k} \sum_{k=1}^{K} \hat{\psi}_k C_{i,k} = \hat{\psi}_k \sum_i p_{i,k} = \hat{\psi}_k$ in the sixth equality. Notice that the term $\sum_{i=1}^{N} p_{i,k} I_{i,j}$ in the last equality represents the value weight of industry j in the actual value-weighted index of country k. Hence, the overall industry effect for country k is measured as the weighted sum of the J industry effects. Now, consider the case that the actual value-weighted index of country k has the same industrial distribution as the actual value-weighted total market index, that is, $\sum_{i=1}^{N} p_{i,k} I_{i,j} = w_j$ for $j = 1, \ldots, J$. Since the actual value-weighted total market index is free of industry effects by definition (because of the restriction in B.11a), the same holds for the the actual value-weighted index of country k in this case. Consequently, the component measuring the overall industry effect of country k in the last equality of B.17 vanishes, e.g. $\sum_{j=1}^{J} \hat{\phi}_j \sum_{i=1}^{N} p_{i,k} I_{i,j} = \sum_{j=1}^{J} \hat{\phi}_j w_j = 0$, and it can be inferred that the remaining expression, $\hat{\alpha} + \hat{\psi}_k$, can be interpreted as (the least squares estimate of) the pure value-weighted index of country k, which is corrected for industry composition and thus industry effects. From this interpretation it follows that the pure country effect, $\hat{\psi}_k$, alone is measuring how well each industry in country k performs relative to the average security from that industry. The component representing the overall industry effect of country k captures the part of R_k^{vw} that can be attributed to the difference between the industrial distribution of the actual value-weighted index of country k and the industrial distribution of the actual value-weighted total market index. If the actual value-weighted index of country k consists of proportionally more securities from industries that outperform (underperform) the total market than the actual value-weighted total market index itself, then the overall industry effect for country k will, ceteris paribus, be positive (negative).

In order to decompose the actual equally-weighted industry and country indices in Specifications B.3 and B.4, Heston and Rouwenhorst (1994) assume that each security i has the same market value, for example $MV_i = 1$ for all i. Under this assumption, a value-weighted index coincides with a corresponding equally-weighted index. The estimate $\hat{\alpha}$ in B.14 therefore becomes equal to the actual equally-weighted total market index, R_M^{ew}, given in Specification B.1. Furthermore, a decomposition of the actual equally-weighted index of industry j can now be obtained from the last equality in B.16 as

$$R_j^{ew} = \hat{\alpha} + \hat{\phi}_j + \sum_{k=1}^{K} \hat{\psi}_k \sum_i \frac{1}{n_j} C_{i,k}, \tag{B.18}$$

where the i-summation is taken over the securities from industry j only. Here, the term $\sum_i \frac{1}{n_j} C_{i,k}$ represents the weight of country k in the actual equally-weighted index of industry j. Similarly, a decomposition of the actual equally-weighted index of country k can be obtained from the last equality in B.17 as

$$R_k^{ew} = \hat{\alpha} + \sum_{j=1}^{J} \hat{\phi}_j \sum_i \frac{1}{m_k} I_{i,j} + \hat{\psi}_k, \tag{B.19}$$

where the i-summation is taken over the securities from country k only. Here, the term $\sum_{j=1}^{J} \hat{\phi}_j \sum_i \frac{1}{m_k} I_{i,j}$ represents the weight of industry j in the actual equally-weighted index of country k.

The cross-sectional regression in B.13 can be performed for every time period $t = 1, \ldots, T$, providing me time series of the estimated industry and country effects and time series of the estimated pure (value- or equally-weighted) industry and country indices. These pure indices can be used to examine the underlying sources of variation in the actual (value- or equally-weighted) industry and country indices.