Dynamic Portfolio Strategies in the European Corporate Bond Market

Mary Pieterse-Bloem* Willem F.C. Verschoor†
Zhaowen Qian‡ and Remco C.J. Zwinkels§

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Abstract

In this paper, we develop and implement a dynamic portfolio strategy for European corporate bonds. We introduce a strategy in which we forecast both future factors as well as bonds' future exposure to these factor. We apply the strategy to a complete sample of monthly European corporate bond returns from 1991 to 2013, on both an index level and an individual bond level. At the index level, we find that the strategy based on forecasted factors outperforms the benchmark strategies, whereas the strategy based on forecasted exposures does not. There is, however, ample time variation in the performance, related to uncertainty and the level of market integration. At the individual bond level, we find significant outperformance of the dynamic strategy over the benchmark.

Keywords: Corporate bonds; portfolio allocation; dynamic strategies
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*Erasmus School of Economics, Erasmus Research Institute of Management, and ABN Amro Bank – pietersebloem@ese.eur.nl
†Vrije Universiteit Amsterdam and Tinbergen Institute – w.f.c.verschoor@vu.nl
‡Erasmus School of Economics – qian@ese.eur.nl
§Vrije Universiteit Amsterdam and Tinbergen Institute – r.zwinkels@vu.nl

1 Introduction

In this paper, we develop and implement a dynamic portfolio strategy for European corporate bonds. Building on an asset pricing model containing country and industry factors, we introduce a dynamic portfolio strategy in which portfolio weights are a function of forecasts of both future factors as well as the future exposure to these factor. We apply the strategy to a complete sample of monthly European corporate bond returns from 1991 to 2013, on both an index level and an individual bond level. At the index level, we find that the strategy based on forecasted factors outperforms portfolios based on an nave allocation and mean-variance and minimum-variance optimisations , whereas the strategy based on forecasted factor exposures does not. There is, however, ample time variation in the performance, related to uncertainty and the level of market integration. At the individual bond level, we find significant outperformance over the nave portfolio. Our results are robust to equal or value weighting, and the exact set of countries.

This paper contributes to a large literature on dynamic portfolio strategies. Several papers propose dynamic portfolio strategies under different settings. These include dynamic portfolio strategies with portfolio insurance (Perold and Sharpe, 1988), for investors facing inflation (Brennan and Xia, 2009), with transaction costs (Dumas and Luciano, 1991), in markets with arbitrage opportunities (Liu and Longstaff, 2004), in either bear or bull market (Cesari and Cremonini, 2003) and optimal strategies with event risks (Lui et al., 2003).

While the results of those papers are significant for these specific settings , we are interested in achieving an outperformance in a more generalized setting. Li and Ng (2000) show how to derive the analytical optimal solution to the mean-variance formulation in multi-period portfolio selection. Brandt and Santa-Clara (2006) propose that the optimal dynamic strategy can be approximated by the static Markowitz solution. While both studies propose more generalized form solutions of the Markowitz model, neither demonstrate performance vis-à-vis a benchmark such as the naïve portfolio. Since they are extensions of the Markowitz solution, they also implicitly carry the problem of estimation error which hampers their ability to outperform the naïve portfolio.

Indeed, the classical Markowitz model ignores estimation error. The implementation of this model in a static setting implies that investors only care about the mean and the variance with moments estimated via their sample analogues. This is prone to lead to extreme weights that fluctuate substantially over time and perform poorly out of sample (DeMiguel et al., 2009). We therefore need to turn to a strand of literature that has devoted considerable effort to the issue of handling estimation error for clues on how we can improve the performance of the Markowitz model. A prominent role in this vast literature is played by the Baynesian approach to estimation error. Multiple implementations range from the purely statistical approach, relying on diffuse priors (e.g.: Barry, 1974; Bawa et al., 1979) to a shrinkage estimator (e.g.: Jobson et al., 1979; Jobson and Korkie, 1980; Jorion, 1985 and 1986). More recent approaches rely on an asset-pricing model for establishing a prior (e.g.: Pastor, 2000; Pastor and Stambauch, 2000). Equally rich is the set of non-Baynesian approaches to reduce estimation error in the Markowitz model. These include robust portfolio allocation rules (e.g.: Goldfarb and Iyengar, 2003; Garlappi et al., 2007), portfolio rules designed to optimally diversify across market and estimation risk (Kan and Zhou, 2007), portfolios that exploit the moment restrictions imposed by the factor structure of returns (MacKinley and Pastor, 2000), methods that focus on reducing the error in estimating the covariance matrix (Best and Grauer, 1992; Chan et al., 1999, Ledoit and Wolf, 2004a and 2004b) and, finally, portfolio rules that impose short-selling constraints (Frost and Savarino, 1988;Chopra, 1993; Jagannathan and Ma, 2003). While the out-of-sample Sharpe ratios of the extended models are better than the classical Markowitz model, a direct statistical comparison on out-of-sample performance is lacking from those papers.

DeMiguel et al. (2009) is the benchmark study to compare the out-of-sample performance of the sample-based mean-variance model with some extensions to the naïve (equally-weighted) portfolio allocation. Using the mean return and variance of the previous period to determine the optimal weights of the next period, they forecast the out-of-sample period returns. Their model extensions include Baynesian approaches to estimation error, moment restrictions, portfolio constraints and optimal combinations of portfolios. They find that their forecasted performances are not consistently better than the naïve portfolio. The explanation is two-fold. First, there are still estimation errors in the expected returns and variance-covariance matrix. Secondly, using portfolios of stocks instead of individual stocks leads to diversified portfolios with less idiosyncratic risk. The loss from the naïve as opposed to the optimal diversification is much smaller when allocating wealth across portfolios. Overall, the gain from optimal diversification is more than off-set by the size of the estimation error. They therefore derive an analytical expression for the critical length of the estimation window that is needed for the sample-based mean-variance strategy to achieve a higher certainty-equivalent (CEQ) return. All the models need very long estimation windows (3,000 months for a portfolio of 25 assets) before they are able to beat the naïve portfolio.

De Miguel et al. (2009) show that there are still many miles to go before the gains promised by optimal portfolio choice can actually be realized out of sample. We are not attempting to improve the Markowitz model by reducing estimation error, but take a different approach altogether using country and industry factors and betas. Different to most other studies is that the European corporate bond market is our domain. Country factors dominate industry factors in the return variation of European corporate bonds over a long period of 1991 to 2013 (Pieterse-Bloem et al., 2013). This result is in contrast to country and industry factor results for stock markets. Studies that use the Heston and Rouwenhorst (1994) decomposition of return variation on equitiesfind that country factors dominate industry factors until around the year 2000 (e.g.: Griffin and Karolyi, 1998; Rouwenhorst, 1999; Brooks and Del Negro, 2001). After the turn of the millennium, industry factors are documented to play an increasingly larger role in stock returns relative to country factors, especially in Europe which introduces the Euro to form one single market at that time (e.g.: Baca et al., 2000; Cavaglia et al., 2000 ; Adjaoute and Danthine, 2003; Flavin, 2004; Phylaktis and Xia, 2006).

The country and industry factors in European corporate bonds also inhibit considerable time-variation, however, whereby it is shown that the relative dominance of country factors changes considerably (Pieterse-Bloem et al., 2016). The dominance of country factors in European corporate bond returns reduces in the years leading up to the European Economic and Monetary Union (EMU), and again after the introduction of the Euro. This coincides with a tendency among European corporate bond portfolio managers to switch from a country to an industry allocation in the financial industry (Brooks, 1999). This change of tact is somewhat misinformed since country factors not only remain dominant in those early and good days of EMU, they also strengthen as the global financial crisis in 2007 develops into the European sovereign debt crisis (Pieterse-Bloem et al., 2016).

In this paper, we are capitalizing on the time-varying country and industry factor findings of Pieterse-Bloem et al. (2016) and define a dynamic portfolio strategy for European corporate bonds. Despite the dominance of country factors over industry factors, we cannot rely on a country allocation alone to deliver a mean-variance outperformance. Rolling spanning and efficiency tests to evaluate the performance of the country-only and industry-only portfolios over time show that we need both. This is consistent with the finding in Pieterse-Bloem and Mahieu (2013), who apply spanning and efficiency tests with country and industry portfolios from a static decomposition but over different time windows. We therefore construct a dynamic portfolio strategy based on both forecasted country and industry factors as well as forecasted betas or factor exposures. We use an Autoregressive Moving-Average (ARMA) model as our prefered method of forecasting the factors. Our second method is to apply the GARCH-BEKK model from Pieterse-Bloem et al. (2016) to forecast the country and industry betas. In both cases, we use the factors and betas calculated over a previous window of 100 months to forecast the weights for the next out-of-sample period. We compare the performance of the indexes that we are thus able to construct to three benchmark portfolios, being the mean-variance portfolio, the minimal-variance portfolio and the naïve portfolios on either an equal-weight and an individual weight basis. We calculate the out-of-sample performance of all three benchmarks from the sample-based weights which we project forward to the next period. We compare performance on maximum Sharpe ratio, minimal variance and highest certainty-equivalent (CEQ) return.

In the corporate bond market, we need to build indexes from individual bond returns. Our dataset contains 8,446 individual bond series over a sample period of January 1991 to January 2013. Through our method of collection, our dataset is representative for the European corporate bond market in this period. Each individual bond belongs to one of eight European countries and one of seven main industries. This closed set allows us to perform a dynamic decomposition of return variance to derive the time-varying country and industry factors and betas, similar to Pieterse-Bloem et al. (2016).

A major finding is that our portfolios constructed from forecasted factors outperforms the naïve strategy, the mean-variance portfolio and the minimum-variance portfolio on Sharpe ratios and CEQ return, though the outperformance is not significant. The difference in our result from De Miguet et al. (2009) is arguably that bond portfolios contain higher idiosyncratic volatility than stock portfolios. The outperformance of the dynamic factor portfolio is not achieved on the minimal variance measure where, naturally, the minimal variance portfolio continues to perform better out-of-sample. The performance of the strategy based on forecasted factors is better than for the forecasted betas in general, and improves specifically in low-volatile periods and in periods when industry factors gain in strength relative to country factors. When looking at different subsets of countries, we find that the results do not change much for core, periphery and non-EU countries.

A practical drawback of the strategy described above is that investors cannot directly buy the indexes that we create; they would have to form them themselves, which might not be feasible for smaller investors. We therefore replicate our dynamic forecasting strategy on the individual bond level. The outperformance that we achieve at an individual bond level over the naïve portfolio is positive, and statistically significant. We find that our dynamic portfolio from forecasted factors and factor exposures for individual bonds beats the naïve portfolio on all three measure of performance. Since this strategy can be replicated by investors, we also consider turnover. We find that the required turnover of our dynamic portfolio strategy is actually less than that of the naïve portfolio. This is because the composition of the European corporate bond market changes every month, while the optimal holding period for our dynamic strategy leaves the portfolio unchanged for five consecutive months.

Our results transcend the finance literature on dynamic portfolio strategies to the level of demonstrated outperformance. Our results are meaningful for the academic debate, since we are among the very few to design a dynamic portfolio strategy that is able to outperform these hard to beat benchmarks. Since the portfolios from individual bonds can be replicated, our results are also very meaningful for investors.

The remainder of his paper is organized as follows. Section 2 describes the data we use and in Section 3 we introduce our dynamic portfolio strategy. Section 4 list the methods we utilize. Section 5 presents the results, and Section 6 a number of robustness checks. Section 7 concludes the paper.

2 Data

In contrast to stocks, corporate bond indexes are not readily available. Therefore, we hand-collect the daily prices of European corporate bonds in local currencies and calculate monthly holding-period returns. To obtain the common returns, the end-of-month exchange rates of the local currencies against the US dollar (USD) are also collected from Datastream.[1].

The final data sample includes 8,446 corporate bonds covering the period from January 1991 to January 2013 containing 265 monthly observations. The data set constitutes a closed set, since each bond belongs to one country and one industry in the sample. In total, we have eight country indexes and seven industry indexes. The countries that are represented in the analysis are Belgium and Luxembourg (BL), France (FR), Germany (GE), the Netherlands (NE), Italy (IT), Spain (SP), Sweden (SW) and the United Kingdom (UK). The industries that are represented are financial and funds (FF), government institutions (GI)[2], consumer goods (CO), communications and technology (CT), basic materials and energy (BE), industries (IN) and utilities (UT).

Insert Table 1 here

[1] More detailed explanations of the data collection process can be found in Pieterse-Bloem et al. (2016).

[2] Government Institutions include the bonds from quasi-sovereigns and local authorities. Quasi-sovereigns are entities within the government but are not the same as the sovereign issuer itself. Examples include KFW in Germany, CADES in France, Nederlandse Waterschapsbank in the Netherlands. Local authorities are provinces and municipalities.

Table 1 shows how the bonds distribute over different countries and industries. Panel A of Table 1 shows that Germany constitutes 37.8% in our sample, which is the largest proportion of European corporate bonds among the eight countries. France and the United Kingdom follow with 15.4% and 15.1% of total sample each. For the industries, Panel B shows that the financial and funds sector dominates with 67.0% of corporate bonds in the whole sample. On a value-weighted basis[3], the dominance of Germany and the financial industry is largely reduced. Panel D indicates that the value-weighted share of Germany now consists of only 19.5% among the whole sample. On a value-weighted basis, the United Kingdom and Italy are among the largest issuing countries besides Germany. Among the industries the dominance of the financial industry is likewise reduced. On a value-weighted basis the financial sector still accounts for 43.4% of the sample. These results imply that both Germany and the financial and funds industry give out a relatively large number of bonds with relative low notional value.

Table 1 indicates that each country has at least one bond in each industry. Therefore, there are good diversification opportunities in our sample and all countries are industrially diversified. Nevertheless, certain patterns of industry concentration in the European countries are visible from Panels C and D. For example, France is more concentrated in the consumer and industrial sectors. Germany, the Netherlands and Sweden have some concentrations in the government sector. The United Kingdom is relatively concentrated in consumers and utilities. All countries have relatively heavy weights in the financial industry.

Insert Table 2 here

Table 2 lists the summary of the monthly percentage mean and standard deviation of European corporate bond returns classified by country (Panel A) and by industry (Panel B). The table shows that although country and industry sector returns are very similar, the variation in average returns and return volatility is larger among the country indexes than the industry indexes. Judging from the value-weighted mean country index returns, countries with above-average returns are the United Kingdom and Spain, while Germany and France are

[3]We use the bonds' notional value to calculate the value-weighted returns.

below the average. For the value-weighted industry index mean returns, the highest returns can be found among the utilities, whereas the industries sector is the lowest. On a value-weighted basis, the difference between the highest and lowest mean index return among all countries is 0.21%, while the difference is only 0.09% among all industries. The range in the standard deviation of the returns is 0.49% for all countries and 0.18% for all industries. The correlation matrixes in Table 2 indicate that different countries are less correlated with each other than different industries are, both on an equal and a value-weighted basis.

3 The Dynamic Portfolio Strategy

We build our dynamic portfolio strategy on an asset pricing model consisting of two factors: an industry factor and a country factor. That is, we assume that individual bond returns are driven by the following model:

$$r_{n,t} = \alpha + \beta_k f_{k,t} + \beta_j f_{j,t} \tag{1}$$

in which $f_{k,t}$ and $f_{j,t}$ are the country and industry factor relevant for bond n at time t.

If we want to forecast the returns of bond n in this framework, we can forecast the country and industry factors. Furthermore, from Pieterse-Bloem et al. (2016), we know that the factor exposures β_k and β_f are also time-varying. Therefore, predicting future factor exposures is also relevant if we want to predict bond returns. A higher exposure to one of the factors results, ceteris paribus, in a higher expected return for the bond given the (unconditionally) positive expected factor returns. Once we have forecasts of factors as well as factor exposures, we use this information to form dynamic portfolios.

We first apply time-varying spanning and efficiency tests to analyze whether country-only or industry-only portfolios outperform during different periods from January 1991 to January 2013. The outcome of this first test will give us an indication about the potential of time-varying investment strategies in the European corporate bond market. Subsequently, we forecast country and industry factors as well as factor exposures and form dynamic portfolios on two levels: the index level and the individual bond level. Specifically, at the index level we approach the country and industry factors themselves as investable assets, and try to find an optimal portfolio of factors. Subsequently we go to the individual bond level and use forecasted bond returns to form portfolios.

3.1 Forecasting Factors using the ARMA Model

We first construct dynamic portfolios from forecasted country and industry factors using the autoregressive-moving-average (ARMA) model. We forecast the country and industry factors $f'_{k,t}$ and $f'_{j,t}$ for month 101 to 265 based on an $ARMA(p,q)$ model with p autoregressive terms and q moving-average terms. The model contains the $AR(p)$ and $MA(q)$ models:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} \tag{2}$$

where X_t and X_{t-1} are the factor returns in time t and $t-1$, c is the constant, $\varepsilon_{t,i}$ is the white noise error terms, and φ_i and θ_i are the parameters to be estimated. We use a rolling window of 100 periods to forecast the country and industry factors for month 101 to month 265. The forecasted factor values are the basis for calculating the weights for the dynamic portfolios.

3.2 Forecasting Factor Exposures using the GARCH Model

We next construct dynamic portfolios from forecasted country and industry betas using the multivariate GARCH (GARCH-BEKK) model from Pieterse-Bloem et al., (2016). We forecast the one-step ahead conditional covariance and variance of bond returns and country (industry) factor using spanning windows. The first window is month 1 to 100 and the last window is month 1 to 265. We only include the bonds that have data on the last month of the estimation periods. With the conditional covariance and variance forecasted, we obtain the conditional country and industry betas for each bond using the following equations:

$$\beta^k_{n,t+1} = \frac{Cov(r_{n,t}, f_{k,t})}{var(f_{k,t})} \tag{3}$$

$$\beta^j_{n,t+1} = \frac{Cov(r_{n,t}, f_{j,t})}{var(f_{j,t})} \tag{4}$$

We use the median value of the betas for the bonds as the country and industry betas to calculate the weights[4].

3.3 Creating Portfolio Weights

The returns of the dynamic portfolios can be written as follows:

$$R_{D,t} = \sum_{k=1}^{K} w_{k,t} R_{k,t} + \sum_{j=1}^{J} w_{j,t} R_{J,t} \tag{5}$$

where $w_{k,t}$ represents the weight country k in the dynamic portfolio at time t and $w_{j,t}$ represents the weight industry j in the dynamic portfolio at time t

The dynamic weights $w_{k,t}$ and $w_{j,t}$ are calculated using two methods, by forecasted factors as in Equation 2 and by forecasted betas as in Equation 3.

$$w_{k,t} = (f^{'}_{k,t})^2 / (\sum_{k=1}^{K} (f^{'}_{k,t})^2 + \sum_{j=1}^{J} (f^{'}_{j,t})^2), w_{j,t} = (f^{'}_{j,t})^2) / (\sum_{k=1}^{K} (f^{'}_{k,t})^2 + \sum_{j=1}^{J} (f^{'}_{j,t})^2) \tag{6}$$

$$w_{k,t} = (\beta^k_t)^2 / (\sum_{k=1}^{K} (\beta^k_t)^2 + \sum_{j=1}^{J} (\beta^j_t)^2), w_{j,t} = (\beta^j_t)^2) / (\sum_{k=1}^{K} (\beta^k_t)^2 + \sum_{j=1}^{J} (\beta^j_t)^2) \tag{7}$$

where $f^{'}_{k,t}$ and $f^{'}_{j,t}$ are the forecasted country and industry factors using the ARMA model, β^k_t is the median value of the forecasted country betas for all the bonds in country k at time t and β^j_t is the median value of the forecasted industry betas for all the bonds in industry j at time t[5].

[4] We also calculate the country and industry betas using value-weighted weights. The results are similar and available upon request.

[5] We also use the value-weighted weights for individual bond betas to calculate the country and industry betas. The results do not change and are available upon request.

4 Methods

4.1 Retrieving Country and Industry Indexes

We obtain the time-series country and industry factors $f_{k,t}$ and $f_{j,t}$ employing the Heston and Rouwenhorst (1994) method using cross-sectional regressions. For each month from January 1991 to January 2013, the returns for the individual bonds that exist in that month can be decomposed into a country, industry, and an idiosyncratic component, using the following regression equation:

$$r_{n,t} = \alpha + \sum_{k=1}^{K} f_{k,t} I_{nk,t} + + \sum_{j=1}^{J} f_{j,t} I_{nj,t} + \varepsilon_{n,t} \tag{8}$$

where $r_{n,t}$ represents the vector of individual bond returns of company n existing in month t. $I_{nj,t}$ is an industry dummy variable which equals one if asset n belongs to industry j at time t and zero otherwise. Likewise, the country dummy $I_{nk,t}$ equals one if asset n belongs to country k in period t and zero otherwise. The coefficients $f_{j,t}$ and $f_{k,t}$ capture the returns that can be assigned to a specific industry and country respectively.

Equation (8) cannot be estimated in its present form because it is unidentified due to perfect collinearity. Intuitively, this is because every bond belongs to both an industry and a country, so that industry and country effects can be measured only relative to a benchmark. To resolve the indeterminacy, we follow Heston and Rouwenhorst (1994) and impose the restriction that the weighted sum of industry and country effects equal zero at every point in time:

$$\sum_{k=1}^{K} v_{k,t} f_{k,t} = 0 \tag{9}$$

$$\sum_{j=1}^{J} w_{j,t} f_{j,t} = 0 \tag{10}$$

where $w_{j,t}$ and $v_{k,t}$ represent the weight of industry j and country k in the total universe of Eurobonds at time t. In this paper, we focus on both equal and value weights. The value weights are constructed from the USD equivalent of the amounts issued. Imposing such restriction is equivalent to measuring the size of each industry and country relative to the average size. The country and industry weights sum to unity:

$$\sum_{k=1}^{K} v_{k,t} = 1 \tag{11}$$

$$\sum_{j=1}^{J} w_{j,t} = 1 \tag{12}$$

4.2 Rolling Spanning and Efficiency Tests

We adopt a time-varying mean-variance approach to test whether the country-only or the industry-only portfolios outperform over time. If this were to be the case, a dynamic strategy giving time-varying weights to country and industry factors will never add value. When none of the factors individually stochastically dominate the others, and that the diversification benefit is time-varying, there is room for a dynamic strategy.

Our starting point is an investor who wants to optimize her portfolio in the European corporate bond market constructed from country and industry sub-indexes. We use both spanning and efficiency tests to compare the performance between the industry-only and the country-only portfolios, building on Pieterse-Bloem and Mahieu (2013) but now in a dynamic setting. The spanning tests inform us whether adding extra country (industry) asset has effects on the mean-variance frontier of a benchmark industry (country) portfolio. If the null hypothesis that the mean-variance frontier of the portfolio consisting of country (or industry) indexes alone coincides with the frontier of both together cannot be rejected, we can say that the country (or the industry) portfolio spans the set of both industry and country indexes together. The efficiency test shows the relative performance of the country-only versus the industry-only portfolios by directly comparing their maximum Sharpe ratios.

We employ rolling-window settings to the spanning and efficiency tests to see how the results of the both tests change over time. We use a rolling window of 36 months. From our sample period we thus obtain 229 time-series spanning and efficiency tests statistics. We also link our rolling spanning and efficiency test statistics to the VIX, also with a rolling window of 36 months, to see if there is a correlation between the volatility of the financial markets and the relative performances of the country-only and industry-only strategies.

4.3 Benchmark Strategies

We use three different portfolio strategies as the benchmarks. They are 1/N naive strategy, the mean-variance portfolio, and the minimum variance portfolio.

The naive strategy involves holding a portfolio weight $w = 1/N$ in each of the N risky assets. There are two reasons for using the naive rule as a benchmark. First, it is easy to implement because it does not rely either on estimation of the moments of asset returns or on optimization. Secondly, investors continue to use such simple allocation rules for allocating their wealth across asset despite the sophisticated theoretical models developed in the last decades and the advances in methods for estimating the parameters of these models . In our case, the nave portfolios are either with equal weights or value-weighted weights. The equal-weighted naive strategy is formed by allocating equal weights to eight country and seven industry indexes. Therefore, we have fifteen assets in total. The returns of the equal-weighted naive portfolios are as follows:

$$R_{Ne,t} = (\sum_{k=1}^{K} R_{k,t} + \sum_{j=1}^{J} R_{j,t})./15 \tag{13}$$

The value-weighted naive strategy allocates the assets based on the values of each country and each industry index. The returns of the value-weighted naive portfolios can be written as follows:

$$R_{Nv,t} = \sum_{k=1}^{K} w_{k,t} R_{k,t} + \sum_{j=1}^{J} w_{j,t} R_{j,t}, \;\; w_{k,t} = \frac{V_{k,t}}{\sum\limits_{k=1}^{K} V_{k,t} + \sum\limits_{j=1}^{J} V_{j,t}}, w_{j,t} = \frac{V_{j,t}}{\sum\limits_{k=1}^{K} V_{k,t} + \sum\limits_{j=1}^{J} V_{j,t}} \tag{14}$$

The second benchmark is the mean-variance portfolio, which maximizes the in-sample Sharpe ratio. In the mean-variance model of Markowitz (1952), the investor optimizes the trade-off between the mean and the variance of portfolio returns. We can think of the optimization problem as follows. At each time t, X_t is selected to maximize expected utility:

$$\max x_t^T u_t - \frac{\gamma}{2} x_t^T \sum_t x_t \tag{15}$$

in which γ can be interpreted as the investor's risk aversion. The solution of the above optimization is $x_t = (1/\gamma) \sum_t^{-1} u$. The vector of relative portfolio weights invested in the N risky assets at time t will then be:

$$w_t = \frac{\sum_t^{-1} u_t}{1_N \sum_t^{-1} u_t} \tag{16}$$

To implement the mean-variance model of Markowitz (1952), we follow the classic "plug-in" method. We use the sample mean and covariance matrix to solve the optimization problem. u_t is the expected return over the risk-free rate. $\sum_t$ is the $N * N$ variance-covariance matrix of returns. I_N to indicate the $N * N$ identity matrix. x_t is the vector of portfolio weights invested in the N risky assets, with $1 - 1_N^T x_t$ invested in the risk-free asset. The constraint that the weights sum to 1 is incorporated implicitly by expressing the optimization problem in terms of returns in excess of the risk-free rate.

The third benchmark is the minimum-variance portfolio. Under the minimum-variance strategy, we choose the portfolio of risky assets that minimizes the variance of the returns as follows:

$$\min w_t^T \sum_t w_t, s.t. 1_N^T w_t = 1 \tag{17}$$

To implement this strategy, we use only the estimate of the covariance matrix of asset returns (the sample covariance matrix) and ignore the estimates of the expected returns.

For both the mean-variance strategy and minimum-variance strategy, we forecast the weights in the next period using the same spanning window as in our dynamic strategy. To be more specific, for month 1 to month 100, we estimate the weights according to different benchmark strategies and we use the estimated weights as the forecasted weights for month 101. To forecast month 102, we estimate the weights for the period from month 1 to month 101. We continue the process until month 265. The portfolio returns can be written as follows:

$$R_t = \sum_{k=1}^{K} w_{k,t} R_{k,t} + \sum_{j=1}^{J} w_{j,t} R_{J,t} \tag{18}$$

where $w_{k,t}$ and $w_{j,t}$ are the one-month ahead forecasted weights using the spanning window for both the mean-variance portfolio and the minimum-variance portfolios.

4.4 Performance Evaluation

We use three performance measures to compare between the different portfolio strategies. First, we measure the out-of-sample Sharpe ratios strategy i, defined as the sample mean of out-of-sample excess returns (over the risk-free rates), μ_i, divided by their sample standard deviation, σ_i:

$$SR_i = \frac{\mu_i}{\sigma_i} \tag{19}$$

To test whether the Sharpe ratios of two strategies are statistically different, we use the method by Iedoit and Wolf (2008). Iedoit and Wolf (2008) argue that the test by Jobson and Korkie (1981) is not valid even with the correction made in Memmel (2003) for returns that have tails heavier than the normal distribution or are of a time series nature. They propose the use of robust inference methods to compare between different Sharpe ratios. Specifically, they suggest to construct a studentized time series bootstrap confidence interval for the difference of the Sharpe ratios and to declare the two ratios different if zero is not contained in the obtained interval. This approach has the advantage that one can simply resample from the observed data as opposed to some null-restricted data.

As a second performance measure, the certainty-equivalent (CEQ) return is defined as the risk-free rate that an investor is willing to accept rather than adopting a particular risky portfolio strategy. The CEQ return of strategy i is computed as follows:

$$CEQ_k = \mu_i - \frac{\gamma}{2}\sigma_i^2 \tag{20}$$

We assume γ to be 1 as common practice. To test whether the CEQ returns from two strategies are statistically different, we compute the p-value of the difference, relying on the asymptotic of functional forms of the estimators for means and variance.

5 Results

5.1 Rolling Spanning and Efficiency Tests

Table 3 shows the results of the rolling spanning tests in Panel A and efficiency tests in Panel B for the country and industry indexes (value-weighted). In Panel A, H0: Spanning $K(J)$ shows the results of testing the null hypothesis that country (industry) indexes are spanned by industry (country) indexes. The critical value at 95% confidence interval are indicated in Column 2 of the Panel A. Column 3 of Panel A shows the median values of the spanning test statistics.

Insert Table 3 here

The results show that spanning tests cannot be rejected at 95% confidence interval. Therefore, country indexes are not spanned by industry indexes on average over our sample period, and vice versa. We argue that the diversification benefits of the portfolio of country (industry) indexes can be further improved by adding industry (country) indexes to the portfolio. Column 3 of Panel B shows the results of rolling efficiency tests. The null hypothesis of equal maximum Sharpe ratios between country and industry portfolios cannot be rejected on average at 95% confidence level. Therefore, the country and industry portfolios cannot be distinguished in terms of their maximum Sharpe ratios. The difference in the values of the Sharpe ratios is consistently defined as that of the industry-based portfolios less that of the country-based portfolios. As we can see from Panel B, the maximum Sharpe ratio is consistently higher for the country portfolios than for the industry portfolios but the difference is not statistically significant. The results confirm the findings in Pieterse-Bloem and Mahieu (2013) from the static spanning and efficiency tests.

The results in Table 3 only show the average test statistics over the full sample. To see how the results vary over time, we link the test statistics to market volatility through VIX data. Columns 4 and 5 of Table 3 show the correlation coefficients and the p-values by linking the VIX with the rolling spanning test statistics in panel A and with efficiency test statistics in Panel B. We see that the correlation between the rolling test statistic of the country indexes (Chi_K) and the VIX is 0.2567. Between that of the industry indexes (Chi_J) and the VIX, the correlation coefficient is 0.2859. Both correlations are positive and highly significant. Therefore, the spanning tests are more likely to be rejected when the market is more volatile, which means that it is more important to include both country and industry indexes during these periods. During high volatility periods, the correlations between the assets tends to increase. Therefore, it is more beneficial to include both country and industry indexes to achieve higher risk reductions. The correlation coefficient between the VIX data and the efficiency test statistics are positive but not significant. The difference in Sharpe ratios of the industry versus the country portfolios are negatively (-0.0405) correlated with the VIX data but also not significant at 90 percent confidence level (p-value of 0.5422). Though not significant, we can say that when the market is more volatile, the industry-only and country-only portfolios differ more in performance, with worse performance of industry-only portfolios relative to country-only portfolios.

All in all, we can conclude that the country (industry) indexes do not significantly dominate the industry (country) indexes. Furthermore, there is ample time-variation in the degree to which the two sets of assets perform and co-move. As such, there is scope for a dynamic investment strategy that takes advantage of this time-variation.

5.2 Dynamic Portfolio Strategy: Index Level

Table 4 shows the performance measures of the dynamic portfolio strategy, including the mean, standard deviation, Sharpe ratio, and CEQ return. The portfolios include the dynamic portfolios constructed using the forecasted factors alone, forecasted betas alone and both forecasted factors and betas, as well as the benchmark strategies[6].

[6]The value-weighted naive strategy has a lower Sharpe ratio and a higher turnover ratio than the equal-weighted naive strategy. Therefore, we use only equal-weighted naive strategy as the benchmark in our analysis.

Insert Table 4 here

The dynamic portfolio based on forecasted factors, DS1, has the highest Sharpe ratio of all portfolios. The dynamic strategy based on forecasted betas, DS2, does not outperform any of the benchmark strategies. This result is consistent across performance measures. This result is driven by both a relatively high expected return and a relatively low standard deviation. The Sharpe ratio is not significantly higher, though. The combined strategy, both forecasted factors and forecasted betas, in DS3, also does not outperform.

We plot the rolling difference in Sharpe ratios of the dynamic strategy using forecasted factors and forecasted betas and the three benchmark strategies using a rolling window of 36 months. Figure 1 shows the differences in Sharpe ratios between the strategy using forecasted factors and the benchmark strategies. Figure 2 plots the rolling differences between the dynamic strategy using forecasted betas and the benchmark strategies.

Insert Figure 1 here

Insert Figure 2 here

From Figures 1 and 2, we observe that there is substantial time-variation in the performance difference between the strategies. The patterns for the two dynamic strategies and across benchmarks is highly comparable: The dynamic strategies outperform the benchmarks in the first part of the sample, roughly until 2007, but underperform the benchmarks in the second half of the sample.

We investigate whether the time-variation of the Sharpe ratios corresponds with market conditions. If this is the case, it helps to decide when to apply the dynamic portfolio strategy. Table 5 shows the relation between the performance difference between the dynamic strategy based on forecasted factors and the benchmark strategies and lagged VIX and lagged market integration. We measure integration by the relative importance of country versus industry factors[7]. for a 36-month rolling period. Likewise, the rolling difference in Sharpe ratios between different strategies with a window of 36 months is calculated for month 101 to 265.

[7]We calculate the median value of country factor squared minus industry factor squared divided by industry factor squared

Insert Table 5 here

Column 2 of Table 5 shows how the differences in performance correlates with market volatility measured by the VIX. We find that the dynamic portfolio performs better than the benchmark portfolios when the VIX is low. The relation is significant at a 99% confidence level. This results is driven by both the return and the volatility component. Therefore, we argue that when the market is more volatile, it is less beneficial to conduct our dynamic portfolio strategy. As for the lagged market integration in column 3 of Table 5, we find that the dynamic strategy performs better when market integration is relatively low. This result is again driven by both the return and the variance part of the Sharpe ratio.

All in all, we can conclude that the performance of the dynamic portfolio strategy at the index level is mainly strong when the strategy is based on forecasted factors. Furthermore, the performance of the strategy is especially strong is periods of low volatility and low market integration. In the next section, we will study the performance of the dynamic portfolio strategy at the individual bond level.

5.3 Dynamic Portfolio Strategy: Individual Bond Level

We apply the dynamic portfolio strategies based on individual bonds instead of bond indexes. The reason is that the country and industry indexes we use as assets in the previous section are not investable indexes; that is, investors would have to create the indexes themselves. This is feasible for larger investors, but perhaps not for small investors.

The dynamic strategy is constructed as follows. For each bond, we calculate the expected returns as the expected betas multiplied by the expected factors, as shown in Equation (1). We use three different combinations. The first is to use the forecasted betas using the GARCH model multiplied by the average of the country/industry factor up until the period in which the forecast is made. The second method is based on the forecasted betas using the GARCH model multiplied by the factors forecasted using the ARMA model. The third combination is to multiply the forecasted factors using the ARMA model by the unconditional betas estimated using OLS until the period when the forecast is made. This approach allows us to isolate the added value of the forecasted betas from the added value of the forecasted factors in the portfolio performance.

Based on the expected returns using the three methods, we form our dynamic portfolio by investing only in the bonds with top 10, 20, 30, or 40 percent expected returns in the previous month. We also construct portfolios using bonds that consistently rank in the top 10% in terms of expected returns in the previous two to six months. As for the benchmark strategies, we can only use the naive strategy because our data is uneven over time. Therefore, it is not possible to calculate the mean-variance nor the minimum-variance portfolios.

We report the returns, the standard deviations, and the Sharpe ratios of these dynamic portfolios together with the benchmark portfolio in Table 6 (with both forecasted factors and forecasted betas), Table 7 (with unconditional beta and forecasted factors), and Table 8 (with forecasted betas and unconditional factors).

Insert Table 6 here

Insert Table 7 here

Insert Table 8 here

As for the dynamic portfolio with both forecasted betas and factors, the results in Table 6 show that the Sharpe ratio is always higher for the dynamic strategy than for the naive strategy. The Sharpe ratios of the portfolios based on the top 10 and top 30 percent expected return deciles are significantly better than that of the naive strategy. We observe that the performance of the dynamic strategies tends to decrease as lower expected return deciles are added to the portfolio, as can be expected. This decrease originates mainly from the return part of the Sharpe ratio, as the standard deviation remains constant.

Since the top 30 percent decile portfolio has the most significant difference with the benchmark, we also construct portfolios consisting of bonds that are consistently in the top 30% expected return decile over the previous 2 to 6 months. We find that for bonds with top 30% performance in the previous 2, 3 and 5 months, the dynamic portfolio significantly outperform the naive strategy.

Therefore, we argue that our dynamic strategy investing in individual bonds based on their expected returns has the potential to significantly outperforms the naive strategy.

The strategy based on the forecasted factors and unconditional betas, shown in Table 7 outperforms the naive strategy for all portfolios. In this case, the performance difference also tends to be significant. For the second strategy, based on forecasted betas only, we find in Table 8 that the dynamic portfolios consistently outperform the naive strategy. The performance difference, however, is never significant. This suggests that the significant performance difference we observed in Table 6 was mainly driven by the forecasted factor returns. This confirms our earlier finding that the significant outperformance in Table 6 was mainly driven by the forecasted factors. This result is consistent with our earlier findings of the performance of the dynamic portfolio strategy at the index level.

6 Robustness Checks

We run a number of robustness tests to see to what extent our results are sensitive to the set of countries in our sample. As such, we separate our data sample into several country groups. First of all, we focus on the core countries, which include Belgium and Luxembourg, France, Germany, and Netherlands; periphery countries, which are Italy and Spain; and non-Euro countries consisting of Sweden and the UK. We form the same dynamic strategies and benchmark strategies as in the main analysis. Tables 9 to 11 present the results.

The results generally hold for different country groups with some minor differences. For the set of core countries, in Table 9, we find highly comparable results. The portfolio based on forecasted factors significantly outperforms the naive strategy whereas the other configurations do not. For the peripheral countries, in Table 10, we also find outperformance for the dynamic strategy, but not significantly so. This is explained by the fact that returns in peripheral are more volatile causing performance differences to be less significant. This finding is also consistent with our earlier finding that the dynamic portfolio strategy performs better in tranquil periods.

When splitting up the sample in Euro versus non-Euro countries, in Tables

11 and 12, we observe substantial outperformance of the dynamic strategies, especially for the non-Euro countries. The differences, though, are not significant. The latter finding implies that the significant outperformance we observed for the full set of countries is partly driven by the combination of Euro and non-Euro countries, which arguably provides for additional diversification benefits.

Insert Table 9 here

Insert Table 10 here

Insert Table 11 here

Insert Table 12 here

7 Conclusions

In this paper, we propose a dynamic portfolio strategy for European corporate bonds based on a two-factor pricing model. Our results show that it is important to include both country and industry factors to improve diversification benefits, especially during periods of high volatility. We construct our dynamic portfolios based on either forecasted factors, forecasted betas, or a combination of both. The results show that the performance of the dynamic portfolio constructed using only forecasted factors significantly outperforms the benchmark strategies. It is especially beneficial to implement the dynamic strategies when market volatility is relatively low or when integration in the European corporate bond market is relatively low. These results hold for both the index level and the individual bond level. The results continue to hold in a subset of core European countries. In addition, we find that a combination of Euro and Non-Euro countries is important for outperformance.

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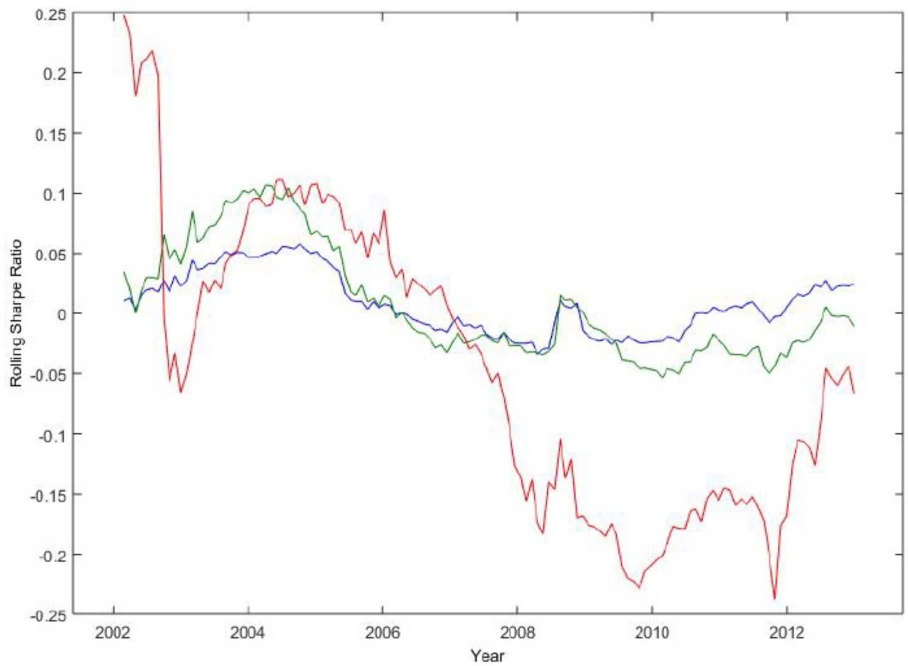
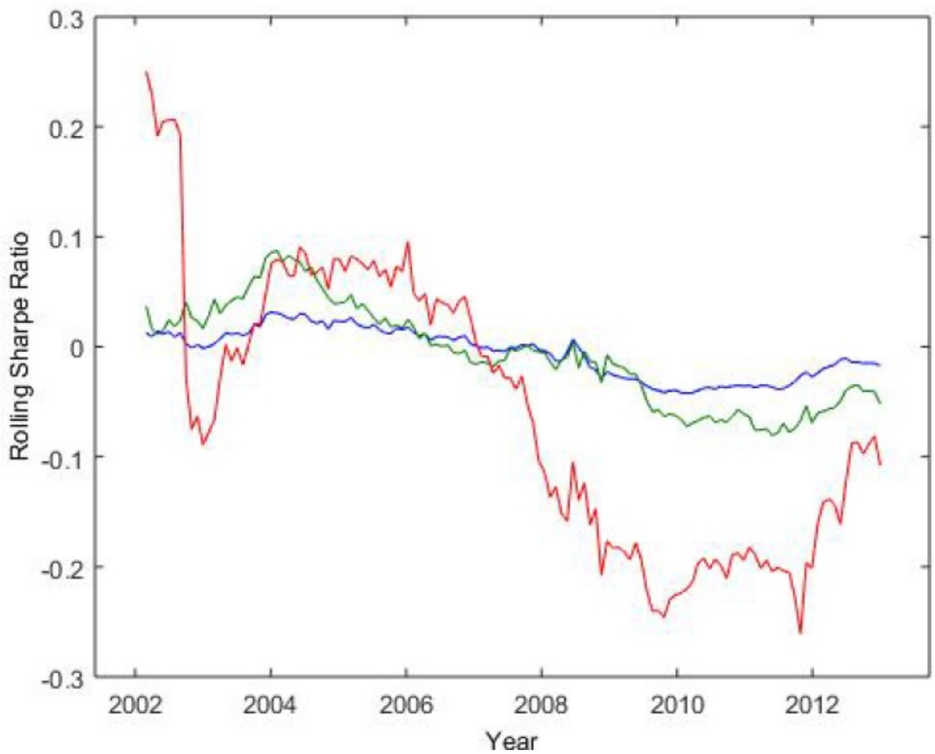
Tables and Figures

Figure 1: Difference in Performance between the Dynamic and Benchmark Strategies



Notes: The graph shows the rolling difference in the Sharpe ratios between the dynamic strategy using only the forecasted factors and the benchmark strategies. We use 36 months as our rolling window period.

Figure 2: Difference in Performance between the Dynamic and Benchmark Strategies



Notes: The graph shows the rolling difference in the Sharpe ratios between the dynamic strategy using only the forecasted betas and the benchmark strategies. We use 36 months as our rolling window period.

Table 1: Country and Industry Composition

A. By country (number and percent of total)							
Belgium/Luxembourg	BL			260			3.08%
France	FR			1305			15.45%
Germany	GE			3196			37.84%
Italy	IT			611			7.23%
Netherlands	NE			997			11.80%
Spain	SP			136			1.61%
Sweden	SW			668			7.91%
United Kingdom	UK			1273			15.07%
Total				8446			100%
B. By industry (number and percent of total)							
Financials&Funds	FF			5662			67.04%
Government Institute	GI			784			9.28%
Consumer Goods	CO			691			8.18%
Comm.Technology	CT			313			3.71%
Basic material&Energy	BE			246			2.91%
Industrials	IN			292			3.46%
Utilities	UT			458			5.42%
Total				8446			100%

C. Number of bonds by country and industry	FF	GI	CO	CT	BE	IN	UT	Total
Belgium/Luxembourg	163	13	16	9	24	16	19	260
France	624	95	203	79	90	111	103	1305
Germany	2652	241	137	40	35	58	33	3196
Italy	454	47	22	28	14	6	40	611
Netherlands	641	206	28	42	24	22	34	997
Spain	78	16	5	12	4	7	14	136
Sweden	336	146	70	38	17	37	24	668
United Kingdom	714	20	210	65	38	35	191	1273
Total	5662	784	691	313	246	292	458	8446

D. Average weights of country/industry in the value-weighted European market: in percentage	FF	GI	CO	CT	BE	IN	UT	Total
Belgium/Luxembourg	0.48	0.33	0.03	0.15	0.19	0.09	0.21	1.48
France	6.14	2.18	2.31	1.92	1.03	1.66	2.28	17.52
Germany	12.08	2.8	1.56	0.72	0.44	1.02	0.74	19.36
Italy	2.32	13.76	0.31	0.73	0.29	0.13	0.6	18.05
Netherlands	6.27	3.63	0.26	0.6	0.3	0.3	0.39	11.75
Spain	0.57	1.95	0.03	0.18	0.11	0.12	0.28	3.24
Sweden	6.43	2.04	0.1	0.2	0.03	0.06	0.32	9.18
United Kingdom	9.87	0.61	3.07	1.76	0.54	0.67	2.87	19.39
Total	44.16	27.21	7.67	6.26	2.93	4.05	7.69	100

Notes: Panels A and B give for each country and industry the number of bonds included in the total 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 total sample. Panel D gives the average weight of the (live) bonds in the country by industry cross-sector in the total value-weighted market over the whole sample. Percentages do not add up to precisely 100 due to rounding.

Table 2: Summary Performance Statistics

A. By country

Country	EW Return		VW Return		Currency return		Correlation matrix								
	Mean	St.dev	Mean	St.dev	Mean		BL	FR	GE	IT	NE	SP	SW	UK	Total
BL	0.6931	3.3048	0.6765	3.3573	0.0387	3.1389	1	0.9567	0.9621	0.8936	0.9672	0.8536	0.9084	0.8512	0.9517
FR	0.6751	3.1109	0.6685	3.2056	0.033	3.1169	0.965	1	0.9763	0.9049	0.9837	0.8765	0.9211	0.8497	0.9669
GE	0.7101	3.2308	0.6369	3.1361	0.039	3.1395	0.9609	0.9698	1	0.9029	0.9793	0.8579	0.9243	0.8781	0.9757
IT	0.7735	3.2133	0.7871	3.3067	0.145	3.2064	0.9296	0.9428	0.9338	1	0.8914	0.8322	0.867	0.8415	0.9582
NE	0.6508	3.2188	0.6402	3.2268	0.0387	3.1372	0.9685	0.9827	0.9572	0.9156	1	0.872	0.9314	0.8459	0.9654
SP	0.8089	3.4862	0.8499	3.6248	0.1569	3.2277	0.8652	0.8947	0.8719	0.8564	0.8803	1	0.8254	0.7608	0.8718
SW	0.7343	3.2665	0.7142	3.3226	0.1141	3.5417	0.9457	0.9439	0.9493	0.9101	0.9444	0.8473	1	0.8264	0.9429
UK	0.904	3.2909	0.8379	3.2075	0.1189	2.7742	0.7961	0.8065	0.7983	0.7801	0.7868	0.7557	0.7922	1	0.9113
Total	0.7578	3.1274	0.7584	3.1057			0.9641	0.9749	0.9736	0.9383	0.9627	0.8892	0.9505	0.8969	1

B. By industry sector

Industry	EW Return		VW Return		Correlation matrix							
	Mean	St.dev	Mean	St.dev	FF	GI	CO	CT	BE	IN	UT	Total
FF	0.7632	3.2282	0.7331	3.2093	1	0.9665	0.9568	0.9541	0.9686	0.9657	0.9562	0.9861
GI	0.7318	3.2481	0.7402	3.2274	0.9521	1	0.9222	0.9182	0.9173	0.9397	0.92	0.9873
CO	0.7509	3.051	0.7315	3.1366	0.9417	0.9391	1	0.9453	0.9656	0.9529	0.9575	0.9574
CT	0.7664	3.1285	0.7359	3.2123	0.937	0.9433	0.9631	1	0.9546	0.9686	0.9388	0.9548
BE	0.75	3.1429	0.7478	3.1906	0.9571	0.9411	0.9669	0.9616	1	0.9649	0.9574	0.9586
IN	0.7335	3.1247	0.6978	3.1635	0.9571	0.9626	0.9651	0.9723	0.9732	1	0.9476	0.9712
UT	0.7961	3.1893	0.7919	3.3134	0.9161	0.9212	0.9582	0.9555	0.939	0.9422	1	0.9542
Total	0.7578	3.1274	0.7584	3.1057	0.99	0.98	0.97	0.97	0.98	0.98	0.95	1

Notes: Panel A (B) summarizes the mean and the standard deviation of the equal-weights (EW) and the value-weighted (VW) monthly returns by country (industry) sector. All returns are in US dollars and expressed in percent per month. The currency return is the proportional change in the exchange rate of the respective country vis-a-vis the US dollar, where a positive number indicates an appreciation. In the correlation matrices, the coefficients above the diagonal refer to the value-weighted returns and below the diagonal to the equal-weighted returns.

Table 3: Rolling Spanning and Efficiency Tests of the Country and Industry Indexes

Country and Industry Indexes from:	Critical Level	Median Statistics	Correlation	P-value
A. Bond Returns (Spanning Tests)				
H0:spanning K	(26.296)	17.382	0.2576	0.0001
H0:spanning J	(23.685	21.964	0.2859	0.0000
B. Bond Excess Returns (Efficiency Tests)				
H0:Efficiency	3.842	2.284	0.0050	0.9369
Difference in Sharpe Ratio (Lamda)		-1.228	-0.0405	0.5422

Notes: The table shows the results of the rolling spanning and efficiency tests performed on value-weighted country and industry indexes. Panel A shows the results of the rolling spanning tests. H0:spanning K (J) is the results for the null hypothesis that country (industry) indexes are spanned by industry (country) indexes. The median value in Column 3 is obtained from the test statistics between January 1991 to January 2013. Column 4 shows the correlation coefficient between the test statistics and the VIX, and column 5 the p-value of this correlation. Panel B lists the results for the rolling efficiency tests. H0: efficiency is the result that the maximum Sharpe ratios of the country and industry portfolios are the same. The results of the spanning and efficiency tests can be compared with the critical levels at the 95% level.

Table 4: Performance of the Dynamic Portfolio Strategies

	DS1	DS2	DS3	NSE	NSV	MeanVS	MinV
A. Mean returns	0.0045	0.0042	0.0039	0.0043	0.0042	0.0044	0.0047
B. Standard Deviation	0.0289	0.0299	0.0296	0.0291	0.0289	0.028	0.0314
C. Sharpe Ratio	0.0827	0.0679	0.0597	0.0749	0.0715	0.0816	0.0822
P-Value	0.4095	0.3331	0.112				
D. CEQ Return	0.0041	0.0037	0.0035	0.0039	0.0038	0.004	0.0042

Notes: The table shows several performance measurements for all the portfolios constructed in this paper. DS1 represents the dynamic portfolio based on the forecasted factors alone. DS2 represents the portfolio using only forecasted betas. DS3 represents the portfolio based on the product of the forecasted factors and forecasted betas. NSE indicate the 1/N equal-weigted naive porfolios. NSV shows this for the value-weighted naive portfolios. MeanVS stands for the portfolios which are mean-variance with the maximum Sharpe ratios. MinV are the portfolios which minimizes the variance. The p-values are the results of comparing our dynamic strategies with the naive strategy.

Table 5: Relative Performance and Market Conditions

Relative Portfolio Performance	Lag Volatility	Lag Integration
A. Dynamic VS Naive SR	-0.4480	-0.1739
P-Value	0.0000	0.0488
B. Dynamic VS Mean-V SR	-0.6702	-0.5398
P-Value	0.0000	0.0000
C. Dynamic VS Mini-V SR	-0.7145	-0.5950
P-Value	0.0000	0.0000
D. Dynamic VS Naive Return	-0.5723	-0.2768
P-Value	0.0000	0.0015
E. Dynamic VS Mean-V Return	-0.6273	-0.4166
P-Value	0.0000	0.0000
F. Dynamic VS Min-V Return	-0.8003	-0.5854
P-Value	0.0000	0.0000
H. Dynamic VS Naive Variance	-0.8441	-0.8716
P-Value	0.0000	0.0000
I. Dynamic VS Mean-V Variance	0.5683	0.7357
P-Value	0.0000	0.0000
J. Dynamic VS Mini-V Variance	-0.3823	0.1651
P-Value	0.0000	0.0615

Notes: The table shows how the relative performance between our dynamic portfolio constructed with forecasted factors and the three benchmark portfolios relate to the lagged volatility (VIX) and the lagged market integration measures.

Table 6: Performance Measures for Individual Bond Strategies: Factors and Betas

	DS1	DS2	DS3	DS4	DS5	DS6	DS7	DS8	DS9	NS
A. Mean returns	0.0053	0.0050	0.0050	0.0048	0.0055	0.0063	0.0059	0.0062	0.0058	0.0042
B. Standard Deviation	0.0278	0.0278	0.0276	0.0276	0.0282	0.0287	0.0285	0.0293	0.0296	0.0282
C. Sharpe Ratio	0.1135	0.1017	0.1049	0.0963	0.1188	0.1451	0.1348	0.1411	0.1261	0.0740
P-Value	0.0972	0.1177	0.0530	0.1041	0.0882	0.0581	0.1115	0.0999	0.2197	
D. Turnover Ratio	7917	13029	17730	20711	7134	7308	7238	7129	6969	5831

Notes: The table shows the performance of our dynamic portfolios based on both forecasted factors and forecasted betas and benchmarks constructed using individual bonds. DS1 represents the portfolio that invests in bonds in the top 10 expected return decile. DS2 represents the portfolio that invests in bonds in the top 20 percent return deciles. DS3 represents the portfolio that invests in bonds in the top 30 percent expected return deciles. DS4 represents the portfolio that invests in bonds in the top 40 percent expected return deciles. DS5 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous two months. DS6 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous three months. DS7 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous four months. DS8 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous five months. DS9 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous six months. NS indicates the 1/N nave portfolio.

Table 7: Performance Measures for Individual Bond Strategies: Forecasted Factors

	DS1	DS2	DS3	DS4	DS5	DS6	NS
A. Mean returns	0.0063	0.0060	0.0058	0.0053	0.0061	0.0062	0.0042
B. Standard Deviation	0.0272	0.0272	0.0273	0.0271	0.028	0.0283	0.0282
C. Sharpe Ratio	0.1548	0.1413	0.1331	0.1183	0.1429	0.1452	0.0740
P-Value	0.0171	0.0405	0.0593	0.1045	0.0933	0.1770	

Notes: The table shows the performance of our dynamic portfolios strategy based on forecasted factors and the naive strategy constructed using individual bonds. DS1 represents the portfolio that invests in bonds in the top 10 expected return decile. DS2 represents the portfolio that invests in bonds in the top 20 percent return deciles. DS3 represents the portfolio that invests in bonds in the top 30 percent expected return deciles. DS4 represents the portfolio that invests in bonds in the top 40 percent expected return deciles. DS5 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous two months. DS6 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous three months. NS indicates the 1/N nave portfolio.

Table 8: Performance Measures for Individual Bond Strategies: Forecasted Betas

	DS1	DS2	DS3	DS4	DS5	DS6	NS
A. Mean returns	0.0045	0.0044	0.0043	0.0044	0.0050	0.0053	0.0042
B. Standard Deviation	0.0279	0.0271	0.0269	0.0269	0.0280	0.0284	0.0282
C. Sharpe Ratio	0.0865	0.0838	0.0813	0.0853	0.1022	0.1126	0.0740
P-Value	0.6774	0.6814	0.7042	0.4375	0.3493	0.3559	

Notes: The table shows the performance of our dynamic portfolios strategy based on forecasted betas and the naive strategy constructed using individual bonds. DS1 represents the portfolio that invests in bonds in the top 10 expected return decile. DS2 represents the portfolio that invests in bonds in the top 20 percent return deciles. DS3 represents the portfolio that invests in bonds in the top 30 percent expected return deciles. DS4 represents the portfolio that invests in bonds in the top 40 percent expected return deciles. DS5 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous two months. DS6 represents the portfolio that invests in the bonds that have been in the top 30 percent expected return deciles in the previous three months. NS indicates the 1/N nave portfolio.

Table 9: Performance Measures for the Core Euro Countries during the Euro Period

	DS1	DS2	DS3	NS	MeanVS	MinV
A. Mean returns	0.0068	0.0057	0.0061	0.0047	0.0061	0.0110
B. Standard Deviation	0.0368	0.0361	0.0363	0.0267	0.0353	0.043
C. Sharpe Ratio	0.1551	0.1281	0.1373	0.1326	0.1406	0.2316
P-Value	0.0152	0.6033	0.6579			
D. CEQ Return	0.0061	0.0051	0.0054	0.0043	0.0054	0.0101

Notes: The table shows the performance measures of the dynamic portfolios based on the core EU countries after January 1999 when the Euro was introduced. DS1 represents the dynamic portfolio using weights from the forecasted factors alone. DS2 represents the portfolio using only forecasted betas. DS3 represents the portfolio using the products from the forecasted factors and forecasted betas. NS indicates the 1/N naive porfolios. MeanVS stands for the portfolios which are mean-variance with the maximum Sharpe ratios. MinV are the portfolios which minimizes the variance. The p-values are the results of comparing the dynamic portfolios with the naive portfolios.

Table 10: Performance Measures for the Periphery Euro Countries During the Euro Period

	DS1	DS2	DS3	NS	MeanVS	MinV
A. Mean returns	0.0060	0.0062	0.0065	0.0036	0.006	0.0111
B. Standard Deviation	0.0350	0.0358	0.0350	0.0209	0.0356	0.0372
C. Sharpe Ratio	0.1394	0.1431	0.1532	0.1190	0.1366	0.2698
P-Value	0.2069	0.5917	0.6579			
D. CEQ Return	0.0054	0.0056	0.0058	0.0034	0.0053	0.0104

Notes: The table shows the performance of the dynamic portfolio for the core EU countries after January 1999 when the Euro was introduced. DS1 represents the dynamic portfolio using weights from the forecasted factors alone. DS2 represents the portfolio using only forecasted betas. DS3 represents the portfolio using the products from the forecasted factors and forecasted betas. NS indicates the 1/N naive porfolios. MeanVS stands for the portfolios which are mean-variance with the maximum Sharpe ratios. MinV are the portfolios which minimizes the variance. The p-values are the results of comparing the dynamic portfolios with the naive portfolios.

Table 11: Portfolio Measures for the Euro Countries during the Euro period

	DS1	DS2	DS3	NS	MeanVS	MinV
A. Mean returns	0.0065	0.0063	0.0061	0.0047	0.0065	0.0084
B. Standard Deviation	0.0347	0.0348	0.0336	0.0357	0.0358	0.0468
C. Sharpe Ratio	0.1545	0.1483	0.1479	0.1452	0.1505	0.1571
P-Value	0.6745	0.6715	0.9289			
D. CEQ Return	0.0059	0.0057	0.0055	0.0056	0.0058	0.0073

Notes: The table shows the performance of the dynamic portfolio for the EU countries after January 1999 when the Euro was introduced. DS1 represents the dynamic portfolio using weights from the forecasted factors alone. DS2 represents the portfolio using only forecasted betas. DS3 represents the portfolio using the products from the forecasted factors and forecasted betas. NS indicates the 1/N naive porfolios. MeanVS stands for the portfolios which are mean-variance with the maximum Sharpe ratios. MinV are the portfolios which minimizes the variance. The p-values are the results of comparing the dynamic portfolios with the naive portfolios.

Table 12: Portfolio Measures for the Non-Euro during the Euro period

	DS1	DS2	DS3	NS	MeanVS	MinV
A. Mean returns	0.0094	0.0080	0.0092	0.0046	0.0071	0.0070
B. Standard Deviation	0.0355	0.0331	0.0359	0.0196	0.0319	0.0374
C. Sharpe Ratio	0.2339	0.2088	0.2267	0.1793	0.1871	0.1585
P-Value	0.1678	0.0751	0.1877			
D. CEQ Return	0.0088	0.0075	0.0086	0.0044	0.0066	0.0063

Notes: The table shows the performance of the dynamic portfolios for the Non-Euro countries after January 1999 when the Euro was introduced. DS1 represents the dynamic portfolio using weights from the forecasted factors alone. DS2 represents the portfolio using only forecasted betas. DS3 represents the portfolio using the products from the forecasted factors and forecasted betas. NS indicates the 1/N naive porfolios. MeanVS stands for the portfolios which are mean-variance with the maximum Sharpe ratios. MinV are the portfolios which minimizes the variance. The p-values are the results of comparing the dynamic portfolios with the naive portfolios.