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Chapter 4

Empirical Support for Fundamental, Factor Models Explaining Major Capital Markets Using Wavelets

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Additional information is available at the end of the chapter

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Abstract

Factor models are used to explain asset returns on all major capital markets. We argue that standard econometric analyses implicitly assume that the relationships between prices, spreads, and interest rates and their respective risk factors are time-scale independent. Furthermore, by applying wavelet analysis, we do not have to assume capital market efficiency; in fact, we explicitly allow for inefficiencies such as noise trading, dispersed information, technical, feedback, fundamental, and rational trading to allow for typical characteristics of capital market data. We use wavelet analysis to decompose capital markets' developments, and the risk factors, using the maximal overlap discrete wavelet transform (MODWT). We proceed by estimating the relationships on a scale-by-scale basis. Our respective empirical analyses for stock and bond markets are summarized and new research is presented with regards to European corporate bonds markets. On stock market, this approach finds more stable relationships between risk factors and price movements. On the bond markets, we find empirical evidence for four significantly evaluated factors. For the European corporate bonds market, the results show that the amount of credit spreads explained by risk factors is in fact high for certain time scales only which is similar to the findings for the other capital markets.

Keywords: maximal overlap discrete wavelet transform, factor models, stock markets, term structure of interest rates, corporate bond spreads

1. Introduction

It has long been acknowledged that risk factors are important in explaining the development of asset prices on all major capital markets. Ross [1] states that the difference between expected and realized asset returns is due to the unexpected development of risk factors. In his arbitrage pricing theory, he derives a relationship between expected asset returns and the sum of assets'

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sensitivities toward these risk factors. Similarities between equity and corporate bond markets' risks have long been recognized and risk factors similar to those applied in stock markets were included in the analysis of bond markets, and corporate bond spreads, for example, see [2]. Other empirical analyses present models for the simultaneous pricing of stock and bond returns [3]. Generally speaking, it has long been recognized that capital markets have similar characteristics [4]. Cutler et al. formulated four important characteristics of data concerning returns in the stock, bond, foreign exchange, and other capital markets. Using monthly return data, there appears to be a positive first-order auto-correlation from 1 month to the next. This does, however, change if the time horizon is medium or even long term. In those cases, the auto-correlation becomes negative. Finally, fundamental factors explain capital market movements significantly in the medium and/or long term which can be explained by allowing for capital markets' inefficiencies, for example, they postulate that the positive 1 month autocorrelation of data could be cause investors who only learn about relevant risk factors with a time lag. In addition to that also traders acting on the basis of technical analyses can cause a positive auto-correlation in the very short run. The negative medium, or long term, auto-correlation is then a direct result from misperceptions that are corrected on those time scales. In addition to those explanations, we consider that market participants have different objectives and therefore also different time horizons for their investments. Arbitrageurs seek to exploit mispricing in nanoseconds. Day-traders want to use knowledge derived from technical analysis on a daily or weekly basis. Although asset and wealth managers can represent investors with all sorts of investment horizons their performance is evaluated at least every month. To summarize, it is highly unlikely that the data generating process is the same for all investment horizons which is the reason why we apply wavelet analysis to allow for discrepancies at different time horizons.

We apply wavelet analysis to shed light on the applicability of factor models for stock, bond, and corporate bond markets. For this purpose, we shortly summarize our respective findings for stock and bond markets. We then present a detailed, exemplary, new analysis for European corporate bond markets and present general ideas why the use of wavelet analysis improves on the applicability of factor models in practice.

The wavelet decomposition we apply allows us to specifically distinguish short, medium, and long run periods and at the same time it is possible to investigate if information from past continues to be of importance for the following time period. There is little information about the frequency content of data if no frequency analysis is performed. The frequency analysis, however, is not able to maintain information about the time location of events. In our empirical analysis of these models, explanatory variables are selected according to general considerations which fundamental variable influence the capital markets and proceed by assuming that the identified k factors contain the important information, so that we assume an approximate factor structure to hold. We investigate if averaging over various time periods veils the fact that the risk factors are of importance in explaining capital markets' asset returns for certain time scales only, i.e., we investigate if risk factors are especially powerful in explaining asset returns at certain time horizons. For that purpose, we decompose asset returns and risk factors into their time-scale components using the maximal overlap discrete wavelet transform

(MODWT) thereby decomposing monthly data to their respective time scales (short term, medium term, and long term). We then proceed by estimating the impact of the risk factors on various capital markets on a scale-by-scale basis. We test for significance using the Fama/MacBeth approach.

Only recently researchers start to analyze relationships to hold for various time periods and not just for the short and long run. This is why wavelet analysis has been applied to macroeconomic and financial theories, for example see [5–10].

This chapter is organized in the following way. First, we review shortly the underlying theoretical backgrounds for the various capital markets' factor models in Section 2. In Section 3, we introduce the basic ideas of wavelet analysis and motivate its use to test for significantly evaluated premiums for risk factors which we test for their significance on different time scales. Our previous results for the stock and bond market are shortly summarized. In Section 4, we describe the respective analysis performed for the European corporate bond market as an example in detail and Section 5 concludes.

2. Factor models in finance

Factor models have always been of great interest to explain price movements on all major capital markets. If risk factors can be identified that are significantly evaluated by the market, that information is valuable for the purpose of general management, determining fair values of firms, asset management, finance, and controlling.

2.1. Stock markets

One of the most important and general approaches to explain price movements on stock markets is the arbitrage pricing theory (APT) developed by Ross [1]. The advantage of the APT is its generality. Various factor models can be derived and require different estimation and testing techniques. A detailed overview of the various possibilities for factor models is given in [7]. The factor models can be distinguished according to the origin of the factors. Statistical factors can be derived from applying factor analysis. Factors can also be determined in advance—derived from theoretical considerations—and observable data of macro-economic variables can be investigated for being risk factors. Since the purpose is to identify risk factors and not to derive fair prices for financial derivatives, the relationship between asset prices and risk factors is restricted to be approximately linear [7].

Ross develops his theory in the context of neo-classical assumptions concerning capital markets without frictions. He assumes that investors differ in their opinion of the exact distribution of the risk factors, however they all agree on a linear k-factor structure. The main assumption is the following: the return at the end of the period is determined by the return that was expected at the beginning of the investment period (μ_i) but also by the returns of the common risk factors ($\tilde{\lambda}_k$). The importance of the risk factors for an asset i depends on how sensitive the asset

is with regards to the k risk factors (b_{ik}). Those sensitivities are called factor loadings. Last but not least there is a white noise error variable ($\tilde{\epsilon}_i$). The k factors are common factors, i.e., every asset reacts to the development of these factors.

$$\tilde{r}_i = \mu_i + b_{i1}\tilde{\lambda}_1 + \ldots + b_{ik}\tilde{\lambda}_k + \tilde{\epsilon}_i \qquad \forall i = 1, \ldots, n \tag{1}$$

with $\tilde{r}_i$ = realization of the random variable asset i's asset return at the end of the investment period; μ_i = expectation of asset i's return at the beginning of the investment period; b_{ik} = factor loading of asset i's return in relation to the risk factor k's realized end-of-period return; $\tilde{\lambda}_k$ = realization of the random variable risk factor k's end of period return; and $\tilde{\epsilon}_i$ = realization of the random variable asset i's idiosyncratic risk.

In matrix notation this becomes Eq. (2):

$$\underset{(nx1)}{\tilde{r}} = \underset{(nx1)}{\mu} + \underset{(nxk)}{B} * \underset{(kx1)}{\tilde{\lambda}} + \underset{(nx1)}{\tilde{\varepsilon}} \tag{2}$$

In this economy, systematic risk is represented through unexpected changes of common risk factor returns. Ross assumes that idiosyncratic risk is diversifiable and that there are no arbitrage opportunities. It is then possible to derive a relationship between asset i's expected return and the factor loadings multiplied by the risk premiums of the k risk factors (λ_1, …, λk). The exact APT equation is given by Eq. (3).

$$\mu_i = \lambda_0 + b_{i1}\lambda_1 + \ldots + b_{ik}\lambda_k \qquad \forall i = 1, \ldots, n \tag{3}$$

This is the APT equation which we use in the empirical analysis to identify statistically significant risk factors. Without idiosyncratic risk, Eq. (3) is an immediate result arising from the absence of arbitrage opportunities, because a riskless portfolio is then simply a combination of assets such that the portfolio is insensitive with regards to the risk of the risk factors and therefore orthogonal to the column space of the B-matrix.

The factor models based on the APT can be summarized by four different model types according to the different ways to choose risk factors. They can be macro-economic, fundamental, statistical or non-linear. Once the factors are determined the asset returns sensitivities toward them must be estimated. In the second step, the estimated sensitivities are incorporated in a cross-section regression and the risk premiums are estimated.

After some transformation, Fama/MacBeth derived an OLS-estimator for risk premiums at every point in time $\widehat{\lambda}_t = \left(\widehat{B}_k{}'\widehat{B}_k\right)^{-1}\widehat{B}_k{}'\tilde{r}_t$ for all t = 1, …, T in a cross-section regression [11]. This results in a time series of estimated risk premiums $\widehat{\lambda}_t$ to which they apply a test statistic that is t-distributed and that allows to test for significantly evaluated risk factors, see Eq. (4).

$$t\left(\overline{\lambda}_k\right) = \frac{\overline{\lambda}_k * T^{\frac{1}{2}}}{s\left(\widehat{\lambda}_k\right)} \tag{4}$$

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with T = numbers of observations, $\overline{\lambda}_k$ = arithmetic mean of $\widehat{\lambda}_{kt}$, and s($\overline{\lambda}_k$) = standard deviation of the monthly estimates $\widehat{\lambda}_{kt}$.

Wavelet analysis is then applied to decompose the risk factors and asset returns. The test for significantly evaluated risk factors is not only performed on an aggregate level but also at different time scales that allow information to be of relevance for certain time periods only. Furthermore, we also apply wavelet to distinguish expected and unexpected components of the risk factors. This approach results in the identification of risk factors that remain significant over longer time periods, the problem of parameter constancy is therefore mitigated as well.

This approach reduces the variance of the estimated means of the risk premiums. Furthermore, it shows that only certain scale information of the risk factors remains important over time. We find that this approach improves on the findings which fundamental factors are significant in explaining stock market returns. For a detailed derivation of the estimation equations and the results in which fundamental factors are significantly evaluated in the stock market, see [7].

2.2. Term structure of interest rates

The models to explain the term structure of interest rates have been of interest to researchers for a long time. The models differ in the purpose they are built for. In our analysis, we assume that the data generating process for term structure of interest rates can be expressed as an approximate factor model as in the previous section. Those types of models are especially meaningful if the task at hand is to forecast future term structures of interest rates. The models that generate good forecasts and are equally satisfying from a theoretical, arbitrage-free viewpoint have been developed, for example, see [12–14]. The risk factors are found to represent information with regards to the level, slope, and curvature of the term structure of interest rates. We find that in this market too, for the same reasons as before, an analysis on an aggregate level can be misleading so that we perform our analysis on a scale-by-scale basis. We then apply the procedure of Fama/MacBeth to test for significance of risk factors. The Nelson-Siegel model approximates the actual yield curve observed in the market on any specific date t for zero rates y with maturity τ through the following Eq. (5):

$$y_t(\tau) = \beta_{0t} + \beta_{1t}\left(\frac{1-e^{-\gamma\tau}}{\gamma\tau}\right) + \beta_{2t}\left(\frac{1-e^{-\gamma\tau}}{\gamma\tau} - e^{-\gamma\tau}\right) \tag{5}$$

with β_{0t}, β_{1t}, β_{2t}, and γ as model parameters [15].

The respective β_i's can be viewed as dynamic factors that represent short-, medium-, and long-term behavior [12]. The factors level (β_0), slope (β_1), curvature (β_2), and γ the mean reversion rate are then identified as risk factors. The models parameters are then estimated by assuming an autoregressive, dynamic data generating process for the factors.

The dynamic generalized Nelson-Siegel [14] embeds the Nelson-Siegel approach in an arbitrage-free setting. In order to ensure the absence of arbitrage, the number of risk factors has to be increased to five.

The above models increase the number of explanatory factors according to theoretical considerations. In our analysis, we test whether there is statistical evidence for the proposed risk factors to be significantly evaluated by the market. As before, we acknowledge that there might be inefficiencies present in the market. Similar to stock markets, we then assume an approximate factor structure to hold in the bond markets. As before, we then test for significance using the Fama/MacBeth approach. The data used consist of European Zero Coupon Curves estimated by ICAP and provided by Thomson Reuters. We then determine whether risk factors are significant for every time scale and not only on an aggregate level. Similar to our analysis with regards to the stock markets, we find that the significance of the risk factors varies with different time scales. By reconstructing the time series using the significant time scales only, we concentrate on a relatively small number of wavelet functions. We then investigate the scaled and significantly evaluated risk factors for their ability to help forecast the term structure of interest rates. In our analysis, we can only detect four significantly evaluated risk factors for the term structure of interest rates [16].

2.3. Corporate bonds

Structural models based on the idea of Merton result in theoretical credit spreads that significantly deviate from observable corporate bond markets spread [17]. The models can only explain a limited proportion of corporate bond market spreads even if tax asymmetries, liquidity, and conversion options are considered. This empirical finding is referred to as the credit spread puzzle [18]. Similarities between equity and corporate bond market's risk have long been recognized and risk factors similar to those applied in stock markets are included in the analysis of corporate bond spreads, for example see [2]. The set of explanatory variables is enriched by other researchers to also account for market inefficiencies. For example, it can be assumed that there are limits to arbitrage which combined with noise leads to predictable deviations of market prices from the asset's fundamental value [19]. A solution could be a dynamic model with dispersed information in which noisy investors only learn about fundamental information with a time delay in order to solve the puzzle. Furthermore, it can be assumed that market participants develop habit formation [20]. Other researchers find that there are higher spreads for bonds for which analysts' forecasts are more diverse, i.e., that higher risk premiums are present for bonds where there is higher disagreement [21, 22]. Furthermore, the necessity to analyze varying frequency behavior in the data has been documented for credit markets, for example see [23]. In contrast to the stock and bond market, we do not impose Ross' approximate factor structure, but instead we use Merton's approach to postulate a straightforward relationship between credit spreads and risk factors that influence the corporate's ability to pay back its debt and credit spreads on corporate bond markets in general (fundamental factors). If the purpose is to analyze corporate bond markets jointly, the assumption of Ross's factor structure would become necessary.

To estimate the proportion of credit spreads (cs) explained by risk factors, Eq. (6) has to be analyzed econometrically.

$$cs_t = \mathrm{a} + \mathrm{b}\,(x_t) + u_t \tag{6}$$

with u_t being a white noise error term, and x_t being the risk factors.

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Risk factors represent risks arising from the possibility to default, term structure of interest rates, equity markets, liquidity from mutual funds, and business cycle. Huang and Kong find that for B (BB) rated corporate bonds approx. 68% (61%) of the variation in credit spreads can be explained by respective risk factors [2]. For investment grade bonds however they find that the proportion explained is much lower. Inefficiencies can lead to a higher proportion being explained by the models, for example see [19, 21]. Again we want to analyze the data at different time horizons and simultaneously allow for inefficiencies such as delayed learning about relevant information or other forms of feedback, or technical trading and account for different investment horizons of market participants.

We decompose the data with wavelet analysis. We then test for significantly evaluated risk factors on a scale-by-scale basis, we find that only four factors can be viewed as significantly evaluated by the market [16].

In the following section, we describe the respective analysis in detail for the European corporate bond market.

3. Estimation techniques

Wavelet analysis estimates the frequency structure of a time series and in addition to that it keeps the information when an event of the time series takes place. This way an event can be localized in the time domain with regards to its time of occurrence although frequencies are analyzed as well. The functions at the heart of our analyses are wavelets. In contrast to co-sine functions (waves), wavelets are not defined over the entire time axis but have limited support. In order to achieve the ability to analyze relationships for different time periods, the wavelets are moved over the time axis and at the various scales the support is accordingly. By doing so it is possible to allow for changing regime shifts and the problem of parameter constancy is less severe which removes the necessity to eliminate extreme market moves from a purely statistical point of view. The length (width) of a wavelet on a certain scale represents an investment period of interest. The maximal overlap discrete wavelet transform (MODWT) increases the support of the dilated wavelet with increasing scale, thereby increasing the investment period. The advantage of this form of discrete wavelet transform is that it can be applied to any number of observations of the time series of interest.

Wavelets ($\psi_{j,\,k}$ and $\phi_{J,k}$) when multiplied with their respective coefficients at a certain level "j" or "J" are called atoms $D_{j,k}$ and $S_{J,k}$ (i.e., $d_{j,k}{}^{*}\psi_{j,k} = D_{j,k}$ and $s_{J,k^{*}}\phi_{J,k} = S_{J,k}$) with $\psi_{j,k}$ and $\phi_{J,k}$ being the wavelet and scaling functions at level "j" or "J" and "k" indicating the location of the wavelet on the time axis. The sum of all atoms $S_{J,k}(t)$ and $D_{j,k}(t)$ over all locations on the time axis $k = 1, \ldots, \frac{n}{2^j}$ at a certain level "j" or "J" are given by Eqs. (7) and (8).

$$S_J(t) = \phi_{J,k} \text{ at level J} \tag{7}$$

$$D_j(t) = \sum_{k=1}^{\frac{n}{2^j}} d_{j,k}\psi_{j,k} \forall j = 1, \ldots, J \tag{8}$$

Defining the importance of information to be valid for a specific time period only, the time series are decomposed into their respective resolutions in time (time scales). The time series are then approximated using only parts of the coefficients and their respective wavelets, i.e., the multiresolution decomposition is applied to the time series which are then in turn reconstructed using only the significant portions at the various scales.

The wavelets used in the analysis are "symmlets." Those wavelets are best suited for the analyses because their characteristics are closest to the functions used in the classical Fourier analysis in that they are symmetric and do not contain jumps. This makes most sense if our goal is to analyze the time series in the time and frequency domain. As co-sine functions, the chosen wavelets should not require an interpretation in itself. In that sense, those wavelets are the most "neutral" functions so that no other wavelet functions are considered that would require additional explanations. Our goal is to be able to allow for an analysis on different scales but we would like to keep as much structure of the original time series as possible. The decomposition of the data is done by identifying significant wavelets at certain scales, i.e., wavelets with a specific support on the time axis. The search for significant wavelets is then repeated on the next higher scale (lower frequency). With each increase of the wavelets′ widths a new scale is defined. The number of scales used in this analysis equals four (i.e., J = 4) which is a direct result of the number of observations available. For an explanation of how many levels are recommendable, see [24]. Level "j" wavelet coefficients are associated with periods $[2^j, 2^{j+1}]$. The sums of all atoms at all levels—one to four—result in the original time series.

We perform the regression analysis at each level. Asset returns are regressed on risk factors at different time scales, i.e., the factor pricing equations are estimated at every time scale 1, …, J using the reconstructed time series as outlined before (see Eqs. (9) and (10)):

$$(cs_t)\left[\mathrm{d_j}\right] = \mathrm{a} + \mathrm{b}\ (\mathrm{x}_t)\ \left[\mathrm{d_j}\right] + u_t \text{ for all d1 to d4} \tag{9}$$

$$(\mathrm{cs}_t)[\mathrm{s_4}] = \mathrm{a} + \mathrm{b}\ (\mathrm{x}_t)\ [\mathrm{s_4}] + u_t\ \mathrm{s4} \tag{10}$$

The proportion explained by the risk factors is therefore estimated at each time scale.

4. Empirical analysis

4.1. The data

The credit index data used in this analysis are taken from Bank of America/Merrill Lynch. We use monthly OAS spreads of corporate bond indexes for the time period January 2000 to January 2013. We analyze EMU corporates in the rating category BBB-A (all EMU Corporates). The analysis is performed by using the indexes for various times to maturities 1–3, 3–5 in case of investment grade corporates. The differentiation is necessary to address the phenomenon that short maturities of investment grade corporate bonds depict a higher extend of the credit spread puzzle. For the Euro high yield market we use the Euro high yield index which contains firms with credit ratings BB and lower. Due to concerns with regards to biases caused

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by low liquidity we do not distinguish the high yield index with regards to time to maturity. As explanatory variables, the level, slope and volatility of the bond markets are calculated from the monthly time series for European government term structures of interest rates available from the same source. Data with regards to the stock index Dax are included in the analysis to capture risk characteristics present in the stock markets. Volatility for the stock market is calculated from that time series. Data with regards to European corporate default probabilities are taken from Moody's. Monthly 1-year and 5-year default rates for European investment grade and Caa-C rated companies are available from January 2000 to April 2012. Due to data availability and quality of the data, the 5-year default rates are combined with 1-year default rates.

4.2. Wavelet analysis

We decompose each time series using the maximal overlap discrete wavelet transform (MODWT), i.e. the time series European credit spreads, Government Yields, Slopes, Volatilities, monthly return of Dax, volatility of monthly return of Dax, and Moody's default rates for European Investment Grade Corporates and CCC-Lower-Rated Corporates are decomposed to their respective time and frequency domain components as explained in section 3. Calculating the volatility from the monthly return data, the number of monthly observations we are left to be able to use is 132 (January 2001 to April 2012). As a result of the number of observations the number is set to four. The MODWT estimates the wavelet coefficients "d1" to "d4" and "s4" scaling coefficients.

The decomposition of the time series and the amount of variation explained with Crystals (sum of wavelets and their estimated coefficients at levels j = 1, …, 4) are summarized in **Table 1**.

The risk factors are well explained by coarse scales (low frequencies, e.g., "s4"). The only variable that has different features is the return of the DAX index. In that case the high

	"d1"	**"d2"**	**"d3"**	**"d4"**	**"s4"**
EMU corporates all maturities spread	0.3	0.4	2.2	5.5	91.5
EMU corporates 1–3 year maturity spread	0.4	0.6	2.7	7.2	89
EMU corporates 3–5 year maturity spread	0.3	0.5	2.4	5.6	91.2
Euro high yield spread	0.4	1	2.1	4.6	92
DAX return	46	25	12	8	8
DAX volatility	0.1	0.4	2.4	3	94.1
Euro government 10-year yield	0.1	0.1	0.3	0.4	99
Euro government yield curve slope	0.4	0.5	1.4	1.7	96
Euro government yield volatility	0.1	0.3	1.9	4.4	93.2
European investment grade default rates	0.1	0.2	0.3	1.7	97.7
European high yield default rates	0.5	0.7	1.6	6.8	90.3

Table 1. Variation of the time series explained by crystals (in %).

frequencies contribute the most in explaining the variation of the time series. The other variables are best explained by time scales ranging from "d4" to "s4," whereas the return of the DAX is best explained by time scales "d1" to "d3."

At each scale "j" the coefficients are associated with time periods $[2^j, 2^{j+1}]$. The decomposition of the monthly data allows us to extract components of the data that prevail in the medium or long term. At the highest frequency of the monthly data—at scale "d1"—coefficients approximate reactions to information for the time period of 2–4 months. At scale two, three, and four, the respective time periods are 4–8 months, 8–16 months, 16–32 months. We associate the scales "d1," "d2," and "d3" with the medium term (short medium term equals 2–4 months, medium term 4–8 months, and longer medium term 8–16 months). The remaining two scales at the lower frequencies represent long-term behavior (1.3–2.6 years and longer). Extracting the components of the data that are influential in the medium or long term allows us to detect patterns that can be a result of different investment behavior or different information used in forming expectations, i.e., we are able to allow for inefficiencies in the credit market as outlined above.

In a next step we regress the credit spreads on the explanatory variables on a scale-by-scale basis, i.e., we restrict features of the data to be of importance in the medium ("d1" to "d3") or long term ("d4" to "s4"). After decomposing the regression variables, we reconstruct the time series using features of the time series at the respective resolutions 1, …, 4 only, thereby restricting their variation to the respective time scale. On the other hand, it allows for the possibility that information from more than just the previous period continues to be of influence in explaining credit spreads. By analyzing the amount of the variation explained in a regression (R^2) of the decomposed data at various time scales, we can infer which of the above outlined possible expectation formations is significant in the medium and long run. **Table 2** summarizes the regression results for regressing European investment grade and European high yield credit spreads on the explanatory variables when the data are decomposed, i.e., when the time series are reconstructed to represent behavior present at scales "d1" to "s4."

Determining significant components gives us insights into how long time periods are for processing information. For the short medium term (2–4 months), we find that the default rate is either not significant ("d1" for EMU Corporate all maturities, and "d1," and "d2" for EMU high yield) or even of negative influence. This is a strong indication that the fundamentals are influential for longer time periods only, but do not explain well the variation in investment grade credit spreads for shorter time periods. The credit spread puzzle therefore manifests itself if the data are analyzed on time scales and in that the default rate is not significant in explaining credit spreads at all at some time scales. At the time scales that carry most of the energy, the default rate is significantly positive in explaining the investment grade credit spreads, i.e., for time periods (1.3–2.6 years). For high yield spreads, the default rate is significant only for a longer time horizon (8 months and above). We find that the influence of other explanatory variables changes at the various time scales as well. At the coarsest scale "s4," we find all explanatory variables of significant influence for the credit spreads. However, at scale "d3" (i.e., for a time period of 8–16 months), the variables that capture the volatilities in the stock and bond markets cannot be viewed as being significant variables. The volatility of the DAX, although of importance in the aggregate data, loses its significance for investment grade credit spreads on several scales. It

	DAX	DAXV	Yield	Yield slope	Yield vola.	Default rate	R^2
EMU corporates all maturities credit spread							
d1	−275	2.3*	40.9	−131	890	257	0.1
d2	−16	0.1*	−21.3*	39.9*	−264.6*	−7079*	0.53
d3	−418*	0.03	−19.8	72.9*	19.3	−10662*	0.61
d4	−365.7*	0.01	−77*	21.7*	323.4*	14632*	0.85
s4	−2278*	0.4*	−114*	65.2*	−645.2*	5518*	0.98
EMU corporates maturity 1–3 years credit spread							
d1	1.1	−0.0	−52.2*	46.2*	−18.1	−4219*	0.48
d2	20.7	0.1*	−18.1*	57*	−317.2*	−8857*	0.55
d3	−336*	0.02	−34.7*	86*	12.7	−6722*	0.61
d4	−399*	0.0	−96.5*	36.8*	368.3*	16641*	0.85
s4	−2201*	0.45*	−112*	83.7*	−670.5*	5381*	0.98
EMU corporates maturity 3–5 years credit spread							
d1	−26	0.05	−42.9*	24.8*	−53.1	−3471*	0.44
d2	−27	0.1*	−29.9*	40.6*	−243.5*	−7071*	0.53
d3	−410*	0.03	−23.4*	76.1*	14.2	−10330*	0.64
d4	−348*	0.0	−79.5*	23.2*	306.5*	14859*	0.87
s4	−2610*	0.4*	−111*	59*	−520*	4130*	0.98
EMU corporates high yield credit spread							
d1	−275	2.2*	40.9	−132	890	257	0.09
d2	−792	2.3*	109.9	−333.5	−1025	1029	0.12
d3	−6267*	0.2	−71.1	700.7*	117.9	2622*	0.38
d4	−4765*	1.3*	−135.9	−404.3*	5096*	4224*	0.84
s4	−9471*	2.8*	−411*	340*	−4762*	6988*	0.96

*Indicates significance at a 5% confidence level.

Table 2. Regression results for the European investment grade and high yield credit spreads on explanatory variables using reconstructed time.

continues to be important in explaining the high yield spreads though (with the exception of "d3"), which is another indication for the fact that stock market characteristics are more influential in the high yield bond markets than in the investment grade bond markets. The R^2 supports the fact that has to be performed allowing for inefficiencies in the markets. We find that the amount of the variation in credit spreads explained by the identified risk factors is highest for time horizons from 1.3 to 2.6 years and above. The R^2 at these time horizons in case of the investment grade bonds is 85–98%. Similar results are achieved to the high yield spreads. For shorter time periods, the amount of variation explained is much lower.

We therefore conclude that if information from the fundamental risk factors is allowed to be of influencing longer time periods (1.3–2.6 years and above), then the variables from Eqs (9) and (10)

are significantly linked and the amount of variation explained is high. This means if we allow information from the previous 1.3–2.6 years at scales "d4"and "s4" to be relevant, the proportion of credit spreads explained by risk factors is higher. At the short horizon, technical trading is perceived to be the most important influence in forming expectations; therefore, the insignificance of the default rate to explain credit spreads for shorter time period is in line with previous results and market data.

We conclude that aggregating over time scales "d1" to "s4" results in misleading interpretations of the influence of the various risk factors in explaining credit spreads. Only at time scales that represent medium terms, the default rate is of significant, positive influence. The amount of variation explainable with the fundamental risk factors is highest at that time scales. This supports the fact that fundamental considerations are more important in longer time periods and that inefficiencies in the credit markets are present at shorter time periods.

5. Conclusion

In this chapter, we give an overview of factor models that are applied to major capital markets. Ross' arbitrage pricing theory is chosen as the theoretical background for the stock and bond markets, since it allows to test for significant risk factors even if there are non-stationary features present in the data. In case of the corporate bond markets, Merton's approach is used to motivate which fundamental factors are chosen to explain market observations. We argue that the assumptions made in standard econometric procedures to test for significantly evaluated risk factors are responsible for the failure of finding the risk factors explain a higher proportion of developments on those markets in practice. We use the maximal overlap discrete wavelet transform to decompose the data into their time-scale components to allow for inefficiencies on capital markets and to allow for different time periods for adjustments to new information. The decomposition of the time series with wavelets in the time domain enables us to interpret data having features at different investment periods. This way we analyze the influence of various variables at different time scales. We examine the significance of risk factors and evaluate the proportion of variation explained at various time scales and find that fundamental factors are especially significant at longer time periods. Wavelet application allows for a thorough discrimination of various time horizons. The analysis is performed by the author for all major capital markets and we present new empirical research with regards to the European corporate bond market in detail as an example. A high percentage of variation in credit spreads explained by fundamental factors can be found in the medium terms (1.3–2.6 years) for investment grade and high yield corporates. We conclude that the adjustment time period to new information is crucial for explaining the credit spreads by risk factors. Aggregating over the time scales veils the fact that a higher proportion in variation of credit spreads is explainable with the fundamental factors for the medium term and that the short term is driven by other factors. These findings confirm our previous findings for major capital markets where estimation and identification of significant fundamental risk factors improved when the analyses were done on a scale-by-scale basis.

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