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The Stability of Factor Sensitivities of German Stock Market Sector Indices: Empirical Evidence and Some Thoughts about Practical Implications

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Abstract: This empirical study estimates 18 single and 18 three-factor models and then tests for structural change. Break dates are identified where possible. In general, there is some empirical evidence for parameter instabilities of the estimated beta coefficients. In most cases there is no or one break point, and in some cases, there are two structural breaks examining the three factor models. The estimated factor sensitivities of single beta models seem to be even less strongly affected by structural change. Consequently, beta factors are probably more stable than some observers might believe. The break dates that have been identified generally seem to coincide with crises or recoveries after stock market slumps. This empirical finding is compatible with the point of view that bull-markets or bear-markets could matter when estimating beta coefficients. In general, the timing of structural change often seems to coincide with either the bursting of the dot-com bubble or the recovery of stock prices thereafter. The banking industry is the most notable exception. In this sector of the German economy, the global financial meltdown and the sovereign debt crisis in Europe have been of high relevance. Consequently, the internet hype of the late 1990s and the early 2000s seems to be more important for the German stock market than the US subprime debacle and the accompanying European sovereign debt crisis.

Keywords: factor models; parameter stability; stock market; sector indices

JEL Classification: C22; G11; G17

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1. Introduction

Factor models of asset returns are of some importance in the fields of asset management and risk assessment. Eisenbeiß et al. (2007), for example, have recently noted that factor models are widely applied in spite of the fact that there probably are more sophisticated models in financial economics. However, some well-known problems do exist using this approach. Most importantly, it is well documented in the relevant literature—and also widely accepted among practitioners—that the factor sensitivities of such models tend to vary considerably over time (see (Bodurtha and Mark 1991; Ng 1991)—and, as more recently examples, (Lewellen and Nagel 2006) as well as (Adrian and Franzoni 2009)). Meanwhile, there is not only empirical evidence from the US. However, Schrimpf et al. (2007) still have argued that the empirical research that has been published up to now has focused primarily on evidence from the US stock market. Their paper is one important motivation for our empirical study. Eisenbeiß et al. (2007) have already examined industry portfolios in Germany. This paper builds on their study and examines data from 18 German stock market sector indices. Techniques of time series analysis are used to search for signs of structural change and parameter instabilities among the estimated factor sensitivities.

More specifically, the timing of structural change is analyzed in some detail. At this point, it is also important to note that this paper follows Bartholdy and Peare (2005) and therefore takes the point of view of a practitioner. They have compared the performance of different factor models trying to give some guidance for applied empirical work in the financial services industry and have argued that therefore simple estimation techniques and readily available data sources should be used. This is also the focus of our empirical study.

The paper is structured as follows: In Section 2, some thoughts with regard to the theoretical background are presented. Section 3 then briefly summarizes the relevant empirical literature with regard to the stability of factor sensitivities examining stock market data. The data examined is discussed in Section 4. Here, some important methodological issues are also addressed. The empirical evidence is presented and discussed in Section 5. Section 6 then concludes.

2. Some Thoughts about the Theoretical Background

It is almost impossible to exaggerate the role of Markowitz (1952) in the formulation of what is now called modern portfolio theory. Elton and Gruber (1997) as well as Rubinstein (2002) have, for example, adequately highlighted the importance of Markowitz's work in shaping how financial markets today see the relationship between risk and return. Building on the pioneering ideas of Markowitz and Sharpe (1964), Lintner (1965) and Mossin (1966) developed the capital asset pricing model (CAPM). Today this model is still an important pillar of financial theory that is explained in all finance textbooks. Moreover, the CAPM is also very popular among practitioners (see, for example, (Graham and Harvey 2001; Bartholdy and Peare 2005)). In fact, it is often used for merger and acquisition analysis as well as for capital budgeting purposes, in the asset management community, and by financial risk managers.

More specifically, the CAPM offers a very simple description of the relationship between the expected return of a specific financial asset and risk in financial markets. The model assumes that the return of this asset minus the risk-free rate should be a linear function of the expected return of the so-called market portfolio minus the risk-free rate:

$$E(R_i) - R_f = \beta \times (E(R_m) - R_f). \quad (1)$$

Therefore, it is called a single factor model. In Equation (1)—which shows the CAPM in its most familiar representation—R_i is the return of asset I, R_f is the risk-free rate, R_m is the return of the market portfolio, β is a linear factor, and $E(\cdot)$ is the expectations operator. The market portfolio is a theoretical construct that should reflect the price movements of all relevant assets in global financial markets. Practically speaking, it is a bundle of all investment opportunities available in the world. The weight of each asset in this hypothetical portfolio should reflect its availability to global investors. It cannot be observed directly and should include all traded and non-traded assets. Therefore, $E(R_m)$ ought to reflect the expected return of "the market" as a whole. Phrased somewhat differently, the market portfolio should be a measure of the return on the aggregate wealth portfolio of all relevant agents in the economy (see, most importantly, (Jagannathan and McGrattan 1995)). The two expressions $E(R_i) - R_f$ and $E(R_m) - R_f$ both can be interpreted as risk premia and β is the so-called beta coefficient which measures how volatile a certain financial asset is considered to be relative to the market portfolio. A beta factor of 1 would, for example, imply that the individual asset i should move up and down proportionally with the market (and therefore is as risky as holding the market portfolio).

Some problems have to be faced when working with the CAPM. There are rather simple ways to cope with a number of difficulties (e.g., the existence of taxes or possible restrictions to short sales—see, for example, (Elton and Gruber 1978; Ross 1977)). Finding a useful proxy for the market portfolio is somewhat more difficult for applied financial econometricians (see, for example, (Jagannathan and McGrattan 1995; Bartholdy and Peare 2005)). However, it is certainly possible to find adequate solutions to handle this problem. There are additional challenges. Markellos and Mills (2001), for example, have discussed possible problems caused by the time series properties of the data examined. The effects of nonlinearities in the relationships among the variables examined will be evaluated in the next section. One of the most important difficulties is the so-called size effect. This is an anomaly that usually cannot be explained by the traditional CAPM. As a matter of fact, empirical research by Banz (1981) has documented that in the US during the period 1936 to 1975, firm size should be considered as an additional factor of relevance for asset pricing. Moreover, there are additional problems (see, for example, (Keim 1986; Schrimpf et al. 2007)). As a consequence, Fama and French (1993) have suggested a three-factor model to explain the expected return $E(R_i)$ of investment opportunity i over the return of the risk-free asset:

$$E(R_i) - R_f = \beta_1 \times (E(R_m) - R_f) + \beta_2 \times (SMB) + \beta_3 \times (HML). \quad (2)$$

In Equation (2) SMB is the difference between the returns of small and big capitalization stock portfolios and HML is the difference between the returns on portfolios including stocks with high to respectively low book-to-market values.

3. A Brief Literature Review

Traditional factor models assume the existence of constant linear relationships between the risk factors and returns. The static CAPM with a constant beta factor can be regarded as the most important example for a model of this type. However, there is also quite a lot of quantitative research showing that CAPM betas behave differently in bull or bear markets (see, for example, (Howton and Peterson 1998; Faff 2001)). In this context, Ghysels (1998) has highlighted the importance of testing for structural change. Moreover, Pettengill et al. (1995) have argued convincingly that empirical tests of factor models that are using realized returns to proxy for expected returns are quite problematic and that the relationship between beta and market returns should be different in up and in down markets. They have also presented empirical evidence supporting this point of view examining data from the US stock market. Meanwhile, Fletcher (2000) also reported international empirical evidence. Splitting the sample into up-market and down-market phases, this study has found support for a significant positive relationship between beta and return in up market periods and a significant negative relationship between beta and return in down market periods. Examining Australian industry portfolios, Woodward and Anderson (2009) have shown that “bull-market” and “bear-market” betas are significantly different for most industries. k have documented signs for instable betas examining different German industry portfolios. They have also argued that the type of industry (cyclical or counter-cyclical) seems to matter. Their empirical findings clearly are of some importance for our empirical study. As already noted, our paper is also motivated by Schrimpf et al. (2007) who have examined data from Germany and have reported empirical evidence for structural parameter instabilities estimating three factor models. These authors have suggested to search for economic reasons that can help to explain the causes of the instabilities of factor sensitivities that has been documented in the literature. In fact, Jagannathan and McGrattan (1995) have also argued that the factor sensitivities of asset returns seem to vary over the business cycle in a systematic way. Moreover, from a slightly different perspective our paper is also closely related to Basse et al. (2009). Their empirical study examines two quite defensive sectors of the US stock market (namely, real estate investment trust and utility stocks) and uses a kind of market model based on the utility sector as benchmark. The results of tests for structural change with unknown timing reported in this paper seem to imply that real estate investment trust have become riskier compared to utility stocks after the bursting of the US house price bubble.

4. Data and Methodology

This paper employs techniques of time series analysis and examines data from all 18 German stock market sector indices that are available for the broad Deutsche Börse Prime All Share Performance Index. This equity index reflects the overall performance of all companies listed in the Prime Standard, which is a very broad measure of stock market activity in Germany. Our empirical study takes the perspective of an international investor. Therefore, our risk-free asset is the 1-month US Treasury Bill. The data for the 18 industry portfolios is taken from Bloomberg (denominated in US dollars). We examine total return sector indices that are value weighted. The need to include the payment of dividends when testing factor models is, for example, discussed by Bartholdy and Peare (2005). Moreover, we examine the three European Fama-French risk factors. These are also denominated in US dollars and are obtained from Kenneth French's web page[1]. The 1-month US Treasury Bill is also taken from this source. Given that our empirical study takes the perspective of an international investor, we have decided to not use the German risk factors which are calculated by the Centre for Financial Research Cologne[2]. Monthly data is examined. In order to avoid problems due to structural change caused by the introduction of the Euro in 1999, we analyze stock price data from January 1999 to March 2019. As a result, we can calculate returns for the period February 1999 to March 2019. Using realized data to proxy for market expectations—a usual practice in the relevant literature that is rarely discussed in a critical way—we estimate 18 single factor models (see (Sharpe 1964; Lintner 1965; Mossin 1966) and Equation (1)) and 18 three factor models (see (Fama and French 1993) and Equation (2)). Given the very high popularity of the point of view (this assumption has already been discussed in some detail above) that factor sensitivities of such models can vary considerably over time and that beta factors can react to changes to the general economic environment, a multiple break point test is then used to search for structural change. More specifically, a sequential test procedure (Bai and Perron 2003) is employed to gain additional insights with regard to the stability of the estimated factors.

We consider the model specified in Equation (2) with $t = 1, 2, 3, \ldots, T$ observations and m potential break points for regime $j = 0, \ldots, m$. This leads to the model specification:

$$\mathrm{E(R_{it}) - R_{ft} = \beta_{1j} \times (E(R_{mt}) - R_{ft}) + \beta_{2j} \times (SMB_t) + \beta_{3j} \times (HML_t) + e_t}. \tag{3}$$

Bai and Perron (2003) use a global optimization procedure which minimizes the sum-of-squared residuals

$$\mathrm{S}(\beta_1, \beta_2, \beta_3 \big| \{\mathrm{T}\}) = \sum_{j=0}^{m} \left\{ \sum_{t=T_j}^{T_{j+1}-1} \mathrm{(E(R_{it}) - R_{ft} - \beta_{1j} * (E(R_{mt}) - R_{ft}) - \beta_{2j} * (SMB_t) - \beta_{3j} * (HML_t)} \right\}^2 \tag{4}$$

of Equation (3) for a specific set of m breakpoints using standard least squares regression to obtain estimates for β_{1j}, β_{2j} and β_{3j}. The set of breakpoints and corresponding estimated coefficients minimize the sum-of-squares across all potential sets of m breaks. This technique is used to analyze and evaluate the timing of structural change. As already indicated, our study builds on Eisenbeiß et al. (2007). More specifically, the timing of structural change is very much in the focus of our attention. In fact, we try to link the empirical evidence for structural change that is obtained either to crises or to stock market recoveries after bear markets.

5. Empirical Evidence

Table 1 summarizes the results of the 18 three factor models. Table 2 provides the same data for the single factor models (CAPM). With only one exception (Food and Beverages), the adjusted R^2s reported here are quite high. Moreover, only a few constant terms are statistically significant in the regression models. These facts at least in general seem to speak for the quality of the models. However, it has to be noted that not all estimated factor sensitivities included in the three factor models are statistically significant. This is one reason for the fact that the three factor models in general offer no major improvement explaining returns from the perspective of practitioners working in the financial services industry (who usually focus quite strongly on R^2s to measure the quality of empirical models).

[1] (International Research Returns 2019).
[2] (German Factors n.d.).

This fact can easily be seen by comparing the adjusted R^2s reported in the two tables and is probably no major surprise (see, most importantly, (Schrimpf et al. 2007)).

Table 1. Three-factor models for 18 German industry portfolios.

Industry	Adj. R^2	Significant Constant
Automobile	0.510	No
Banks	0.676	Yes
Chemicals	0.727	Yes
Media	0.544	No
Basic Resources	0.601	No
Food & Beverages	0.163	No
Technology	0.580	No
Insurance	0.583	No
Industrial	0.710	No
Transportation & Logistics	0.735	No
Construction	0.632	No
Pharma & Healthcare	0.517	No
Retail	0.639	No
Software	0.540	No
Telecommunications	0.388	No
Utilities	0.483	No
Financial Services	0.640	No
Consumer	0.548	No

Table 2. Single factor models for 18 German industry portfolios.

Industry	Adj. R^2	Significant Constant
Automobile	0.502	No
Banks	0.628	Yes
Chemicals	0.714	No
Media	0.433	No
Basic Resources	0.572	No
Food & Beverages	0.149	No
Technology	0.565	No
Insurance	0.583	No
Industrial	0.706	No
Transportation & Logistics	0.727	No
Construction	0.559	No
Pharma & Healthcare	0.514	No
Retail	0.639	No
Software	0.540	No
Telecommunications	0.388	No
Utilities	0.431	No
Financial Services	0.626	No
Consumer	0.548	Yes

The results of the sequential multiple break point test that is used to search for structural change (see (Bai and Perron 2003)) are reported in the Tables 3 and 4. With regard to the three-factor model, there are no signs for parameter instabilities in four sectors (Automobile, Food & Beverages, Industrials, and Financial Services). Interestingly, three of these four industry groups are considered to be quite traditional sectors of the German economy. There is no empirical evidence for more than two breakpoints. In fact, using the approach suggested by Fama and French (1993), there are three factor models of sector stock market returns in Germany where two break points have been identified (Technology, Telecommunications, and Insurance). Two of these three sector stock market indices are comprised of "classic" dot-com companies. In all other cases there is empirical evidence for just one break point estimating three factor models. Interestingly, most empirical evidence for structural change coincides with either the bursting of the dot-com bubble or the recovery of stock prices thereafter. Only in the case of the German bank stock market index the timing of structural change observed (November 2009) coincides with the global financial crisis using the three-factor model. Given the role of the banking industry in this crisis, our result should probably not be regarded as a major surprise (see, for example, (Bullard et al. 2009; Wegener et al. 2019)). Examining the technology stock market index the two breakpoint dates identified correspond with the recovery after the busting of the dot-com bubble and with the European sovereign debt crisis (May 2003 respectively June 2010) estimating the three-factor model. In this context, it is quite interesting to note that there is no sign for structural change examining the single factor model for the German banking sector stock market index. As a matter of fact, the models estimated using the CAPM approach in general seem to be even more robust to structural change than the three factor models. More specifically, while 17 breakpoints have been identified estimating the three factor models, only 12 breakpoints could be found using the CAPM approach. Given that many investors use a sector rotation approach in asset management, the results of our empirical investigations could be of some importance in the field of applied financial economics.

Table 3. Testing for structural change—the three factor models.

Industry	Number of Breaks	Break Dates
Automobile	0	-
Banks	1	2009/11
Chemicals	1	2003/5
Media	1	2002/6
Basic Resources	1	2015/9
Food & Beverages	0	-
Technology	2	2003/11, 2010/5
Insurance	2	2002,3, 2005/3
Industrial	0	-
Transportation & Logistics	1	2002/4
Construction	1	2005/5
Pharma & Healthcare	1	2002/5
Retail	1	2002/9
Software	1	2003/11
Telecommunications	2	2002/9, 2005/5
Utilities	1	2015/8
Financial Services	0	-
Consumer	1	2002/7

Table 4. Testing for structural change—the single factor models.

Industry	Number of Breaks	Break Dates
Automobile	0	-
Banks	0	-
Chemicals	0	-
Media	1	2003/6
Basic Resources	2	2004/6, 2008/7
Food & Beverages	0	-
Technology	1	2010/11
Insurance	2	2002/7, 2005/8
Industrial	0	-
Transportation & Logistics	0	-
Construction	1	2002/7
Pharma & Healthcare	1	2016/1
Retail	0	-
Software	1	2003/11
Telecommunications	1	2005/2
Utilities	1	2003/2
Financial Services	1	2011/9
Consumer	0	-

Moreover, the timing of structural change identified here generally seems to coincide with crises or recoveries after stock market slumps. Comparing the findings of this study using data from Germany with the results that have been reported examining time series from the US, there seems to be a remarkable difference. In fact, Ghysels (1998) has estimated different factor models, and depending on the structure of the model, has either found not that much evidence for parameter instabilities, or for structural change that is quite dispersed and that does not occur in different industries at the same moment. Our empirical evidence from Germany paints a somewhat different picture. As already noted, the signs for structural change that can be identified examining the data reported in Tables 3 and 4 seem to be related to financial or economic crises or recoveries after stock market slumps. This important empirical finding is some more or less indirect additional empirical evidence for the assumption that beta coefficients of factor models are related to bull and bear markets. However, given the popularity of variable beta coefficient models, one might probably have expected to find even more empirical evidence for structural change. At this point, it has to be stressed again that there is no factor model with more than 2 break points. Moreover, focusing on the estimated three factor models, our empirical evidence shows that in 4 cases, no signs for structural change can be found. Generally speaking, the single factor models are even more robust to structural change. This might be one reason explaining their popularity among practitioners. In sum, beta factors could be more stable than some observers seem to believe.

There might be some problems cause by heteroscedasticity. Therefore, we have employed (results are not reported in order to conserve space) the test suggested by Harvey (1976). In most cases, the null hypothesis of homoscedasticity cannot be rejected. There is only one exception—the three-factor model estimated for the German insurance sector. Still, we re-estimate all models with heteroscedasticity and autocorrelation robust standard errors using the technique suggested by Newey and West (1987) as a kind of robustness check. Using this approach, of course, does not change the adjusted R^2 in Tables 1 and 2. The significance of the estimated constants can be affected. However, this is only the case in one model (namely the single factor model for the German pharmaceutical and healthcare stocks where the constant becomes significant). We have then again used the test of Bai and Perron (2003) to search for structural change in the single and three factor models estimated with heteroscedasticity and autocorrelation robust standard errors. The results are reported in the two Tables 5 and 6. In many cases the results are not affected. However, there are some differences. Most importantly, there now are three break points estimating the three-factor model for German bank stocks. Moreover, no break can be found examining the three-factor model explaining the return of the German technology stock market sector index. Still, the results reported in the Tables 5 and 6 also do suggest that the estimated parameters are quite robust over time and that timing of structural change to be observed in the empirical models in general seems to coincide with crises or recoveries after stock market slumps.

Table 5. Testing for structural change—the three factor models with HAC (Heteroskedasticity and Autocorrelation Consistent Covariances) covariances.

Industry	Number of Breaks	Break Dates
Automobile	0	-
Banks	3	2002/11, 2009/11, 2016/1
Chemicals	1	2003/5
Media	1	2002/6
Basic Resources	1	2015/9
Food & Beverages	0	-
Technology	0	-
Insurance	2	2002/3, 2005/3
Industrial	0	-
Transportation & Logistics	0	-
Construction	1	2005/5
Pharma & Healthcare	1	2002/5
Retail	1	2002/9
Software	1	2003/11
Telecommunications	2	2002/9, 2005/9
Utilities	1	2015/8
Financial Services	1	2013/6
Consumer	1	2002/7

Table 6. Testing for structural change—the single factor models with HAC covariances.

Industry	Number of Breaks	Break Dates
Automobile	0	-
Banks	0	-
Chemicals	1	2012/10
Media	0	-
Basic Resources	2	2004/6, 2008/7
Food & Beverages	0	-
Technology	1	2010/11
Insurance	2	2002/7, 2005/8
Industrial	0	-
Transportation & Logistics	0	-
Construction	0	-
Pharma & Healthcare	1	2016/1
Retail	0	-
Software	1	2003/11
Telecommunications	0	-
Utilities	1	2003/2
Financial Services	1	2011/9
Consumer	0	-

6. Conclusions

This empirical study has examined the stability of factor sensitivities of German stock market sector indices. First of all, 18 single factor models (see (Sharpe 1964; Lintner 1965; Mossin 1966)) and 18 three-factor models (see (Fama and French 1993)) have been estimated. Then, tests for structural change have been performed. Moreover, break dates have been identified. In general, there is some empirical evidence for parameter instabilities of the estimated beta factors. In most cases there is no or one, and in some cases, there are two structural breaks in the models. Consequently, beta factors probably seem to be more stable than some observers might believe. The timing of structural change is also very interesting. In fact, the break dates that have been identified generally seem to coincide with crises or recoveries after stock market slumps. This empirical finding is compatible with the point of view that the existence of bull-markets or bear-markets could matter when estimating beta coefficients. In many models, the timing of structural changes seems to coincide with either the bursting of the dot-com bubble or the recovery of stock prices thereafter. Consequently, this crisis seems to be more important for the German stock market than the US subprime crisis. The only exception is the banking industry. More empirical research seems to be necessary. It would, for example, be interesting to take the perspective of a German investor. This would allow (respectively, even require) the use of the German factors. In any case, the empirical evidence that has been reported above seems to imply that structural change could be of high relevance for all users of factor models. This is not only important for asset managers trying to construct attractive portfolios. Without a doubt, risk managers in the financial service industry should also consider the possibility that beta is not necessarily stable over time.

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