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The Alternative Three-Factor Model: Evidence from the German Stock Market

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Abstract

This article applies the alternative three-factor model introduced by *Chen/Novy-Marx/Zhang* (2010) to the German stock market for the sample period of 2004 through 2015. We construct two new factors *INV* ("investment") and ROA ("return on assets") for companies listed on the highest segment of the Frankfurt Stock Exchange, and examine whether they can explain various stock market anomalies using linear time series regressions. Our results reveal that the theoretical assumptions of the model are valid for the German stock market. Firms with higher investments generally exhibit lower returns, while more profitable firms exhibit higher returns. However, we find that the alternative three-factor model does not explain capital market anomalies in the German market better than the factors of the traditional *Fama/French* (1993) three-factor model.

Die Erklärungskraft des alternativen Dreifaktorenmodells für den deutschen Aktienmarkt

Zusammenfassung

Das alternative Dreifaktorenmodell von *Chen/Novy-Marx/Zhang* (2010) hat sich als gut geeignet erwiesen zur Erklärung von Aktienrenditen auf dem US-amerikanischen Aktienmarkt. Um die Validität auch im internationalen Kontext zu verstehen, wird es für alle im höchsten Marktsegment der Frankfurter Wertpapierbörse gelisteten Aktiengesellschaften im Zeitraum von 2004 bis 2015 überprüft. Mithilfe von linearen Zeitreihen-Regressionen wird anschließend ermittelt, ob die Faktoren des alternativen Dreifaktorenmodells verschiedene Kapitalmarktanomalien erfassen können. Die Ergebnisse zeigen, dass die Erklärungskraft des Modells auch am deutschen Aktienmarkt gegeben ist: Un-

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ternehmen, die viel investieren, erwirtschaften niedrigere Renditen, und Unternehmen, die eine höhere Profitabilität aufweisen, erreichen höhere Aktienmarktrenditen. Das alternative Dreifaktorenmodell scheint insgesamt aber weniger geeignet zu sein, um Anomalien am deutschen Aktienmarkt zu erfassen, als die traditionellen Risikofaktoren des *Fama/French*-Dreifaktorenmodells (1993).

Keywords: Multifactor models, cross-section of stock returns, *Fama/French* three-factor model

JEL Classification: G12

I. Introduction

Explaining and predicting equity returns is one of the central challenges of stock market research (*Ziegler* et al. 2003), and it has become an increasingly important topic in Germany (*Kaserer/Hanauer* 2017). *Fama/French's* (1992) analysis of the U.S. stock market showed that market capitalization and the price-to-book ratio significantly raised the explanatory power of the classical Capital Asset Pricing Model (CAPM). *Fama/French* (1993) then expanded the original CAPM (introduced by *Sharpe* 1963, and *Lintner* 1965) by adding those two risk factors (market capitalization for size, SMB, small minus big, and the price-to-book ratio for HML, high minus low).

The *Fama/French* three-factor model remains the international standard for describing stock returns (*Subrahmanyam* 2010). However, numerous other empirical studies, beginning with *Jegadeesh/Titman* (1993) on the medium-term momentum effect, show there are additional factors that can contribute to the explanation and prediction of stock returns. The influence of these factors – such as the size effect in the origin of the size factor – is often defined as an anomaly because these factors are (still) not incorporated into capital market pricing models (*Fama/French* 1996; *Kaserer/Hanauer* 2017).

Against this background, *Chen/Novy-Marx/Zhang* (2010) developed an alternative three-factor model. Similarly to *Fama/French's* (1993) classic factor model, their alternative model explains the excess returns of stock portfolios compared to risk-free investments using three factors. However, their factors differ.

First, the alternative three-factor model explains stock returns by means of the market risk premium (MKT). Second, the excess return depends on portfolios consisting of companies with high and low investments (INV). Third, the excess return depends on the return on assets (ROA), or firm profitability in the stock portfolio.

Chen/Novy-Marx/Zhang (2010) describe a model for the U.S. market based on a multitude of anomalies, such as, e.g., the medium-term momentum effect, or the new equity puzzle (*Pontiff/Woodgate* 2008). The results indicate that their alternative model addresses these anomalies more efficiently than the *Fa-*

ma/French model. It can thus serve as an essential contribution to the understanding of the effects of investments and profitability on stock returns. However, as *Walkshäusl/Lobe* (2014) note, it is possible that *Chen/Novy-Marx/Zhang's* (2010) findings are strongly influenced by the special characteristics of the U.S. market. Our paper aims to provide a fuller examination of the explanatory power of this alternative three-factor model on the German stock market.

The remainder of this paper is structured as follows. Section II. provides a brief description of the alternative three-factor model. Section III. introduces our dataset, outlines the current literature, and clarifies the method for constructing the INV and ROA factors for the German stock market. Section IV. gives our results for the alternative three-factor model based on four known anomalies in order to compare it with the CAPM and the *Fama/French* three-factor model. Section V. summarizes our findings and concludes.

II. The Alternative Three-factor Model

The *Fama/French* three-factor model is the standard in the literature for the explanation and prediction of stock market returns. Nevertheless, it is somewhat deficient when it comes to explaining diverse anomalies in the market. Examples are the medium-term momentum effect (*Jegadeesh/Titman* 1993), low company returns connected to share offerings, and asset growth.

Chen/Novy-Marx/Zhang's (2010) model was created explicitly to explain these anomalies. In their model, the expected excess return is the difference between the expected return and the risk-free interest rate, $E[r_i]-r_f$. It depends on three factors: the excess return of the market compared to a risk-free investment (MKT), the difference between the returns of portfolios consisting of companies with high and low investments (INV), and the difference between the returns of portfolios consisting of highly and less profitable (ROA) companies. In this context, investment activities are defined as the ratio of investments to assets, I/A, and the profitability of a company is defined by the return on assets, ROA.

We formally describe the alternative three-factor model as follows:

$$E[r_i]-r_f = \beta_{CNZ,i} E[MKT] + d_i \ E[INV] + p_i \ E[ROA] \quad (1)$$

where $E[MKT]$, $E[INV]$, and $E[ROA]$ correspond to the expected risk premiums and $\beta_{CNZ,i}$, d_i, and p_i to the respective factor weightings (*Chen/Novy-Marx/Zhang* 2010). In contrast to the empirically motivated *Fama/French* three-factor model, *Chen/Novy-Marx/Zhang* (2010) derive their factors from the "q-theory of investment." This model explains stock returns from a production or company perspective, and makes a direct connection between stock returns and certain company characteristics (*Cochrane* 1991). For this reason, we note that the

INV and ROA factors are not actually risk factors, because they do not compensate for risk in a traditional sense.

III. Fundamental Findings in the German Stock Market

1. Data

We use monthly returns of German stocks to examine the explanatory power of *Chen/Novy-Marx/Zhang's* (2010) model. All the stock-specific data for the Frankfurt Stock Exchange (Frankfurter Wertpapierbörse) come from the Thomson Reuters Datastream/Worldscope database. Monthly stock return and market capitalization data come from Datastream, while balance sheet data and financial statement information are from Worldscope. We use Worldscope's "WSCOPEBD" directory for our dataset creation.

Our sample period is July 2004–June 2015, which covers 132 months. All companies in the official and the regulated markets at the Frankfurt Stock Exchange are included, except for financial service providers.[1] We thus focus on the highest market segment at any given time. This is considered information efficient because of the high liquidity and the strong monitoring by analysts. In this market, it is especially relevant to determine whether multifactor models can explain excess returns of stock portfolios better than the classical CAPM (*Ziegler* et al. 2007).

We impose the condition that all data for the monthly stock returns, as well as all the necessary information for the calculation of I/A and ROA, must be available. We thus exclude any companies with negative or no available book values at the end of fiscal year $y-1$ (*Chen/Novy-Marx/Zhang* 2010), as well as those with no market value available in June of year y. Penny stocks are also excluded because of the danger of price manipulation (*Stehle/Schmidt* 2015). Therefore, all companies with a market value lower than 5 million Euros in July of year y, or a share price lower than one Euro, are ultimately excluded (*Brückner* et al. 2015).

The data for the traditional risk factors MKT, SMB, HML, and WML come from *Stehle*'s (2016) website. We use the "TOP" dataset because we are only analyzing companies from the highest market segment. However, in order to calculate the monthly returns of stock market portfolio r_{mt}, we include all listed companies. Thus, we consider banks, insurance companies, and joint stock companies that show negative book values of equity.

[1] We do not consider financial services companies such as banks or insurance companies for the construction of the INV and ROA factors because they are valued differently by the market than industrial companies. They are therefore subject to different accounting regulations (*Ziegler* et al. 2007).

We use the one-month Euro Interbank Offered Rate (EURIBOR) as a proxy for the return of the risk-free investment rate, r_{ft} (*Ziegler* et al. 2007). We obtain the market value-weighted returns of the examined portfolios based on market capitalization and the price-to-book ratio, as well as the analyzed portfolios based on market capitalization and the short-term momentum effect, from *Stehle's* (2016) website.

2. *Explanatory Variables*

a) The Investment Factor

The ratio of investments to assets (I/A) is defined as the annual change in (gross) fixed assets,[2] plus the annual change in inventories[3] from the end of fiscal year y – 2 to the end of fiscal year y – 1 divided by the assets[4] at the end of fiscal year y – 2:

$$(2) \quad (I/A)_y = \frac{\left(\text{fixed assets}_{y-1} - \text{fixed assets}_{y-2}\right) + \left(\text{inventories}_{y-1} - \text{inventories}_{y-2}\right)}{\text{assets}_{y-2}}$$

Changes in gross fixed assets reflect investments in durable assets, which can be used by companies over longer periods of time. Durable assets typically include, e.g., buildings, machines, furniture, equipment, etc. Changes in inventories, on the other hand, usually denote investments in short-term assets, which are used in a company's supply chain for shorter periods of time. Growth and investments are closely linked, because growing companies obviously invest more than other companies, although we note that investments are not the only indicator of a company's growth potential. Increases in the number of employees or in R&D can also be strong indicators of growth (*Chen/Novy-Marx/Zhang* 2010).

b) The Return on Assets Factor

Chen/Novy-Marx/Zhang (2010) measure ROA as the ratio of net income before extra items[5] to the assets (total assets) of a company in the prior quarter. They argue this is the most accurate way to calculate current ROA. It should serve as a reliable proxy because ROA is highly persistent (*Chen/Novy-Marx/Zhang* 2010). Furthermore, current profitability is the best indicator of

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[2] Worldscope item: Property, Plant and Equipment Gross.
[3] Worldscope item: Inventories Total.
[4] Worldscope item: Total Assets.
[5] Worldscope item: Net Income Before Extra Items/Preferred Dividends.

expected profitability. As *Fama/French* (2006) note, inserting any further regressors into the specification of ROA would decrease the explanatory powers of the model.

However, a quarterly consideration of ROA is not really possible for the German stock market dataset, because quarterly reporting is not standard outside the U.S. Previous studies of the German stock market by *Ammann/Odoni/Oesch* (2012) and *Walkshäusl/Lobe* (2014) provided a footnote to this problem. They use a definition of *ROA* based on annual intervals. They also use different specifications of ROA, and obtain fundamentally divergent findings.

Ammann/Odoni/Oesch (2012) confirm the explanatory power of the alternative three-factor model for an integrated dataset that consists of ten states from the European Monetary Union. In contrast, *Walkshäusl/Lobe* (2014), using an international dataset of forty states, show that the explanatory power of the alternative three-factor model for stock returns is quite similar to that of the CAPM. In order to capture any possible sensitivities of the ROA definition to the results of the model on the test, we introduce and consider various other definitions of return on assets.

Walkshäusl/Lobe (2014) define ROA^A as the ratio of net income before extra items at the end of fiscal $y-1$ divided by the assets at the end of fiscal year $y-2$:

$$RoA_y^A = \frac{Net\ income\ before\ extra\ items_{y-1}}{Assets_{y-2}} \tag{3}$$

Ammann/Odoni/Oesch (2012), on the other hand, define ROA^B as the ratio of net income before extra items at the end of fiscal year y – 1 divided by the assets at the end of fiscal year y – 1:

$$RoA_y^B = \frac{Net\ income\ before\ extra\ items_{y-1}}{Assets_{y-1}} \tag{4}$$

Just as in the factor construction of the *Fama/French* three-factor model, we divide our sample companies into portfolios that correspond to the ROA at the end of June for each year y. We then calculate the market value-weighted returns of these portfolios for the next twelve months. Some of the companies have a balance sheet date in January. In this situation, the time period between the portfolio construction at the end of June of year y and the balance sheet announcement of the annual profit before extra items in year $y-1$ would be eighteen months, and up to thirty months for the assets in year $y-2$. However, we question whether the definitions are appropriate for calculating current ROA as a proxy for expected ROA, as *Chen/Novy-Marx/Zhang* (2010) suggest. We therefore introduce two more definitions that we believe are more precise.

Proceeding chronologically, our first possible definition of ROA is the ratio of net income before extra items at the end of fiscal year y divided by the assets at the end of fiscal year $y - 1$:

$$ROA_y^C = \frac{Net\ income\ before\ extra\ items_y}{Assets_{y-1}} \tag{5}$$

Income at the time of portfolio creation is uncertain for companies whose fiscal years end after June of year y, but this definition fulfills an especially literal interpretation of topicality.

Our second possible definition of ROA is the ratio of net income before extra items at the end of fiscal year y, divided by the assets at the end of year y:

$$ROA_y^D = \frac{Net\ income\ before\ extra\ items_y}{Assets_y} \tag{6}$$

In this case, note that the essential financial statement information for ROA is not known at the time of portfolio creation for most companies. The definition of the factor, however, is not irrelevant for the results, as shown in Table 1. Over our entire sample period, a typical company on average invests 8.38 % of the value of last year's assets (median: 1.80 %). Depending on the definition, average ROA is thus between –3.55 % and 27.96 %. While there are clear differences from using the average, median ROA varies between 3.09 % and 3.42 %, depending on the definition.

Table 1

Summary Statistics for the Explanatory Variables

Variable	Mean	Standard deviation	Median
I/A	8.38	249.76	1.80
ROA^A	21.57	1314.15	3.26
ROA^B	–3.55	167.93	3.09
ROA^C	27.96	1533.82	3.42
ROA^D	–3.46	170.33	3.22

This table shows the averages, standard deviations, and medians for the explanatory variables for our sample period of 2004 through 2015. The ratio I/A is defined by the annual change in (gross) fixed assets plus the annual change in inventories from the end of fiscal year $y - 2$ until the end of fiscal year $y - 1$ divided by the assets at the end of fiscal year $y - 2$. RoA^A is the ratio of net income before extra items at the end of fiscal $y - 1$ divided by the assets at the end of fiscal year $y - 2$. RoA^B is the ratio of net income before extra items at the end of fiscal year $y - 1$ divided by the assets at the end of fiscal year $y - 1$. RoA^C is the ratio of net income before extra items at the end of fiscal year y divided by the assets at the end of fiscal year $y - 1$. RoA^D is the ratio of net income before extra items at the end of fiscal year y divided by the assets at the end of fiscal year y.

3. *Decile Results for I/A and ROA*

To assess whether the variables can explain differences between certain portfolio returns, we first divide the companies into ten portfolios, and then analyze the excess returns. We assign the companies to one of the ten portfolios according to their I/A at the end of June of each year. The companies with the lowest I/A and ROA, respectively, are assigned to the first portfolio ("low"), while the companies with the highest are assigned to the tenth portfolio ("high"). The companies remain in these portfolios until the end of June of the subsequent year, at which point they are re-formed. From July of year *y* until July of year *y* + 1, the average equal-weighted excess return is calculated for each of the ten portfolios.

Table 2

Average Monthly Excess Return of Deciles Based on I/A and ROA

Low	2	3	4	5	6	7	8	9	High	H–L
Panel A: Decile based on INV										
0.76*	0.80*	1.08**	1.07***	1.13***	0.87**	0.82**	0.97**	0.54	0.24	–0.52*
1.76	1.94	2.50	2.81	2.90	2.39	2.24	2.48	1.26	0.52	–1.73
Panel B: Decile based on ROA^A										
0.08	0.60	0.56	1.01***	1.03***	0.86**	1.10***	0.94**	0.93**	0.59	0.51
0.14	1.22	1.47	2.94	2.74	2.16	3.01	2.38	2.43	1.37	1.31
Panel C: Decile based on ROA^B										
0.35	0.38	0.46	1.02***	1.18***	0.68*	0.85**	1.00**	0.99**	0.78**	0.43
0.64	0.79	1.23	2.64	3.08	1.81	2.27	2.52	2.55	1.99	1.12
Panel D: Decile based on ROA^C										
–0.69	–0.13	0.66	0.93**	1.08***	1.08***	1.36***	1.33***	1.53***	2.03***	2.72***
–1.26	–0.29	1.59	2.49	3.02	2.88	3.47	3.35	4.12	4.49	6.77
Panel E: Decile based on ROA^D										
–0.71	–0.08	0.59	0.98**	1.18***	1.18***	1.30***	1.19***	1.52***	2.02***	2.73***
–1.34	–0.16	1.55	2.51	3.23	3.10	3.19	3.11	3.89	5.07	7.14

This table shows the average monthly excess returns and their corresponding t-statistics for ten equal-weighted portfolios. The definitions of I/A and ROA^k ($k = A, \dots, D$) are given in Table 1. The companies are assigned to one of the ten portfolios at the end of June each year according to their *I/A*. The companies with the lowest I/A and ROA are assigned to the first portfolio ("low"), and the companies with the highest *I/A* and ROA are assigned to the tenth portfolio ("high"). The companies remain in these portfolios until the end of June of the following year, at which point we re-form the portfolios. From July of year y until July of year y + 1, the average equal-weighted excess return is calculated for each of the ten portfolios. H–N is the difference in returns between the highest and lowest portfolio. All calculations are based on the monthly returns from July 2004 through June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively.

Table 2 shows the average monthly excess returns for deciles based on I/A and ROA. We find that the companies in portfolios based on I/A, ROA^C, and ROA^D exhibit particularly significant differences from the excess returns of the tenth portfolio. Companies with high I/A reveal excess returns that are on average −0.52 % lower than companies with lower I/A. Moreover, it appears that companies with lower investments earn higher stock market returns than companies with higher investments.

Depending on the definition of ROA, the average excess returns of the ten portfolios show substantial differences. Using the definitions of Equations (3) and (4) applied in the literature, no significant difference in excess returns between companies with high and low ROA are found. The differences between the returns are positive, but not statistically significant. In contrast, the difference between the returns of the highest and lowest portfolios based on ROA^C and ROA^D is highly statistically significant at about 2.7 %. Using the "current" definition of ROA corresponding to Equations (5) and (6), companies with high ROA earn substantially higher returns than companies with low ROA. In this context, the influence of the availability of financial statement information and the definition of ROA is clear.

4. *Investment Factor (INV)*

Our next step is to construct investment factor INV. We form six portfolios based on the market capitalization and I/A of each company at the time of portfolio construction each year (end of June). We thus calculate the median of the market value, as well as the 30 % and 70 % percentiles of I/A, for each joint stock company at the end of June in year *y*. These three values are the basis for the creation of our six stock portfolios:

- S-I: Small-Invest, low market value, high I/A
- $S\text{-}M_{Inv}$: $Small\text{-}Medium_{Inv}$, low market value, medium I/A
- S-D: Small-Disinvest, low market value, low I/A
- B-I: Big-Invest, high market value, high I/A
- $B\text{-}M_{Inv}$: $Big\text{-}Medium_{Inv}$, high market value, medium I/A
- B-D: Big-Disinvest, high market value, low I/A

We assign the companies to one of the six portfolios according to their market values as of the end of June of year *y* and to their I/A. The companies remain in these portfolios from July of year *y* through June of the following year (year *y* + 1). At the end of June, we re-sort the six portfolios.

Note that we eliminate companies if there is no data available for the calculation of their stock returns for one month or longer, or if the necessary financial statement information for the I/A calculation is missing. Table A.1 in the appendix shows the number of companies that have all the necessary data for the construction of INV available.

The monthly returns r_t^{S-I}, $r_t^{S-M_{Inv}}$, r_t^{S-D}, r_t^{B-I}, $r_t^{B-M_{Inv}}$, and r_t^{B-D} for the stock portfolios described above are determined at the end of the month for the observation period from July of year y until June of year $y+1$. We calculate the portfolio returns by using the market value-weighted average of the monthly stock returns for all companies in the portfolio. To replicate the differences between the stock returns concerning I/A, we note that the investment factor INV_t for each month results in the difference between the average return of the two portfolios with low and high I/A companies.

(7) $$INV_t = \left(r_t^{S-D} + r_t^{B-D}\right)/2 - \left(r_t^{S-I} + r_t^{B-I}\right)/2$$

The arithmetic mean for INV_t (the average premium for the investment factor) is 0.54 % for the sample of the German stock market. This mean is significantly different from 0 at the 5 % level, and higher than the 0.28 % mean for the U.S. stock market detected by *Chen/Novy-Marx/Zhang* (2010) for the 1972–2009 period.

As part of the development of the alternative three-factor model, *Chen/Novy-Marx/Zhang* (2011) find an investment factor of 0.41 % ($t = 5.32$), which is much closer to the value for the German sample. *Ammann/Odoni/Oesch* (2012) calculate an average investment factor of 0.44 %, while *Walkshäusl/Lobe* (2014) find an investment factor of –0.07 % for their international analysis, which is not significant. These results show that the investment factor can vary depending on the sample and the country.

Moreover, the results in Table 3 show that neither the *Fama/French* factors nor the *Carhart* (1997) factors can entirely explain the investment factor. If it is regressed on the market factor MKT, it results in a 0.57 % regression constant, which is significant at the 5 % level. If we regress it on the four factors of the *Carhart* (1997) model, the regression constant is reduced to 0.43 %, but it remains statistically significant at the 5 % level.

Table 3

Descriptive Statistics for INV

Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2_{korr}
0.54**	0.57**	–0.04				0.01
(2.46)	(2.60)	(–0.76)				
	0.46**	–0.06	–0.09	0.11		0.03
	(2.15)	(–1.34)	(–1.00)	(1.35)		
	0.43**	–0.05	–0.07	0.12	0.03	0.03
	(2.03)	(–0.93)	(–0.95)	(1.44)	(0.41)	

This table shows the descriptive statistics for INV (the average premium for the investment factor) for the German stock market for the July 2004-June 2015 period. I/A is defined as in Table 1. For the construction of *INV*, we form six portfolios based on the market capitalization and the I/A ratio of each company at the time of portfolio construction each year (end of June). We thus calculate the median of the market value, as well as the 30 % and 70 % percentiles of I/A, for each joint stock company in our sample as of the end of June for every year y. These three values form the basis of the six stock portfolios (S-I, S-M_{Inv}, S-D, B-I, B-M_{Inv}, and B-D). Next, the companies are assigned to the six portfolios according to their market values as of the end of June of year y and their I/A. The companies remain in these portfolios from July of year y through June of the following year (year y + 1). At the end of June of year y + 1, the six portfolios are re-sorted. We calculate the portfolio returns by using the market value-weighted average of the monthly stock returns for all companies in the portfolios for the observation period from July of year y until June of year y + 1. The INV_t for each month is the difference between the average return of the two portfolios with low I/A and high I/A companies. Column 1 shows the mean and the t-statistics for the INV in the observation period. Table 3 also shows the result of a regression where INV is regressed on the factors of the CAPM, the *Fama/French* three-factor model, and the *Carhart* four-factor model (MKT, SMB, HML, and WML). All calculations are based on the monthly returns from July 2004 until June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is indicated by ***, **, and *, respectively. The t-values are adjusted for heteroscedasticity.

5. Return on Assets Factor (ROA)

For the construction of the ROA factor (ROA), we form six portfolios based on the market capitalization and the ROA of each company at the time of portfolio construction in each year *y*. The median of the market value, the 30 % and 70 % percentiles of the ROA, are calculated for all the joint stock companies in our sample as of the end of June in each year *y*. According to Equations (4), (5), (6), and (7), the four specifications of the ROA are measured separately, and the three quantiles form the basis of the construction as follows:

- S-P: Small-Profitable, low market value, high ROA
- S-M_{ROA}: Small-$Medium_{RoA}$, low market value, medium ROA
- S-U: Small-Unprofitable, low market value, low ROA
- B-P: Big-Profitable, high market value, high ROA
- B-M_{ROA}: Big-$Medium_{ROA}$, high market value, medium ROA
- B-U: Big-Unprofitable, high market value, low ROA

Next, we assign the companies to the six portfolios according to their market values at the end of June in year *y* and their ROA. The companies remain in these portfolios from July of year *y* through June of the following year (*y* + 1). At the end of June, we re-sort the portfolios. The monthly returns r_t^{S-P}, $r_t^{S-M_{ROA}}$, r_t^{S-U}, r_t^{B-P}, $r_t^{B-M_{ROA}}$, and r_t^{B-U} for the portfolios described above are also determined at the end of the month for the observation period from July of year *y* through June of year *y* + 1. We again calculate the portfolio returns by using the market value-weighted average of the monthly stock returns for all companies in the portfolios. To replicate the differences between the stock returns concerning profitability, we note that the ROA factor ROA_t results in the difference between the average return of the two portfolios consisting of companies with high and low ROA:

$$ROA_t = \left(r_t^{S-P} + r_t^{B-P}\right)/2 - \left(r_t^{S-U} + r_t^{B-U}\right)/2 \tag{8}$$

Panel A in Table 4 gives the descriptive statistics of the ROA factor ROA^A. Surprisingly, the mean is statistically significantly negative at the 5 % level, with a value of –0.61 %. Thus, companies that are profitable based on ROA^A earn significantly lower returns than those that are unprofitable. And the positive relationship derived from the ROA hypothesis between company profitability and expected returns does not appear to exist for the ROA definition in Equation (3). On the contrary, the relationship is negative. *Walkshäusl/Lobe* (2014) obtain a positive 0.17 % ROA factor in their international sample, but with no statistical significance. The regression of ROA^A on the factors of the *Fama/French* model shows a statistically insignificant α, at least when considering SMB and HML. We find that a large part of ROA^A is covered by the HML factor.

Table 4

Descriptive Statistics of the ROA Factor

Panel A: Descriptive statistics for ROA^A

Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2_{korr}
–0.61**	–0.65**	0.05				0,01
(–2.36)	(–2.49)	(0.77)				
	–0,44	0.06	0.04	–0.26***		0.07
	(–1,65)	(0.79)	(0.40)	(–3.42)		
	–0,29	0.02	0.00	–0.29***	–0.10	0.09
	(–1,20)	(0.37)	(–0.02)	(–3.54)	(–1.46)	

Panel B: Descriptive statistics for ROA^B

Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2_{korr}
−0.45*	−0.46*	0.01				0.00
(−1.67)	(−1.68)	(0.20)				
	−0.25	0.02	0.04	−0.26***		0.06
	(−0.92)	(0.30)	(0.32)	(−2.81)		
	−0.17	0.004	0.01	−0.27***	−0.06	0.06
	(−0.66)	(0.05)	(0.11)	(−2.88)	(−0.75)	

Panel C: Descriptive statistics for ROA^C

Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2_{korr}
0.81***	0.89***	−0.10				0.02
(2.84)	(3.15)	(−1.25)				
	0.94***	−0.09	0.01	−0.07		0.02
	(3.26)	(−1.15)	(0.12)	(−0.72)		
	0.69**	−0.03	0.09	−0.02	0.18**	0.08
	(2.31)	(−0.37)	(0.80)	(−0.16)	(2.21)	

Panel D: Descriptive statistics for ROA^D

Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2_{korr}
0.70***	0.77***	−0.08				0.02
(2.64)	3.02	−1.22				
	0.84***	−0.08	0.00	−0.10		0.02
	(3.38)	(−1.15)	(0.00)	(−1.04)		
	0.68**	−0.04	0.05	−0.06	0.11	0.05
	(2.49)	(−0.65)	(0.43)	(−0.60)	(1.32)	

This table summarizes the descriptive statistics of all the ROA factors ROA^k ($k = A,\ldots,D$) on the German stock market from the July 2004-June 2015 period. ROA^k ($k = A, \ldots, D$) is as defined in Table 1. For the construction of the ROA factor *ROA*, we form six portfolios based on the market cap and ROA of each company at the time of portfolio construction for each year *y*. We thus calculate the median of the market value, as well as the 30 % and 70 % percentiles of the ROA, for each joint stock company in our sample as of the end of June for every year y. The three quantiles form the basis of the six stock portfolios (S-P, S-M_{ROA}, S-U, B-P, B-M_{ROA}, and B-U). Next, the companies are assigned to the six portfolios according to their market values as of the end of June of year y and their ROA. The companies remain in these portfolios from July of year y through June of the following year (year y + 1). At the end of June of year y + 1, the six portfolios are re-sorted. We calculate the portfolio returns by using the market value-weighted average of the monthly stock returns for all companies in the portfolios. The ROA factor PMU_t for each month is the difference between the average return of the two portfolios with high and low ROA companies. Column 1 shows the mean and the t-statistics for PMU^k ($k = A, \ldots, D$) in the observation period. Table 4 also shows the result of a regression where ROA^k ($k = A, \ldots, D$) is regressed on the factors of the CAPM, the *Fama/French* three-factor model, and the *Carhart* four-factor model (*MKT*, *SMB*, *HML*, and *WML*). All calculations are based on the monthly returns from July 2004 until June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively. The t-values are adjusted for heteroscedasticity.

The descriptive statistics of the ROA factor ROA^B shown in panel B of Table 4. Note again that the arithmetic mean is negative, with a value of –0.45 %. This is statistically significant at least at the 10 % level. *Ammann/Odoni/Oesch* (2012) calculate an average ROA factor of 0.84 %, which is highly significant. This may be attributable to their international focus and to the older observation period. The regression of ROA^B on the factors of the *Fama/French* three-factor model show no statistically significant α when considering SMB and HML. Similarly to ROA^A, a large part of ROA^B is captured by HML.

In contrast to the means of ROA^A and ROA^B, the descriptive statistics of ROA^C in panel C of Table 4 show a positive value of 0.81. This value is highly statistically significant. If ROA is defined according to Equation (5), the results indicate a positive relationship between ROA and the returns of a company. Profitable companies earn significantly higher returns than unprofitable companies.

Chen/Novy-Marx/Zhang (2010) find a 0.76 % mean for the ROA factor for a sample of U.S. stock market companies from 1972 to 2009. This value is very close to the calculated mean of our ROA^C. Furthermore, *Ammann/Odoni/Oesch's* (2012) value of 0.84 % is (surprisingly) close to the calculated 0.81 %, despite a different ROA definition.

In contrast, neither the factors of the *Fama/French* model nor those of the *Carhart* (1997) model can explain ROA^C. If ROA^C is regressed on the *Carhart* (1997) factors, the regression constant of 0.69 % is statistically significant at the 5 % level. It is remarkable that the momentum factor WML has explanatory power for ROA^C, but the HML factor does not. ROA^C and WML therefore seem to be correlated.

ROA^D exhibits similar effects to those of ROA^C. The average premium for this factor is 0.70 %, and it is also highly significant.

IV. Results

We begin with the CAPM, and estimate the factor weights of the one-factor model using the ordinary least squares method (OLS) for the developed portfolios. Next, we expand the one-factor model that is comparable to the CAPM by the size factor SMB and the value factor HML. If both factors represent risks that are not included in the market return, SMB and HML should have significant factor weights, s_i and h_i.

We then compare these models to the alternative three-factor model. We conduct linear time series regressions with a three-factor model containing the investment factor INV and the ROA factor ROA^C. However, we only present the results of the regression with ROA^C here, because they seem most comparable to

Chen/Novy-Marx/Zhang's (2010) ROA factor. The results of the time series regressions with the other ROA factors do not change the basic findings. We can formally state the results as:

$$r_{it} - r_{ft} = \alpha_{CNZ} + \beta_{CNZ,i}\ MKT_t + d_i\ INV_t + p_i\ ROA_t^C + \varepsilon_{it} \tag{9}$$

To fully judge the quality of the models, however, we use different criteria. At first, we consider the corrected degree of certainty R^2_{korr}. The higher the value of R^2_{korr}, the better the model will explain the variance of the portfolio returns. However, as *Lewellen/Nagel/Shanken* (2008) note, for the valuation of factor models, using only R^2_{korr} is insufficient. Therefore, the explanatory power of a model is judged mainly on the basis of the regression constant α_i, but we also present the average corrected degree of certainty $\varnothing$ - R^2_{korr} including all portfolio regressions.

In a model that includes all relevant risk factors, the constant α_i should not be significantly different from 0. All α_i are first tested against this hypothesis individually. The quality of the model as a whole can be judged by using the mean absolute error (MAE), which is calculated by the sum of all constants $\sum_i |\alpha_i|$. To make a statistically robust statement, we compute the *White* (1980) standard error, based on the proceedings of *Chen/Novy-Marx/Zhang* (2010). The *White* (1980) correction does not change the estimated coefficients, so the OLS coefficients can be extended further.

1. *Price-to-book Ratio*

To examine the anomalies of the CAPM and the *Fama/French* three-factor model, and following *Fama/French* (1993) and *Ziegler* et al. (2007), we conduct an analysis of share portfolios based on market cap and the price-to-book ratio. In contrast to *Fama/French* (1993), we construct only sixteen stock portfolios, instead of twenty-five. And we analyze them in the context of linear time series regressions, taking into account the substantially lower amount of stock- and joint-listed companies in Germany (*Ziegler* et al. 2007).

The independent construction of the sixteen portfolios takes place in a similar manner as the construction of the portfolios used to develop SMB and HML. For all joint stock companies in our sample, we calculate the quartiles of the market values as of the end of June in each year *y*. We also calculate the quantiles of the price-to-book ratios at the end of December of the previous year *y* – 1. Each company is then assigned to one of the sixteen portfolios formed from the six quartiles based on its market value at the end of June of year *y* and its price-to-book ratio at the end of December of *y* – 1. The companies remain in these portfolios from July through June of year *y* + 1.

We define the monthly excess return r_{it} of the sixteen stock portfolios as the average monthly stock return of each company at the respective time, minus the return of a risk-free investment, r_{ft}. We refer to the sixteen stock portfolios as 1-1 (Small-Low), …, 1-4 (Small-High), …, 4-1 (Big-Low), … and 4-4 (Big-High), based on their market value and price-to-book ratio.

Table 5 gives the descriptive statistics and the results of the linear time series regressions for the monthly excess returns of the sixteen portfolios based on their market cap and price-to-book ratio.

Table 5

Descriptive Statistics and Linear Timeline Regression with ROA^{C} for the Monthly Excess Returns of the Sixteen Portfolios on the Market Cap and Price-to-book Ratio

	Low	2	3	High	H–L	Low	2	3	High	H–L
			Mean					t(Mean)		
Panel A: Monthly returns										
Small	–0.20	0.56	0.68	0.72*	0.92*	–0.40	1.19	1.43	1.68	1.76
2	0.31	0.31	1.02**	1.14**	0.83*	0.69	0.81	2.46	2.05	1.80
3	0.75*	1.04**	0.86*	1.31***	0.56*	1.80	2.37	1.89	2.79	1.69
Big	0.43	0.88*	1.04**	1.07**	0.65*	0.97	1.83	2.12	2.47	1.89
Panel B: CAPM										
			α_{CAPM}					$t_{(\alpha CAPM)}$		
Small	–0.60	0.17	0.22	0.33	0.93*	–1.30	0.39	0.55	0.87	1.76
2	–0.25	–0.14	0.60*	0.48	0.73	–0.74	–0.46	1.68	1.12	1.56
3	0.18	0.41	0.26	0.66**	0.48	0.62	1.48	0.77	2.10	1.36
Big	–0.25	0.09	0.24	0.37**	0.62*	–1.05	0.41	1.01	2.02	1.81
				MAE = 0.33; $\varnothing - R^2_{korr} = 0.50$						
Panel C: Fama/French three-factor model										
			α_{FF}					$t_{(\alpha FF)}$		
Small	–0.34	0.04	0.11	0.28	0.63	–0.82	0.09	0.37	0.85	1.18
2	0.31	–0.10	0.29	0.01	–0.29	1.45	–0.43	1.04	0.05	–0.96
3	0.23	0.42	0.12	0.37	0.13	0.87	1.55	0.35	1.38	0.37
Big	0.10	0.03	0.19	0.12	0.02	0.49	0.14	0.81	0.74	0.08
				MAE = 0.19; $\varnothing - R^2_{korr} = 0.66$						

Panel D: Alternative three-factor model

	α_{CNZ}					$t_{(\alpha CNZ)}$				
Small	–0.34	0.17	0.20	0.69*	1.03*	–0.70	0.37	0.46	1.86	1.89
2	–0.07	–0.13	0.67*	0.37	0.43	–0.17	–0.40	1.72	0.97	0.93
3	0.19	0.36	0.31	0.63*	0.44	0.68	1.24	0.93	1.92	1.22
Big	–0.20	0.07	0.15	0.46**	0.65*	–0.87	0.35	0.73	2.39	1.97
MAE = 0.31; $\varnothing - R^2_{korr} = 0.51$										
	d					$t(d)$				
Small	–0.10	0.12	0.10	–0.12	–0.02	–0.53	0.76	0.49	–0.73	–0.08
2	–0.09	–0.13	–0.11	0.13	0.22	–0.84	–1.09	–0.70	0.63	1.08
3	–0.05	0.13	0.17	0.15	0.19	–0.45	1.21	1.29	1.12	1.44
Big	–0.19	0.14	0.05	0.06	0.25	–1.45	1.39	0.43	0.77	1.43
	p					$t(p)$				
Small	–0.23	–0.08	–0.04	–0.33***	–0.10	–1.48	–0.63	–0.30	–3.02	–0.63
2	–0.15	0.06	–0.01	0.04	0.19	–1.31	0.69	–0.12	0.32	1.23
3	0.02	–0.03	–0.16	–0.06	–0.09	0.26	–0.29	–1.55	–0.68	–0.74
Big	0.06	–0.07	0.07	–0.14*	–0.20*	0.85	–0.93	0.84	–1.94	–1.76

The data on the return of the risk-free investment r_{ft} and the *Fama/French* factors MKT, SMB, and HML for the German stock market come from the website of *Stehle* (2016). Tables 3 and 4 illustrate the construction of INV and ROA^C. For all joint stock companies, we calculate the quartiles of the market values as of the end of June for every year *y*. We calculate the quantiles of the price-to-book ratio at the end of December of the previous year y – 1, independently. Each company is assigned to one of the sixteen portfolios formed from the six quartiles based on market value at the end of June of year y, and price-to-book ratio at the end of December of year y – 1. The companies remain in these portfolios from July of year y through June of year y + 1. The monthly excess return r_{it} of the sixteen stock portfolios is defined as the average monthly stock return of each company in the portfolios at the respective time, minus the return of a risk-free investment r_{ft}.

Panel A gives the descriptive statistics for the monthly excess returns of the sixteen portfolios. Panel B gives the regression constants $\alpha_{CAPM,i}$ and their affiliated t-statistics, which result from a linear timeline regression of the monthly excess returns of the sixteen portfolios on the MKT risk factor ($r_{it} - r_{ft} = \alpha_{CAPM,i} + \beta_{CAPM,i}\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}$). Panel C gives the regression constants $\alpha_{FF,i}$ and their affiliated t-statistics, which result from a linear timeline regression on the *Fama/French* factors MKT, SMB, and HML ($r_{it} - r_{ft} = \alpha_{FF,i} + \beta_{FF,i}\ MKT_t + s_i\ SMB_t + h_i\ HML_t + \varepsilon_{it}$). Panel D gives the summary statistics for the monthly excess returns of the sixteen portfolios on the factors of the alternative three-factor model MKT, INV, and ROA^C ($r_{it} - r_{ft} = \alpha_{CNZ} + \beta_{CNZ,i}\ MKT_t + d_i\ INV_t + p_i\ ROA^C_t + \varepsilon_{it}$). The MAE and the average adjusted coefficient of determination $\varnothing - R^2_{korr}$ are also given. H–L is the difference in returns between the highest and lowest portfolios. All calculations are based on the monthly returns from July 2004-June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively. The t-values are adjusted for heteroscedasticity.

We note that companies with a high price-to-book ratio are characterized by significantly higher returns across all market capitalization groups. The H–N portfolios are exclusively positive and significantly different from 0 at the 10 % level. The difference in the H–L returns for companies with the smallest market values is 0.92 % on average, and 0.65 % for the highest market values.

Consistent with the results for the SMB risk factor (see Table A.2 in the appendix), it cannot be proven that companies with lower market caps earn higher returns than those with higher market caps. Panel B of Table 5 shows that the CAPM can explain thirteen of the sixteen portfolios. Moreover, the H–L portfolio of the smallest and largest market cap groups reveals statistically significant regression constants of 0.93 % and 0.62 %. The linear time series regressions of the H–L portfolios enable a meaningful test of the model's total quality. This is because, due to their diversification, they exhibit a lower variance than the other sixteen (*Walkshäusl/Lobe* 2014). The mean absolute error is 0.33 %, while the average corrected degree of certainty, $\varnothing - R^2_{korr}$, is 50 %.

Overall, the results show that the CAPM can explain to a large extent the excess returns of the sixteen portfolios based on market value and price-to-book. The regression constant of the *Fama/French* three-factor model α_{FF} (from panel C in Table 5) shows the high quality of the model. None of the portfolios analyzed – including the four H–L portfolios – shows a statistically significant α_{FF}. Moreover, with a value of 0.19 %, the MAE is substantially below that of the CAPM, and the mean corrected degree of certainty $\varnothing - R^2_{korr}$, with a value of 66 %, is higher than that of the CAPM. Thus, the *Fama/French* three-factor model essentially exhibits greater explanatory power for these portfolios. The MAE of the alternative three-factor model of panel D in Table 5, with a value of 0.31 %, is only slightly lower than that of the CAPM. The average corrected degrees of certainty, $\varnothing - R^2_{korr}$, are on the same level as well.

Comparing the regression constants of the CAPM with those of the alternative three-factor model, we find that both models have statistically significant α_i on the same portfolios (2-3, 3-4, and 4-4). And the regression constants of both regressions are also statistically significant in the same market capitalization groups for the differences in returns. Note further that the alternative three-factor model does not exhibit any explanatory power for the portfolio 1-4 returns, and the α_{CNZ} of 0.69 % is statistically significant. These findings reveal a certain weakness of the alternative three-factor model.

From the second to the fourth market value group, the companies with high price-to-book ratios have higher INV coefficients than the growing companies. According to the investment hypothesis (*Chen/Novy-Marx/Zhang* 2010), this indicates that value companies invest less overall than growing companies, and earn higher returns. There is no statistically significant coefficient in any portfolio for the investment factor, and the ROA factor also shows statistically insignificant values for fourteen of the sixteen portfolios.

To summarize, the quality of the alternative three-factor model is about the same as the CAPM. The hypothesis that companies with a high price-to-book ratio invest less and earn more than companies with a low price-to-book ratio cannot be confirmed for the German stock market.

2. *Short-term Momentum Effect*

In our next step, we test the relationship between the short-term momentum effect and stock returns. Similarly to the portfolios based on market cap and price-to-book, we again form sixteen portfolios. In the context of this anomaly, the portfolios are based on the market cap and prior year performance. In contrast to *Chen/Novy-Marx/Zhang* (2010), the portfolios are formed based on the "11/1/1" scheme, instead of the "6/1/6" scheme from *Stehle*'s (2016) website.

For each month t from July of year y until June of year $y + 1$, we sort the shares based on performance from the beginning of month $t – 12$ through the beginning of month $t – 2$. The quartiles are therefore determined according to prior year performance, and we calculate the quartiles of the market values as of the end of June in each year y.

Next, all companies are individually assigned to one of the sixteen portfolios formed from the six quartiles based on their market value at the end of June in year y and their prior performance. The portfolios are re-formed every month, just as with the construction of the risk factor WML. The sixteen stock portfolios are termed 1-1 (Small-Loser), …, 1-4 (Small-Winner), …, 4-1 (Big-Loser), …, and 4-4 (Big-Winner). Table 6 shows the descriptive statistics and the results of the linear time series regressions for the monthly excess returns for the sixteen portfolios.

Table 6

Descriptive Statistics and Linear Timeline Regression with ROA^C for the Monthly Excess Returns of the Sixteen Portfolios on the Market Cap and Prior Year Performance

	Loser	2	3	Winner	W–L	Loser	2	3	Winner	W–L
			Mean					t(Mean)		
Panel A: Monthly returns										
Small	–0.74	0.12	0.45	1.52***	2.26***	–1.21	0.25	1.18	3.10	3.19
2	–0.19	0.33	0.92**	1.60***	1.78***	–0.29	0.84	2.37	3.85	3.19
3	0.40	1.05**	1.20***	1.36***	0.96*	0.61	2.40	2.77	3.36	1.72
Big	0.57	0.59	1.16***	0.93*	0.36	0.98	1.21	2.62	1.70	0.59

(Continue next page)

(Table 6: Continued)

	Loser	2	3	Winner	W–L	Loser	2	3	Winner	W–L
	Mean					t(Mean)				
Panel B: CAPM										
	α_{CAPM}					$t_{(\alpha CAPM)}$				
Small	–1.20**	–0.37	0.08	1.16***	2.36***	–2.19	–0.83	0.25	2.66	3.37
2	–0.90*	–0.12	0.43	1.11***	2.02***	–1.74	–0.39	1.45	3.54	3.58
3	–0.50	0.46	0.59**	0.85***	1.35***	–1.18	1.47	2.06	2.97	2.75
Big	–0.33	–0.20	0.42**	0.24	0.57	–1.19	–0.83	2.43	0.54	0.89
	MAE = 0.56; $\varnothing$ - R^2_{korr} = 0.48									
Panel C: Fama/French three-factor model										
	α_{FF}					$t_{(\alpha FF)}$				
Small	–1.06**	–0.35	0.12	1.00***	2.06***	–2.00	–0.90	0.41	2.69	2.94
2	–1.09***	–0.07	0.43*	1.09***	2.18***	–3.44	–0.27	1.92	4.00	4.27
3	–0.57	0.42	0.42	0.80***	1.38***	–1.57	1.42	1.46	2.84	2.83
Big	–0.38	–0.26	0.40**	0.42	0.80	–1.32	–1.14	2.24	1.04	1.28
	MAE = 0.56; $\varnothing$ - R^2_{korr} = 0.61									
Panel D: Alternative three-factor model										
	α_{CNZ}					t(α_{CNZ})				
Small	–1.08*	0.00	0.30	1.11**	2.19***	–1.82	–0.01	0.93	2.37	2.94
2	–0.56	–0.05	0.40	1.05***	1.61***	–1.20	–0.17	1.42	2.87	3.03
3	–0.21	0.49	0.63**	0.66*	0.87	–0.49	1.49	2.14	1.92	1.48
Big	–0.02	0.05	0.38**	0.04	0.05	–0.05	0.25	2.03	0.11	0.09
	MAE = 0.44; $\varnothing$ - R^2_{korr} = 0.49									
	D					t(*d*)				
Small	–0.18	–0.33*	0.04	0.38*	0.56*	–0.87	–1.78	0.28	1.95	1.95
2	–0.27	–0.12	0.05	0.03	0.30	–1.14	–1.02	0.40	0.21	1.15
3	0.02	0.01	0.13	0.13	0.11	0.10	0.11	1.15	1.19	0.47
Big	–0.13	–0.04	0.10	–0.06	0.06	–0.88	–0.33	1.40	–0.24	0.17
	p					t(*p*)				
Small	–0.02	–0.20	–0.27***	–0.18	–0.16	–0.10	–1.56	–3.07	–1.25	–0.84
2	–0.22	0.00	0.00	0.05	0.27	–1.41	0.00	0.00	0.45	1.51
3	–0.35**	–0.04	–0.12	0.13	0.48**	–2.02	–0.41	–1.44	1.17	1.99
Big	–0.28*	–0.26***	–0.01	0.27*	0.54**	–1.83	–3.30	–0.19	1.75	1.98

	Loser	2	3	Winner	W–L	Loser	2	3	Winner	W–L
			Mean					t(Mean)		
Panel E: Carhart four-factor model										
			$\alpha_{Carhart}$					$t(\alpha_{Carhart})$		
Small	–0.67	–0.05	0.21	0.66*	1.33*	–1.24	–0.12	0.65	1.73	1.95
2	–0.34	0.18	0.39*	0.47**	0.81*	–1.13	0.72	1.72	2.01	1.94
3	0.26	0.62*	0.45	0.45	0.19	0.78	1.98	1.40	1.47	0.40
Big	0.42*	0.18	0.38*	–0.57*	–0.98**	1.67	1.04	1.95	–1.81	–2.26
MAE = 0.39; $\varnothing$ - R^2_{korr} = 0.67										
			w					$t(w)$		
Small	–0.27**	–0.21**	–0.06	0.24**	0.51***	–2.26	–2.32	–1.06	2.60	3.13
2	–0.52***	–0.17***	0.03	0.43***	0.96***	–5.13	–3.80	0.49	8.18	7.58
3	–0.58***	–0.14**	–0.02	0.24***	0.83***	–5.65	–2.08	–0.37	3.99	6.02
Big	–0.56***	–0.31***	0.02	0.69***	1.25***	–6.42	–4.93	0.39	6.72	10.14

The data on the return of the risk-free investment r_{ft} and the *Fama/French* factors MKT, SMB, and HML for the German stock market come from the website of *Stehle* (2016). Tables 3 and 4 illustrate the construction of INV and ROA^C. For all joint stock companies, we calculate the quartiles of the market values as of the end of June for every year *y*. We calculate the quantiles of the price-to-book ratio at the end of December of the previous year y – 1, independently. Each company is assigned to one of the sixteen portfolios formed from the six quartiles based on market value at the end of June of year y, and their prior year performance. The companies remain in these portfolios from July of year y through June of year y + 1. The monthly excess return r_{it} of the sixteen stock portfolios is defined as the average monthly stock return of each company in the portfolios at the respective time, minus the return of a risk-free investment r_{ft}.

Panel A gives the descriptive statistics for the monthly excess returns of the sixteen portfolios. Panel B gives the regression constants $\alpha_{CAPM,i}$ and their affiliated t-statistics, which result from a linear timeline regression of the monthly returns of the sixteen portfolios on the MKT risk factor ($r_{it} - r_{ft} = \alpha_{CAPM,i} + \beta_{CAPM,i}\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}$). Panel C gives the regression constants $_{FF\ i}$ and their affiliated t-statistics, which result from a linear timeline regression on the *Fama/French* factors MKT, SMB, and HML ($r_{it} - r_{ft} = \alpha_{FF,i} + \beta_{FF,i}\ MKT_t + s_i\ SMB_t + h_i\ HML_t + \varepsilon_{it}$). Panel D gives the summary statistics for the monthly excess returns of the sixteen portfolios on the factors of the alternative three-factor model MKT, INV, and *ROAC* ($r_{it} - r_{ft} = \alpha_{CNZ} + \beta_{CNZ,i}\ MKT_t + d_i\ INV_t + p_i\ ROA_t^C + \varepsilon_{it}$). Panel E gives the regression constants $\alpha_{Carhart,i}$ and the coefficient w_i, as well as their t-statistics, from a linear timeline regression of the monthly excess returns of the sixteen portfolios on the Carhart factors MKT, SMB, HML, and WML ($r_{it} - r_{ft} = \alpha_{Carhart,i} + \beta_{Carhart,i}\ MKT_t + s_i\ SMB_t + h_i\ HML_t + w_i WML_t + \varepsilon_{it}$). The MAE and the average adjusted coefficient of determination $\varnothing$ - R^2_{korr} are also given. W–L is the monthly average difference in returns between the "winner" and "loser" portfolios. All calculations are based on the monthly returns from July 2004-June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively. The t-values are adjusted for heteroscedasticity.

The descriptive statistics of the excess returns in panel A of Table 6 show that the difference in the W–L return between companies with high and low performance is always positive. The values range from 0.36 % to 2.26 %. The short-term momentum effect is particularly strong in companies with smaller market capitalizations. The difference in W–L returns between the smallest and the second smallest market value group are statistically significant at the 1 % level.

The third market value group also shows a statistically significant difference for W–L returns of 0.96 %. The difference is not statistically significant only for companies with bigger market caps. The short-term momentum effect seems to have less of an influence on companies with bigger market caps than on those with smaller market caps.

Panel B in Table 6 shows that the CAPM reveals problems in the explanation of the difference in the W–L return for the market capitalization groups 1 (small) to 3. All regression constants for the corresponding W–L portfolios are statistically significant at the 1 % level. The α_{FF}s of the *Fama/French* three-factor model are on the same level as the regression constants generated by the CAPM, α_{CAPM}.

The risk factors of the *Fama/French* three-factor model seem to offer no additional explanatory power for the short-term momentum effect. This confirms the findings of *Carhart* (1997). Although the average corrected degree of certainty $\varnothing - R^2_{korr}$ is higher for the *Fama/French* regressions, the MAEs of both models are 0.56 %.

The difference in W–L returns for companies with the smallest market caps in the alternative three-factor model generates a α_{CNZ} of 2.19 %. This value is between the corresponding values of the CAPM and the *Fama/French* three-factor model, and indicates that the alternative model does not improve the quality. Therefore, the alternative three-factor model can significantly reduce the regression constant of the W–L portfolio in the second market cap group. Nevertheless, α_{CNZ} remains statistically significant at the 1 % level.

In contrast, the α_{CNZ} of the third market capitalization group for the W–L portfolio is only 0.87 %. This is contrary to the regression constants for the corresponding W–L portfolios of the CAPM and the *Fama/French* three-factor model, which are not statistically significant. The constant α_{CNZ} for the W–L portfolios of the companies with the highest market caps is lower than those for α_{CAPM} and α_{FF}. As for the significance levels of the ROA constants, we find that the superior explanatory power is primarily attributable to the ROA factor. The alternative three-factor model has a MAE of 0.44 %, which is better than that of the CAPM and the *Fama/French* three-factor model.

At this point, we believe it is unlikely that the alternative three-factor model will be able to prevail over the *Carhart* (1997) four-factor model, which uses the WML risk factor to explicitly compensate for the short-term momentum effect. Panel E in Table 6 shows that the W–L portfolio of the group with the smallest market value has a constant $\alpha_{Carhart}$ of 1.33 %. In the second market value group, the regression constant is 0.81 %, and the $\alpha_{Carhart}$ for the W–L portfolio of the third market value group is 0.19 %.

In contrast, however, the *Carhart* four-factor model can reduce the regression constants and their significances, despite revealing one important weakness. Neither the CAPM, nor the *Fama/French* three-factor model, nor the alternative three-factor model, can explain the regression constant of the large W–L portfolio, but the $\alpha_{Carhart}$ of the *Carhart* four-factor model is significant at the 5% level, with a value of –0.98%.

Comparing the factor weights p_i and w_i, we find there are more statistically significant weights for the risk factor WML than for ROA. Thus, WML contributes more to the explanation of the short-term momentum effect than ROA.

The *Carhart* four-factor model has a MAE of 0.39% and an average corrected degree of certainty $\varnothing - R^2_{korr}$ of 67%. Therefore, it performs better than the alternative three-factor model. However, note that the ROA^C factor in our alternative model is based on financial statement information that is not fully known at the time of portfolio construction for most companies. This is not the case for the WML risk factor. Thus, we posit that the *Carhart* four-factor model should be preferred over the alternative three-factor model. Nevertheless, *Chen/Novy-Marx/Zhang*'s (2010) alternative three-factor model is better than the CAPM or the *Fama/French* three-factor model when it comes to the short-term momentum effect.

3. New Equity Puzzle

Companies with smaller share offerings earn higher returns than companies with larger share offerings. *Chen/Novy-Marx/Zhang* (2010) analyze how share offerings and buybacks influence company returns. They follow *Pontiff/Woodgate* (2008), who conclude that there is a strongly negative relationship between the volume of a share offering and a company's future returns. In contrast, companies conducting share buybacks generally earn higher returns (*Pontiff/Woodgate* 2008).

Based on *Loughran/Ritter* (1995), *Pontiff/Woodgate* (2008) focus on IPOs. The main difference between the two studies is that *Loughran/Ritter* (1995) consider share offerings related only to capital increases, while *Pontiff/Woodgate* (2008) also include share buybacks in their analysis. *Chen/Novy-Marx/Zhang* (2010) argue that, as per the investment hypothesis, offering companies tend to invest more but earn lower returns from an IPO due to higher earnings.

Loughran/Ritter (1995) opt for a benchmarking approach, but *Chen/Novy-Marx/Zhang* (2010) measure share offerings as the natural logarithm of the ratio of outstanding shares at the end of fiscal year y − 1, divided by the outstanding shares at the end of fiscal year y – 2. To obtain a comparable measurement of a share offering related to an IPO, we would need to know the amount of outstanding shares before and after the IPO. However, this information is available for only a few companies in our dataset. Thus, this measurement is not feasible.[6]

[6] The dataset includes 74 IPOs from 2004 to 2014. However, only seventeen, or 20%, contain the necessary data on shares outstanding before and after the IPO.

Next, we divide our sample companies into two broad portfolios. This is done to gain knowledge about the influence of capital measures on corporate returns, and to assess whether the alternative three-factor model can explain eventual differences in portfolio returns. Each company without an IPO in fiscal year $y - 1$ is included in the "No IPO" portfolio at the end of June. Companies with an IPO in fiscal year $y - 1$ are included in the "IPO" portfolio at the end of June. The market value-weighted returns of all portfolios are then calculated from July of year y through June of year $y + 1$. All calculations are based on the monthly returns from July 2005 through June 2015, because our dataset contains no IPOs until 2004.

Table 7 gives the descriptive statistics and the results of the linear time series regressions for the monthly excess returns for the "No IPO" and "IPO" portfolios.

Table 7

Descriptive Statistics and Linear Timeline Regression with ROA^C for the Monthly Excess Returns of Two Portfolios Based on IPO

	No IPO	IPO	Return difference	MAE	$\varnothing - R^2_{korr}$
Panel A: Monthly returns					
Mean	2.42**	1.04	–1.39***		
t-value	2.10	1.15	–3.34		
Panel B: CAPM					
α_{CAPM}	1.05	0.30	–0.75***	0.68	0.39
β_{CAPM}	1.90***	1.03***	–0.88***		
$t_{\alpha CAPM}$	1.40	0.39	–4.88		
$t_{\beta CAPM}$	13.14	6.53	–15.85		
Panel C: Fama/French three-factor model					
α_{FF}	0.90	0.18	–0.72***	0.54	0.41
β_{FF}	1.99***	1.16***	–0.83***		
s	0.28	0.45	0.17**		
h	0.26	0.26	0.00		
$t_{\alpha FF}$	1.06	0.22	–5.13		
$t_{\beta FF}$	12.81	6.46	–20.05		
t_s	0.93	1.48	2.06		
t_h	0.97	0.94	–0.02		

	No IPO	IPO	Return difference	MAE	$\varnothing - R^2_{korr}$
Panel D: Alternative three-factor model					
α_{CNZ}	1.22*	0.54	–0.68***	0.88	0.41
β_{CNZ}	1.89***	1.00***	–0.89***		
d	0.19	0.07	–0.12		
p	–0.36	–0.38	–0.01		
$t_{\alpha_{CNZ}}$	1.66	0.74	–6.70		
$t_{\beta_{CNZ}}$	13.44	6.56	–18.52		
t_d	0.41	0.15	–1.58		
t_p	–1.25	–1.29	–0.34		

The data on the return of the risk-free investment r_{ft} and the *Fama/French* factors MKT, SMB, and HML for the German stock market come from the website of *Stehle* (2016). Tables 3 and 4 illustrate the construction of *INV* and the ROA factor ROA^C. Each company without an IPO in fiscal year y – 1 is included in the "no IPO" portfolio at the end of June of each year; each company with an IPO in fiscal year y – 1 is included in the "IPO" portfolio at the end of June of each year. We re-form the portfolios at the end of June in year y + 1. The monthly excess return r_{it} of the portfolios is defined as the average monthly stock return of each company in the portfolios at the respective time, minus the return of a risk-free investment r_{ft}.

Panel A gives the descriptive statistics for the monthly returns of the portfolios. Panel B gives the summary statistics for the linear timeline regression of the monthly excess returns of the portfolios on the MKT risk factor ($r_{it} - r_{ft} = \alpha_{CAPM,i} + \beta_{CAPM,i}\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}$). Panel C gives the summary statistics for the linear timeline regression on the *Fama/French* factors MKT, SMB, and HML ($r_{it} - r_{ft} = \alpha_{FF,i} + \beta_{FF,i}\ MKT_t + s_i\ SMB_t + h_i\ HML_t + \varepsilon_{it}$). Panel D gives the summary statistics for the linear timeline regression on the factors of the alternative three-factor model MKT, INV, and ROA^C ($r_{it} - r_{ft} = \alpha_{CNZ} + \beta_{CNZ,i}\ MKT_t + d_i\ INV_t + p_i\ ROA_t^C + \varepsilon_{it}$). The MAE and the average adjusted coefficient of determination $\varnothing - R^2_{korr}$ are also given. The difference in returns is the monthly average difference between the returns of the "IPO" and "no IPO" portfolios. All calculations are based on the monthly returns from July 2004-June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively. The t-values are adjusted for heteroscedasticity.

The excess returns in panel A of Table 7 show that companies conducting an IPO earn lower returns than companies without an IPO. These findings are in line with those of *Pontiff/Woodgate* (2008), *Chen/Novy-Marx/Zhang* (2010), and *Loughran/Ritter* (1995). The returns are –1.39 % lower on average. This difference is statistically significant at the 1 % level, and generates a highly significant α_{CAPM} of –0.75 %. By using the SMB and HML risk factors, we can reduce the regression constant of the *Fama/French* regression α_{FF} to –0.72 %, which is still highly significant. Using the alternative three-factor model reduces it further to –0.68 %, which is also statistically significant at the 1 % level.

The coefficient on the investment factor INV for the "difference in return" portfolio is negative, with a value of –0.12 %. This is consistent with the findings of *Chen/Novy-Marx/Zhang* (2010), and indicates that companies tend to invest more in the context of an IPO despite earning lower returns. Note that the factor weight d_i is not statistically significant. Due to the small dataset, this is not surprising.

Comparing the average corrected degrees of certainty $\varnothing - R^2_{korr}$ indicates that the explanatory power of the different models rarely differs. The MAE with a value of 0.88 % for the alternative three-factor model is worse than those for the CAPM or the *Fama/French* three-factor model. While those models explain the returns of the "No IPO" and "IPO" portfolios, the alternative three-factor model exhibits an α_{CNZ} of 1.22 % for the "No IPO" portfolio, which is statistically significant at the 10 % level.

To summarize, for the "No IPO" and the "IPO" portfolios, the alternative three-factor model can neither reduce the regression constants, nor generate statistically significant coefficients for INV or ROA. Thus, the alternative three-factor model cannot explain the new equity puzzle.

4. *Asset Growth*

The last anomaly we analyze is the asset growth anomaly. In the context of their analysis for the U.S. stock market, *Cooper/Gulen/Schill* (2008) divide companies based on increases in their assets from year $y - 2$ to year $y - 1$ into ten portfolios. Then they evaluate the equal- and market value-weighted returns. They are able to show that companies with lower asset growth earn higher returns than those with higher asset growth.

Cooper/Gulen/Schill (2008) define asset growth as the difference between assets at the end of fiscal year $y - 1$, minus assets at the end of fiscal year $y - 2$, divided by the assets at the end of fiscal year $y - 2$. All companies are assigned to one of the ten portfolios based on their asset growth as of the end of June in each year y. Table 8 gives the descriptive statistics and the results of the linear time series regressions for the monthly excess returns of these ten portfolios.

Table 8

Descriptive Statistics and Linear Timeline Regression with ROA[C] for the Monthly Excess Returns of the Ten Portfolios Based on Asset Growth

	Low	3	5	8	High	H–L	MAE	$\varnothing - R^2_{korr}$
Panel A: Monthly returns								
Mean	1.74***	1.36***	1.45**	1.18**	1.49***	–0.25		
t-value	2.71	2.72	2.03	2.39	2.77	–0.53		
Panel B: CAPM								
α_{CAPM}	0.89**	0.64**	0.85	0.41	0.68**	–0.21	0.63	0.61
β_{CAPM}	1.14***	0.97***	0.80**	1.02***	1.09***	–0.05		
$t_{\alpha CAPM}$	2.05	2.13	1.01	1.65	2.33	–0.45		
$t_{\beta CAPM}$	7.89	12.90	2.51	14.65	14.05	–0.52		

	Low	3	5	8	High	H–L	MAE	$\varnothing - R^2_{korr}$
Panel C: Fama/French three-factor model								
α_{FF}	0.60	0.57*	0.82	0.51*	0.66**	0.06	0.55	0.63
β_{FF}	1.23***	0.94***	0.99	1.02***	1.11***	0.13		
s	0.28*	–0.08	–0.70	–0.01	0.07	–0.21		
h	0.42***	0.07	–0.10	–0.12	0.03	–0.39**		
$t_{\alpha_{FF}}$	1.36	1.80	0.99	1.82	2.22	0.13		
$t_{\beta_{FF}}$	9.22	12.71	1.35	12.51	12.68	–1,06		
t_s	1.74	–0.72	–1.43	–0.13	0.48	–1,09		
t_h	3.07	0.80	–0.48	–1.31	0.33	–2.23		
Panel D: Alternative three-factor model								
α_{CNZ}	1.20***	0.64*	0.37	0.68**	0.99***	–0.21	0.66	0.64
β_{CNZ}	1.11***	0.96***	0.84***	1.00***	1.06***	–0.04		
d	0.17	0.27**	0.38	–0.28***	–0.19*	–0.37**		
p	–0.46***	–0.17	0.30	–0.13	–0.24**	0.23		
$t_{\alpha_{CNZ}}$	2.71	1.95	0.64	2.47	3.17	–0.42		
$t_{\beta_{CNZ}}$	9.75	12.63	2.98	16.20	15.97	–0.49		
t_d	0.91	2.31	0.95	–2.88	–1.87	–2.00		
t_p	–2.79	–1.64	1.30	–1.42	–2.44	1.59		

The data on the return of the risk-free investment r_{ft} and the *Fama/French* factors MKT, SMB, and HML for the German stock market come from the website of *Stehle* (2016). Tables 3 and 4 illustrate the construction of INV and ROA^C. We define asset growth as the difference between assets at the end of fiscal year y – 1 and the end of fiscal year y – 2, divided by assets at the end of fiscal year y – 2. Each company is assigned to one of the ten portfolios based on asset growth at the end of June for each year y. Market value-weighted returns of the previously formed portfolios are calculated from July of year y through June of year y + 1. We re-form the portfolios at the end of June in year y + 1 using the new asset growth values. The monthly excess return r_{it} of the portfolios is defined as the average monthly stock return of each company included in the portfolios at the respective time, minus the return of a risk-free investment r_{ft}.

Panel A gives the descriptive statistics for the monthly portfolio returns. Panel B gives the summary statistics for a linear timeline regression of the monthly excess returns of the portfolios on the *MKT* risk factor ($r_{it} - r_{ft} = \alpha_{CAPM,i} + \beta_{CAPM,i}\left(r_{mt} - r_{ft}\right) + \varepsilon_{it}$). Panel C gives the summary statistics for a linear timeline regression on the *Fama/French* factors MKT, SMB, and HML ($r_{it} - r_{ft} = \alpha_{FF,i} + \beta_{FF,i}\ MKT_t + s_i\ SMB_t + h_i\ HML_t + \varepsilon_{it}$). Panel D gives the summary statistics for a linear timeline regression on the factors of the alternative three-factor model MKT, INV, and ROA^C ($r_{it} - r_{ft} = \alpha_{CNZ} + \beta_{CNZ,i}\ MKT_t + d_i\ INV_t + p_i\ ROA_t^C + \varepsilon_{it}$). The MAE and the average adjusted coefficient of determination $\varnothing - R^2_{korr}$ are also given. H–L is the difference in returns between the highest and lowest portfolios. All calculations are based on the monthly returns from July 2004-June 2015, but we only display the results for deciles 1, 3, 5, 8, and 10 here. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively. The t-values are adjusted for heteroscedasticity.

The descriptive statistics in panel A of Table 8 show no significant influence of asset growth on the future returns of a company. The difference in return H–L is negative, with a value of –0.25, but not statistically significant. Companies with higher asset growth do not show significantly lower returns than companies with lower asset growth. Although there is no statistical significance for this anomaly, the excess returns of the ten portfolios are regressed on the factors of the CAPM, the *Fama/French* three-factor model, and the alternative three-factor model. For the H–L-portfolio, α_{CAPM} is –0.21 % and α_{FF} is 0.06 %. Both models explain the (slightly) different returns based on asset growth. α_{CNZ} has a value of –0.21 %.

The explanatory power of the alternative three-factor model is similar to that of the CAPM. The almost identical MAEs of 0.63 % and 0.66 % confirm this result. However, following *Chen/Novy-Marx/Zhang* (2010), we can confirm that the explanatory power of the *Fama/French* three-factor model mainly relates to the value factor HML, while the explanatory power of the alternative three-factor model is based on the investment factor INV. Companies with lower asset growth exhibit statistically significantly higher factor weights d_i. This indicates that companies with high asset growth invest more and earn lower returns, according to the investment hypothesis. Overall, the investment factor INV seems to be less appropriate for explaining the differences in portfolio returns.

V. Conclusion

The aim of this study was to test the explanatory power of *Chen/Novy-Marx/Zhang's* (2010) alternative three-factor model on the German stock market. We applied the model to all companies listed on the highest market segment of the Frankfurt Stock Exchange from June 2004 through June 2015 in order to determine the factors INV and ROA. We also tested whether the alternative three-factor model could explain capital market anomalies better than the CAPM or the *Fama/French* three-factor model.

The investment factor INV has a statistically significant mean of 0.54 % during the observation period. The ROA definitions used in previous analyses of the German stock market led to negative ROA factors. In this case, the assumptions of the alternative three-factor model are not fulfilled. Two further definitions of ROA were introduced for the construction of the factor ROA, and they were better able to meet the demands for topicality.

The ROA factor ROA^C, with a highly significant mean, comes very close to the results of *Chen/Novy-Marx/Zhang* (2010) for the U.S. stock market. Except for the short-term momentum effect, the explanatory power of the alternative three-factor model using ROA^C is only at the CAPM level. Moreover, statistically significant factor weights cannot be found for either the investment factor or for the ROA factor.

Ultimately, our results indicate that the explanatory power of the alternative three-factor model is visible on the German stock market: Companies with higher levels of investments earn lower returns, while (currently) more profitable companies earn higher returns. However, the investment factor INV and the

ROA factor ROA seem to be less suitable to explain some of the anomalies for the German market that we tested here than the risk factors of the *Fama/French* three-factor model.

References

Aharoni, G./*Grundy*, B./*Zeng*, Q. (2013): Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis, Journal of Financial Economics, 110(2), 347–357.

Ammann, M./*Odoni*, S./*Oesch*, D. (2012): An alternative three-factor model for international markets: Evidence from the European Monetary Union, Journal of Banking & Finance, 36(7), 1857–1864.

Brückner, R./*Lehmann*, P./*Schmidt*, M. H./*Stehle*, R. (2015): Another German Fama/French Factor Data Set, Working Paper: http://dx.doi.org/10.2139/ssrn.2682617.

Campbell, J. Y./*Hilscher*, J./*Szilagyi*, J. (2008): In search of distress risk, Journal of Finance, 63(6), 2899–2939.

Carhart, M. M. (1997): On persistence in mutual fund performance, Journal of Finance, 52(1), 57–82.

Chan, L. K./*Jegadeesh*, N./*Lakonishok*, J. (1996): Mometum strategies, Journal of Finance, 51(5), 1681–1713.

Chen, L./*Novy-Marx*, R./*Zhang*, L. (2010): An alternative three-factor model, Working Paper, Washington University, St. Louis.

– (2011): An alternative three-factor model, Working Paper, Washington University, St. Louis.

Cochrane, J. H. (1991): Production-based asset pricing and the link between stock returns and economic fluctuations, Journal of Finance, 46(1), 209–237.

Cooper, M. J./*Gulen*, H./*Schill*, M. J. (2008): Asset growth and the cross-section of stock returns, Journal of Finance, 63(4), 1609–1651.

Fama, E. F./*French*, K. R. (1992): The cross-section of expected stock returns, Journal of Finance, 47(2), 427–465.

– (1993): Common risk factors in the returns on stocks and bonds, Journal of Financial Economics, 33(1), pp. 3–56.

– (1996): Multifactor explanations of asset pricing anomalies, Journal of Finance, 51(1), 55–84.

– (2006): Profitability, investment and average returns, Journal of Financial Economics, 82(3), 491–518.

Jegadeesh, N./*Titman*, S. (1993): Returns to buying winners and selling losers: Implications for stock market efficiency, Journal of Finance, 48(1), 65–91.

Kaserer, C./*Hanauer*, M. X. (2017): 25 Jahre Fama-French-Modell: Erklärungsgehalt, Anomalien und praktische Implikationen, Perspektiven der Wirtschaftspolitik, 18(2), 98–116.

Lewellen, J./*Nagel*, S./*Shanken*, J. (2008): A skeptical appraisal of asset pricing tests, Journal of Financial Economics, 96, 175–194.

Lintner, J. (1965). The valuation of risky assets and the selection of risky investments in stock portfolios and capital budgets, Review of Economics and Statistics, 47(1), 13–37.

Loughran, T./*Ritter*, J. R. (1995): The new issues puzzle, Journal of Finance, 50(1), 23–51.

Novy-Marx, R. (2013): The other side of value: The gross profitability premium, Journal of Financial Economics, 108(1), 1–28.

Ohlson, J. A. (1980): Financial ratios and the probalistic prediction of bankruptcy, Journal of Accounting Research, 18(1), 109–131.

Pontiff, J./*Woodgate*, A. (2008): Share issuance and cross-sectional returns, Journal of Finance, 63(2), 921–945.

Sharpe, W. F. (1963): A simplified model for portfolio analysis, Management Science, 9(2), 277–293.

Stehle, R. (2016): Fama/French Factors for Germany, abgerufen am 20. Juli, 2016 von https://www.wiwi.hu-berlin.de/de/professuren/bwl/bb/data/fama-french-factors-germany/fama-french-factors-for-germany.

Stehle, R./*Schmidt*, M. H. (2015): Returns on German Stocks 1954 to 2013, Credit and Capital Markets – Kredit und Kapital, 48(3), 427–479.

Subrahmanyam, A. (2010): The cross-section of expected stock returns: What have we learnt from the past twenty-five years of research? European Financial Management, 16(1), 27–42.

Walkshäusl, C./*Lobe*, S. (2014): The alternative three-factor model: An alternative beyond US Markets? European Financial Management, 20(1), 33–70.

White, H. (1980): A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, Econometrica, 48(4), 817–838.

Ziegler, A./*Eberts*, E./*Schröder*, M./*Schulz*, A./*Stehle*, R. (2003): Multifaktormodelle zur Erklärung deutscher Aktienrenditen: Eine empirische Analyse, Discussion Paper No. 03–45 (Zentrum für Europäische Wirtschaftsforschung).

Ziegler, A./*Schröder*, M./*Schulz*, A./*Stehle*, R. (2007): Multifaktormodell zur Erklärung deutscher Aktienrenditen: Eine empirische Analyse, Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschung, 59, 355–389.

Appendix

Table A.1

Number of Companies for Each Year

Column 1 shows the respective year, and column "Regulierter/Amtlicher Markt" shows the number of companies listed on the highest stock market segment of the Frankfurt stock exchange. Column "INV" represents the number of companies with all the necessary data for the construction of the investment factor *INV*. Columns ROA^k ($k = A$, …, D) represent the number of companies with all the necessary data for the construction of the investment factor ROA^k. These companies are the basis for all the analyses in the alternative three-factor model for the German stock market.

Year	Regulierter/ Amtlicher Markt	Firms	*INV*	ROA^A	ROA^B	ROA^C	ROA^D
2002	466	393					
2003	462	388					
2004	466	391	289	303	305	301	301
2005	471	396	298	309	310	308	308
2006	495	417	317	328	330	329	328
2007	513	433	335	352	355	353	352
2008	515	435	345	364	367	363	363
2009	497	422	345	360	362	351	350
2010	489	417	332	345	345	334	333
2011	482	410	323	337	337	332	332
2012	457	388	322	336	337	330	330
2013	441	375	315	327	327	314	313
2014	419	358	297	311	314	295	294
2015	403	348	278	297	299	271	270
Total	6.576	5.571	3.794	3.967	3.986	3.877	3.872

Table A.2

Descriptive Statistics for the Traditional Risk Factors

This table shows the descriptive statistics for the risk factors *MKT* ($r_{mt} - r_{ft}$, excess return of the stock market portfolio), *SMB* ("small minus big," difference in the return based on market capitalization), *HML* ("high minus low," difference in the return based on book-to-market ratio), *WML* ("winners minus losers," difference in the return based on prior year performance), and their affiliated t-statistics. All factors come from the website of *Stehle* (2016), and the calculations are based on the monthly returns from July 2004-June 2015. Statistical significance at the 1 %, 5 %, and 10 % levels is denoted by ***, **, and *, respectively.

	MKT	*SMB*	*HML*	*WML*
Mean	0.75*	–0.40	0.81***	1.10***
t-value	1.80	–1.48	3.24	2.65