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Working Papers on Finance No. 2012/2

Swiss Institute of Banking and Finance (S/BF – HSG)

August 2012

An alternative three-factor model for international markets: Evidence from the European Monetary Union

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This version: 1 February 2012

Abstract

In this paper, we construct the three-factor model introduced by Chen et al. (2010) for a European sample covering 10 countries from the European Monetary Union and the period from 1990 to 2006. Two key findings result. First, we show that the properties of the European factors are comparable to those of the U.S. factors. Second, we show that the alternative three-factor model's explanatory power is either equal or superior to the explanatory power of traditional models when applied to five commonly known stock market anomalies. Our results thus suggest the use of international versions of the Chen et al. (2010) factor model in addition to traditional factor models in international empirical finance research.

JEL classification: E44; G12; G14
Keywords: Multi-factor models; Cross-section of stock returns; Fama and French three-factor model

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[#] We are grateful to an anonymous referee, Ike Mathur (the editor), and research seminar participants at the University of St. Gallen for helpful comments. Part of this research was completed while Oesch was a visiting scholar at NYU's Stern School of Business. Financial support from the Swiss National Science Foundation is gratefully acknowledged.

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1. Introduction

Over the last decades, various stock market anomalies such as the asset growth effect (see e.g., Cooper et al., 2008), the short-term prior return effect (see e.g., Jegadeesh and Titman, 1993), or the net stock issues effect (see e.g., Pontiff and Woodgate, 2008) have been discovered and empirically analyzed. These persistent return patterns are called anomalies because they cannot be explained by traditional factor models such as the Fama and French (1993, 1996, FF) three-factor model.

Chen et al. (2010, CNZ) suggest an alternative three-factor model, consisting of a market factor, an investment factor and a return on asset (RoA) factor. The motivation behind this alternative three-factor model comes from investment-based asset pricing. In such an investment-based model, firms make optimal investment decisions given discount rates and expected future profitability. The actual investment of a company thus reveals information about the discount rate. All else being equal, a higher discount rate leads to lower net present values and thus lower investment, a lower discount rate leads to higher net present values and higher investment. Investment predicts returns because high costs of capital imply low net present values of new capital and low investment. Low costs of capital, on the other hand, imply high net present values of new capital and thus high investment. Performing a sort on investment is thus equivalent to sorting on the discount factor. This is the intuition behind CNZ's investment factor. As for the RoA factor, firms with higher expected RoA should have higher discount rates. These high discount rates are needed to offset the high RoA and generate low net present values of new capital and consequently low investment. If the discount rates are not high enough, these firms would experience high net present values of new capital and invest more. For the U.S. stock market sample used in CNZ, this alternative three-factor model outperforms the traditional FF model and is able to better explain a number of previously documented anomalies.

Given this evidence for the U.S market, the natural question that arises is whether the alternative three-factor model has more explanatory power than the traditional factor models in international markets as well. An evaluation of the international potential of the three-factor model proposed by CNZ is especially relevant given the growing number of empirical research that uses local versions of traditional factor models, for instance Ang et al. (2009) or Bekaert et al. (2009). If the alternative three-factor model is able to perform well internationally, this would call for its applicability not only in future U.S. studies but also in studies covering international stock markets. In this paper, we contribute to the literature on empirical factor models by constructing and evaluating the performance of the three-factor model proposed by CNZ in a pan-European sample covering the period from 1990 to 2006. The sample includes the main countries of the European Monetary Union (EMU), namely Austria, Belgium, Finland, France, Germany, Italy, Ireland, Netherlands, Portugal, and Spain. The choice of this pan-European sample is based on its economic relevance, its high development stage, the large number of available sample companies even in earlier years, and especially the mitigation of potential currency effects.

In a first step, we construct the investment factor and the RoA factor for our European sample. The return of the investment factor, r_{INV}, is calculated as the difference between the performance of a portfolio that is long in low-investment growth stocks and short in high-investment growth stocks. The return of the RoA factor, r_{RoA}, is calculated as the difference between the performance of a portfolio that is long in high-RoA stocks and short in low-RoA stocks. Following CNZ, the formula for the alternative three-factor model is then

$$E[r]-r_f=\beta_{MKT}E[r_{MKT}]+\beta_{INV}[r_{INV}]+\beta_{RoA}[r_{RoA}] \quad (1)$$

where $E[r_{MKT}]$, $E[r_{INV}]$, and $E[r_{RoA}]$ are expected premia and β_{MKT}, β_{INV}, and β_{RoA} are the factor loadings. We document that the investment factor has a time-series average of 0.44% per month, and the RoA factor has a time-series average of 0.84% per month. These properties are comparable to those reported by CNZ for the U.S., where the investment factor has a time-series average of 0.28% per month, and the RoA factor has a time-series average of 0.76% per month.

In a second step, we test the performance of the alternative three-factor model. To do so, we compare the ability of the model to explain five anomalies (the asset growth effect, the short-term prior return effect, the net stock issues effect, the total accruals effect, and the value effect) with the corresponding performance of the FF model and the CAPM one-factor model. Our results indicate that, depending on the anomaly investigated, the alternative three-factor model either performs similarly well or better than traditional models. When using our version of the CNZ model and comparing it to a single-factor CAPM or the FF model, the alphas generated by the asset growth effect, the short-term prior returns effect, and the total accruals effect are substantially reduced in size and significance. For the net stock issues effect and the value effect, the performance of the alternative three-factor model is comparable to the performance of the traditional FF model. Overall, our evidence indicates that the ability of the alternative three-factor model to potentially better explain stock market anomalies can also be observed in an international sample. Our results thus suggest that future empirical finance research using international samples could consider international versions of the CNZ three-factor model in addition to the CAPM and the traditional FF model.

The paper proceeds as follows. In Section 2, we describe the data used in our paper and detail the way in which we construct the CNZ three-factor model as well as the FF benchmark model for our sample. In Section 3, we compare the performance of the alternative factor model to the performance of the FF model and the CAPM. Section 4 concludes.

2. Data and factor construction

In this section, we first describe the data used in this paper. We then describe how we construct the international version of the CNZ factors and the FF benchmark model for our sample.

2.1. Data

We perform our analyses on an integrated European sample which consists of the largest countries in the European Monetary Union (EMU), namely Austria, Belgium, Finland, France, Germany, Italy, Ireland, Netherlands, Portugal, and Spain.[1] We choose this integrated European sample because of its important economic relevance, the high development stage of those markets, the large number of available sample companies even in earlier years, and especially the mitigation of potential currency effects. To be able to meaningfully construct the factor models, a sufficiently large number of observations is imperative.[2] For the construction of the factors, we use data from two data providers: Thompson Datastream for monthly observations of market values (MV), book-to-market values (BM) and stock returns and Thomson Worldscope for end-of-year accounting data. Table 1 provides an overview of

[1] Officially, Cyprus, Greece, Luxembourg, Malta, Monaco, San Marino, Slovakia, Slovenia, and the Vatican are also members of the EMU but not considered in our paper due to lack of data.

[2] One potential concern resulting from pooling the data across countries might be that our results could be driven by certain countries. To determine if our results are mainly driven by certain countries, we repeat all analyses in the paper for different sub-samples, excluding one country at a time. The results we obtain from these analyses are in line with the full sample results reported throughout the paper, indicating that our results do not seem to be driven by single countries.

the countries included in our sample and the resulting number of observations per year. Due to lack of data availability in earlier years, we start our sample in 1990 only, even though Worldscope provides data for some countries beginning in 1987 or even earlier. We use all companies for which data is available on Datastream and Worldscope and exclude financial firms because of their special balance sheet composition by excluding companies with a four digit SIC-code starting with a six.

Table 2 presents descriptive statistics for the main variables of interest in our sample. We calculate the means and medians as time-series averages of the respective yearly cross-sectional values. The large difference between means and medians is responsible for the left-tailed yearly cross-sectional dispersion of total assets and MV among companies in our sample. Although these differences might be surprising at first sight, comparable samples for the U.S. market show similar characteristics (see e.g., Cooper, Gulen and Schill, 2008). To mitigate concerns about results being driven by outliers, we repeat all empirical analyses in the following sections after trimming our sample at the 1% and 5% level. The results remain virtually the same, therefore we do not report these results.

2.2. Benchmark FF model

We construct the benchmark FF model for our European sample by following the methodology for local FF risk factors applied by Ang et al. (2009). The market factor r_{MKT} of the European sample is defined as the value-weighted excess return of the specific European market portfolio over the risk-free interest rate. To construct *SMB* and *HML*, we calculate returns of zero-cost portfolios. For *SMB*, we go long in the bottom tercile of the sample companies and short in the top tercile of the largest companies after we sort companies by their market value. For *HML*, we go long in the top BM-tercile and short in the bottom BM-tercile. All portfolios are formed on the first day of each month and are held for one month before rebalancing. To calculate abnormal returns (alphas), we use

$$r - r_f = \alpha_{FF} + \beta_{MKT} r_{MKT} + \beta_{SMB} r_{SMB} + \beta_{HML} r_{HML} + \varepsilon \qquad (2)$$

where r is the portfolio return of the European sample, r_f the risk-free interest rate, α_{FF} the risk-adjusted return, $r_{MKT,}$ r_{SMB} and, r_{HML} are the respective factor returns, and $\beta_{MKT,}$ β_{SMB} , and β_{HML} are the respective factor loadings.

2.3. *The investment factor*

Investment growth (*INVESTG*) is defined as the absolute change in PPE (Property, Plant, and Equipment) and Inventory from fiscal year ending in *t-2* to fiscal year ending in *t-1* divided by total assets of year *t-2*:

$$INVESTG_t = \frac{(PPE_{t-1} + Inventory_{t-1}) - (PPE_{t-2} + Inventory_{t-2})}{Total\ Assets_{t-2}} \qquad (3)$$

The left-hand side of Figure 1 plots the development of yearly cross-sectional average and median investment growth rates over the sample period. Our sample shows high levels of investment growth in 1995/1996 and in 1999 directly followed by sharp decreases of *INVESTG*. The large increase during 2004/2005 is followed by almost zero investment growth during 2006.

The model presented in CNZ predicts a negative relation between *INVESTG* and expected stock performance. We perform a mechanical sort including all sample companies into deciles ranked by *INVESTG* to check this prediction. Panel A of Table 3 presents the results of this exercise. Each year in July, stocks are assigned to one decile according to *INVESTG* with the lowest investment growth rate firms being in decile 1, the second lowest in decile 2 and so on. The portfolios are then held for one year before rebalancing. As can be seen in Table 3, the return spread between the extreme deciles 1 and 10 is negative but not significant. However, the lowest *INVESTG* companies (decile 1 to decile 3) earn significantly higher returns from July 1, *t* to July 1, *t+1* (*RET12*) than the highest *INVESTG* firms. This leads us to conclude that in our sample, low investment growth seems to be associated with comparatively high future returns.

To construct the investment factor, stocks are assigned to one of six portfolios according to MV and *INVESTG*. To do so, we perform a two-by-three sort on size and *INVESTG*. Based on the findings of Fama and French (2008), CNZ propose to control for size in the construction of the investment factor.

Each year *t* on July 1, all companies of our sample are divided into three different groups based on whether they are in the bottom 30%, the middle 40%, or the high 30% when ranked according to *INVESTG*. In addition, all sample stocks are split into two size groups using the median MV as breakpoint. Six different portfolios are then formed, and these portfolios are held for one year before rebalancing. For each of the six portfolios, we calculate monthly value-weighted returns. The investment factor is then computed as the difference of the average of the portfolio returns of the two low *INVESTG* portfolios minus the average of the portfolio returns of the two high *INVESTG* portfolios.

We show the main properties of the investment factor r_{INV} in Table 4. It has a statistically significant time-series average of 0.44%. Regressing r_{INV} on the market factor results in a statistically significant CAPM alpha of 0.46%. A regression on the FF factors still results in a significantly positive alpha, even though the coefficient is smaller, both in size and in significance. These results indicate that the investment factor cannot simply be explained by the FF risk-factors. Properties of the European sample's r_{INV} are comparable to the results in CNZ who obtain an average of 0.28% and similar results for the factor regressions.

2.4. The RoA factor

We calculate RoA as the yearly net income of a company divided by its total assets at the end of year *t-1* or[3]:

$$RoA_t = \frac{Net\ Income_{t-1}}{Total\ Assets_{t-1}} \tag{4}$$

The average RoA over our sample period is 3.21% with a corresponding cross-sectional standard deviation of 19.60%. In the right-hand side of Figure 1, we illustrate the development of the yearly mean and median RoA over the sample period from 1990 to 2006. After a sharp decline in 1999, RoA recovers somewhat after 2003/2004 and increases over the following period.

To empirically investigate the suggested positive relation between stock returns and RoA for our sample, we perform the same sorting procedure as for the investment factor. Panel B of Table 3 shows the results of the mechanical sort into deciles ranked by RoA. The calculated spread between the realized returns (*RET12*) of decile 10 and decile 1 is significant with an annualized value of 14.05%. In our sample, it thus seems to hold that low return on assets is associated with low future returns and vice versa.

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[3] The reason why we do not follow CNZ and use quarterly data to construct the RoA factor is due to data limitations. Worldscope provides quarterly data for selected companies starting from 1998. Unfortunately, however, the coverage for this quarterly data is sparse. Specifically, the number of companies for which we are able to obtain quarterly information needed to construct the RoA factor ranges from 114 (12% of sample companies) in 1998 to 920 (60% of sample companies) in 2006. It is only from 2003 onward that we are able to obtain the quarterly information for at least 50% of our sample. We thus do not use quarterly data to construct the RoA factor because this would reduce both the time-series and the cross-section of our sample too significantly to allow for meaningful statistical analysis and to compare the use of quarterly and annual data for the construction of the RoA factor.

The methodology we apply to construct the RoA factor is comparable to the one we use for the investment factor. Our definition of the RoA factor is based on CNZ instead of the modified version proposed by Chen et al. (2011). Each year *t* on July 1, we split our sample into three subsamples based on whether a company is in the low 30%, the middle 40%, or the high 30% of companies after they are sorted according to RoA. The MV breakpoints are the same as for the investment factor. Each stock is then assigned to one of the six portfolios formed by the intersections of the two size and three RoA groups. Portfolios are held for one year before rebalancing, and we calculate monthly value-weighted returns for each portfolio. The RoA factor is the difference between the average of the returns of the two high RoA portfolios minus the average of the returns of the two low RoA portfolios calculated on a monthly basis.

Table 5 shows the main properties of r_{RoA} and the results of simple regressions on the FF factors. The RoA factor has a statistically significant times-series average of 0.84% over the sample period from 1990 to 2006. Similar to our findings for r_{INV}, simple time-series regressions of the monthly RoA factor against the market factor or the FF model do not change the significantly positive alpha. Controlling for the market factor yields a significant CAPM alpha of 0.86%. Applying the FF model reduces the alpha somewhat to 0.79% but the statistical significance is not changed. As for the investment factor, the results presented in Table 5 are comparable to CNZ who find an average of 0.76% and similar results for the time-series regressions.

3. Performance of the alternative three-factor model

In this section, we evaluate the performance of the alternative three-factor model in our sample. To do this, we compare the ability of the alternative three-factor model to explain five well-known and documented stock market anomalies, the asset growth effect, the short-term prior return effect, the net stock issues effect, the total accruals effect, and the value effect. To empirically evaluate the model's performance, we estimate the following equation, where r denotes the return on the respective anomaly:

$$r - r_f = \alpha_q + \beta_{MKT} r_{MKT} + \beta_{INV} r_{INV} + \beta_{RoA} r_{RoA} + \varepsilon \qquad (5)$$

If it is the case that the alternative three-factor model does a better job than the traditional FF model, the resulting alternative three-factor alpha α_q should be smaller than α_{FF}, the alpha obtained when using the traditional three-factor model.

3.1. *Asset growth effect*

The asset growth effect describes the anomaly that there is a negative relationship between expected future returns and previous asset growth rates. This relationship has been well-documented for the U.S. stock market by Cooper et al. (2008). The asset growth effect is present in our sample as well. To show this and construct the returns of an asset growth strategy, the following methodology is applied. Companies are assigned to deciles according to their percentage change in total assets (*ASSETG*) from fiscal year ending in year *t-2* to fiscal year ending in year *t-1*. Firms with the lowest *ASSETG* are in decile 1, firms with the second lowest *ASSETG* in decile 2 and so on. Such portfolios are formed each year *t* on July 1 and held for one year before rebalancing. We calculate monthly value-weighted cross-sectional portfolio returns for each decile. The time-series average of monthly cross-sectional differences between the calculated returns of decile 10 and decile 1 is shown in Table 6 (denoted as *Spread*) and gives some indication of the relationship between *ASSETG* and expected returns.

Over the sample period from 1990 to 2006, the time-series average of monthly cross-sectional raw returns is 1.09% for the lowest asset growth rate companies and 0.33% for the highest asset growth rate companies. The spread is -0.76% and statistically significant. The event study around the portfolio formation date shows that the return spread changes from positive in year *t-2* to negative in year *t+1*. Those findings are in line with empirical analyses for a U.S. sample as shown in Cooper et al. (2008).

In Table 7, we compare the performance of the benchmark FF model with the alternative three-factor model in explaining the asset growth effect. We show the results of the regressions of the monthly spread portfolio returns on the market factor, on the FF factors, and on the alternative factors. Regressing the spread portfolio against the market factor yields a statistically significant CAPM alpha of -0.78%. The FF model reduces the spread from -0.76% to -0.60%, but the reduced spread is still statistically significant. The estimated betas for *SMB* and *HML* are statistically insignificant and therefore do not add much explanatory power. Regressing on the monthly factors of the alternative three-factor model, the alpha is reduced to -0.38%, and, more importantly, rendered insignificant. From Table 7 it also becomes evident that the alternative three-factor model takes its explanatory power mainly from the investment factor r_{INV} which has a beta of 0.46 for decile 1, -0.37 for decile 10 and -0.83 for the spread portfolio.

3.2. Short-term prior return effect

We now turn to a second return anomaly which we use to assess the performance of the alternative three-factor model in our sample. The short-term prior return effect describes the positive relation between short-term prior returns and expected stock returns. First, we document the existence of this anomaly in our sample. To do this, we form different size and momentum portfolios. We deviate somewhat from the proposed methodology by Jegadeesh and Titman (1993) and form only nine size and momentum portfolios instead of the proposed

25, due to limited data availability in our sample. To assign all sample stocks to 9 size/momentum portfolios, we use the 6/1/6 convention and rank stocks each month *m* according to their prior returns over the months *m-7* to *m-2*. Additionally, we determine the future return from month *m* to *m+5* for each stock. To control for size, stocks are sorted into three size groups (bottom, medium, and top tercile). Stocks are then assigned to one of the nine portfolios formed at the intersections of the three size and three momentum breakpoints. As can be seen in Table 8, we find highly significant stock returns for the Winner-minus-Loser (W-L) portfolio for small-sized companies (Small; average return 0.91%) and large caps (Big; average return 0.88%).

Table 8 also shows the results of regressions of the different W-L portfolios on the market factor, the FF factors, and the alternative three-factor model. The CAPM alpha for small caps is 0.92% and highly significant and for large firms 0.88% and highly significant as well. Applying the FF model reduces the alphas somewhat to 0.74% (Small) and 0.69% (Big). The time-series regression on the alternative three-factor model further reduces the W-L alpha to 0.63% for small companies and to 0.64% for big firms. Even though the W-L portfolio still shows a significant abnormal return, applying the alternative three-factor model reduces the spread, and this reduction is mainly driven by the RoA factor.

3.3. Net stock issues

The next anomaly we investigate describes the higher average returns that companies with low net stock issues earn compared to companies with high net stock issues. Following the U.S. evidence in Fama and French (2008) and Pontiff and Woodgate (2008) and the international evidence in McLean et al. (2009), we measure net stock issues as the difference between the natural logarithm of the adjusted number of shares outstanding in year *t-1* and the natural logarithm of the adjusted number of shares outstanding in year *t-2*. In July of each year *t*, we sort all companies and assign them to deciles. We then compute monthly value-weighted portfolio returns from July of year *t* to June of year *t+1*. To account for the large number of companies with zero net stock issues, we follow CNZ and assign all companies with negative net issues to the lowest decile and all companies with zero net issues to decile two.

In Table 9, we first document the existence of the net stock issues anomaly in our sample. The average return for low net issues companies is 0.79% and the average return for high net issues companies is 0.18%. The spread portfolio of high-minus-low net issues companies has an average return of -0.61% and is statistically significant. The CAPM alpha of the high-minus-low spread portfolio is -0.64% and also statistically significant. Next, we compare the performance of the benchmark FF model with the alternative three-factor model in explaining the net stock issues effect. The results in Table 9 indicate that both models do an equally good job at explaining the net stock issues effect. Both the FF model and the alternative three-factor model produce an alpha that is very similar in size (-0.23% for the FF model and -0.22% for the alternative three-factor model) and insignificant in both cases. We also note that the significantly negative coefficient on the RoA factor of the alternative factor model is consistent with CNZ, who argue that firms with relatively high net issues are less profitable compared to companies with low net issues at portfolio formation, a finding that is consistent with Lie (2005), who shows that companies that repurchase stocks have better operating performance than their industry peers.

3.4. Total accruals

We next turn to the accruals anomaly, which describes the empirical finding that companies with high total accruals earn lower returns than companies with low total accruals. Following Sloan (1996), we compute total accruals as follows:

$$Accruals = (\Delta CurrentAssets - \Delta Cash) - (\Delta CurrentLiabilities - \Delta DebtinCurrentLiabilities - \Delta TaxesPayable) - Depreciation \quad (6)$$

We scale total accruals with average total assets (defined as the mean of total assets of the current and the lagged fiscal year). To construct the anomaly, we proceed as follows. In July of each year *t*, we sort all companies into deciles based on their total accruals for the end of year *t-1*. We then calculate value-weighted returns from July of year *t* to June of year *t+1* and rebalance the portfolios after a year. In Table 10, we first show that the high-minus-low accruals spread portfolio earns a statistically significant average return of -0.57%. The CAPM alpha of the spread portfolio is also -0.57% and significant. The FF model is not able to explain the total accruals effect, and the FF model alpha is significant and -0.65%, even slightly higher than the CAPM alpha. The alternative three-factor model, however, reduces the alpha substantially to -0.38%. Even though the alternative three-factor model is not able to fully explain the total accruals effect and the alpha is still statistically significant, the significance of the alpha also drops compared to the CAPM and the FF model alpha. The alternative three-factor model thus seems to have better explanatory power than the traditional models for the total accruals anomaly. Consistent with the findings in CNZ, we find the increased explanatory power of the alternative three-factor model for the accruals anomaly to largely come from the high loading on the investment factor for the high-minus-low accruals spread portfolio.

3.5. Value

Finally, in Table 11, we report results from factor regressions using size and BM portfolios. Similar as for the short-term prior return effect above, we form only nine size and book-to-market portfolios instead of the 25 used by Fama and French (1993), due to limited data availability in our sample. First, we show that value stocks (stocks with high book-to-market ratio) earn higher returns on average than growth stocks (stocks with low book-to-market ratio). For small-size companies, the average high-minus-low portfolio return is 1.05% per month. For large-size companies, the average high-minus-low portfolio is 0.45% per month. Both of these returns are statistically significant at the 1% level. The high-minus-low portfolio for small stocks has a significant CAPM alpha of 1.06% and a significant FF model alpha of 0.79%. For large companies, the high-minus-low portfolio has a CAPM alpha of 0.45% and a FF model alpha of 0.41%. As in CNZ, we note the existence of the small-growth effect, and this particular portfolio has a negative average return of -0.73% and negative CAPM and FF model alphas (-0.78% and -0.37%, respectively). As for the comparison of the explanatory power of the FF model and the alternative three-factor model, the results presented in Table 11 indicate that both models' overall performance is similar. The alphas of the spread portfolios are equally significant for the FF model and the alternative three-factor model and the alphas resulting from the FF model are slightly smaller than the alphas form the alternative three-factor model. Our results in Table 11 also show that, consistent with CNZ, value stocks have higher loadings on the investment factor than growth stocks.

4. Conclusion

In this paper, we construct the alternative three-factor model proposed by CNZ for a European sample comprising 10 countries of the European Monetary Union and covering the period from 1990 to 2006. We find that the factors we construct show similar properties to the corresponding U.S. factors. To test the explanatory power of the alternative three-factor model, we document its ability to explain five well-known return anomalies, the asset growth effect, the short-term prior return effect, the net stock issues effect, the total accruals effect, and the value effect. Overall, our results show that the alternative three-factor model proposed by CNZ performs at least equally well or better than the traditional CAPM and FF models in explaining the anomalies considered in this paper. Depending on the anomaly investigated, the alternative three-factor model is able to fully explain (asset growth effect) or better explain (short-term prior return effect and total accruals effect) three out of five anomalies. For the net stock issues effect and the value effect, the explanatory power of the three-factor model is comparable to the FF model. Overall, we believe that our empirical analyses gives an indication of the international applicability of the alternative three-factor model. Given that both the factors' properties and their explanatory power seem to be similar in our international sample and the U.S. sample, our results indicate that the alternative three-factor model proposed by CNZ might deserve a role in future empirical finance research for international samples where a factor model is used to evaluate fund performance, measure abnormal returns in event studies or to calculate the cost of equity for capital budgeting.

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Table 1: Sample countries included in the sample

year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006
Austria	9	15	22	24	29	30	32	37	40	40	49	45	40	45	43	46	44
Belgium	12	24	30	39	42	44	45	47	46	45	54	69	69	69	72	67	68
Finland	-	5	13	26	27	27	31	49	48	52	67	86	96	100	103	96	101
France	135	193	220	237	252	266	279	291	274	282	411	471	491	513	506	489	460
Germany	59	153	170	182	198	207	226	261	267	272	317	371	448	466	490	495	481
Ireland	1	6	10	18	19	18	23	25	27	23	22	20	24	23	24	20	24
Italy	12	45	61	70	70	70	71	69	67	66	80	87	98	133	142	141	145
Netherlands	20	34	65	79	97	101	106	112	105	95	103	107	113	110	101	96	95
Portugal	-	7	15	21	23	30	31	29	33	30	37	34	37	39	41	39	37
Spain	11	24	40	52	56	65	68	69	69	70	80	82	86	89	89	89	87
Europe	**259**	**506**	**646**	**748**	**813**	**858**	**912**	**989**	**976**	**975**	**1220**	**1372**	**1502**	**1587**	**1611**	**1578**	**1542**

Table 1 presents an overview of all sample countries together with the included number of firms for each year from 1990 to 2006. All countries are members of the European monetary union. Financial firms (defined as firms with a four digit SIC-code starting with a six) are excluded from the sample.

Table 2: Descriptive statistics of the sample from 1990 to 2006

		Mean	Median
Total Assets		**2629.33**	**230.79**
	CAGR	*4.20%*	*-2.84%*
MV		**1604.05**	**131.05**
	CAGR	*9.46%*	*2.91%*
BM		**0.74**	**0.59**
	CAGR	*-3.00%*	*-2.00%*
INVESTG		**0.07**	**0.01**
	CAGR	*-16.78%*	*-4.43%*
RoA		**0.03**	**0.04**
	CAGR	*-5.42%*	*0.48%*

Table 2 shows descriptive statistics for key financial and accounting variables used in the paper. *MV* denotes market value, *BM* denotes book value, *INVESTG* denotes investment growth, calculated as the absolute change in *PPE* (Property, Plant, and Equipment) and Inventory from fiscal year ending in *t-2* to fiscal year ending in *t-1* divided by total assets from fiscal year ending in *t-2*. RoA is calculated as the yearly net income of a company divided by its total assets at the end of year *t-1*. *CAGR* denotes the compounded annual growth rate (*CAGR*).

Table 3: INVESTG and RoA ranked deciles

Panel A

Decile	INVESTG	RoA	RET12	ASSETS	MV	BM	BHRET24	EBIT
1 (low)	-0.1354	0.0145	0.0336	128.32	50.52	0.6326	-0.1159	3.60
2	-0.0457	0.0274	0.0536	154.98	75.87	0.6665	-0.0085	6.44
3	-0.0117	0.0351	0.0594	234.86	116.42	0.6671	0.0361	12.32
4	0.0132	0.0402	0.0775	249.30	129.46	0.6706	0.0532	13.80
5	0.0299	0.0459	0.0627	291.22	171.11	0.6294	0.0901	19.74
6	0.0559	0.0487	0.0605	321.03	180.84	0.6080	0.1184	21.11
7	0.0835	0.0523	0.0616	289.63	173.17	0.6092	0.1379	21.82
8	0.1166	0.0548	0.0422	282.93	173.21	0.5782	0.1391	20.65
9	0.1865	0.0550	0.0430	260.47	157.35	0.5793	0.1668	19.68
10 (high)	0.4140	0.0545	0.0144	260.76	149.84	0.5787	0.2260	18.03
Spread	0.5494 ***	0.0400 ***	-0.0192	132.44 ***	99.32 ***	-0.0539 *	0.3419 ***	14.43 ***

Panel B

Decile	RoA	INVESTG	RET12	ASSETS	MV	BM	BHRET24	EBIT
1 (low)	-0.1313	-0.1062	-0.0684	174.07	62.44	0.5131	-0.5741	-6.32
2	-0.0181	-0.0073	-0.0107	264.61	81.53	0.7166	-0.2629	3.94
3	0.0126	0.0180	0.0170	296.1	104.96	0.7203	-0.0449	10.38
4	0.0291	0.0448	0.0557	311.36	124.35	0.7415	0.0273	14.85
5	0.0400	0.0596	0.0648	359.06	173.96	0.7268	0.1019	21.92
6	0.0505	0.0710	0.0742	354.72	173.88	0.7118	0.1435	26.99
7	0.0614	0.0773	0.0741	354.49	197.90	0.6544	0.2158	31.16
8	0.0747	0.0850	0.0665	291.25	205.25	0.6011	0.2107	30.93
9	0.0949	0.0978	0.0875	205.49	192.14	0.5208	0.2876	26.40
10 (high)	0.1435	0.1410	0.0720	117.05	141.57	0.3974	0.3460	22.27
Spread	0.2748 ***	0.2472 ***	0.1404 ***	-57.02 ***	79.13 ***	-0.1157 ***	0.9201 ***	28.59 ***

Table 3 shows financial and accounting variables for the sample split into deciles. Each year *t* on July 1, all stocks are assigned to one decile ranked by *INVESTG* (panel A), or RoA (panel B). *RET12* denotes the future 12-month decile return from July 1 of year *t* to July 1 of year *t+1*. *ASSETS* denotes total assets at the end of year *t-1*. *BHRET24* denotes the 24-month lagged decile return from July 1 of year *t-2* to July 1 of year *t*. *EBIT* denotes Earnings Before Interest and Taxes at the end of year *t-1*. All other variables are explained in Table 2. All numbers are time-series averages of yearly cross-sectional medians covering the sample period from 1990 to 2006. Spreads are calculated as time-series average of monthly cross-sectional differences between decile 10 and decile 1. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 4: Properties of the investment factor r_{INV}

	average		α		β_{MKT}		β_{SMB}	β_{HML}	R^2
r_{INV}	0.44%		0.46%		-0.13				0.07
	2.77	***	*2.96*	***	*-3.61*	***			
r_{INV}			0.35%		-0.14		-0.05	0.06	0.08
			1.97	**	*-3.98*	***	*-0.87*	*1.30*	

Table 4 shows the properties of the investment factor over the sample period from 1990 to 2006. Each year *t* on July 1, stocks are split into three *INVESTG* groups depending on whether they are in the top 30%, the medium 40% or the bottom 30% of the empirical *INVESTG* distribution. Additionally, all stocks are divided into two size groups (low 50%, high 50%) using the median MV at the end of year *t-1*. For each of the resulting six portfolios, monthly value-weighted returns are calculated. Portfolios are held for one year before rebalancing. Each month, r_{INV} is calculated as the difference between the average return of the two low *INVESTG* portfolios minus the average return of the two high *INVESTG* portfolios. r_{INV} is regressed on traditional FF factors such as the market factor, *SMB* and *HML*. All *t*-statistics are in italics below the coefficients. They are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 5: Properties of the RoA factor r_{RoA}

	average		α		β_{MKT}		β_{SMB}		β_{HML}		R^2
r_{RoA}	0.84%		0.86%		-0.15						0.08
	4.72	***	*5.00*	***	*-4.23*	***					
r_{RoA}			0.79%		-0.23		-0.31		-0.17		0.32
			4.66	***	*-6.76*	***	*-5.65*	***	*-3.77*	***	

Table 5 shows the properties of the RoA factor over the sample period from 1990 to 2006. Each year *t* on July 1, stocks are split into three RoA groups depending on whether they are in the top 30%, the medium 40% or the bottom 30% of the empirical RoA distribution. Additionally, all stocks are divided into two size groups (low 50%, high 50%) using the median *MV* at the end of year *t-1*. For each of the resulting six portfolios, monthly value-weighted returns are calculated. Portfolios are held for one year before rebalancing. Each month, r_{RoA} is calculated as the difference between the average return of the two low RoA portfolios minus the average return of the two high RoA portfolios. r_{RoA} is regressed on traditional FF factors such as the market factor, *SMB* and *HML*. All *t*-statistics are in italics below the coefficients. They are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 6: Monthly raw returns for asset growth rate deciles

Year	1(low)	2	3	4	5	6	7	8	9	10(high)	Spread
-2	-0.0062	0.0027	0.0063	0.008	0.0092	0.0118	0.011	0.0126	0.019	0.0193	0.0255 ***
-1	0.0047	0.007	0.0112	0.0106	0.0084	0.0091	0.0118	0.0108	0.0101	0.0168	0.0121 ***
1	0.0109	0.0061	0.0082	0.008	0.0067	0.0082	0.0059	0.004	0.0026	0.0033	-0.0076 ***

Table 6 shows the returns of different asset growth deciles. The asset growth rate is calculated as the percentage change of total assets from the end of fiscal year *t-2* to the end of fiscal year *t-1*. Each year *t* on July 1, stocks are assigned to one decile according to the ranked *ASSETG*. For each portfolio, monthly value-weighted returns are calculated. In the row Year -2, returns are calculated from July in year *t-2* to July in year *t-1*. In the row Year -1, returns are calculated from July in year *t-1* to July in year *t*. In the row Year 1, returns are calculated from July in year *t* to July in year *t+1*. All numbers are time-series averages of monthly cross-sectional value-weighted returns. The spread is the time-series average of monthly return differences between decile 10 and decile 1. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 7: Regression analysis of the asset growth effect

Decile1	Decile5	Decile10	Spread	Decile1	Decile5	Decile10	Spread
Mean				**α_q**			
0.0109 ***	0.072 **	0.0033	-0.0076 **	0.0049 *	0.0221	0.0011	-0.0038
α_{CAPM}				**β_{INV}**			
0.0059 **	0.041 **	-0.0019	-0.0078 **	0.4621 ***	0.1124 *	-0.3742 ***	-0.8330 ***
α_{FF}				**β_{RoA}**			
0.0063 **	0.0048 *	0.0003	-0.0060 *	-0.1375	-0.1388	-0.1492	-0.0050

Table 7 presents average return of asset growth portfolios, alphas obtained from time-series regressions on the market factor (*CAPM*), the FF risk factors (*FF*), and the alternative three-factor model (*q*), and the factor loadings for the investment factor and the RoA factor. All *t*-statistics are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 8: Regression analysis of the short-term prior return effect

	Loser		Middle		Winner		Spread		Loser		Middle		Winner		Spread	
	Mean								α_q							
Small	-0.0007		-0.0001		0.0084	***	0.0091	***	-0.0013		0.0027		0.0050	**	0.0063	***
Big	-0.0036		0.0008		0.0052	***	0.0088	***	0.0008		0.0024		0.0056	*	0.0064	***
	α_{CAPM}								β_{INV}							
Small	-0.0048	*	-0.0011		0.0044	**	0.0092	***	-0.3024	***	-0.3831	**	-0.1409		0.1615	*
Big	-0.0038		0.0007		0.0051	***	0.0088	***	-0.2209	**	-0.1802	**	-0.1204		0.1005	*
	α_{FF}								β_{RoA}							
Small	-0.0008		0.0031	*	0.0066	***	0.0074	***	-0.2447	**	-0.2426	*	0.0020		0.2467	***
Big	-0.0002		0.0033	*	0.0068	***	0.0069	***	-0.2294	**	-0.122	*	-0.0006		0.2288	***

Table 8 presents average return of short-term prior return portfolios, alphas obtained from time-series regressions on the market factor (*CAPM*), the FF risk factors (*FF*), and the alternative three-factor model (*q*), and the factor loadings for the investment factor and the RoA factor. All *t*-statistics are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 9: Regression analysis of the net issuance effect

Decile1	Decile5	Decile10	Spread	Decile1	Decile5	Decile10	Spread
	Mean				**α_q**		
0.0079 **	0.0065 *	0.0018	-0.0061 **	0.0071 **	0.0044 *	0.0050 *	-0.0022
	α_{CAPM}				**β_{INV}**		
0.0069 ***	0.0053 **	0.0005	-0.0064 **	-0.0942	-0.1662	-0.1104	-0.0161
	α_{FF}				**β_{RoA}**		
0.0036 *	0.0031	0.0013	-0.0023	0.0225	0.0145	-0.4599 ***	-0.4824 ***

Table 9 presents average return of net issuance portfolios, alphas obtained from time-series regressions on the market factor (*CAPM*), the FF risk factors (*FF*), and the alternative three-factor model (*q*), and the factor loadings for the investment factor and the RoA factor. All *t*-statistics are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 10: Regression analysis of the total accruals effect

Decile1	Decile5	Decile10	Spread	Decile1	Decile5	Decile10	Spread
Mean				**α_q**			
0.0035	0.0011	-0.0022	-0.0057 **	0.0058 **	0.0033 *	0.0020	-0.0038 **
α_{CAPM}				**β_{INV}**			
0.0026	0.0001	-0.0032 *	-0.0057 ***	0.1620	0.0029	-0.2173 *	-0.3728 ***
α_{FF}				**β_{RoA}**			
0.0074 ***	0.0057 **	0.0010	-0.0065 ***	-0.4634 ***	-0.4421 **	-0.4867 **	-0.0108

Table 10 presents average return of accruals portfolios, alphas obtained from time-series regressions on the market factor (*CAPM*), the FF risk factors (*FF*), and the alternative three-factor model (*q*), and the factor loadings for the investment factor and the RoA factor. All *t*-statistics are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 11: Regression analysis of the value effect

	Low	Middle	High	Spread	Low	Middle	High	Spread
	Mean				**α_q**			
Small	-0.0073 ***	-0.0011	0.0032 **	0.0105 ***	-0.0043 ***	0.0027	0.0038 **	0.0081 ***
Big	0.0004	0.0011	0.0049 ***	0.0045 ***	0.0005	0.0031 **	0.0054 ***	0.0049 ***
	α_{CAPM}				**β_{INV}**			
Small	-0.0078 ***	-0.0019	0.0029 **	0.0106 ***	-0.4426 ***	-0.1543 **	0.1224	0.4873 ***
Big	-0.0001	0.0009	0.0043 ***	0.0045 ***	-0.2054 ***	-0.0196 **	0.0159	0.2748 ***
	α_{FF}				**β_{RoA}**			
Small	-0.0037 ***	0.0026 *	0.0042 **	0.0079 ***	-0.2897 **	-0.4540 ***	-0.5675 ***	-0.3079 **
Big	0.0012 *	0.0021 **	0.0041 ***	0.0041 ***	-0.0611 **	-0.0641 **	-0.2526 ***	-0.1883 **

Table 11 presents average return of value portfolios, alphas obtained from time-series regressions on the market factor (*CAPM*), the FF risk factors (*FF*), and the alternative three-factor model (*q*), and the factor loadings for the investment factor and the RoA factor. All *t*-statistics are adjusted for heteroscedasticity and autocorrelation. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Figure 1: Yearly INVESTG and RoA for sample companies

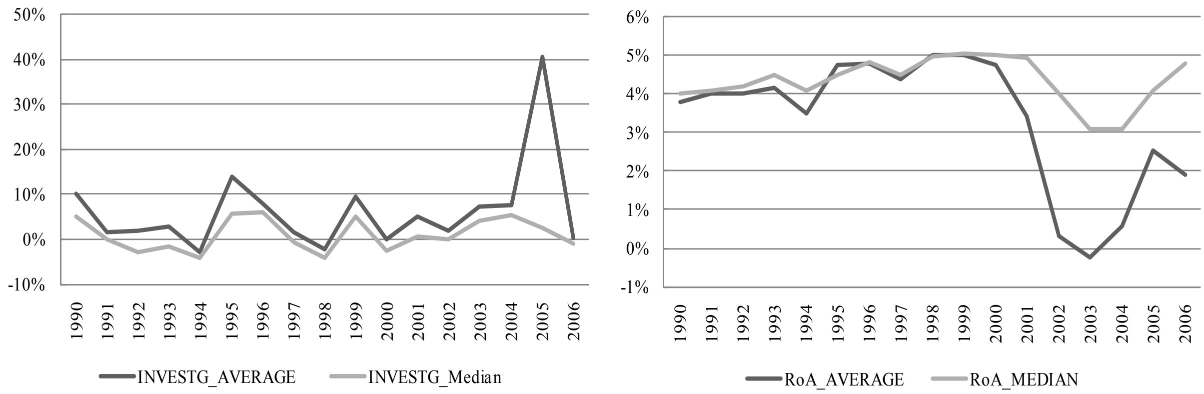

Figure 1 shows the cross-sectional development of annual INVESTG and RoA for the sample from 1990 to 2006. INVESTG_AVERAGE (INVESTG_MEDIAN) and RoA_AVERAGE (RoA_MEDIAN) denote yearly cross-sectional means (medians) of INVESTG and RoA.