2. MODELING PORTFOLIO RETURNS ON BUCHAREST STOCK EXCHANGE USING THE FAMA-FRENCH MULTIFACTOR MODEL

Andrei ANGHEL[1]
Dalina DUMITRESCU[2]
Cristiana TUDOR[3]

Abstract

The Fama–French three-factor model is known to explain the cross-section of average returns better than the market beta alone across various international equity markets. No such implementation exists, however, for the Romanian capital market. This paper contributes to the existing literature by calibrating the model on the Bucharest Stock Exchange and by relying on a complex, correct and complete database. We show that the three-factor model captures more variation in portfolio returns than the classical model (as attested by the higher adjusted R^2) while it also passes standard diagnosis tests (the hypothesis that pricing errors are jointly equal to 0 cannot be rejected by the GRS test statistics on the regressions intercepts). Robustness check demonstrates that the model is informative on seemingly unrelated time series; further, we also provide a simple application of performance attribution.

Keywords: Fama–French three-factor model, asset pricing, GRS test, Romanian equity market

JEL Classification: G12, G14, G15

Introduction

There is compelling evidence that the cross-section of average stock returns is not completely explained by the market beta alone. This finding is extensively covered in the financial literature for various international stock markets (see Fama and French, 1992, for a thorough review).

[1] *FABBV, Bucharest University of Economic Studies, andrei.anghel@strade.ro.*
[2] *FABBV, Bucharest University of Economic Studies, dalina.dumitrescu@fin.ase.ro.*
[3] *REI, Bucharest University of Economic Studies, cristiana.tudor@net.ase.ro.*

For the Romanian stock market, Tudor (2009) shows that the relation between stock returns and beta is insignificant, while Dragotă (2007) also points out some of the difficulties in applying CAPM for pricing the Romanian stocks.

In addition, a whole list of other variables which show reliable power in explaining the cross-section of average stock returns has emerged in the financial literature. Among these, the most notorious are:

- size - Banz (1981), Fama and French (1992)

  book-to-market equity - Fama and French (1992, 2012), Rosenberg, Reid, and Lanstein (1985)
- dividend yield – Litzenberger and Ramaswamy (1979)
- momentum - Jegadeesh and Titman (1993)
- earnings yield - Basu (1983)
- leverage - Bhandari (1988)

Fama and French (1993) proposed the elegant solution of defining risk factors as zero-investment portfolios capturing variability associated with some variables, such as Size or P/BV; their conjecture was that these factors, next to the market factor, would have a better chance of explaining the cross-section of average returns. The now famous three-factor model takes the following form:

$$R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + e(t),$$

where: $RM(t)- RF(t)$ is the excess market return, $HML(t)$ is the return on Value minus Growth stocks and $SMB(t)$ is the return on small minus big stocks.

Built on the success of the above equation, several variations have been added since, either by including other factors (such as momentum – Carhart, 1997) or constructing regional and global versions of the initial factors (Fama and French, 2012).

However, in spite of its evident merits, and more than 20 years since its development, the Fama- French three-factor model has not yet been implemented on the Romanian capital market. It is this gap that our study tries to fill in.

A previous study (Tudor, 2009) proposes a multifactor model that shows that firm characteristics such as book-to-market equity or earnings yield could explain returns of the Romanian stocks market. However, most of the other studies dedicated to the Romanian equity market concentrate on modeling returns or volatility using only past prices as dependent variables (Acatrinei and Caraiani, 2011; Necula, 2009; Pele and Voineagu, 2008) or use other global indices or macro variables (Panait, 2011).

The reason why researchers seem to ignore fundamental factors in modeling prices on the Romanian market is, in our opinion, twofold: the quality of fundamental financial data is questionable; and the cross-section of listed companies is limited to less than 77 companies at best. It is only by benefiting from a new, revised database and by carefully adjusting all available data, that we were now able to gather enough information for this study.

We show that multifactor models are a better way than the CAPM for explaining stock returns on our database; while it is unclear whether the additional variables *per se* are responsible for the observed effect (such as size or growth/value effect) or they just proxy for other true unknown factors, they manage nevertheless to extract more of the already available information. Although multifactor models such as the current one could hardly be rejected in formal statistical tests such as GRS (given the short sample size), their value is obvious because of the higher level of explained variation even when applied to unrelated time-series (see the robustness checks). Also, these models provide the advantage of allowing for further improvement of the existing factors, or for adding new ones.

The step-by-step implementation of the standard three-factor model is detailed in the following sections. The remainder of the paper is organized as follows. Section 1 describes the data, underlines the pitfalls of the typical data sources for the Romanian equity market and explains the way we have handled them; also in section 1 the methodology for the construction of the variables is presented. Section 2 details the added benefit of using multifactor models as expressed by R^2; Section 3 analyses the model by comparing and formally testing that all intercepts are equal to 0; Section 4 verifies whether the factor model can be used on seemingly unrelated time series and provides a simple application on real data; Section 5 summarizes and concludes the paper.

1. Data

This section explains some of the unique characteristics of our database and details some critical inputs and adjustments made to this data. The last part describes the methodology for constructing the quintessential dependent and independent variables.

Companies Included

We have included in our research all the 98 companies ever listed under the "BVB" section[4] of the Bucharest Stock Exchange on the First and Second Categories[5] at any time during July 2006 until December 2013. In this way, the database contains a minimum of 59 companies in 2006 and a maximum of 84 companies in year 2011 (see Table 1).

We have used financial data from two sources, which makes our database more thorough and more correct than any other set of similar financial data ever used when analyzing companies listed on BSE. First of all, this is most likely the first time when the StockGround[6] database concerning Romania was used in a research paper. Their database covers financial information starting with the first quarter of 2004 and has some unique characteristics among similar databases: they allow the critical adjustment of prices to changes in the number of shares and/or dividends, and also allow the use of newer IFRS (as the preferred alternative to Romanian Accounting

[4] *The other section of Bucharest Stock Exchange is RASDAQ.*

[5] *There are other 3 categories: 3rd Category, International Category and Category "Unlisted": we did not include any of these, due primarily to the more relaxed reporting requirements for these companies (except International), which would have made our data collecting task extremely difficult.*

[6] *Courtesy of Rasyonet (see www.rasyonet.com for details).*

Standards) when these data were available. Consequently, this paper is among the few studying the Romanian Stock Market that uses closer-to-fair accounting values, stock prices that were adjusted to incorporate dividend returns and that is not plagued by the misleading effect that capital increases have on prices and returns[7].

However, since the information were collected mainly with the practitioner's needs as a concern, the Stockground database suffers as of this date from survivorship bias (until 2010 at least). As a consequence, some companies that were no longer listed in 2010 were never included in the database for earlier periods. This brings us to our second source of data, as the BSE's database is more thorough and includes all the companies ever listed. On the other hand, BSE's database exposes the researcher to the danger of backfill bias (when listed, some history of a specific company would be filled in and the company is included in statistics since the moment of the oldest report, although the company did not start trading but later in the categories that we follow). It also allows users to retrieve information concerning financial ratios only down to November 2006.

In order to mitigate these difficulties, we proceeded as follows: we used the companies included in the BET-C index plus the SIFs (investment companies, which are very popular judged by trading volume, but were not included in BET-C) as of the end of each month for the next month; these historics of BET-C constituency was provided by Stockground. Further, we used Stockground data on Price on Book values (P/BV) if available; else, we used BSE's data on book values and (the correct) Stockground adjusted prices. Some companies started trading during the covered period: although we did have book values for the prior end of year, we did not have returns for all the months (unless starting trading in January). To mitigate this, we eliminated those companies from the database for the first month of their listing (if transferred from another category) or for the first year of their listing (if the company was newly listed through IPO). How we handled such events it is described later. The number of companies per year that were used in our research is presented in Table 1.

Table 1

Number of Companies Included in Research

year	2005	2006	2007	2008	2009	2010	2011	2012
no of comp.	65	59	64	70	73	81	84	82

Book and Market Values of Equity (BE and ME)

There are no companies with preferable shares listed on Bucharest Stock Exchange so there is no need of a correction of stated book equity; we did not compute any allowances regarding deferred taxes or investment tax credit to be added up to book value. Common equity is simply the company's capitalization (number of shares, multiplied by adjusted price per share). In order to eliminate any suspicion regarding some look-ahead bias when sorting companies based on book value, we have allowed for full 6 months to pass from the end of each year until the actual sorting took

[7] *Legal procedures concerning capital increases, dividends, splits and GSMs were different before 2005; as a result, any attempt to adjust and use prices en masse for earlier periods might result in serious errors.*

place at the end of June. This is because many listed companies publish their reports with some delay, and while 3 months would be a more accurate estimate for the typical delay, a 6 months allowance is a more cautious approach. Consequently BE/ME or Book to common equity is defined as book value of equity at the end of year *t*-1 divided by market cap at 30 June, year *t*.

Handling Unusual Market Events

There are 98 companies that, at some point in time, were part of BSE's 1st or 2nd categories. 37 out of them or added at some point during June 2006 and November 2013, as a result of IPOs or transfer from other categories of BSE. There were also 16 events when companies were dropped from the two main categories, as a result of de-listing, transfer or bankruptcy. More generally, we treated these types of events as follows:

- IPOs - when a company is listed before July of year *t*, we include it in July, the same year. Otherwise we include that company only in July, *t*+1
- Transfers in – we include the company two months after the event. For example, if a company is transferred on 14 July, we include that company starting with September; the company's return in September is the first monthly return included for that company (transferred company, unlike IPOs, already have reliable *ME* and *BE* for year *t*-1. We exclude it however for two months to allow for the readjustment of price that some might suspect to occur when a company is promoted to a superior category)
- Transfers out – the last return is the return in the last month when the company was listed, irrespective of the company's new category
- De-listing – the last return is the return in the last month when the company was listed.
- Bankruptcy – the last return is -100% in the month following the month when a company was traded for the last time, irrespective of the time when the company is actually officially excluded from trading. This treatment might introduce some looking forward bias (an investors could not possibly know in advance that a company in financial difficulties is about to either (1) go bankrupt or (2) never be traded again). However, since the alternative would be to arbitrarily allocate the 100% loss to some other month when the bankruptcy might have become apparent, we prefer to chose this simpler approach. We don't think that this treatment and the number of cases involved would actually influence our inferences. We have no information whatsoever regarding recovering values, if any.
- Investment funds - we have also excluded companies that traded as investments funds, as the book value was hard to estimate, being related to some other financial derivatives/indices, etc. These companies were seldom traded and were never part of BET-C index so this treatment is consistent with that of BSE. We must mention that this approach does not apply to investment *companies* (not *funds*) which are some of the most popular companies listed on BSE and thus a very integral part of our research.

- Negative book-value companies are excluded starting with July year *t* if the book value at the end of year *t*-1 is negative. We keep those companies excluded irrespective of the fact that (most of them) continued trading or, in rare cases, recovered. It is worth noticing that we do not eliminate these companies before the BV turns negative. However, only for the sake of computing market return (*RM*) we still include these companies; otherwise they are discarded for the computation of any factor-portfolios.
- Momentum factor requires a full year of trading data before any company is included in its computation; however those companies that did not satisfy this condition were not excluded, as they could still be part of other factor-portfolios.

In consequence, from a total of 98 companies, as few as 21 and as many as 44 were excluded each month from the database as result of adjustments made to eliminate back-fill bias, negative book-values, bankruptcies, companies with difficulty to estimate BV, companies transferred outside our research area, etc. This leaves us with at least 54 companies each month, or as much as 77 in more recent months.

Further, we describe the independent variables of our regressions (the factors) and the returns to be explained.

The Factors – Local Setting

We use the market factor *RM-RF*, constructed in the usual way. Furthermore, as in Fama and French (1993), we use six portfolios formed from sorts of stocks on ME and BE/ME: these portfolios are meant to mimic the underlying risk factors in returns related to book-to-market equity (*HML)* and size (*SMB*). Similarly, we compute a momentum factor (*WML*) as in Jegadeesh and Titman (1993), Carhart (1997) and Fama and French (2012).

RM-RF

As usually, the proxy for the market factor in stock returns is the excess market return over the risk free rate, *RM-RF*. For each month, *RM* is the value-weighted return of all the stocks listed on the first or second categories of BSE with a history of at least two months. Negative *BE* companies are included. *RF* is the midpoint between the one-month interbank bid and ask rates, available at the beginning of that specific month and published on the NBR's website.

HML and SMB

In June of year *t* (*t* from 2006 to 2013) we rank all stocks listed on Bucharest Stock Exchange (categories 1 and 2) on Size (*ME* – market equity), and we use the median to split them into two equal groups, the Big and Small stocks. Independently we also split all the stocks ranked on *BE/ME*[8] into three groups corresponding to the bottom 30% (Low), middle 40% (Medium) and top 30% (High). Please, notice that high *BE/ME* (which gives the name to the *HML* factor) is actually equivalent to Low P/BV –

[8] *Book to market equity; equivalent to 1/PBV (PBV = price to book value).*

the well-known ratio. We exclude negative BE companies (see the Data section for a detailed analyses of how we handled unusual events). We use *ME* and *BE* as of the end of *t*-1 to eliminate looking-forward bias. We use only companies listed at *t*-1 to eliminate back-filling bias.

From the intersection of the two *ME* and three *BE/ME* groups we construct six portfolios (B/L, B/M, B/H, S/L, S/M, S/H). For each portfolio we calculate monthly value-weighted returns from July of year *t* to June of *t*+1, when the groups are re-set.

HML – The Growth/Value Factor

In each month, the *HML* return is the simple average return of the *high* portfolios (S/H and B/H) minus the simple average return of the *low* portfolios (S/L and B/L).

SMB – The Size Factor

For each month, the *SMB* return is computed as the simple average return of the *small* portfolios (S/L, S/M, S/H) minus the simple average return of the *big* portfolios (B/L, B/M, B/H). We thus use averages of the *BE/ME* groups to eliminate the influence of the *BE/ME* factor; we differentiate these averages for the two size groups to single out the influence of Size factor.

WML – the Momentum Factor

For each month *t* included in our study (*t* from July 2006 to December 2013), we compute the previous year return for each stock as the cumulative return from months *t*-11 to *t*-1 (we skip the sort month to follow precisely the methodology in Fama and French (2012)). We rank the stocks on the above return and we split them into three groups corresponding to the bottom 30% (Losers), middle 40% (Neutral) and top 30% (Winners).

From the intersection of these three groups of stocks formed on Momentum and two groups of stocks formed on the Size (the same two size groups were used for the *HML* and *SMB* factors – see the explanation above) we construct six portfolios (B/W, B/N, B/Lose, S/W, S/N, S/Lose).

For each portfolio, we calculate monthly value-weighted returns. Unlike previous factors, portfolios are re-set at the end of each month (as the Winners or Losers portfolio of stocks changes every month).

Finally, our proxy for the momentum factor *WML* is computed as the simple average return of the *winner* portfolios (B/W and S/W) minus the simple average return of the *loser* portfolios (B/Lose and S/Lose).

The Factors – Regional (European) and Global Setting

In addition to the factors computed using only information on stocks listed at BSE and local interest rate (the local setting), we also employ the same factors computed similarly but for a substantially larger universe: European and global stocks. Since the methodology is similar to what we have described above, we will not discuss it here. However, details can be found in Fama and French (2012) or on Kenneth French website[9]. Table 2 presents the factors employed throughout this paper and the corresponding names for different settings:

Table 2

Factor name	Local setting	European (regional) setting	Global setting
Market	*RM-RF*	*eRM-eRF*	*gRM-gRF*
Value/Growth	*HML*	*eHML*	*gHML*
Size	*SMB*	*eSMB*	*gSMB*
Momentum	*WML*	*eWML*	*gWML*

The Returns to Be Explained

Our dependent variables in the time-series regressions are the excess returns on 9 portfolios, formed on size and book-to-market equity. The reason why we used these portfolios is to provide a more intuitive depiction of the impact of the descriptive factors. However the choice of dependent variables is arbitrary, and later on checking the robustness of our inferences we use portfolios constructed differently (by sorts of stocks ranked by E/P and D/P[10]– their methodology is detailed in that section).

Methodology

At the end of June each year we have divided our companies by thirds: once based on tertiles points of these companies sorted on P/BV, and secondly based on tertiles points of the companies sorted by size. From the intersections of these 2 groups of thirds resulted our (3x3=) 9 portfolios of companies, thus grouped both by size and by P/BV.

As one may see in Table 3, the market value is heavily concentrated in the "Big, Growth" portfolio (with an average annual percentage of market value of 71%); this is not an unusual situation, and other papers documented the same situation. For example, Fama and French (1992) reported that 30.13% of the combined market value was concentrated in their *Big Growth* portfolio. Put differently, a relatively few number of shares dominates all the others combined in terms of market value.

Also, companies are not uniformly distributed across the two dimensions (Size and P/BV) and, thus, some portfolios might include an insufficient number of companies for some periods. We tried to overcome this by using tertiles and not quintiles when forming our portfolios (Griffin, 2002, uses the same solution when adapting the Fama-French model to a portfolio of Canadian stocks). In particular, the rarest of the companies are those that are big but have low P/BV, or those that are small but have high P/BV. As a future research it would be possible to choose the percentile points such that the distribution would become more uniform (similar to Fama and French (1993) use of NYSE breakpoints for their entire universe of stocks). The portfolio construction for dependent variables is nevertheless pretty arbitrary and not the focus

[9] The latter is also the source for the factor's returns for the global and European settings, from July, 2006 to December, 2013.

[10] Earnings and dividend yields, respectively.

of our research. While recognizing the potential for other ways of constructing portfolios, we proceed with this method. When checking the robustness of our inferences we have also used as dependent variables portfolios constructed using quartiles of companies sorted by E/P or D/P (earnings and, dividend divided by market equity respectively) or portfolio mimicking some indices (BET-XT – as application), which we hope that will provide a much clear picture.

Table 3

Descriptive Statistics for 9 Portfolios Formed by P/BV and Size: July 2006 – December 2013, 90 Months

	Low P/BV	Medium P/BV	High P/BV	Low P/BV	Medium P/BV	High P/BV
Average of annual averages of firm size (millions RON)				Average of annual P/BV ratios for portfolio		
Small	19.8	32.2	57.0	0.39	0.99	6.78
Medium	145.7	108.7	222.5	0.50	1.00	2.14
Big	649.1	2,861.2	2,880.5	0.58	0.93	2.23
Average of annual percentage of market value in portfolio				Average of annual number of firms in portfolio		
Small	0.5%	0.3%	0.1%	14.25	6.25	1.63
Medium	1.1%	1.7%	2.6%	5.50	8.75	6.50
Big	2.1%	21.3%	70.5%	1.88	5.25	13.13

2. Variation in Time-Series Returns

This section explains how different combinations of variables capture the variation through time in the returns on stocks. We begin with an overview of dependent and independent returns. The more important third part focuses on the slopes and R^2 of competing models: the goal is to show that mimicking portfolio of risk factors related to size and P/BV capture shared variation in stocks.

An Overview of the Dependent Returns

As one may see in Table 4, the average excess returns that we try to explain are very dispersed, ranging from -0.7% to +2.5% per month. The reason for this variability could of course be that well-chosen criteria (Size and P/BV) do a good job for differentiating between stock returns. However, it could also mean that firm-specific factors consistently influence the return of these 9 portfolios: in spite of our relatively large database, this hypothesis cannot be rejected given the limited number of companies that are actually available. This still remains one of the hardships that we have to accept when analyzing the Romanian Stock Market.

However, the usual patterns that were documented thoroughly on other markets appear to emerge here as well: small stocks seem to outperform big stocks (0.80% vs. 0.50% average monthly return) and value stocks seem to outperform growth stocks (0.82% for low P/BV stocks vs. -0.43% for high P/BV stocks). In fact, the highest return (2.5%) belongs to the *small, value* portfolio, while the *large, growth* portfolio lost on average 0.26% per month. This relation is a bit muddled if we move towards the centre of the distribution, as medium sized stocks seem to have on average the lowest returns among the three Size groups. Just to ensure that firm-specific factors or outliers did not have any material impact on this finding, we have double checked it on nine portfolios constructed similarly on sorts of stocks on Size and P/BV, but with each stock having equal weighting in portfolios. We were able to confirm that the expected relation between small and big stocks, or between growth and value stocks, *at the end of the spectrum*, seems to hold even after partially controlling for outliers or firm specific effect. And that the unusually low return of medium stocks is present on average values as well, which, we have no doubt, will negatively impact the power of our models.

Moreover, because stocks in general – and Romanian stocks in particular - have large standard deviations – up to 16% per month - none of the portfolio returns is statistically different from 0. The Fama and French (1993) study faced similar difficulties.

Table 4

Descriptive Statistics for Dependent Variables

	Low P/BV	Medium P/BV	High P/BV			Low P/BV	Medium P/BV	High P/BV
Mean					Std.			
Small	2.50%	0.19%	-0.31%			15.86%	10.66%	11.79%
Medium	-0.50%	-0.18%	-0.72%			14.18%	10.83%	10.29%
Big	0.45%	1.37%	-0.26%			11.57%	10.75%	11.30%
t(mn)							Autocorr. For lag 1	
Small	1.50	0.17	-0.25			0.24	0.36	0.32
Medium	-0.33	-0.16	-0.67			0.34	0.20	0.18
Big	0.37	1.21	-0.22			0.15	0.27	0.27
		Autocorr. for lag 2					Autocorr. For lag 12	
Small	0.02	0.17	-0.18			0.04	-0.02	0.13
Medium	0.15	0.03	0.07			-0.09	-0.03	-0.12
Big	0.15	0.06	-0.05			-0.05	0.09	0.07

An Overview of the Explanatory Returns

The average values of the explanatory variables are equivalent to average risk premiums for the common factors. As in Table 5, the average risk premium for the market factor is almost 0%, affected by the short and very turbulent time period that we covered (the financial crisis of 2007-2008).

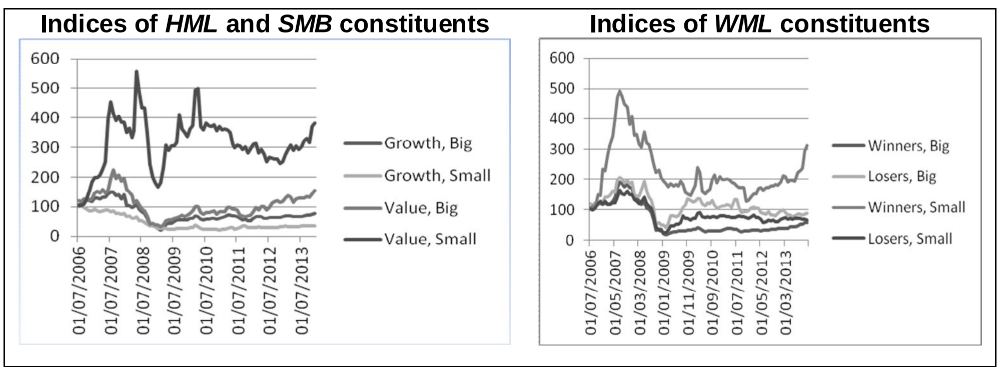
Table 5

Summary Statistics for Monthly Explanatory Returns From July 2006 to December 2013 (90 Observations)

				Autocorr. for lag		
Name	Mean	Std.	*t*(mn)	1	2	12
RM	0.56%	9.84%	0.54	0.29	0.02	0.09
RFR	0.59%	0.25%	22.46	0.97	0.92	0.39
RM-RF	-0.03%	9.87%	-0.03	0.30	0.03	0.09
HML	1.97%	7.89%	2.36	0.09	-0.08	-0.12
SMB	-0.27%	6.50%	-0.40	0.13	-0.12	-0.11
WML	0.60%	9.25%	0.61	0.09	0.23	-0.03

The average risk premium for the Value/Growth factor (*HML*) is large (almost 2% per month) and significant both in practical and statistical terms (t = 2.36). We can't say the same about the Size (*SMB*) and Momentum (*WML*) factors which are both very close to 0. The slightly negative value of *SMB* poses an interesting challenge, as it seems to contradict our previous confirmation of the expected relation between small and big stocks. However, we have already noticed that medium-sized stocks seem to have an abnormally low return: since the factor construction aggregates a larger number of shares for the "Small" group of stocks, those few "Medium" stocks that made it into the "Small" group are enough – because of their relative size – to bring the whole average return lower and into negative territory. Indeed, using a *SMB* portfolio with equal weighting instead of size-weighting would bring the average *SMB* return above 0, although not significantly (values are available on request). This suggests that there is room for improvement of the *SMB* factor both by using a finer granulation of the selection process, and by reducing the individual impact of larger stocks.

Figure 1



The risk factors are constructed using differences in average returns of constituent portfolios. The evolutions for some of these constituent portfolios are depicted in Figure 1. Apparently Value, Small stocks have the largest average return, followed by Value, Big stocks (the left side of Figure 1). A portfolio formed of past *Winners, Small* stocks has a larger return than the rest of momentum portfolios (the right side of Figure 1).

Table 6 presents a general picture of correlations between factors computed in local, European or global setting. If markets are integrated, we would expect European or global computed factors to manifest some degree of (positive) correlation with their locally-computed counterparts. Indeed, the market factor is significantly positively correlated across the three settings. However, neither *HML* nor *SMB* factor has a correlation statistically different from 0 with their European or global versions. This is similar to other findings in this respect, for example in Griffin (2002). Interestingly enough, the momentum factor *WML* is positively correlated with both the European (*eWML*) and the global (*gWML*) momentum factors. As expected, all the European factors are positively correlated with their global counterparts.

Table 6

Correlation of Factors in Three Different Settings: Local, European and Global

Factor:	*RM-RF*	*HML*	*SMB*	*WML*	*eRM-eRF*	*eHML*	*eSMB*	*eWML*	*gRM-gRF*	*gHML*	*gSMB*	*gWML*
RM-RF	1											
HML	0.12	1										
SMB	-0.48	0.04	1									
WML	-0.24	-0.21	0.3	1								
eRM-eRF	0.74	0.08	-0.4	-0.14	1							
eHML	0.44	-0.04	-0.16	-0.12	0.61	1						
eSMB	0.11	0.37	0.06	-0.06	-0.03	-0.13	1					
eWML	-0.56	0.04	0.38	0.42	-0.48	-0.54	-0.07	1				
gRM-gRF	0.77	0.09	-0.42	-0.16	0.98	0.55	-0.02	-0.47	1			
gHML	0.3	-0.06	-0.12	-0.02	0.34	0.81	-0.21	-0.41	0.33	1		
gSMB	0.12	0.32	0.07	-0.05	0.06	-0.1	0.77	-0.07	0.09	-0.19	1	
gWML	-0.46	-0.01	0.37	0.42	-0.38	-0.43	-0.1	0.93	-0.38	-0.38	-0.07	1

Regressions of the Asset-pricing Models

The Market (1F)

As one may see in Table 7, the one factor model (1F - the excess return on the market portfolio over the risk-free rate) captures most of the variation in *Growth, Big* companies. The R^2 for this portfolio is 0.94 and it is very unlikely that any other factor could (ever) add something significantly to that. The best chance for other factors to show their usefulness is in the Medium Size and Small Size groups of portfolios where the R^2 is, for example, only 0.33 for the *Small, Value* companies.

Table 7

Regressions of Excess Stocks Returns of 9 Portfolios Formed on *ME* and *BE/ME* (Dependent Variables) on the Excess Market Return, *RM-RF*

July 2006 to December 2013 (90 Months) $R(t) - RF(t) = a + b[RM(t) - RF(t)] + e(t)$						
	Value	Medium	Growth	Value	Medium	Growth
		b			$t(b)$	
Small	0.94	0.74	0.09	6.73	8.80	0.66
Medium	0.91	0.91	0.87	7.64	14.00	14.18
Big	0.86	0.98	1.11	9.25	19.05	37.79
		R^2			se	
Small	0.33	0.46	-0.01	0.13	0.08	0.13
Medium	0.39	0.69	0.69	0.11	0.06	0.06
Big	0.52	0.80	0.94	0.09	0.05	0.03

The Growth/Value and Size Factors (2F)

As one may see in Table 8, the two factors related to P/BV (*HML*) and Size (*SMB*) could never entirely explain returns by themselves. However, by temporarily excluding the dominant market factor from the regressions we are in a better position to judge whether these factors capture substantial time-series variation in stock returns. By doing so we were already able to exclude the momentum (*Winners minus Losers – WML*) factor from the regression: its added benefit judged by the increase in R^2 was negligible and only two portfolios had the *w* coefficient corresponding to *WML* factor statistically different from 0. By contrast, the *HML* factor is highly significant for all portfolios, except the *Growth, Big.* Also the *SMB* factor is statistically significant in all but *Small, Medium P/BV* portfolio. It is interesting that the two factors might explain more of the time-series variation in the *Small, Value* and *Small, Growth* portfolio than the market factor does.

Table 8

Regressions of Excess Stocks Returns of 9 Portfolios Formed on *ME* and *BE/ME* (Dependent Variables) by the Growth/Value and Size Factors

July 2006 to December 2013 (90 Months) $R(t) - RF(t) = a + hHML(t) + sSMB(t) + e(t)$						
	Value	Medium	Growth	Value	Medium	Growth
		h			$t(h)$	
Small	1.16	0.56	-0.55	6.72	4.27	-3.30
Medium	1.00	0.48	0.28	6.44	3.57	2.11
Big	0.54	0.29	0.11	3.94	2.29	0.82
		S			$t(s)$	
Small	0.37	-0.19	0.59	1.79	-1.17	3.09
Medium	-0.50	-0.45	-0.45	-2.66	-2.81	-2.82
Big	-0.92	-0.80	-0.86	-5.65	-5.32	-5.29
		R^2			se	
Small	0.35	0.16	0.18	0.13	0.10	0.11
Medium	0.34	0.17	0.10	0.12	0.10	0.10
Big	0.36	0.26	0.23	0.10	0.09	0.10

The Three Fama-French Factors (3F)

From Table 9 it becomes obvious that using the three factors is the best alternative in terms of explanatory power. If by using just the market factor it produced only four R^2 greater than 0.6, now there are eight out of nine portfolios with higher R^2. Also, most of the slopes moved several standard deviations from 0: while barely significant in the 2F model, now the *s* coefficient for the *SMB* factor in the *Small, Value* portfolio is more than 10 standard deviations away from 0. The R^2 for the same portfolio is now 0.82, more than double compared to the previous two models and the second higher of all the portfolios, after being the second worse in the CAPM model (1F).

Table 9

Regressions of Excess Stocks Returns of 9 Portfolios Formed on *ME* and *BE/ME* (Dependent Variables) on the Excess Market Return, and Growth/Value and Size Factors

July 2006 to December 2013 (90 Months) $R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + e(t)$						
	Value	Medium	Growth	Value	Medium	Growth
		b			*t*(*b*)	
Small	1.26	0.84	0.46	15.08	10.22	3.39
Medium	0.87	0.97	0.94	7.96	14.56	13.73
Big	0.69	0.93	1.11	7.12	15.88	33.47
		h			*t*(*h*)	
Small	0.93	0.41	-0.66	10.12	4.57	-4.15
Medium	0.84	0.30	0.11	7.02	4.15	1.45
Big	0.41	0.12	-0.09	3.83	1.86	-2.45
		S			*t*(*s*)	
Small	1.31	0.44	0.95	10.39	3.53	4.56
Medium	0.15	0.27	0.25	0.89	2.66	2.42
Big	-0.41	-0.11	-0.03	-2.79	-1.29	-0.64
		*R*2			*se*	
Small	0.82	0.62	0.28	0.07	0.07	0.11
Medium	0.61	0.76	0.71	0.09	0.05	0.05
Big	0.61	0.81	0.94	0.08	0.05	0.03

The Case of a Regional or Global Setting

We have already discussed how adding the *WML* factor would not benefit the factors model significantly. This is shown in Table 10

Adjusted R2 for 9 Portfolios, Using 4 Models*, Applied on 3 Settings where the differences in the R^2 of 3F and 4F local models are barely noticeable, while the significance of the coefficients would drop (not shown here). There still remains however the question whether regionally- or globally-computed factors might do a better job at explaining time-series variation in local returns. With only a few exceptions, all the R^2s obtained using the local model are higher than their European or global counterparts. This however doesn't mean that these models should be discarded: they truly are the proper tool to use for a more realistic setting – which is portfolio management at a global or at least European level, in which case these models could prove their worth on selecting portfolios, evaluating performance, etc. Our results seem to support similar evidence found by Griffin (2002) that domestic factor models explain much more time-series variation in returns than the world factor model does. We do not explore in this paper the advantages of a using a local-global mixed model.

There is also a very interesting observation regarding the *WML* factor that we found useless in the local setting. That might well be the case for the local setting, however when the *eWML* or even *gWML* were added to their corresponding 4F models, we could witness a remarkable increase in R^2 especially for the *Big, Growth* companies. These are, after all, the most (economically) important companies – as they are responsible for more than 70% of the combined market value of Romanian listed companies. Thus, although we have concentrated on those companies where statistically we could make a difference by using a model other than the CAPM, we stumbled upon a factor (European momentum) that clearly has a significant effect on our framework, the local market factor itself. It would thus be very interesting to find out how a mixed-settings factor model would perform in explaining time-series variation in local returns; however, this is not our focus in this investigation.

Table 10

Adjusted R^2 for 9 Portfolios, Using 4 Models*, Applied on 3 Settings**

		Local			**European**			**Global**		
		Value	Medium	Growth	Value	Medium	Growth	Value	Medium	Growth
1F	Small	0.33	0.46	-0.01	0.11	0.22	-0.01	0.13	0.25	-0.01
	Medium	0.39	0.69	0.69	0.22	0.36	0.35	0.24	0.39	0.4
	Big	0.52	0.8	0.94	0.21	0.48	0.45	0.23	0.53	0.49
2F	Small	0.35	0.16	0.18	0.07	0.17	-0.02	0.05	0.12	0
	Medium	0.34	0.17	0.1	0.26	0.27	0.17	0.1	0.16	0.06
	Big	0.36	0.26	0.23	0.16	0.12	0.19	0.07	0.05	0.11
3F	Small	0.82	0.62	0.28	0.13	0.29	0	0.14	0.29	0.01
	Medium	0.61	0.76	0.71	0.4	0.44	0.38	0.29	0.44	0.4
	Big	0.61	0.81	0.94	0.27	0.49	0.45	0.23	0.53	0.49
4F	Small	0.82	0.62	0.27	0.12	0.28	0.01	0.13	0.28	0
	Medium	0.62	0.76	0.72	0.43	0.48	0.44	0.32	0.47	0.44
	Big	0.62	0.81	0.95	0.28	0.53	0.54	0.23	0.55	0.53

*The 4 models are:
1F: $R(t) - RF(t) = a + b[RM(t) - RF(t)] + e(t)$
2F: $R(t) - RF(t) = a + hHML(t) + sSMB(t) + e(t)$
3F: $R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + e(t)$
4f: $R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + wWML(t) + e(t)$

**The European and Global versions of the models were implemented with the corresponding factors downloaded from the website of Kenneth French at Darmouth College.
No adjustment for different exchange rates was made.

3. The Cross-section of Average Returns

This section documents how well the average premiums for the identified risk factors explain the cross-section of average returns on stocks. The focus here is on the intercepts of competing models. The goal is to show that models are well specified and thus produce intercepts that are indistinguishable from 0.

Analysis of Intercepts

An overview of intercepts and their corresponding (absolute) *t*-values is presented in Table 11

Intercepts and Absolute *t-values* for 9 Portfolios, Using 4 Models,

Applied on 3 Settings. When only the market factor (*RM-RF*) is used in the time-series regression model, the intercepts shows the same Size effect and Value/Growth effect observed at the dependent variables *at the extremes of the spectrum*. Thus, it becomes apparent that the market factor alone is unable to model such differences and the simple model leaves the cross-sectional differences related to Size and Value partially unexplained.

When only the *HML* and *SMB* factors are used in the regression, intercepts increase in absolute values and become predominantly negative. That because the two zero-investment portfolios are unable to explain large negative returns that characterize a period of financial crisis, a job that should be properly left to the market factor.

Finally, when the three factors *RM-RF*, *HML* and *SMB* are used together in the regressions, the table of intercepts presents a mixed picture. As expected, average intercept moves closer to zero, and we will later formally test the hypothesis that they are 0 by using the GRS statistic. However, the move towards zero is apparent only in the extreme portfolios – *Small, Value* and *Big, Growth*. The Middle Size portfolios, as we feared in the beginning of our analyses, apparently follow some logic of their own. It is remarkable however that the Growth/Value effect is not apparent anymore, while the size effect is considerably reduced. However, we now turn our attention to formally test these assumptions.

Joint Test on Regression Intercepts (GRS)

We follow the related literature and employ the GRS test statistics to evaluate model performance suggested by Gibbons *et al*. (1989). The test is based on the assumption that in a highly performing multifactor model, *i.e.*, a model where expected returns are fully explained by the linear sensitivity of the portfolios to the risk factors, all of the regression intercepts (pricing errors) should be equal to zero (H_0). Therefore, the GRS statistics tests whether intercepts from previous regressions are jointly zero, and is given by:

$$GRS = \left(\frac{T}{N}\right) \times \left(\frac{T-N-L}{T-L-1}\right) \times \left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\mu'\hat{\Omega}^{-1}\mu}\right] \sim F(N, T-N-L),$$

where: T is the number of monthly observations (90 here), N is the number of portfolios (9) and L is the number of independent risk factors in the multifactor models (3 in our case, i.e. market risk premium, *SMB* and *HML,* respectively).

Table 11

Intercepts and Absolute *t*-values for 9 Portfolios, Using 4 Models, Applied on 3 Settings

		Local			European			Global		
		Value	Medium	Growth	Value	Medium	Growth	Value	Medium	Growth
1F	Small	2.5% (1.9)	0.2% (0.3)	-0.3% (0.2)	2.6% (1.6)	0.3% (0.3)	0.2% (0.2)	2.4% (1.5)	0.1% (0.1)	0.3% (0.2)
	Medium	-0.5% (0.4)	-0.1% (0.2)	-0.7% (1.2)	-0.6% (0.4)	-0.2% (0.2)	-0.7% (0.8)	-0.7% (0.6)	-0.4% (0.4)	-0.9% (1.1)
	Big	0.7% (0.7)	1.4% (2.8)	-0.2% (0.8)	0.8% (0.6)	1.3% (1.5)	-0.4% (0.4)	0.7% (0.5)	1.1% (1.4)	-0.6% (0.7)
2F	Small	0.3% (0.2)	-1.0% (0.9)	1.1% (0.8)	3.1% (1.9)	0.8% (0.8)	0.3% (0.2)	3.0% (1.9)	0.7% (0.7)	0.1% (0.1)
	Medium	-2.6% (2.1)	-1.2% (1.2)	-1.4% (1.3)	0.1% (0.1)	0.5% (0.5)	-0.1% (0.1)	0.1% (0.0)	0.3% (0.3)	-0.2% (0.2)
	Big	-0.7% (0.6)	0.6% (0.6)	-0.7% (0.7)	1.5% (1.1)	2.0% (1.9)	0.4% (0.4)	1.3% (0.9)	1.9% (1.7)	0.2% (0.2)
3F	Small	1.1% (1.5)	-0.5% (0.6)	1.5% (1.1)	2.6% (1.7)	0.3% (0.4)	0.4% (0.3)	2.5% (1.6)	0.2% (0.2)	0.2% (0.2)
	Medium	-2.1% (2.2)	-0.7% (1.1)	-0.8% (1.4)	-0.5% (0.5)	-0.1% (0.1)	-0.7% (0.8)	-0.6% (0.5)	-0.3% (0.3)	-0.9% (1.0)
	Big	-0.2% (0.3)	1.1% (2.2)	-0.1% (0.2)	0.9% (0.8)	1.2% (1.4)	-0.3% (0.4)	0.8% (0.6)	1.1% (1.4)	-0.5% (0.6)
4F	Small	1.0% (1.3)	-0.6% (0.8)	1.4% (1.1)	2.9% (1.8)	0.5% (0.5)	0.8% (0.5)	2.6% (1.7)	0.3% (0.3)	0.3% (0.2)
	Medium	-1.9% (1.9)	-0.5% (0.9)	-0.7% (1.2)	0.1% (0.1)	0.4% (0.5)	-0.1% (0.2)	-0.3% (0.2)	0.0% (0.0)	-0.6% (0.7)
	Big	-0.3% (0.4)	1.1% (2.1)	0.0% (0.0)	1.2% (1.0)	1.7% (2.1)	0.4% (0.5)	0.9% (0.7)	1.3% (1.7)	-0.2% (0.3)

*The 4 models are:
1F: $R(t) - RF(t) = a + b[RM(t) - RF(t)] + e(t)$
2F: $R(t) - RF(t) = a + hHML(t) + sSMB(t) + e(t)$
3F: $R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + e(t)$
4f: $R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + wWML(t) + e(t)$

**The European and Global versions of the models were implemented with the corresponding factors downloaded from the website of Kenneth French at Darmouth College.
No adjustment for different exchange rates was made.

Description of the Test

While the test has exact small-sample properties when asset returns are multivariate normal, it also requires a strong assumption that errors are independent and identically distributed and follow the normal rule. The test is, however, reasonably robust with respect to typical levels of non-normality (Affleck-Graves and Mcdonald, 1989).

In order to compute the GRS test for our data, we firstly created the Nx1 vector of $\hat{\alpha}$, *i.e.*, the estimated intercepts from the multifactor models ($\hat{\alpha}'$ is the transpose of $\hat{\alpha}$).

Next, we computed the estimated residual for each observation (*T*= 90) and regression (*N*=9):

$$\hat{\varepsilon}_{it} = (R_{it} - R_{ft}) - \hat{\alpha}_i - \hat{b}_i(R_{Mt} - R_{ft}) - \hat{h}_i HML_t - \hat{s}_i SMB_t$$

We formed $\hat{\varepsilon}$– the T x N matrix of the estimated residuals:

$$\hat{\varepsilon} = \begin{bmatrix} \hat{\varepsilon}_{11} & \cdots & \hat{\varepsilon}_{1N} \\ \vdots & \ddots & \vdots \\ \hat{\varepsilon}_{T1} & \cdots & \hat{\varepsilon}_{TN} \end{bmatrix}$$

and, subsequently, we estimated $\hat{\Sigma}$– the N x N unbiased covariance matrix of residuals:

$$\hat{\Sigma} = \frac{\hat{\varepsilon}'\hat{\varepsilon}}{T-L-1} \text{ or : } \hat{\Sigma} = cov(\hat{\varepsilon})\frac{T-1}{T-L-1}$$

Afterwards, the L x 1 vector of factor means was created: $\hat{\mu} = \begin{bmatrix} \bar{F}_1 \\ \vdots \\ \bar{F}_L \end{bmatrix}$

then the F=T x L factor matrix: $F = \begin{bmatrix} F_{11} & \cdots & F_{1L} \\ \vdots & \ddots & \vdots \\ F_{T1} & \cdots & F_{TL} \end{bmatrix}$

so that we were able to compute the unbiased estimate of the L x L covariance matrix of the factors:

$$\hat{\Omega} = \frac{(F-\bar{F})'(F-\bar{F})}{T-1}\text{, where } \bar{F} = \begin{bmatrix} \bar{F}_1 & \cdots & \bar{F}_L \\ \vdots & \ddots & \vdots \\ \bar{F}_1 & \cdots & \bar{F}_L \end{bmatrix}$$

The GRS statistic is then computed as:

$$GRS = \left(\frac{T}{N}\right) \times \left(\frac{T-N-L}{T-L-1}\right) \times \left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\mu'\hat{\Omega}^{-1}\mu}\right] \sim F(N, T-N-L)$$

Test Results

The *GRS* statistic for the three-factor model in local setting is equal to 1.53, which correspond to a *p*-value of 0.15 based on the *F* distribution with 9 degrees of freedom in the numerator and 78 degrees of freedom in the denominator. Thus the *null* hypothesis that all 9 intercepts are equal to 0 cannot be rejected at standard confidence levels. This result is apparently better than that of similar studies (Fama and French, 1993; Griffin, 2002) that "succeeded" in rejecting the *null* and it is probably due to the small data sample. Testing the one- or two-factor models yields similar results (not shown here).

4. Robustness Check and Applications

A few tests are routinely employed to check for the statistic robustness of factor models. Most of these are difficult, if not impossible, to implement using our data. Fama and French (1993) use regressions to check whether residuals can be predicted using variables such as (annual) dividend yield, short-term interest rates, term and default spreads, etc. The logic behind such test is that, if factors indeed capture the cross-section of expected returns, the residuals should be unpredictable. Another more controversial test is to check whether "price anomalies" such as the January effect is still apparent even after modeling returns using the factors model. However, the short time span (we only have 6 "Januaries" in our sample and 7 observations of annual dividend yields) does not allow for any of these tests.

Also – probably most important, the split sample test could not be implemented either, as the relatively low number of stocks was already a serious constraint in our study. Further splitting the sample is almost impossible and, maybe, conducive to other more serious errors. Using the same variables to construct our explanatory "factors" and as dependent variables as well could potentially trigger some grave errors, and no study on this topic is entirely free from such a danger (see W. Ferson, S. Sarkissian and T. Simin, 1999)

Because of these constraints, we conduct only two tests on robustness – we check whether the factor model prove its use on seemingly unrelated regressions of portfolios formed by dividend yield and earnings yield (D/P and E/P).

Portfolios Formed by E/P

We check whether the two factors – Size and Value/Growth are able to explain return on portfolios formed by other popular variables, such as E/P.

Table 12

Summary Statistics for Portfolios Formed by EP*			
	mean	std.	*t*(mn)
EP<0	-0.3%	11.4%	-0.25
Low	1.3%	8.3%	1.49
EP2	-0.9%	6.5%	-1.34
EP3	-0.3%	8.3%	-0.33
EP4	-0.2%	8.7%	-0.23
High	0.5%	13.5%	0.35
Summary statistics for portfolios formed on DP**			
	mean	std.	*t*(mn)
DP=0	0.4%	7.9%	0.43
Low DP	-1.6%	10.4%	-1.46
Medium	0.5%	10.9%	0.44
High DP	0.0%	14.8%	0.00

*EP portfolios: In June of year *t* (*t* from 2006 to 2013) we rank stocks by Earnings at December, year *t*-1 divided by Price at the end of June, year *t*. Negative earnings companies form a separate portfolio (EP<0). The other companies are split by quintiles, from low earnings (Low EP) to high earnings.

**DP portfolios: In June of year *t* (*t* from 2006 to 2013) we rank stocks by Dividend received in year *t*-1 divided by Price at the end of June, year *t*. Companies that did not distribute dividends in the preceding year form a separate portfolio (DP=0). The other companies are split based on thirds, from low dividend yield (Low DP) to high dividend yield (High DP).

From Table 12, we can get a general idea about the U-shaped distribution of average returns for the portfolios constructed by E/P and D/P, documented in Fama and French (1993, 1992). Only negative EP portfolios and those with high dividend yield don't quite fall in this general pattern. Suffice to say that the lowest return belongs to portfolios situated closer to the middle of the distribution, and not at the extremes. This apparently non-linear dependence on the sorting variable should make the task of the explanatory variables particularly difficult.

Table 13 shows evidence (similar to that acknowledged in Fama and French (1993) and Basu (1983)) that the one factor model could not explain the relation between average returns and E/P: the intercepts from the one-factor model follow the same U-pattern that average return followed in Table 12. Adding the *HML* and *SMB* factors to the regression equation takes care of this and the intercepts that emerge manifest no clear relation with EP. We would have liked to see intercepts getting closer to 0 but this is not the case. It is also apparent that the higher the EP, the higher the stocks' beta and the lower their loading on the *HML* factor. Thus higher earnings yield seems to be a characteristic of portfolios with lower loadings on the *HML* factor, or the so-called *Growth* stocks. This finding is different from that of Fama and French (1993) and is just an example of how useful factor models are in discerning the peculiarities of a specific market. Moreover, negative EP stocks loads in similar fashion to *Value,* and *Medium* stocks, which is only natural and might be related to companies in financial distress (these companies fall under the *Value* heading as they trade at low prices compared to Book Value. Negative or depressed earnings also characterize them). Except for the EP4 portfolio (formed, apparently, from large stocks), the Size factor loads in about the same way for each EP portfolio.

Table 13

Regression Summaries for Portfolios Formed on EP

$R(t) - RF(t) = a + b[RM(t) - RF(t)] + e(t)$										
	a	*t*(a)	b	*t*(b)					R^2	*se*
EP<0	0.1%	0.11	0.68	6.0					0.28	0.10
Low	0.4%	0.49	0.68	7.9					0.41	0.08
EP2	-0.9%	-1.72	0.84	16.1					0.74	0.05
EP3	0.0%	0.06	1.15	16.9					0.76	0.06
EP4	0.3%	0.84	1.04	26.8					0.89	0.04
High	0.5%	0.76	1.19	16.3					0.75	0.07
$R(t) - RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + e(t)$										
	a	*t*(a)	b	*t*(b)	H	*t*(h)	s	*t*(s)	R^2	*se*
EP<0	-1.3%	-1.36	0.68	6.37	0.74	6.32	0.23	1.44	0.52	0.09
Low	-0.4%	-0.54	0.73	8.35	0.46	4.86	0.27	2.09	0.55	0.07
EP2	-1.2%	-2.57	0.89	16.16	0.21	3.49	0.21	2.54	0.79	0.04
EP3	-0.1%	-0.11	1.19	15.35	0.08	0.98	0.17	1.45	0.77	0.06
EP4	0.4%	1.16	1.01	23.09	-0.08	-1.72	-0.13	-2.00	0.90	0.04
High	0.3%	0.37	1.23	15.09	0.17	1.87	0.20	1.63	0.76	0.07

Portfolios Formed by D/P

Applying the one-factor model to portfolios formed by D/P, as in the case of E/P portfolios, does not eliminate the specific shape observed in Table 12. On the other hand, the three-factor model not only eliminates this shape but, in this case, also brings intercepts closer to 0. However, the information that *HML* and *SMB* adds to the market factor is almost indistinguishable from 0, as judged by adjusted R^2. Only the Low Dividend Yield portfolios seem to have a statistically significant negative loading on the *HML* factor, which is a characteristic of *Growth* stocks, this time in line with other findings on this subject (in other words, *Growth* stocks are characterized by low dividend, if any).

Table 14

Regression Summaries for Portfolios Formed on DP

$R(t)$ - $RF(t) = a + b[RM(t) - RF(t)] + e(t)$										
	a	*t*(a)	b	*t*(b)					R^2	*se*
DP=0	0.0%	-0.01	0.94	20.09					0.82	0.04
Low DP	-0.4%	-0.64	1.11	19.67					0.81	0.05
Medium	1.2%	1.53	1.27	15.45					0.73	0.08
High DP	0.7%	0.91	0.99	12.27					0.63	0.07
$R(t)$ - $RF(t) = a + b[RM(t) - RF(t)] + hHML(t) + sSMB(t) + e(t)$										
	a	*t*(a)	b	*t*(b)	h	*t*(h)	s	*t*(s)	R^2	*se*
DP=0	-0.2%	-0.41	0.92	17.03	0.09	1.54	-0.03	-0.41	0.82	0.04
Low DP	-0.1%	-0.22	1.12	17.13	-0.12	-1.72	-0.03	-0.31	0.82	0.05
Medium	1.0%	1.17	1.27	13.27	0.13	1.27	0.02	0.17	0.73	0.08
High DP	0.5%	0.61	1.00	10.72	0.13	1.24	0.08	0.55	0.63	0.07

Applications

There are some applications where the factors model can prove their worth. Among them, the factor model is often used for selecting portfolios, evaluating performance, measuring abnormal return in event studies, estimating the cost of capital, etc. We will just give a brief example of how the three-factor model can be used to quickly assess and attribute performance in case of a mutual investment fund.

The mutual fund that we analyze is benchmarked against the BET-XT index. The period of comparison is March 2010 – December 2013 (46 months). The decomposed performance in excess of the risk free rate is presented in Table 15.

Table 15

	m[R(*t*)-R*F*(*t*)]	*a*	*b*	m[*RM*(*t*)-*RF*(*t*)]	*h*	m*HML*(*t*)	*s*	m*SMB*(*t*)
XT fund	0.14%	-0.33%	1.03	0.5%	0.21	0.3%	0.09	-0.7%
BET-XT	0.10%	-0.41%	1.08	0.5%	0.15	0.3%	0.05	-0.7%
Difference	0.04%	0.07%	-0.02%		0.02%		-0.03%	

The mutual fund appears to surpass its benchmark by a tiny 0.04% percent/month. Both investments seem to incur negative alphas (both have negative intercepts, which are pretty large from an investor's point of view). The difference in intercepts is the largest component of the differences in average returns. In other words, the model expects that both investments should have performed better but is unable to indicate the main source of underperformance. We, however, can, at least in the case of the index: Bucharest Stock Exchange does not adjust the value of indices with the dividends received by included companies. This turns the indices into a very popular benchmark for mutual funds, which have an easy-to-beat target. The underperformance of -0.4% per month for the index is equivalent to about -5% per year – which is also an approximate level for the average dividend over the period (we have calculated an average of 4.95% annual dividend yield for the 2010-2013 period, for the entire market). Mutual funds, however, do include dividends in their return, so the three-factor model is unable to explain the fund's -0.3% per month under-performance (negative *alpha*).

We can suspect trading and management fees as being possible causes. However, using the three-factor model (and this is where the model can prove its worth) we can rule out factor tilts – a component of active management, as the main cause of underperformance: the slight tilt toward low beta stocks (b is 1.03 vs. 1.08 for the index) resulted in a -0.02% underperformance, offset however by a tilt towards Value stocks (h is 0.21 for the fund compared to 0.15 for the index) which resulted in a 0.02% gain. The similar tilt towards small stocks (s is 0.09 compared to 0.05 for the index) might have been also ill-inspired, however we refrain from interpreting this coefficient for the *SMB* factor as it was not statistically significant (t = 1.15 for the mutual fund).

In conclusion: at a first glance, the mutual fund seems to be a slightly better performer with an excess of 0.04% per month. By factoring in dividends (approximately 0.40% per month, on average), however, the fund is no longer the better investment. Moreover, its underperformance can only partially be explained by factor tilts (-0.03%), the rest to -0.36% per month (4.2% per year) being probably caused by trading fees, management fees and other possible components of active management (tactical selection of stocks, market timing, etc) not picked up by the factor model.

5. Summary and Conclusions

We attempted in this paper to implement a three-factor model in the Romanian capital market. Factor models have been popular in the international financial literature since over 20 years; however, we could not find a proper implementation in the Romanian equity market for any of them. We thus consider that our findings could well serve as benchmarks for some future related research.

There is a reason why Romanian capital market was not the subject of similar studies before: data availability for listed companies is rather scarce, and it also used to be poorly organized and prone to errors. To the best of our knowledge, this paper might be the first related to Romanian Stock Market that uses prices adjusted for dividends and capital increases, at least on such a large sample of companies. The potential for information regarding Romanian listed stocks is also a limitation, as the now re-born capital market is one of the youngest (so we can only deal with short time-series), and the number of listed companies in the "respectable" categories is still very limited. These difficulties probably deterred other researchers of tackling this information-intensive area and also constituted a serious challenge to our study as well. We hope that by fully disclosing our sources of information, or by detailing our approaches to cleaning our database of unreliable information while keeping it large enough to be significant, we might have been of service to some researchers (this was thoroughly covered in Section 1 - *Data*).

There is common variation in returns that is not directly related to market risk. We showed that by using three factors instead of one we were able to increase the adjusted R^2 from as low as 0.33 to 0.82 for the *Small, Value* stocks and obtain remarkable progress in explaining time-series variation in other portfolios as well (except for the one closest to "the market" portfolio). We have also considered for inclusion another popular factor – *momentum* – but we were not able to find it relevant in the format proposed by Jegadeesh and Titman (1993). Trying other variation in momentum factors is similar to data-mining and since there are better ways to account for it, we did not cover them in this paper. There is still great potential to discover other factors, or choose other settings, such as regional (European) or global. Our paper indicates that regionally computed factors (such as European *momentum*) could have meaningful and structural impact on local market, so there is potential to improve the model. We covered this in Section 2 –V*ariation in time-series returns*.

There is significant progress in using a multiple factor model as compared to the CAPM model; however it remains a model – prone to errors from handling or interpreting often insufficient data. When judging how close to 0 intercepts get, the results are better for some portfolios and worse for others: we are satisfied that the best results were obtained for the portfolios that we hoped to confirm (*Small, Value*). Results are worse for *Big, Growth* portfolios where the one-factor model had no rival; or for extreme portfolios with individual risk poorly diversified. There is undoubtly room for improvement of the models and especially for the initial selection procedure. Encouragingly, the hypothesis that the three-factor model is sufficient to explain market returns could not be rejected using a standard test. This was covered in Section 3 – *The cross section of average returns.*

There was a looming question over the results of our research: is it the case that the model seemed to work only because the portfolios were created by the same variable, albeit constructed differently, for the right- and left-hand-side of our regression equations? To answer this question and to concomitantly eliminate this doubt a robustness test that was implemented, consisting in testing both the model and the factors on seemingly unrelated time series – e.g. portfolios constructed by earnings or dividend yields. The factors confirmed their worth again. Although their contribution in shedding light on sources of return is different from one portfolio to another, the progress is obvious. Finally, there are areas where the factor model could be used, and just to prove a rapid implementation of the factor model we showed how easily portfolio performance for some mutual fund could be assessed. This was covered in Section 4 – *Robustness Check and Applications*.

This study could be developed further in several ways. Most important – the initial selection of factors can be improved. As it is now, it suffers from market-value concentration in one portfolio and from insufficient number of stocks in others. The advantage was that the study was directly comparable to other papers on this subject. However, having done this, some sort of stratified sampling allowing for disproportionate allocation could be further used in order to spread the stocks optimally across dimensions of choice. Also another viable solution for a future research could be the use of simple averages instead of weighting-averages as a way to reduce the impact of large stocks (and their individual risk) on portfolios, at the expense of increasing risk related to small, insignificant stocks. Liquidity weighting could also be an alternative worth considering, as well as the exploration of regional or global settings for computing factors. In this respect, this paper provides exactly the benchmark needed against which other variations in factors could be tested.

Acknowledgements:

The contribution of Andrei Anghel to this work was cofinanced from the European Social Fund through Sectoral Operational Programme Human Resources Development 2007-2013, project number POSDRU/159/1.5/S/142115 „Performance and excellence in doctoral and postdoctoral research in Romanian economics science domain”.

The contribution of Cristiana Tudor to this research was supported by CNCS-UEFISCDI, Project number IDEI 303, and code PN-II-ID-PCE-2011-3-0593.

References

Acatrinei, M.C. and Caraiani, P., 2011. Modeling and Forecasting the Dynamics in Romanian Stock Market Indices Using Threshold Models. *Romanian Journal of Economic Forecasting*, 14(2), pp. 42-54.

Affleck-Graves, J. and Mcdonald, B., 1989. Nonnormalities and Tests of Asset Pricing Theories. *The Journal of Finance*, XLIV(4), pp. 889-908.

Basu, S., 1983. The relationship between earnings yield, market value, and return for NYSE common stocks: Further evidence. *Journal of Financial Economics*, 12, pp. 129-156.

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics,* 9, pp. 3-15.

Bhandari, L. C,, 1988. Debt, equity ratio and expected common stock returns: Empirical evidence. *Journal of Finance,* 43 (2), 507-528.

BVB, 2014. Database. Available at <http://www.bvb.ro/IndicesAndIndicators/Indicators.aspx> [Accessed in January 2014].

Carhart, M., 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance,* LII(1), pp. 57-82

Dragota, V., 2007. Some Difficulties in Estimating the Discount Rate Based on CAPM in Romania. *The Valuation Journa*l, 1(2), pp. 50-57.

Fama, E. and French, K., 2012. Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105, pp. 457–472.

Fama, E. and French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, pp. 3-56.

Fama, E. and French K.,1992. The Cross-Section of Expected Stock Returns.*The Journal of Finance,* XLVII(2), pp. 427-465

Ferson, W, Sarkissian, S. and Simin, T., 1999. The Alpha Factor Asset Pricing Model: A Parable. *Journal of Financial Markets,* 2(1), pp. 49–68.

French, K., 2014. European and Global factors. Database. [online]. Available at <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html> [Accessed in January 2014].

Gibbons, M. Ross, S. and Shanken, J., 1989. A test of the efficiency of a given portfolio. *Econometrica,* 57, pp. 1121-1152.

Griffin, J., 2002. Are the Fama and French Factors Global or Country Specific?. *The Review of Financial Studies*, 15(3), pp. 783–803

Jegadeesdh, N. and Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance*, XLVIII(1), pp. 65-91

Litzenberger, R. and Ramaswamy, K., 1979. The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *Journal of Financial Economics,* 7, pp. 163-195.

Necula, C., 2009. Modeling Heavy-Tailed Stock Index Returns Using the Generalized Hyperbolic Distribution. *Romanian Journal of Economic Forecasting*, 10(2), pp. 118-131.

Panait, I., 2011. Study of the correlation between the Romanian stock market and S&P500 index during 2007-2009, The Romanian Economic Journal, 39, pp. 233-255

Pele, D. and Voineagu, V., 2008. Testing Market Efficiency Via Decomposition Of Stock Return. Application To Romanian Capital Market, *Romanian Journal of Economic Forecasting*, 9(3), pp. 63-79.

Rasyonet, 2014. Database. Available at: <www.rasyonet.com> [Accessed in January 2014].

Rosenberg, B, Reid, K. and Lanstein, R., 1985. Persuasive evidence of market inefficiency. *Journal of Portfolio Management* II. pp. 9-17.

Tudor, C., 2009. Price Ratios and the Cross-section of Common Stock Returns on Bucharest Stock Exchange: Empirical Evidence, *Romanian Journal of Economic Forecasting*, 10(2), pp. 132-146.