An Application of Factor Pricing Models to the Polish Stock Market

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Abstract

We evaluate and compare the performance of four popular factor pricing models: the capital asset pricing model, the Fama and French three-factor model, Carhart's four-factor model, and the five-factor model of Fama and French. We aim to establish which of these models is most applicable in the Polish stock market. To do so, we employ a battery of tests—cross-sectional regressions, examination of one-way and two-way sorted portfolios, tests of monotonic relationships, and factor redundancy tests—and apply them to a sample of more than 1100 stocks for the years 2000–2018. The results indicate that the four-factor model outperforms the other models; it has the greatest explanatory ability for cross-sectional returns and is therefore well-suited for asset pricing in Poland.

Keywords: asset growth, asset pricing, equity anomalies, factor models, momentum, Poland, Polish stock market, profitability, size, the cross-section of returns, value

The last three decades have led to a proliferation of research into cross-sectional patterns and return anomalies in financial markets. Studies conducted by Hou, Xue, and Zhang (2015) and Jacobs and Muller (2017) identify hundreds of return regularities and are widely documented in top-tier finance journals. The ongoing discovery of new anomalies ultimately undermines the reputation of the capital asset pricing model (CAPM) (Sharpe 1964) and motivates research into the applicability of new asset pricing models. The development of the Fama and French (1993) three-factor model, which adds size and value factors to market risk, was quickly followed by the development of the four-factor Carhart (1997) model, which incorporates a momentum factor. Both models are now widely accepted and are employed in the majority of asset pricing studies in a developed market. Recently, Fama and French (2015) proposed a five-factor model that also captures return patterns related to profitability and investment. Although still not as popular as the four-factor model, the five-factor model is garnering attention and traction amongst both academics and practitioners and is becoming the subject of extensive research.

Although the application of these multifactor models is popular in developed markets, these models are still relatively rarely used in frontier and emerging markets—Poland in particular. There are two possible reasons for this. First, emerging market investors and researchers frequently lack high-quality data with factor returns that can be directly employed in such studies. Second, and perhaps more importantly, there is insufficient research verifying which model is best suited for a particular country. The characteristics of various markets may differ significantly and thereby result in notably different return patterns and risk premia. The well-known case of Japan with a missing momentum effect serves as an example.[1] More recently, Jacobs (2016) showed that international markets might differ markedly regarding the presence of various equity anomalies, or in a broader sense, cross-sectional patterns. Consequently, it is essential to understand which factor premia are present in a given market and which factor pricing model is the most suitable for that market. Moreover, given that investors in emerging stock markets should rely on local rather than international asset pricing factors, the question of the most suitable asset pricing model for a given market is crucial for both researchers and practitioners (Hanauer and Linhart 2015).

The primary aim of this article is to determine the most appropriate asset pricing model for the Polish stock market. Therefore, we evaluate and compare the performance of four popular multifactor models in the finance literature: the CAPM, the Fama and French (1993) three-factor model, Carhart's (1997) four-factor model, and the five-factor model proposed by Fama and French (2015).

The Polish stock market continues to attract investors from all over the world. As an emerging market, it is likely to provide higher risk premia than developed markets.[2] Furthermore, while it is open to international investors and is becoming increasingly integrated with developed and emerging markets, it offers diversification opportunities for investors from developed markets even in the current post-liberalization period (Bekaert and Harvey 2002). The Warsaw Stock Exchange (WSE) is currently by far the largest stock market in Central Eastern Europe, both in terms of stock market capitalization and listings. With more than 850 firms worth more than 300 billion EUR, the WSE lists the majority of firms in the region.[3] Furthermore, the presence of international investors in the Polish stock market is increasing, with 50% of total turnover attributable to international investors in 2016.[4] Nevertheless, Polish investors still lack insight into a simple question: which of the popular asset pricing models is most applicable to the Polish stock market?

To answer this question, we investigate a sample of more than 1100 stocks in the Polish equity universe for the years 2000–2018. To compare the performance of the four asset pricing models, we apply a battery of tests, some of which are well-known in the literature and others that are more recent in nature. We estimate Fama-MacBeth (1973) regressions, form and examine portfolios from one-way and two-way sorts using the GRS (Gibbons, Ross, and Shanken 1989) and generalized method of moments (GMM) methods, apply simulation-based tests of monotonic relationships proposed by Pattern and Timmermann (2010), calculate maximum ex-post Sharpe ratios following Ball et al. (2016) and Barillas and Shanken (2018), and implement factor redundancy checks as in Huo, Xue, and Zhang (2015) and Medhat (2017).

This research makes two contributions. First, this is the first study to comprehensively compare, using the recently developed methodology, the performance of these four asset pricing models in Poland, including the five-factor model of Fama and French (2015). The prior research investigates the exclusive application of the three-factor (Czapkiewicz and Skalna 2010; Olbryś 2010; Urbański 2012; Waszczuk 2013b) or four-factor model (Czapkiewicz and Wojtowicz 2014). None of these studies contains a comprehensive investigation of and comparison with the five-factor model.

Second, we provide new evidence relating to the widely recognized cross-sectional patterns in the Polish stock market regarding firm size, the value effect, the momentum effect, profitability, and investment. Although size, value, and momentum have been investigated by multiple authors (e.g., Borys and Zemcik 2009; Czapkiewicz and Wojtowicz 2014; Lischewski and Voronkova 2012; Waszczuk 2013a), less research has been conducted on profitability and investment patterns.

The main findings of this study may be summarized as follows. Carhart's (1997) four-factor model is the best performing model out of the four alternatives examined. All the variables that comprise the model, when considered jointly, are reliable predictors of future cross-sectional returns. Moreover, the model adequately explains the cross-sectional variation in stock returns, whereas the other models fail to adequately explain the momentum effect. Furthermore, the value and momentum factors are the only factors that pass the factor redundancy test, and Carhart's (1997) model is the only one that includes both of these factors. The remaining factors—firm size, profitability, and investment—are explained by other portfolios, confirming their redundancy for asset pricing in Poland. In summary, practitioners and researchers in Poland should consider using Carhart's (1997) four-factor model for asset pricing and related applications.

Literature Review

Earlier research on the size and value effects in the Polish market produced somewhat contradictory results. These studies found that the CAPM adequately describes the cross-sectional variation in returns or found evidence of value and size premia in returns. Zhang and Wihlborg (2003) examined different variations—local and international—of the CAPM for 221 firms listed on the WSE. Importantly, this early study was—by its nature—limited in scope and sample size and was not able to accommodate a state-of-the-art examination of cross-sectional patterns in equity markets. The authors found that the domestic CAPM is appropriate for Polish stock returns. The authors also report that firm size is positively correlated with cross-sectional returns, whereas the book-to-market ratio has no explanatory ability. A further study by Borys and Premcik (2009) compared four Visegrad markets and, in general, provides support for the findings of Zhang and Wilhlborg (2003): the CAPM proves useful, whereas size and value premia are relevant for a few industries. Sekuła (2013) reports that the correlation between market value and expected returns is very low. However, this study is based on a very limited research period (2002–2010) and does not include the classical asset pricing tests. Roszkowska and Langer (2016b) compare the CAPM and the three-factor model and report that the former model performs well, whereas the latter provides only a minor improvement.

In contrast to these results, Czapkiewicz and Skalna (2010) tested the three-factor model using the GMM and found that the cross-sectional variation in returns cannot be explained solely by excess market returns. They further argue that size and value are also relevant. The significance of size and book-to-market ratio effects, in addition to the effect of excess market returns on Polish equity, are also confirmed by Lischewski and Voronkova (2012), Olbrys (2010), Waszczuk (2013b), and Urbański (2017). In a survey of 630 firms listed on the WSE, Czapiewski (2016) concludes that the three-factor model adequately explains returns.

The findings of studies on the momentum effect are somewhat ambiguous. Czapkiewicz and Wojtowicz (2014) tested Carhart's (1997) four-factor model and found that size and value become significant only after the inclusion of the momentum factor. Buczek (2005), Wójtowicz (2011), Czapiewski (2013), and Merło and Konarzewski (2015) identified a strong momentum effect. However, Pawłowska (2015) did not find evidence that supported these findings. One of the explanations for this observation might be that Pawłowska relies on a relatively short sample period (2005–2015), which was highly influenced by the famous momentum crash of 2009 (Daniel and Moskowitz 2016). Roszkowska and Langer (2016b) conclude that it is impossible to unambiguously confirm the existence of a momentum effect in Poland. These authors observe that not only winners but also losers display abnormal returns, which remains an intriguing observation in comparison with earlier studies.

Studies of the profitability and investment effects on the Polish stock market are relatively scarce and rudimentary and are limited almost exclusively to those by Roszkowska and Langer (2016a, 2016b). These studies report a clear and persistent profitability effect, but the findings on investment related patterns are mixed. In contrast, Czapiewski (2016) found no significant profitability or investment premia. This discrepancy in results poses a puzzle, especially when considering that both studies relied on similar profitability measures and research samples.

In conclusion, the existing discourse on the applicability of cross-sectional asset pricing models in the Polish stock market is sparse and presents conflicting and inconsistent results. The results of the previous studies exhibit a strong dependency on sample size. A comprehensive and exhaustive investigation and comparison of multifactor models is clearly missing.

Data Source and Sample Preparation

Our sample encompasses equities listed on all stock exchanges in Poland, including the main board of the WSE and NewConnect. We use price and financial data from Bloomberg and include both listed and delisted firms to eliminate survivorship bias. Our calculations are based on monthly time series, and returns are adjusted for corporate actions and cash distributions. The sample period spans the period between January 2000 and May 2018, although prior data (dating back to August 1998) is used for constructing factors when necessary. For example, we use historical asset growth or prior returns for constructing momentum. Importantly, our sample period is longer and "fresher" than any earlier studies of cross-sectional asset pricing models in the Polish market. For example, the research period of Czapkiewicz and Wojtowicz (2014) ended in 2012, that of Roszkowska and Langer (2016b) ended in 2013, and the research period in the most recent article by Czapiewski (2016) ended in 2014.

A firm is included in the sample in month t if at least two variables are available: returns in month t and total capitalization at (the end of) month $t-1$. To ensure the quality of our sample and to align with market practices, we apply a number of static and dynamic filters. We consider only common stocks and exclude closed-end funds, exchange-traded funds, global depository receipts, and similar investment vehicles. Importantly, we do not discard financial companies, as is frequently done in asset pricing studies—for example, by Novy-Marx (2013) and by Roszkowska and Langer (2016a, 2016b) in their investigations of the Polish stock market. Our motivation is that the financial companies, including the banking sector, in particular, constitute an essential part of the Polish stock market. Only equities for which Poland is the primary market are included. After considering the practical problems associated with penny stocks, we exclude any firm from the sample in month t if in the preceding month its total capitalization was below 20 million PLN or its market share price dropped below 0.20 PLN. This approach was employed in the study of Waszczuk (2013b), who discarded stocks with a market price below 0.50 PLN, but most other studies, including those by Czapkiewicz and Wojtowicz (2014) and Czapiewski (2016), have not imposed any restrictions on penny stocks and micro-caps.[5] Finally, we screen the data for outliers and exclude observations of returns that are less than 98% or more than 500% as these are most likely errors in the database. Thus, we are less restrictive than, for instance, Waszczuk, who discarded observations with absolute returns exceeding 50%. Our final sample of eligible firms comprises 1108 firms, constituting the biggest sample ever investigated in the Polish equity market. Naturally, the total number and market value of firms listed in Poland was not constant in time and has grown with the development of the local stock market. This growth is shown in Figure S1 in the Supplementary Material, available online.

All data is denominated in PLN. Whenever our computations rely upon financial data, we employ lagged values up to month $t-5$ to eliminate look-ahead bias. Finally, we use the 1-month mid-price WIBOR/WIBIRD rate (ACT/365) as a proxy for the risk-free rate.

Asset Pricing Models and Factors

We evaluate and compare the performance of four different multifactor asset pricing models of the following general form:

$$E(R_t) = \gamma_0 + \gamma_1\beta_1 + \ldots + \gamma_K\beta_K, \tag{1}$$

where R_t is a vector of portfolio excess returns at time t, $\beta_1 \ldots \beta_K$ are vectors of risk factor sensitivities or loadings, and $\gamma_0, \ldots, \gamma_K$ denote the risk premium parameters associated with the corresponding risk factors.

Similarly as in Zaremba and Czapkiewicz (2017a), we consider five different models. The first model is the classic CAPM, which assumes that stock returns are related to movements of the market portfolio:

$$R_t = \alpha + \beta_{MKT} MKT_t + \varepsilon_t, \tag{2}$$

where MKT_t is the excess market return (the market risk factor) observed at time t, α is the intercept, and ε_t is the random error term.

The second model is the Fama and French (1993) three-factor model (henceforth abbreviated as FF3F) that accounts for value and size effects in equity returns:

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t. \tag{3}$$

The two additional factors—small minus big (*SMB*) and high minus and high minus low (HML)—represent size and value effects; SMB_t is the difference between returns on diversified portfolios of small and large stocks, and HML_t is the difference between returns on diversified portfolios of high book-to-market ratio (*BM*) and low *BM* stocks.

The third model, Carhart's (1997) four-factor model (henceforth abbreviated as the C4F model), extends the FF3F model by introducing a momentum factor:

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{UMD} UMD_t + \varepsilon_t, \tag{4}$$

where UMD_t is the return on the "up minus down" portfolio, calculated as the difference between diversified portfolios of stocks with high and low prior returns.[6]

The final model considered is the Fama and French (2015) five-factor model (henceforth abbreviated as the FF5F model). This model incorporates a profitability factor—robust minus weak (RMW)—and an investment factor—conservative minus aggressive (CMA):

$$R_t = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t + \beta_{CMA} CMA_t + \varepsilon_t. \tag{5}$$

In this model, RMW_t is the difference in returns between diversified portfolios of firms with high and low profitability, and CMA_t is the difference in returns between diversified portfolios of firms with high and low asset growth. Hence, these two factors represent the risk premia linked to the outperformance (underperformance) of the companies of high (low) operating profitability, and outperformance (underperformance) of the companies of low (high) investment, respectively.

The asset pricing models investigated include, in total, six asset pricing factors, namely: MKT, SMB, HML, UMD, RMW, and CMA. All the factor portfolios are constructed using conventional methods employed in the literature (see, e.g., Waszczuk (2014) for a survey). The excess return on the market portfolio—MKT_t—is the value-weighted average return on all firms in the sample.

Thea SMB and HML factors are constructed using the six value-weighted portfolios formed on size and the *BM* ratio, closely following the approach of Fama and French (2012). These portfolios are based on the intersections of two portfolios formed on size (defined as the natural logarithm of the total stock market capitalization at the end of $t-1$, abbreviated *MV*) and three portfolios formed on the *BM* ratio.

The big firms are those in the top 90% of the market capitalization of the stock market, and small firms are those in the bottom 10%.[7] The *BM* ratio for month t is the book equity at the end of month $t-5$ divided by total stock market capitalization at the end of month $t-1$. As in Fama and French (2012), the *BM* breakpoints are the 30th and 70th percentiles of the firms in the sample of large companies. Notably, our definition of the HML factor portfolio departs from the original approach employed by Fama and French (1993). Instead of using the six-month lagged book-to-market ratio updated annually, we update the *BM* variable more regularly. Thus, our approach is aligned with the framework advocated by Asness and Frazzini (2013) as being more effective.

Finally, SMB_t and HML_t returns are estimated as follows: SMB_t is the average return on three small firm portfolios minus the average return on three big firm portfolios. HML_t is the average return on value firm portfolios minus the average return on two growth firm portfolios.

The returns on the three remaining factors—UMT_t, RMW_t, and CMA_t—are estimated in the same manner as the HML_t factor return with the difference being that the *BM* ratio is substituted with alternative sorting criteria. To derive the UMT_t, factor return, stocks are ranked on prior cumulative log-returns in months $t - 12$ to $t - 2$ (*MOM*). The RMW portfolios are constructed using sorts on return on assets (*ROA*), which may be interpreted as a ratio of four-quarter trailing net profits to total assets in month $t - 5$. Importantly, by using *ROA*, we employ a slightly different approach than Fama and French (2015) in their seminal study, which relied on operating profit minus interest expenses. Our motivation for this minor methodological departure is ROA provides us with broader coverage of the Polish equities than the original measure of Fama and French (2015). Our definition also differs from the studies of Czapiewski (2016) and Roszkowska and Langer (2016a, 2016b), which used operating profits scaled by book value of equity, mixing the leverage and profitability effects.

Finally, the sorting criterion for CMA is the investment intensity, which is defined as the total percentage asset growth between months $t - 5$ and $t - 17$. Importantly, in this particular case, the CMA portfolio is long (short) the stock with low (high) asset growth.

Table 1 reports monthly returns on the pricing factors.[8] Interestingly, the mean of the majority of the factors is insignificantly different from zero. The notable outliers are the HML (value) and *UMD* (momentum) factors which have statistically significant monthly mean returns of 1.02% (*t*-statistic = 3.98) and 1.25% (*t*-statistic = 3.38), respectively. This supports prior findings of strong value and momentum effects in Poland (see Waszczuk 2013b).

Correlations between factors are generally low, indicating that the factor portfolios capture a broad set of *independent* return patterns. The value and momentum factors (HML and UMD) exhibit a low negative correlation, with an ordinary (Pearson's) correlation coefficient of −0.10 (*t*-statistic = −1.52). This is in line with the findings of Asness and Frazzini (2013) and Asness, Frazzini, and Pedersen (2013) who find that returns on the value and momentum strategies are negatively correlated and therefore permit for efficient portfolio diversification.

To provide a better overview of the performance of factor portfolios, we also display their cumulative returns within the study period (Figure 1). Again, the momentum factor clearly stands out with the highest long-run payoffs. Importantly, a comprehensive review of the results reveals some resemblances to the time-series patterns in other emerging markets, including the remarkable momentum crash in 2009 (Daniel and Moskowitz 2016).[9]

Notably, the time-series behavior of the factor portfolios displayed in Figure 1 may constitute a source of differences between the outcomes of this study and earlier research. Most notably, our research sample covers the periods of robust momentum performance in the years 2013–2018, which were not included in the earlier studies of Waszczuk 2013a, 2013b) or Roszkowska and Langer (2016a, 2016b), among others. Furthermore, the performance of the size effect in recent years was rather mediocre, which may undermine the robustness and significance of the size premium in our study in comparison with earlier examinations.

Evaluation Methods and Testing

In general, the selection and implementation of factor models' evaluation tools follows Zaremba et al. (in press). We begin our investigation by examining the predictive abilities of the variables underlying the asset pricing factors in the cross-section of returns. Hence, we apply a

Table 1. Monthly returns on asset pricing factors.

	MKT	SMB	HML	UMD	RMW	CMA	RF
			Panel A: Basic Statistics				
Mean	–0.05	0.14	1.02**	1.25**	0.35	0.06	0.48**
	(–0.30)	*(0.37)*	*(3.98)*	*(3.38)*	*(1.17)*	*(0.25)*	*(17.85)*
Volatility	6.06	4.83	4.11	4.58	4.62	3.91	0.39
Skewness	0.07	0.00	–0.36	–1.37	–0.40	–0.21	1.77
Kurtosis	1.22	4.02	6.26	6.48	5.27	2.17	2.17
			Panel B: Pairwise Correlation Coefficients				
MKT		–0.29**	0.03	–0.15*	–0.07	–0.23**	–0.14*
		(–4.45)	*(0.45)*	*(–2.30)*	*(–1.04)*	*(–3.52)*	*(–2.03)*
SMB			–0.05	0.04	0.01	0.04	–0.02
			(–0.67)	*(0.61)*	*(0.11)*	*(0.62)*	*(–0.34)*
HML				–0.10	–0.17**	0.06	0.03
				(–1.52)	*(–2.58)*	*(0.92)*	*(0.44)*
UMD					0.22**	0.09	–0.01
					(3.35)	*(1.41)*	*(–0.22)*
RMW						–0.18**	–0.06
						(–2.64)	*(–0.89)*
CMA							–0.04
							(–0.61)

Notes. This exhibit displays the characteristics of the asset-pricing factors considered in this study: excess market returns (*MKT*), small minus big (*SMB*), high minus low (*HML*), up minus down (*UMD*), robust minus weak (*RMW*), and conservative minus aggressive (*CMA*). The last column is the risk-free rate (*RF*). *Mean* is the mean of monthly returns, *Volatility* is the monthly standard deviation of returns, *Skewness* is the skewness of monthly returns, and *Kurtosis* is the kurtosis of monthly returns. Panel A reports descriptive statistics and panel B reports (Pearson's) pairwise product–moment correlation coefficients. *Mean* and *Volatility* are expressed in percentage. The numbers in brackets are bootstrap *t*-statistics. The symbols ** and * denote values reliably differing from 0 at 1% and 5% levels, respectively.

specification that is based upon that of Fama and MacBeth (1973). In particular, we follow the approach pioneered by Brennan, Chordia, and Subrahmanyam (1998), where the returns are regressed on pricing characteristics:

$$R_{i,t} = \beta_{0,t} + \sum_{j=1}^{J} \beta_{j,t} K_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where $R_{i,t}$ is the excess return on portfolio i in month t and $\beta_{0,t}$ and $\beta_{j,t}$ are the regression coefficients. $K_{i,t}$ is a variable that is hypothesized to predict returns and this variable is used to construct the asset pricing factors.[10] In other words, $K_{i,t}$ is one of the following: stock market beta estimated based on 36-month trailing period (*BETA*), the natural logarithm of market value (*MV*), momentum (*MOM*), the natural logarithm of the book-to-market ratio (*BM*), return on assets (*ROA*), and asset growth (*AG*).[11]

Having established preliminary cross-sectional relationships, we proceed with time-series tests. The four asset pricing models are examined using two distinct portfolio types. First, we evaluate model performance using value-weighted portfolios constructed on the basis of one-way sorts, according to *MV, BM, MOM, ROA*, and *AG*. Second, we use portfolios based upon independent two-way sorts as in Fama and French (2012) and Cakici, Fabozzi, and Tan (2013). The 4 × 4 two-way sort portfolios are formed according to combinations of the same five variables, namely *MV, BM,*

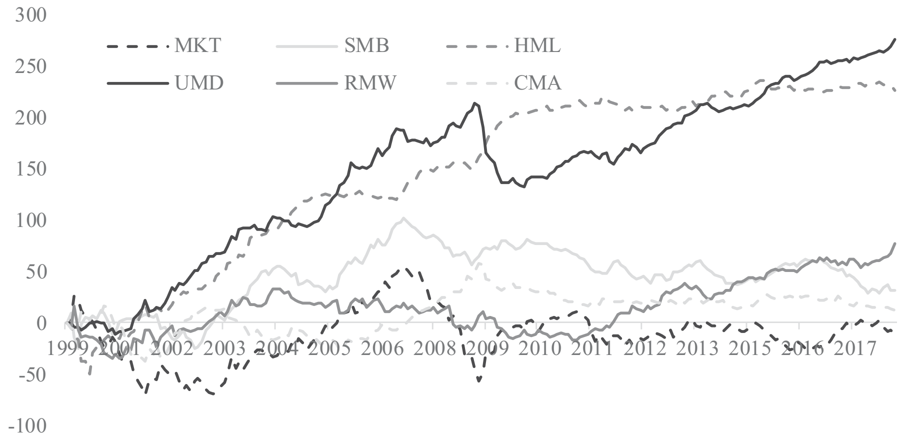

Figure 1. Cumulative returns on the factor portfolios.

Note. This figure reports cumulative returns on the six factor portfolios considered in this study: market excess return (*MKT*), small minus big (*SMB*), high minus low (*HML*), up minus down (*UMD*), robust minus weak (*RMW*), and conservative minus aggressive (*CMA*). The returns are expressed as percentages and cumulative returns are estimated additively.

MOM, ROA, and *AG*, used for the one-way sorted portfolios. This approach orders all securities in the sample according to the chosen variable following which the 25th, 50th, and 75th percentile breakpoints are determined. The intersection of the independent 4 × 4 sorts on two variables leads to the formation of 16 double-sorted value-weighted portfolios.[12]

To investigate the performance of the four models—CAPM, FF3F, C4F, and FF5F—using portfolios from one-way sorts and two-way sorts, we first construct a seemingly unrelated regressions (SUR) SUR model that follows equation (1) where R_t is the excess returns on a portfolio. We then investigate whether the betas in the CAPM, FF3F, C4F, and FF5F models accurately capture the cross-sectional variation in excess returns, R_{it}, on the ith portfolio at time t. Specifically, we examine the proposition that factors in each model generate efficient portfolios or, in other words, that the intercepts (alphas) are simultaneously equal to zero for all portfolios. Therefore, we test the null hypothesis $H_0: \ \alpha = 0$ against the alternate hypothesis H_1 using two tests: the GRS test of Gibbons, Ross, and Shanken (1989) and a test based on the GMM. Although the GRS test is widely applied, the primary advantage of the GMM approach is its robustness to both conditional heteroscedasticity and serial correlation in the changes in the explanatory factors and returns on the test portfolios. The methodology for testing H_0 in the GMM framework follows that of MacKinlay and Richardson (1991) and Cochrane (2005), and the procedure employed by Zaremba and Czapkiewicz (2017b).

As in Hou, Xue, and Zhang (2015) and Medhat (2017), we supplement our analyses with the factor redundancy test. To do so, we run time-series regressions of one factor on all the other factors. We seek to establish whether there any abnormal returns on individual factor portfolios that are unexplained after controlling for all the other factors. Therefore, we again test the null hypothesis $H_0: \ \alpha = 0$ against H_1 that assumes the opposite. If H_0 holds, then a given factor is fully accounted for by the other factors and is therefore redundant.

Eventually, to evaluate the economic significance of our results from an investor's standpoint, we follow Ball et al. (2016) and Barillas and Shanken (2018) and compute Sharpe ratios associated with different sets of factors. In this exercise, we form ex-post tangency portfolios from the factor portfolios incorporated in the respective asset pricing models. Differences in these Sharpe ratios measure how much investors could improve the mean-variance efficiency of their portfolios by extending the investment opportunity set with additional factors.

Results

Table 2 reports the results of cross-sectional Fama-MacBeth regressions. Let us first focus on Panel A, referring to the study of the full sample. When the variables are considered individually (specifications [1]–[6]), only three of them turn out to be significant predictors of the returns in the cross-section: *BM, MOM*, and *ROA*. The remaining variables—*BETA, MV*, and *AG*—are statistically insignificant. Also, when we consider *BETA, MV*, and *BM* together (specification [7]), as in the FF3F model, only the *BM* coefficient significantly departs from zero. Specification [8] examines the

Table 2. Results of cross-sectional Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Panel A: All Companies					
BETA	0.10						0.06	–0.01	–0.16	–0.16
	(0.59)						*(0.36)*	*(–0.09)*	*(–0.64)*	*(–0.80)*
MV		–0.08					–0.09	–0.16	–0.11	–0.17
		(–0.76)					*(–0.86)*	*(–1.43)*	*(–0.95)*	*(–1.59)*
BM			0.62**				0.56**	0.55**	0.64**	0.61**
			(4.60)				*(4.60)*	*(5.30)*	*(3.98)*	*(4.33)*
MOM				1.80**				2.09**		2.10**
				(4.38)				*(4.33)*		*(4.71)*
ROA					4.07				5.23*	3.83
					(1.95)				*(2.01)*	*(1.89)*
AG						0.06			–0.09	–0.23
						(0.21)			*(–0.29)*	*(–0.65)*
$\bar{R}^2$	1.62	1.19	1.96	2.34	1.87	1.59	4.19	6.73	7.87	10.54
					Panel B: Microcaps Excluded					
BETA	–0.08						–0.09	–0.05	–0.01	0.00
	(–0.37)						*(–0.44)*	*(–0.37)*	*(–0.06)*	*(–0.01)*
MV		–0.88**					–0.70**	–0.71**	–0.65**	–0.67**
		(–5.64)					*(–4.24)*	*(–4.50)*	*(–4.04)*	*(–4.42)*
BM			0.56**				0.57**	0.54**	0.78**	0.70**
			(3.43)				*(3.24)*	*(3.82)*	*(4.02)*	*(4.26)*
MOM				2.16**				2.40**		2.41**
				(3.68)				*(3.84)*		*(3.54)*
ROA					4.95				4.10	2.09
					(1.55)				*(1.29)*	*(0.82)*
AG						0.41			0.74*	0.38
						(0.97)			*(2.03)*	*(1.02)*
$\bar{R}^2$	2.26	2.47	2.29	3.49	3.27	2.54	6.49	9.89	11.50	14.81

Notes. This exhibit displays Fama and MacBeth (1973) regression coefficients (multiplied by 100) with corresponding *t*-statistics for excess returns on individual or multiple factors described by the following specification:

$$R_{i,t} = \beta_{0,t} + \sum_{j=1}^{J} \beta_{j,t} K_{i,t} + \varepsilon_{i,t},$$

where $R_{i,t}$ is the excess return on a security i in month t, and $\beta_{0,t}$, and $\beta j,t$ are the coefficients. We used six predictors: the 36-month stock market beta (*BETA*), the natural logarithm of the market value (*MV*), the natural logarithm of a book-to-market ratio (*BM*), momentum (*MOM*), return on assets (*ROA*), and asset growth (*AG*). Reported values are the β_j coefficients and the numbers in brackets are Newey and West (1987) adjusted *t*-statistics. The $\bar{R}^2$ is the average adjusted coefficient of determination. The symbols ** and * denote values reliably differing from 0 at 1% and 5% levels, respectively. Panel A reports results based on the full research sample while panel B reports results for the sample excluding that excludes the smallest companies with an aggregate market value of 3% of the full capitalization of the research sample.

variables in the C4F model. In this case, two variables—*BM* and *MOM*—are statistically significant. As documented by Asness, Moskowitz, and Pedersen (2013) and confirmed in Table 1, the value and momentum factors are negatively correlated. Following the reasoning of Balvers and Wu (2006), it appears that together these variables to some extent reinforce each other leading to a higher *MOM* coefficient. Furthermore, isolating the cross-sectional variation in returns generated by these two factors captures the size effect, *MV*.

Interestingly, incorporating the remaining variables does not necessarily result in the same benefits. Specification [9] is the FF5F model: this specification considers *MV, BM, ROA*, and *AG* together. However, in this case, *BETA, MV*, and *AG* remain insignificant. Importantly, even when all variables (specification [10]) are considered jointly, *BETA, MV, ROA*, and *AG* are statistically insignificant in predicting future cross-sectional returns. Only *BM* and *MOM* are significant across all of the specifications. Bearing that in mind, the specification (7), the C4F model, is particularly interesting. This sole framework includes exactly these two variables.

Panel B of Table 2 reports the results of an additional robustness check for microcaps. Instead of dropping all of the companies with stock market capitalization below 20 million PLN, we exclude all of the smallest firms with an aggregate market value lower than 3% of the total capitalization of all companies in the sample. This results in about 50% fewer firms in the sample than in Panel A. The results of this robustness test are predominantly consistent, with strong *BM* and *MOM* effects evident. However, there are two notable differences; the negative coefficient on size (*MV*) becomes significant across all of specifications and profitability (*ROA*) loses its explanatory ability for the cross-section of returns. In summary, there are only two return predictors that remain significant across all approaches and specifications, namely *BM* and *MOM*.

Table 3 reports the performance of portfolios formed using one-way sorts on *MV, BM, MOM, ROA*, and *AG*. These results confirm those in Table 2. Momentum is the most distinctive determinant of cross-sectional returns. The long-short portfolio in the "*H-L*" column is significantly profitable for this one-way sort, resulting in mean monthly returns of 1.78% (*t*-statistic amounts to 3.22). Also, the zero-investment portfolios formed on *BM* and *ROA* deliver remarkable payoffs amounting to 1.05% (*t*-statistic = 2.63) and 1.53% (*t*-statistic = 2.78), respectively. This finding corroborates the earlier results of Roszkowska and Langer (2016a, 2016b), who found that profitability can be used to engage in profitable investment strategies in Poland. None of the other sorts produces positive and significant mean returns on the long-short portfolios.

We also follow Waszczuk (2013b) and supplement our examination of the one-way sorted portfolios with the formal simulation-based test of Patton and Timmermann (2010) to detect monotonicity in cross-sectional returns. The last column of Table 3 reports the *p*-values from this test (*MR*). The results point toward strong monotonicity in cross-sectional returns that are related to momentum (*p*-value equaling 0.17%) and value (*p*-value equaling 4.52%). For the other cases, monotonicity is not detected. This includes sorts on return on assets, which produced significant profits on the long-short portfolios. Summing up, value and momentum once again prove to be the most robust phenomena in the cross-section of returns.

Table 4 summarizes the overall performance of the models—CAPM, FF3F, C4F, and FF5F—for portfolios formed on the basis of one-way sorts. The CAPM (Table 4, Panel A) performs well in explaining cross-sectional returns on portfolios formed on the basis of *MV, ROA*, and *AG*, but not for *BM* and *MOM*-sorted portfolios. The *p*-values for the GRS (GMM) test statistics for portfolios formed on value and momentum are 4.05% and 0.85% (6.40% and 2.24%), respectively, suggesting that the CAPM fails to explain the cross-sectional variation in returns on this portfolio. Also, the MR test displays evidence of monotonicity in returns on MOM-sorted CAPM-adjusted returns confirming that this model is not able to explain the momentum effect.

The results of the FF3F model reported in Panel B of Table 4 show improvement over the CAPM results. The average $\overline{R}^2$ rises from 62.66% for the CAPM model to 70.03% for the FF3F model. However, the average value and dispersion of the absolute intercepts remain essentially the same and

Table 3. Monthly returns on portfolios from one-way sorts.

	Low	2	3	4	High	H-L	MR
			Panel A: Market Value				
R	0.49	0.16	–0.04	0.04	–0.06	–0.56	11.55
	(0.99)	*(0.31)*	*(–0.19)*	*(–0.06)*	*(–0.31)*	*(–1.52)*	
Vol	7.28	6.87	6.64	6.02	6.25	5.97	
SR	0.24	0.08	–0.02	0.02	–0.03	–0.32	
			Panel B: Book-to-Market Ratio				
R	–0.37	–0.50	0.07	–0.06	0.69	1.05**	4.52*
	(–0.94)	*(–1.26)*	*(0.02)*	*(–0.27)*	*(1.65)*	*(2.63)*	
Vol	7.43	6.91	6.95	6.40	6.71	5.92	
SR	–0.17	–0.25	0.03	–0.03	0.35	0.62	
			Panel C: Momentum				
R	–1.07*	–0.39	0.03	0.16	0.79	1.85**	0.17**
	(–2.02)	*(–0.80)*	*(–0.12)*	*(0.32)*	*(1.56)*	*(3.09)*	
Vol	8.03	7.85	6.41	6.39	7.26	7.43	
SR	–0.46	–0.17	0.02	0.09	0.38	0.86	
			Panel D: Return on Assets				
R	–0.72	–0.27	0.28	–0.24	0.82	1.53**	63.23
	(–1.48)	*(–0.73)*	*(0.53)*	*(–0.76)*	*(1.45)*	*(2.78)*	
Vol	7.78	6.36	6.92	6.51	8.17	8.35	
SR	–0.32	–0.15	0.14	–0.13	0.35	0.64	
			Panel E: Asset Growth				
R	–0.01	–0.27	–0.07	0.20	–0.22	–0.21	27.69
	(–0.16)	*(–0.76)*	*(–0.28)*	*(0.37)*	*(–0.60)*	*(–0.47)*	
Vol	6.06	6.13	6.87	7.63	7.26	6.36	
SR	0.00	–0.15	–0.03	0.09	–0.10	–0.11	

Notes. This exhibit displays average monthly returns (*R*) and the standard deviation for returns (*Vol*) on quintile value-weighted portfolios formed on one-way sorts on market value (*MV*) (Panel A), book-to-market (*BM*) ratio (Panel B), momentum (*MOM*) (Panel C), return on assets (*ROA*) (Panel D), and asset growth *(AG)* (Panel E). *High* and *Low* are the quintile portfolios with the highest and lowest underlying variables, respectively, and *H-L* is the long-short portfolio, which is long (short) in the *High* (*Low*) portfolio. *R* is the mean of monthly returns, *Vol* is the monthly standard deviation of returns, and *SR* is the annualized Sharpe ratio. This table also reports *p*-values for the Patton and Timmermann (2010) test of monotonic relationship (*MR*). *R, Vol*, and *MR* are expressed in percentage. The numbers in brackets are bootstrap *t*-statistics. The symbols ** and * denote values reliably differing from 0 at 1% and 5% levels, respectively.

the model does not perform well for the momentum portfolio.[13] The *p*-value for the GRS (GMM) test statistic is 0.40% (0.29%), indicating that the model is not well-suited to explaining the cross-sectional variation in returns associated with momentum.

The results for the C4F model presented in Panel C of Table 4 show that this model explains abnormal returns for all portfolios. The average absolute intercept declines change for this specification relative to the FF3F model (0.28% vs. 0.36%), the average $\overline{R}^2$s increase marginally (71.60% vs. 70.03%), and the null hypotheses are not rejected for the GRS and GMM tests. Additionally, the MR test detects no monotonicity in any set of model-adjusted returns. Specifically, these results suggest that the four-factor model satisfactorily accounts for the cross-sectional patterns in returns related to the book-to-market ratio, market value, momentum, return on assets, and asset growth.

Finally, Panel D of Table 4 reports the results of the FF5F model. When compared against the C4F model, the results of the FF5F model are similar in terms of the average absolute

Table 4. Model results for returns on one-way sorted portfolios.

	$\bar{\alpha}$	$\overline{t-\text{stat}}$	$s(\alpha)$	$s(t-\text{stat})$	$\overline{R^2}$	MR	GRS	GMM
				Panel A: Capital Asset Pricing Model				
Market value	0.16	0.38	0.22	0.40	59.48	65.40	49.73	66.30
B/M ratio	0.33	1.26	0.28	1.03	70.53	9.47	4.05*	6.40
Momentum	0.49	1.53	0.41	1.04	66.78	0.13**	0.85**	2.24*
Return on assets	0.46	1.36	0.30	0.75	54.01	63.23	10.93	19.94
Asset growth	0.14	0.53	0.11	0.44	62.49	53.20	86.93	87.27
Average	0.32	1.01	0.26	0.73	62.66	38.29	30.50	36.42
				Panel B: Three-Factor Model				
Market value	0.13	0.65	0.13	0.33	79.80	66.57	49.74	64.22
B/M ratio	0.30	1.03	0.12	0.36	74.57	86.97	36.01	73.35
Momentum	0.56	1.95	0.45	1.42	69.31	0.07**	0.40**	0.29**
Return on assets	0.59	1.88	0.40	1.23	61.44	44.47	1.06*	3.93*
Asset growth	0.21	0.78	0.19	0.75	65.01	29.60	37.44	59.35
Average	0.36	1.26	0.26	0.82	70.03	45.53	24.93	40.23
				Panel C: Four-Factor Model				
Market value	0.15	0.77	0.13	0.44	80.05	61.27	33.55	54.26
B/M ratio	0.26	0.76	0.15	0.43	74.52	83.50	49.86	88.39
Momentum	0.22	0.79	0.21	0.67	75.98	61.27	52.21	62.60
Return on assets	0.48	1.48	0.23	0.63	62.21	69.00	8.96	29.56
Asset growth	0.28	1.01	0.25	0.93	65.22	30.63	9.79	9.20
Average	0.28	0.96	0.19	0.62	71.60	61.13	30.88	48.80
				Panel D: Five-Factor Model				
Market value	0.12	0.55	0.15	0.43	80.01	69.77	31.14	42.93
B/M ratio	0.22	0.85	0.14	0.56	76.52	80.13	52.94	77.19
Momentum	0.50	2.00	0.38	1.27	71.02	0.03**	1.09*	5.24
Return on assets	0.45	1.66	0.26	0.81	66.62	73.33	2.68*	0.32**
Asset growth	0.17	0.76	0.16	0.72	69.81	22.73	37.77	48.40
Average	0.29	1.16	0.22	0.76	72.80	49.20	25.13	34.82

Notes. This exhibit displays the results of models investigated applied to value-weighted quintile portfolios from one-way sorts on market value *(MV)*, the book-to-market *(BM)* ratio, momentum *(MOM)*, and return on assets *(ROA)*, and asset growth (*AG*). Panel A reports results for CAPM, Panel B for the Fama and French (1993) three-factor model, Panel C for Carhart's (1997) four-factor model, and Panel D for the Fama and French (2015) five-factor model. The $\bar{\alpha}$ and $s(\alpha)$ are the average absolute intercept and the standard deviation of the intercept, respectively, while $\overline{t}$stat and $s(t\text{stat})$ is the average absolute t-statistic and the t-statistic's standard deviation. *GRS* is the p-value for the *GRS* test of Gibbons, Ross, and Shanken (1989) and GMM is the p-value for the GMM approach estimated according to the procedure described in the methodology section. $\bar{R}^2$ is the mean adjusted coefficient of determination for a set of portfolios. *MR* is the p-value for the Patton and Timmermann (2010) test of monotonic relationship. The t-statistics are adjusted for heteroscedasticity and serial correlation using Newey and West (1987) robust standard errors. The intercepts, *GRS, GMM*, and $\bar{R}^2$ are expressed in percentage. *Average* refers to the average value of statistics across various sets of portfolios. The symbols ** and * denote values reliably differing from 0 at 1% and 5% levels, respectively.

intercepts (with slightly lower dispersion), although the average $\overline{R}^2$ (72.80% vs. 71.60%) is slightly higher. However, the model shares a common drawback with the CAPM and FF3F models: the model fails to account for the momentum effect in returns. The p-values for the GRS test applied to the portfolios formed using one-way sorts on past returns is 1.09%, respectively. This suggests that the FF5F model fails to explain the cross-sectional variation in returns that are driven by momentum.

In conclusion, inferences from an analysis of the one-way sorted portfolios align with conclusions drawn from the Fama-MacBeth regressions; the C4F model outperforms all other models considered. This model's advantage lies in its exclusive ability to account for the momentum effect.

Table S1 in the Supplementary Material presents monthly returns on sets of portfolios created using two-way sorts on *MV, BM, MOM, ROA*, and *AG*. The cross-sectional patterns related to certain variables after controlling for the other variables are somewhat ambiguous and frequently insignificant. Notable outliers are the momentum and value effects, as in the previous set of results. These phenomena often remain sizeable and robust, even after controlling for other variables. This suggests that the value (momentum) strategy works well and yields significant profits, not only in the full sample, but also within subsets of the entire sample formed by additional sorts on *MV, ROA, AG*, and *MOM* (*BM*). None of the remaining variables shows a similar ability and hardly any of the long-short portfolios (*H-L*) produce significant returns.

Table S2 in the Supplementary Material presents the results of the application of the factor models to two-way sorted portfolios. A preliminary overview of the results suggests that the results somewhat resemble those obtained using one-way sorted portfolios. The CAPM (Table S2, Panel A) does not provide an adequate description of portfolios that are sorted according to momentum or book-to-market ratio. When these effects are considered, the null hypothesis is rejected in both the GRS and GMM test. Furthermore, the FF3F model (Table S2, Panel B) suffers from a similar drawback: an inability to deal with the momentum effect. Although the average $\overline{R}^2$ increases substantially from 41.58% to 50.64%, six of the ten tested portfolio sets show significant GRS and GMM test statistics which have *p*-values lower than 5%. Finally, this model is unable to account for the momentum effect in returns.

The results are clearer for the C4F model (Table S2, Panel C). The mean monthly intercept decreases from 0.54% for the FF3F model to 0.41% for the C4F model and the average $\overline{R}^2$ increases marginally from 50.64% to 52.36%. Most importantly, the model provides a more satisfactory explanation of cross-sectional returns with the null hypothesis for the GRS rejected only in one instance: the two-way sorted portfolios on *MOM* and *AG*. Also, the GMM test indicates rejection in only three cases (*MV & MOM, MOM & ROA, MOM & AG*), much fewer than in cases of other models.

The final panel, Panel D of Table S2, reports the results for the FF5F model. As is the case for one-way sorted portfolios, the FF5F model underperforms the C4F model in terms of explanatory ability for portfolios formed on momentum. For each portfolio set ranked upon the basis of past returns, the FF5F model fails to explain the cross-sectional variation in returns, resulting in a rejection of the null hypotheses with the GRS and GMM tests. Also, the average $\overline{R}^2$ coefficient is close to that of the C4F model and the average absolute intercept is 0.49%, thereby exceeding that of the C4F model by 0.08 percentage points. In summary, the analysis of the two-way sorted portfolios confirms our earlier inferences relating to the C4F model. The C4F model, with the lowest average absolute intercept and the smallest number of rejections of the null hypothesis by the GRS and GMM tests, demonstrates its superiority over the CAPM, and the FF3F and FF5F models.[14]

Our next analysis that supplements earlier cross-sectional and time-series tests are the factor redundancy test. We seek to determine which factors show abnormal returns after controlling for the influence of all other factors. The results are reported in Table 5.

Four of the six factors considered, namely MKT, SMB, RMW, and CMA, fail our factor redundancy test. This suggests that these factors do not deliver any significant abnormal returns after controlling for all the other factors. This is not surprising as no portfolios considered have significant mean (raw) returns, as reported in Table 1. Only two factors show significant intercepts: UMD and HML. The momentum factor—UMD—produces a high and significant alpha of 1.24% (*t*-statistic: 3.77%). The value factor—HML—is also associated with a significant alpha after this factor is regressed into the other factors. The monthly intercept is 1.15%, with the corresponding (statistically significant) *t*-statistic equal to 3.18%. These observations provide support for Asness,

Table 5. Factor redundancy test results.

	MKT	SMB	HML	UMD	RMW	CMA
α	0.21	0.19	1.15**	1.24**	0.25	−0.05
	(0.44)	*(0.45)*	*(3.18)*	*(3.77)*	*(0.90)*	*(−0.14)*
MKT		−0.24**	0.01	−0.08	−0.07	−0.15**
		(−2.68)	*(0.07)*	*(−0.70)*	*(−0.81)*	*(−2.80)*
SMB	−0.34**		−0.03	0.00	−0.02	−0.02
	(−3.99)		*(−0.44)*	*(0.00)*	*(−0.25)*	*(−0.35)*
HML	0.01	−0.05		−0.08	−0.15	0.04
	(0.08)	*(−0.41)*		*(−0.54)*	*(−1.69)*	*(0.35)*
UMD	−0.13	0.00	−0.06		0.22**	0.09
	(−0.79)	*(0.00)*	*(−0.53)*		*(3.05)*	*(1.24)*
RMW	−0.11	−0.03	−0.13	0.22*		−0.18**
	(−0.76)	*(−0.27)*	*(−1.84)*	*(2.46)*		*(−2.95)*
CMA	−0.35*	−0.03	0.05	0.13	−0.24**	
	(−2.54)	*(−0.34)*	*(0.35)*	*(1.10)*	*(−3.59)*	
R^2	13.32	6.43	1.52	6.19	9.21	8.30

Notes. This exhibit displays the results of time-series regressions of one factor on all other factors. Each column corresponds to a regression specification with rows reporting the abnormal return (intercept, α), factor loadings (i.e., regression coefficients), and the R^2. The six factors considered are the excess market return (*MKT*), small minus big (*SMB*), high minus low (*HML*), up minus down (*UMD*), robust minus weak (*RMW*), and conservative minus aggressive (*CMA*). The values in parentheses are *t*-statistics adjusted for heteroscedasticity and serial correlation using Newey and West (1987) robust standard errors. The intercepts and R^2 are expressed in percentage. The symbols ** and * denote values reliably differing from 0 at 1% and 5% levels, respectively.

Moskowitz, and Pedersen (2013) who state that value and momentum are two pricing factors that play an important role in asset pricing. Of the four models considered—CAPM, FF3F, C4F, and FF5F—only the C4F incorporates both factors. The other models do not incorporate UMD and include factors that fail the redundancy test, with the exception of HML. The results in Table 5 again support the proposition that Carhart's (1997) four-factor model is best suited to the Polish stock market.

Finally, in our last examinations, we supplement the earlier tests with the estimation of maximum Sharpe ratios following Ball et al. (2016) and Barillas and Shanken (2018). The results are reported in Table 6.

An investor who passively invests in the market portfolio earns a Sharpe ratio amounting to about zero. Augmenting the opportunity set by the value and momentum strategies represented by the SMB

Table 6. Maximum ex-post Sharpe ratios.

	Weights						
Model	MKT	SMB	HML	UMD	RMW	CMA	Sharpe ratio
CAPM	100%						0.03
Three-factor model	−1%	12%	89%				0.88
Four-factor model	5%	6%	45%	44%			1.36
Five-factor model	1%	8%	61%		25%	5%	0.97

Notes. This table presents the maximum ex-post Sharpe ratios that can be achieved by using different combinations of factor portfolios and the weights on each factor necessary to achieve the maximum Sharpe ratio. The six factors considered are the excess market return (*MKT*), small minus big (*SMB*), high minus low (*HML*), up minus down (*UMD*), robust minus weak (*RMW*), and conservative minus aggressive (*CMA*). The Sharpe ratios are reported on an annualized basis.

and HML factor increases the Sharpe ratio to 0.88. Nonetheless, the crucial surge in the risk-adjusted performance is recorded only after the momentum-based portfolio (UMD) is included in the universe. Then, the Sharpe ratio increases to as much as 1.36. Finally, including all the factors considered in the five-factor model—MKT, SMB, HML, RMW, and CMA—leads to deterioration of performance: the new Sharpe ratio amounts to 0.97. Clearly, these outcomes once again underline the crucial role of the momentum factor in asset pricing, supporting the validity of the four-factor model in the Polish equity market.

Concluding Remarks

In this study, we investigate and compare the performance of four popular factor pricing models for the Polish market: the CAPM (Sharpe 1964), the Fama and French (1993) three-factor model, Carhart's (1997) four-factor model, and the recently developed Fama and French (2015) five-factor model. Relying upon a battery of tests and methods, we show that the C4F model outperforms the other models considered and is best suited to explain the cross-section of Polish stock returns. The other models fail to account for the momentum effect, whereas the C4F model explains the remaining residual cross-sectional patterns. Our results provide not only new insights into asset pricing on the Polish stock market but also have practical implications. These findings may be used for portfolio performance evaluation or may be applied by quantitatively oriented equity managers with an investment mandate orientated toward Poland.

Future studies on the topics discussed and investigated in this article may be pursued along at least two avenues. First, the scope of examined asset pricing models could be extended to consider factors representing, for instance, illiquidity (e.g., Amihud 2002; Pastor and Stambaugh 2003) or a low-risk anomaly (Frazzini and Pedersen 2014). Second, it would be worthwhile to investigate the level of integration of the Polish stock market with its international counterparts in the spirit of Hanauer and Linhart (2015). Such an investigation would aim to establish whether Polish investors should use local or international asset pricing factors or a combination of both. Finally, our tests, including the results reported in Table 3, indicate that only two factors play a crucial role in the Polish market: HML and UMD. This observation provides a foundation for developing an alternative asset pricing model focusing on these two particular factors.

Funding

This paper is a part of the project no. 2016/23/B/HS4/00731 of the National Science Centre of Poland.

Notes

1. For an overview, see Rouwenhorst (1998), Chui, Wei, and Titman (2000, 2010), Fama and French (2012), and Asness (2011).

2. Salomons and Grootveld (2003) and Donadelli and Persha (2014) provide direct evidence of higher risk premia in emerging markets. Dyck, Lins, and Pomorski (2013) and Huij and Post (2011) find that active management outperforms passive management in emerging markets. Also, Bekaert and Harvey (2002) and

Bhattacharya et al. (2000) conclude that pricing inefficiencies tend to be larger in emerging markets. Nonetheless, the recent studies of Jacobs (2016) and Li et al. (2016) argue that many anomalies are actually more pronounced in developed than in emerging markets.

3. Data sourced from https://www.gpw.pl/statystyki-gpw and https://newconnect.pl/statystyki-okresowe.

4. Data sourced from https://www.gpw.pl/analizy.

5. Roszkowska and Langer (2016a, 2016b) examined only stocks from the Main List of the WSE. This operation—by its nature—excluded a large number of the smallest and least liquid stocks from the sample.

6. We use the abbreviations MKT, SMB, HML, UMD, RMW, and CMA to denote the general concept of factors. On the other hand, the abbreviations in italics with the subscript t—MKT_t, SMB_t, HML_t, UMD_t, RMW_t, and CMA_t—are used to indicate the factor return in month t.

7. Our approach differs from Czapiewski (2016) and Roszkowska and Langer (2016b), who rely on median stock market capitalization. Waszczuk (2013b) used the median capitalization of 50% of the largest stocks as the breakpoint. Moreover, Czapkiewicz and Wojtowicz (2014) group stocks so that the "big firms" subset contains stocks with a total log-capitalization equal to 50% of the aggregated log-capitalization of the whole market. The group of small stocks contains all remaining companies.

8. The factor returns data are available from the authors.

9. See also Figure 1 in Cakici, Fabozzi, and Tan (2013) for direct comparison with emerging and developed markets.

10. The Fama MacBeth regression based on characteristics was used, e.g., in the study of the Polish market by Waszczuk 2013b). For the comparison of characteristics-based and betas-based cross-sectional regressions, see Goyal (2012) and Chordia, Goyal, and Shanken (2015).

11. Following Novy-Marx (2013), we use the natural logarithm of the market value and book-to-market ratio rather than the raw market value. For the stock market beta, we require a minimum of 12 monthly observations to calculate the variable.

12. The relatively low number of portfolios in comparison with other studies, such as those of Fama and French (2012) or Cakici, Fabozzi, and Tan (2013), is due to the relatively low number of securities in the sample investigated. In particular, we closely followed Czapkiewicz and Wojtowicz (2014) who used 16 portfolios to study the Polish equity market.

13. Notably, the intercepts in Tables 4 and 5 are estimated using time-series regressions. We employ an ordinary least squares approach and the t-statistics are adjusted for heteroscedasticity and serial correlation using Newey and West (1987) robust standard errors.

14. As an additional robustness check, we conducted analyses similar as in Tables 4 and S2 in subsamples the smallest firms with an aggregate market value of the 3% of the total capitalization of the full sample excluding. The results were qualitatively consistent, pointing out to the superiority of the C4 model. For brevity, we do not report these outcomes in details.

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