STATISTICS IN TRANSITION new series, March 2020
Vol. 21, No. 1 pp. 73–94, DOI 10.21307/stattrans-2020-005
Submitted – 10.10.2018; accepted for publishing – 30.09.2019

Using the ICAPM to estimate the cost of capital of stock portfolios: empirical evidence on the Warsaw Stock Exchange

Stanisław Urbański[1], Jacek Leśkow[2]

ABSTRACT

The aim of this paper is to present the method for estimating the cost of capital of typical portfolios available on the Warsaw Stock Exchange. The authors introduce the three factor Fama-French model and its two modifications. They also apply the bootstrap method to evaluate the variability of their estimation method. The cost of capital they refer to is related to portfolios of real options linked to projects. The market returns are generated both by stock companies running such projects and by real options modifying selected projects. The estimated cost of capital can serve as a valuable indicator for investors and for managers overseeing portfolios of stocks. Also, such an indicator can serve as a general reference while making business decisions related to new. The study demonstrated that the estimated cost of capital assumes highest values for value portfolios and stock companies with high financial indicators and, at the same time, low market prices compared to their book value. By the same token, the estimated cost of capital assumes low values for growth portfolios and for stock companies characterised by low financial indicators and, at the same time, high market prices compared to their book values.

Key words: ICAPM, cost of capital, risk premium, bootstrap method.
JEL: G11, G12

1. Introduction

The classical Capital Asset Pricing Model (CAPM), defined by Sharpe (1964) and Lintner (1965), plays a key role in the process of making investment decisions by managements of stock companies. It is widely applied to estimating the cost of capital and assessing the efficiency of the investment projects run. The research by Graham and Harvey (2001) or Welch (2008) provide some interesting examples of this use of the CAPMs. The former paper presents a survey of 392 Chief Financial Officers and the

[1] AGH University of Science and Technology, Faculty of Management, 30-067 Krakow, 10 Gramatyka Street, Poland. E-mail: surbansk@zarz.agh.edu.pl. ORCID: https://orcid.org/0000-0002-8020-8471.
[2] Institute of Teleinformatics, Cracow University of Technology, 31-155 Krakow, 24 Warszawska, Poland. E-mail: jleskow@pk.edu.pl.

capital budgeting they have supervised together with methods of estimating the cost of capital and assessing the structure of capital. This study suggests that the classical CAPM, the mean return and the multifactor CAPM, are the most popular methods of estimating the cost of capital. The method of dividend discounts, on the other hand, was quoted as the least popular. The authors state that: "… it is not clear that the model is applied properly in practice." (see: Graham and Harvey, 2001, p. 201). They also write that the main problem lies in the structure of the capital, for example in the effect of big or small companies. Some companies with higher capitalization more frequently apply the Net Present Value NPV or the CAPM method. This can cause price anomalies related to capitalization or to book to market value effects (see: Banz (1981), Rosenberg et al. (1985), Bhandari (1988) or Fama and French (1992)). Other anomalies impeding the CAPM-based pricing are analysed in papers of Lakonishok et al. (1994) or Jegadeesh and Titman (1993). Also, the research of Reinganum (1981) and Lakonishok and Shapiro (1986), whose results were confirmed by Fama and French (1992), is worth mentioning. The research advocates perceiving risk as a multidimensional factor. The applications of the Intertemporal Capital Asset Pricing Model (ICAPM) proposed by Fama and French (1993, 2015) or Carhart (1995) introduce capitalization-dependent risk factors such as book to market, profitability and investment. However, Welch (2008) favours the CAPM over the theoretical models such as the ICAPM or the Arbitrage Pricing Theory (APT).

Jagannathan and Wang (1996), Berk et al. (1999), Bernardo et al. (2007) and Zhi Da et al. (2012) attempt to explain the pricing that can be partially inconsistent with the pricing done via the CAPM model. These authors state that the stock companies frequently insure planned and carried out projects using the real options related to those projects. Therefore, the stock company can be described via a portfolio of current and future projects together with options related to such projects.

It is possible to assume that the CAPM-based estimate of the cost of the project is appropriate even in the case when pricing of the company is not consistent with CAPM. For example, Zhi Da et al. (2012, p. 205) clearly state that the risk premium and the beta factors related to them are related to the risk of such project and options related to projects. Therefore, they state that "… the CAPM could work well on the option-adjusted risk premium and beta." The quoted authors propose procedures to modify the relations between options and pricing and construct the option-adjusted beta, and option-adjusted stock returns.

Using the above literature survey we can state that if all projects of stock companies are not secured with real options then the necessary and sufficient condition to estimate the cost of capital using classical CAPM or ICAPM is to use pricing according to CAPM or ICAPM. Therefore, the estimate of the cost of capital will be more reasonable for the assets more resistant with the respect to price anomalies. Assuming that the correctness of CAPM-based pricing was established for portfolios, it is interesting to estimate the capital cost for characteristic portfolios of a given market, see Cochrane (2001, p.445). Ferson and Locke (1998) indicate that the necessary condition for proper estimation of the CAPM-based cost of capital is proper estimation of the risk premium. This is more important than the estimation of betas, which are sometimes not adequate. Therefore, a precise estimation of the risk premium and pricing, which can be used when ICAPM or CAMP are appropriate, requires pricing that leads to generation of multifactor-efficient portfolios.

Our paper presents different methods of estimating of the cost of capital using stocks coming from the Warsaw Stock Exchange (WSE). We provide estimate of the cost of capital for the characteristic portfolios. In order to precisely estimate the risk premium we apply selected applications of ICAPM. Research regarding the Polish market is mainly focused on testing the classical CAPM. See also paper of Zarzecki et al. (2004-2005), and Czapkiewicz and Wójtowicz (2014) regarding the role of ICAPM in estimating the risk premium.

Our previous research (see Urbański et al. (2014) and Urbański (2015)) show that elimination of speculative and penny stocks enables generating multifactor-efficient portfolios using selected applications of ICAPM. In the first part of our work we show the precise and wide research in this direction. In order to obtain that, we apply the classical Fama-French model, a modified Fama-French model (see Urbański (2012)) and a new modification of the Fama-French model, which is presented in Section 2.1 of the paper.

Estimation of the cost of capital is also related to calculating the error of such estimation at a given significance level. To accomplish that, we present a method of building the confidence interval for the cost of capital. In our approach the cost of capital is the product of systematic risk and risk premium components. The risk and the risk premium components are defined as parameters of the corresponding regression models. In such regression models the monthly returns have a distribution that is close to normal. Therefore, the distribution of the regression parameter estimators should be also close to normal. However, as the capital cost is a nonlinear function of estimated normal distributions, it cannot be assumed to be normal. In order to deal with this difficulty, the bootstrap method is applied.

In Section 2 of our paper we present various methods of estimating the cost of capital using ICAPM. Section 3 describes the bootstrap of residuals as a method to investigate the distribution and variability of the estimator of the capital cost. Section 4 of our paper presents the results of estimation of the risk premium using pricing applications for different boundary conditions for penny and speculative stocks. In this Section we also show the distribution of the estimated cost of capital and the related confidence intervals for characteristic portfolios. Section 5 contains the summary and the conclusion of our work.

2. Cost of equity capital using the ICAPM applications

Our starting point is ICAPM expressed as follows:

$$E(r_i) = E(RF) + \sum_{k=1}^{K} \beta_{ik} E(F_k), \tag{1}$$

where $E(F_k)$ is the systematic risk premium vector for the analysed market, and β_{ik} is the systematic risk vector of stock (portfolio) i, $E(RF)$ is the expected return of risk free asset, and $E(r_i)$ is the expected return of analysed asset.

The corresponding econometric model, useful for estimating the parameters β from (1), is expressed as follows: (layer 1)

$$r_{it} - RF_t = \beta_{i0} + \sum_{k=1}^{K} \beta_{ik} F_{kt} + e_{it};\ t = 1,\dots,T;\ \forall i=1,\dots m, \tag{2}$$

where F_{kt} is the value of k factor model in the period t.

Once the estimators $\widehat{\beta_{ik}}$ are calculated using (2), then we use them to get the estimator $\widehat{\gamma_k}$ of the parameter γ_k using the following equation: (layer 2)

$$r_{it} - RF_t = \gamma_0 + \sum_{k=1}^{K} \gamma_k \widehat{\beta_{ik}} + e_{it};\ t = 1,\dots,T;\ i=1,\dots m, \tag{3}$$

We use the estimators γ_k to get the point value of capital cost ($Ccap_i$) for each analysed stock (portfolio), using the equation (1) (layer 3). The period of estimating systematic risk components β_{ik} is subjective. Betas were most often estimated using 60 monthly periods, due to the average duration of the business cycle. However, it seems reasonable to extend the beta estimation period due to the observable extended business cycles in the last two decades. Thus, we estimate $Ccap_i$ based on the T months, according to Eq. (4):

$$Ccap_i = E(RF) + \widehat{\gamma_0} + \sum_{k=1}^{K} \widehat{\gamma_k} \widehat{\beta_{ik}^T};\ \forall\ i=1,\dots, m \tag{4}$$

The estimator $\widehat{\beta_{ik}^T}$ in equation (4) is obtained from the following equation:

$$r_{it} = \beta_{i0}^T + \sum_{k=1}^{K} \beta_{ik}^T F_{kt} + s_{it};\ t = 1,\dots,T;\ \forall i=1,\dots, m. \tag{5}$$

The purpose of this work is to study the variability of assessing the value $Ccap_i$. The most direct and comprehensive method to do this is to apply the bootstrap technique. For regression models like (2) and (3), the popular bootstrap method is bootstrapping the residuals. We will present details of this method in Section 3.

2.1. Three different ICAPM applications

We test the following three pricing applications to estimate the risk premium.

1) The classical three factor Fama-French model (see: Fama and French, 1993) - this application hereafter is denoted as FF model.
2) The modified three factor Fama-French model - this application hereafter is called M93FF, see Urbański (2012).
3) The modified three factor Fama-French model according to Fama and French (1995) work – this application hereafter is called M95FF. This application is presented below.

Based on the statements of Fama and French (1995), Urbański (2017, p. 84) assume that "The economic state variable that produces variation in the future earnings and returns related to size and *BV/MV* is a vector of structure of the past long-term differences in profitability." However, in fact, the results of Fama and French's (1995) research indicate that future returns are generated by changes in long-term relationships of past earnings to the book value of the company (see: Fama and French 1995, pp. 134-140, Figs 1 and 2, and Table 1).

Therefore, the pricing application, proposed by Urbański (2011), is modified. According to this new modification the adopted general state variable can be reflected by functional *FUN*, defined by equations (6), (7) and (8).

$$FUN = \frac{NUM}{DEN} = \frac{nor(ROE)\times nor(ASB)\times nor(APOB)\times nor(APNB)}{nor(MV/E)\times nor(MV/BV)}, \tag{6}$$

where

$$ROE = F_1; ASB = F_2 = \frac{\{\sum_{t=1}^{i}[S(Q_t)]\}/BV(Q_t)}{\sum_{t=1}^{i}\overline{SBV(nQ_t)}};\ \ APOB = F_3 = \frac{\{\sum_{t=1}^{i}[PO(Q_t)]\}/BV(Q_t)}{\sum_{t=1}^{i}\overline{POBV(nQ_t)}};$$
$$APNB = F_4 = \frac{\{\sum_{t=1}^{i}[PN(Q_t)]\}/BV(Q_t)}{\sum_{t=1}^{i}\overline{PNBV(nQ_t)}};\ MV/E = F_5;\ \ MV/BV = F_6. \tag{7}$$

F_j (j=1,…,6) are transformed to normalized areas $<a_j ; b_j>$, according to Eq. (10):

$$nor(F_j) = [a_j + (b_j - a_j)\times \frac{F_j - c_j\times F_j^{min}}{d_j\times F_j^{max} - c_j\times F_j^{min} + e_j}]. \tag{8}$$

In Equations (6) and (7), the corresponding indications are as follows: *ROE* is return on book equity; $\sum_{t=1}^{i} S(Q_t), \sum_{t=1}^{i} PO(Q_t), \sum_{t=1}^{i} PN(Q_t)$ are values that are accumulated from the beginning of the year as net sales revenue (*S*), operating profit (*PO*) and net profit (*PN*) at the end of '*i*' quarter (Q_i); $\sum_{t=1}^{i}\overline{SBV(nQ_t)}$; $\sum_{t=1}^{i}\overline{POBV(nQ_t)}$; $\sum_{t=1}^{i}\overline{PNBV(nQ_t)}$ are average values, accumulated from the beginning of the year as *S/BV*, *PO/BV* and *PN/BV* at the end of Q_i over the last *n* years (the present research assumes that *n*=3 years); *BV* is the book value, *MV/E* is the market-to-earning value ratio; E is the average earning for the last four quarters; MV/BV is the market-to-book value ratio; a_j; b_j; c_j; d_j; e_j are variation parameters. In equilibrium modelling, F_j (j=1,…,6) can be transformed into equal normalized area <1;2> (see Urbański, 2011).

In the case of the proposed multifactor model, as the modification of FF three factor model, the factors of equation (2) are defined as follows:

$$F_{1t} = RM_t - RF_t,\ F_{2t} = HLMN_t,\ F_{3t} = LMHD_t, \tag{9}$$

where $HMLN_t$ (high minus low) is the difference between the returns from the portfolio with the highest and lowest NUM_t values in period t; $LMHD_t$ (low minus high) is the difference between the returns from the portfolio with the lowest and highest DEN_t values in period t; $RM_t - RF_t$ is the market factor, defined as excess return of stock index – WIG (RM) over the risk-free rate (RF).

Considering (9), it can be shown that pricing model (1) can be written as follows:

$$E(r_i) = E(RF) + \beta_{i,M}E(RM - RF) + \beta_{i,HMLN}E(HMLN) + \beta_{i,LMHD}E(LMHD). \tag{10}$$

We analyse the research proposed by Kan and Zhang (1999) in order to check the possibility of incorrect specification of the model which is evidenced through the incorrect selection of factors (selection of useless factors). The results obtained by Kan and Zhang (1999) refer mainly to asymptotic cases, i.e. to study large samples of time series. Urbański (2011) carried out tests recommended by Kana and Zhang (1999), regarding the usefulness of the proposed factors, defining the applied M93FF applications and showed that the tested factors are not useless.

Our research regarding both M93FF and M95FF pricing applications cannot be considered as asymptotic. Our sample is at most 252 data points. It is frequently observed that even for samples of the size 200 in a very simple autoregressive AR(1) model the estimators do not necessarily achieve the normality of their distribution.

This is why we have decided to use the bootstrap approach. For small and medium-sized samples from time series, bootstrap is known to produce more reliable results when constructing confidence intervals and tests. The proposed new factors, of the M95FF application, result from a linear modification of the state functional, defining the factors of the M93FF application. The state functional, defining the factors of the M93FF application, is proposed in work of Urbański (2012, p. 555). The state functional, defining the factors of the M95FF application, is described by Eqs. 6, 7 and 8. An additional argument for the usefulness of the M95FF factors is the adjusting for errors-in-variables, by using Shanken's (1992) t-statistic. This is one of the tests recommended by Kan and Zhang (1999). Therefore, it can be assumed that the proposed changes do not result in uselessness factors of the M95FF application.

In connection with the above-mentioned argumentation, we conclude that in our case carrying out the other uselessness factors tests suggested by Kan and Zhang (1999) is not required.

3. Residuals bootstrap and variability of capital cost

In this section we propose the bootstrap of residuals in each of the layers of the three layer model introduced in the previous Section. Bootstrap methods are widely described by Efron and Tibshirani (1993). Below, we present the bootstrapping algorithm that leads to assessment of the variability of *Ccap*.

STEP 1 Bootstrapping of $\widehat{\boldsymbol{\beta}_{ik}}$

In this step apply the GLS method to get the estimator $\widehat{\beta_{ik}}$ from Eq. 2.

Bootstrap replication *j* = 1, first run.

Sample with replacement $\left\{\widehat{e_{i1}^{*1}}, \dots, \widehat{e_{iT}^{*1}}\right\}$ from the residuals $\{\widehat{e_{i1}}, \dots, \widehat{e_{iT}}\}$ of Eq. 2.

Treating $\widehat{\beta_{ik}}$ as given, use Eq. 2 to get bootstrap replication of excess returns $\{(r_{i1} - RF_1)^{*1}, \dots, (r_{iT} - RF_T)^{*1}\}$ corresponding to bootstrap replicates of $\left\{\widehat{e_{i1}^{*1}}, \dots, \widehat{e_{iT}^{*1}}\right\}$.

Put values $\{(r_{i1} - RF_1)^{*1}, \dots, (r_{iT} - RF_T)^{*1}\}$ back to the model (2) to get the first bootstrap replication of $\widehat{\beta_{ik}^{*1}}$.

STEP 2 Bootstrapping of $\widehat{\boldsymbol{\gamma}_{k}}$

In this step put $\widehat{\boldsymbol{\beta}_{ik}^{*1}}$ into Eq. 3 to get the bootstrap replicate $\widehat{\boldsymbol{\gamma}_{k}^{*1}}$ of the estimator $\boldsymbol{\gamma}_{k}$.

Repeat STEP1 and STEP2 *j*=1, …, B times. Again, taking at least B=1000.

As a result, obtain bootstrapped values of beta and gamma estimators:

$\left\{(\widehat{\boldsymbol{\beta}_{i1}^{*1}}, \dots, \widehat{\boldsymbol{\beta}_{iK}^{*1}}), \dots, (\widehat{\boldsymbol{\beta}_{i1}^{*B}}, \dots, \widehat{\boldsymbol{\beta}_{iK}^{*B}})\right\}$, and $\left\{(\widehat{\boldsymbol{\gamma}_{1}^{*1}}, \dots, \widehat{\boldsymbol{\gamma}_{K}^{*1}}), \dots, (\widehat{\boldsymbol{\gamma}_{1}^{*B}}, \dots, \widehat{\boldsymbol{\gamma}_{K}^{*B}}\right\}$.

STEP 3 Bootstrapping of $\boldsymbol{\beta}_{ik}^{T}$

In model (5) proceed identically as in STEP 1, and STEP 2. Bootstrapping residuals will give you B replicates of the estimator $\widehat{\beta_{ik}^{T}}$, that is

$\left\{(\widehat{\boldsymbol{\beta}_{i1}^{T1}}, \dots, \widehat{\boldsymbol{\beta}_{iK}^{T1}}), \dots, (\widehat{\boldsymbol{\beta}_{i1}^{TB}}, \dots, \widehat{\boldsymbol{\beta}_{iK}^{TB}})\right\}$ for stock (portfolio) *i* and *k*=1, …, *K* factors.

STEP 4 Bootstrapping of $\boldsymbol{E(RF)}$

Focus now on independent risk free rates *RF*. The natural estimate of the parameter E(*RF*) is $\boldsymbol{\mu} = \boldsymbol{1/T} \sum_{t=1}^{T} \boldsymbol{RF_t}$.

Obtain bootstrap replicates $\{\widehat{\boldsymbol{\mu}^{*1}}, \dots, \widehat{\boldsymbol{\mu}^{*B}}\}$ drawing samples $\{\boldsymbol{RF_1^{*j}}, \dots, \boldsymbol{RF_T^{*j}}\}$; *j*=1, …, B with replacement from $\{\boldsymbol{RF_1}, \dots, \boldsymbol{RF_T}\}$,

here: $\widehat{\boldsymbol{\mu}^{*j}} = \boldsymbol{1/T} \sum_{t=1}^{T} \boldsymbol{RF_t^{*j}}$.

STEP 5 Bootstrapping of $\widehat{Ccap_\iota}$

Use the replication $\left\{(\widehat{\gamma_1^{*1}},\dots,\widehat{\gamma_K^{*1}}),\dots,(\widehat{\gamma_1^{*B}},\dots,\widehat{\gamma_K^{*B}}\right\}$ and $\left\{(\widehat{\beta_{\iota 1}^{T1}},\dots,\widehat{\beta_{\iota K}^{T1}}),\dots,(\widehat{\beta_{\iota 1}^{TB}},\dots,\widehat{\beta_{\iota K}^{TB}})\right\}$ to create $\left\{Ccap_i^{*1},\dots,Ccap_i^{*B}\right\}$. Use the formula:

$$\widehat{Ccap_\iota^{*J}} = \widehat{\mu^{*J}} + \widehat{\gamma_0^{*J}} + \sum_{k=1}^{K}\widehat{\gamma_k^{*J}}\widehat{\beta_{\iota k}^{TJ}}; \qquad \forall i=1,\dots,m, \qquad (11)$$

With the bootstrap sample $\left\{Ccap_i^{*1},\dots,Ccap_i^{*B}\right\}$, for each portfolio separately, we are able to assess the variability of $Ccap_i$ and also the sampling distribution of $Ccap_i$.

In the next Section of our paper we show practical applications of the procedure described above. Here, we would like to make an additional point regarding bootstrapping $\hat{\gamma}$ and $\widehat{\beta^T}$ in formula (4). In financial applications, one usually takes shorter samples to get the estimates of $\widehat{\beta^T}$. This is motivated by the stability requirements. On the other hand, to get estimates of $\widehat{\beta^T}$ one prefers longer samples, for the sake of accuracy. From the methodological point of view, this does not create problems as long as the shorter sample includes at least 100 observations. The residual bootstrap was proven to be a consistent procedure (see, e.g. Lahiri (2003)) in regression context as well as in the time series context.

4. Data and interpretation of results

We analyse monthly returns of the stocks listed on the WSE in 1995-2017. Data referring to the fundamental results of the inspected companies are taken from the database drawn up by Notoria Serwis Company. Data for defining returns on securities are provided by the WSE.

The cost of capital is evaluated using three ICAPM applications presented in Section 2.1. In the case of FF model the quintile portfolios are formed on *BV/MV*. These portfolios, in turn, are divided into other quintiles formed using the capitalization (*CAP*) calculated for each stock company. In the case of the M93FF and M95FF models the quintile portfolios are formed using the *NUM* function. Again, these portfolios are, in turn, divided into other quintiles formed using the *DEN* function. Our analysis is then conducted for the 25 most characteristic portfolios of the market.

4.1. Risk premium vector components

In order to test whether the pricing application generates multifactor-efficient portfolios ten modes of samples are analysed. Mode 1 considers all the WSE stocks except companies characterized by a negative book value. In modes: from 2 to 8 penny stocks, with market values lower than 0.5, 1.0, 1.5, 2.0, 3.0, 4.0 and 5.0 PLN are eliminated, while modes 9 and 10 examine hypothetical cases of the exclusion speculative stocks. Mode 9 (indicated SPEC1) rejects the stocks that meet the following conditions: 1) $MV/BV > 100$; 2) $ROE < 0$ and $BV > 0$; and 3) $MV/BV > 30$ and $r_{it} > 0$, Mode 10 (indicated SPEC2) rejects the stocks meeting additional condition 4) $MV/E < 0$.

In Tables 1, 2 and 3 below we show the estimated values of the risk premium vector, estimated from second-pass regressions by the classical FF, M93FF and M95FF models, for eliminated penny stocks and speculative stocks.

Table 1. The values of the risk premium vector (γ) estimated from second-pass regressions for the classical Fama-French model

$$r_{it} - RF_t = \gamma_0 + \gamma_M\widehat{\beta_{i.M}} + \gamma_{HML}\widehat{\beta_{i.HML}} + \gamma_{SMB}\widehat{\beta_{i,SMB}} + \varepsilon_{it};\ t=1.....252;\ i=1.....25$$

Parameter	Excluded penny stocks below (PLN)								Excluded speculative stocks	
	0.0 Mode 1	0.5 Mode 2	1.0 Mode 3	1.5 Mode 4	2.0 Mode 5	3.0 Mode 6	4.0 Mode 7	5.0 Mode 8	SPEC1 Mode 9	SPEC2 Mode 10
γ_0, %	-3.01	-3.16	-3.70	-3.48	-3.51	-2.96	-3.17	-3.24	-2.74	-2.81
t-stat	-1.94	-2.08	-2.57	-2.58	-2.62	-2.49	-2.74	-2.63	-1.77	-1.96
SH t-stat	-1.79	-1.90	-2.29	-2.32	-2.35	-2.28	-2.50	-2.38	-1.69	-1.82
p-value, %	7.39	5.76	2.22	2.04	1.88	2.25	1.25	1.76	9.18	6.83
γ_{HML}, %	2.11	1.99	1.89	1.54	1.32	1.80	1.32	1.43	-0.67	1.17
t-stat	3.44	3.40	3.32	2.53	2.10	2.91	2.20	2.35	-1.23	2.05
SH t-stat	3.57	3.50	3.42	2.58	2.11	2.91	2.21	2.33	-1.24	2.07
p-value, %	0.04	0.05	0.06	1.00	3.51	0.37	2.73	1.98	21.38	3.89
γ_{SMB}, %	-0.05	-0.02	0.09	0.35	0.46	0.24	0.31	0.24	-1.63	0.69
t-stat	-0.10	-0.05	0.19	0.75	0.99	0.51	0.66	0.49	-3.75	1.60
SH t-stat	-0.10	-0.05	0.20	0.78	1.03	0.52	0.67	0.50	-3.76	1.65
p-value, %	91.68	96.03	83.91	43.42	30.30	60.49	50.37	61.72	0.02	9.98
γ_M, %	2.58	2.75	3.29	3.15	3.17	2.66	2.87	2.96	1.76	2.46
t-stat	1.52	1.65	2.08	2.10	2.13	2.00	2.24	2.16	1.04	1.58
SH t-stat	1.41	1.52	1.87	1.90	1.93	1.85	2.06	1.97	0.99	1.48
p-value, %	15.79	12.97	6.19	5.74	5.36	6.49	3.93	4.84	32.34	14.02
GRS-F	1.83	1.38	1.50	1.41	1.67	1.29	1.99	1.40	3.29	1.18
p-value, %	1.16	11.21	6.70	10.23	2.84	16.92	0.46	10.49	0.00	25.58
$Q^A(F)$	1.00	1.05	0.99	0.92	1.07	0.83	0.80	0.86	2.33	0.77
p-value, %	46.91	39.98	47.13	56.85	38.71	67.80	71.52	64.20	0.12	75.43
R^2_{LL}	68.45	64.15	54.33	47.74	40.92	68.88	66.69	56.66	25.61	34.79

Note: This table presents Fama-MacBeth cross-sectional regressions using the excess returns on 25 portfolios sorted by BV/MV and capitalization CAP. 252 monthly periods are analysed from May 1995 through May 2017. RF_t is the 91-day Polish Treasury bill return. $\widehat{\beta_{i.M}}$ is the loading on the market factor estimated from first-pass time-series regressions. $\widehat{\beta_{i.HML}}$ and $\widehat{\beta_{i,SMB}}$ are loadings on the HML and SMB factors. GRS-F is F-statistic of Gibbons et al. (1989). $Q^A(F)$ reports F-statistic and its corresponding p-value indicated below in brackets for Shanken's (1985) test that the pricing errors in the model are jointly zero. SH t-stat is Shanken's (1992) statistic adjusting for errors-in-variables. Following Lettau and Ludvigson (2001), R_{LL}^2 is a measure that shows the fraction of the cross-sectional variation in average returns that is explained by each model and is calculated as follows: $R_{LL}^2 = [\sigma_c^2(\bar{r}_i) - \sigma_c^2(\bar{\varepsilon}_i)] / \sigma_c^2(\bar{r}_i)$, where σ_c^2 denotes a cross-sectional variance, and variables with bars above denote time-series averages. The Prais-Winsten procedure for correction of first-lag autocorrelation is used. SPEC1 eliminates speculative stocks meeting one of the following boundary conditions: 1) $MV/BV > 100$; 2) $ROE < 0$ and $BV > 0$; and 3) $MV/BV > 30$ and $r_{it} > 0$, where MV is stock market value. ROE is return on book value (BV). r_{it} is return of portfolio i during period t. SPEC2 eliminates speculative stocks meeting additional condition 4) $MV/E < 0$, where E is average earning for last four quarters. Source: own research.

Table 2. The values of the risk premium vector (γ) estimated from second-pass regressions for the modified Fama-French model M93FF

$$r_{it} - RF_t = \gamma_0 + \gamma_M \widehat{\beta_{i.M}} + \gamma_{HMLN} \widehat{\beta_{i.HMLN}} + \gamma_{LMHD} \widehat{\beta_{i,LMHD}} + \varepsilon_{it}; \quad t=1.....252; \; i=1..... 25$$

Parameter	Excluded penny stocks below (PLN)								Excluded speculative stocks	
	0.0	0.5	1.0	1.5	2.0	3.0	4.0	5.0	SPEC1	SPEC2
	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7	Mode 8	Mode 9	Mode10
γ_0, %	-3.72	-3.34	-3.02	-2.72	-2.42	-1.89	-1.18	-1.89	-9.85	-7.02
t-stat	-3.18	-2.94	-2.84	-2.46	-2.18	-1.41	-1.02	-1.36	-8.49	-7.35
SH t-stat	-2.75	-2.59	-2.56	-2.22	-2.00	-1.32	-0.97	-1.26	-4.53	-5.63
p-value, %	0.59	0.96	1.05	2.64	4.52	18.82	33.41	20.66	0.00	0.00
γ_{HMLN}, %	0.85	1.05	0.96	0.99	0.92	0.97	0.97	1.04	4.01	1.65
t-stat	2.81	3.47	3.12	3.23	3.18	3.44	3.32	3.71	14.85	6.22
SH t-stat	2.82	3.44	3.10	3.20	3.14	3.40	3.28	3.65	15.28	5.77
p-value, %	0.48	0.06	0.20	0.14	0.17	0.07	0.10	0.03	0.00	0.00
γ_{LMHD}, %	0.97	0.91	0.86	1.03	1.01	1.07	1.03	0.95	2.84	1.28
t-stat	3.13	2.93	2.75	3.29	3.39	3.76	3.60	3.38	9.93	4.87
SH t-stat	3.24	2.96	2.75	3.25	3.36	3.76	3.61	3.40	9.70	5.13
p-value, %	0.12	0.30	0.60	0.12	0.08	0.02	0.03	0.07	0.00	0.00
γ_M, %	3.65	3.25	2.88	2.67	2.24	1.59	0.89	1.68	9.48	5.12
t-stat	2.84	2.61	2.48	2.20	1.82	1.14	0.69	1.09	7.56	4.43
SH t-stat	2.50	2.33	2.26	2.01	1.69	1.07	0.66	1.02	4.22	3.50
p-value, %	1.26	2.00	2.38	4.50	9.11	28.57	50.70	30.85	0.00	0.05
GRS-F	3.64	2.82	3.02	2.63	2.52	2.34	1.93	2.42	9.84	7.92
p-value, %	0.00	0.00	0.00	0.01	0.02	0.06	0.67	0.03	0.00	0.00
$Q^A(F)$	2.27	2.08	1.94	1.32	1.87	1.61	1.37	1.70	2.59	1.27
p-value, %	0.17	0.47	0.96	16.45	1.36	4.78	13.19	3.14	0.03	19.66
R_{LL}^2	41.76	47.67	42.72	57.25	52.86	57.63	38.43	53.61	77.67	74.27

Note: see Table 1. Source: own research.

The M95FF model turns out to be the application generating the portfolio closest to the multifactor-efficient portfolio if penny stocks below 1.5 PLN are excluded. This is evidenced by the test results: GRS-F=1.53 with corresponding p-value=5.58%, and $Q^A(F)$=1.51 with p-value=7.47%, and γ_0=0.99 with p-value=53.52%. The use of the modified pricing application M95FF significantly improves the description of returns in comparison with the M93FF application. As opposed to M93FF, M95FF generates zero value intercepts at the significance level over 20% for almost all tested cases. In the light of ICAPM, the application M95FF gives a good description of returns if penny stocks below 2.0 PLN, 4.0 PLN and 5.0 PLN are excluded, as well as the classical FF model if penny stocks below 0.5 PLN are excluded. The hypothetical mode 10 (SPEC2) generates a good description of returns, especially using the M95FF application. The statistic $Q^A(F)$ and coefficient R^2_{LL} take small and high values: 0.70 and 87.82% respectively. However, for this case the intercept is significant, assuming high negative value -7.02% with corresponding p-values about 0.00%. In the case of mode 9 and mode 10, the prices of rejected speculative stocks vary over a wide range. However, 22.28% SPEC1 stocks and 20.35% SPEC2 stocks have a price of less than 2.00 PLN, and the largest number of speculative stocks is in the range from 1.00 PLN to 2.00 PLN, see Urbański et al. (2014).

Table 3. The values of the risk premium vector (γ) estimated from second-pass regressions for the modified Fama-French model M95FF

$r_{it} - RF_t = \gamma_0 + \gamma_M \widehat{\beta_{i.M}} + \gamma_{HMLN} \widehat{\beta_{i.HMLN}} + \gamma_{LMHD} \widehat{\beta_{i,LMHD}} + \varepsilon_{it}$; t=1…..252; i=1….. 25

Parameter	Excluded penny stocks below (PLN)								Excluded speculative stocks	
	0.0	0.5	1.0	1.5	2.0	3.0	4.0	5.0	SPEC1	SPEC2
	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7	Mode 8	Mode 9	Mode10
γ_0, %	0.35	0.25	-0.69	0.99	1.69	0.22	-1.17	-2.24	-9.67	-7.02
t-stat	0.20	0.15	-0.46	0.66	1.00	0.12	-0.86	-1.40	-8.13	-8.07
SH t-stat	0.19	0.14	-0.45	0.62	0.92	0.12	-0.81	-1.27	-4.30	-5.96
p-value, %	84.95	88.55	65.35	53.52	35.87	90.58	41.90	20.50	0.00	0.00
γ_{HMLN}, %	0.74	0.83	0.79	0.87	1.02	0.80	0.87	0.78	3.45	2.58
t-stat	2.31	2.68	2.58	2.80	3.32	2.60	2.99	2.59	12.01	9.68
SH t-stat	2.30	2.68	2.57	2.78	3.32	2.60	2.98	2.56	14.43	9.63
p-value, %	2.21	0.79	1.07	0.58	0.10	0.99	0.31	1.10	0.00	0.00
γ_{LMHD}, %	0.83	0.88	0.73	0.84	0.83	0.90	1.18	1.18	2.80	0.99
t-stat	2.64	2.93	2.55	2.87	2.92	3.07	3.98	3.79	9.64	3.69
SH t-stat	2.67	2.92	2.55	2.86	2.89	3.04	3.92	3.72	9.80	3.69
p-value, %	0.81	0.38	1.13	0.45	0.41	0.26	0.01	0.02	0.00	0.01

Table 3. The values of the risk premium vector (γ) estimated from second-pass regressions for the modified Fama-French model M95FF (cont.)

$$r_{it} - RF_t = \gamma_0 + \gamma_M \widehat{\beta_{\iota,M}} + \gamma_{HMLN} \widehat{\beta_{\iota,HMLN}} + \gamma_{LMHD} \widehat{\beta_{\iota,LMHD}} + \varepsilon_{it};\ t=1\ldots.252;\ i=1\ldots.25$$

Parameter	Excluded penny stocks below (PLN)								Excluded speculative stocks	
	0.0	0.5	1.0	1.5	2.0	3.0	4.0	5.0	SPEC1	SPEC2
	Mode 1	Mode 2	Mode 3	Mode 4	Mode 5	Mode 6	Mode 7	Mode 8	Mode 9	Mode10
γ_M, %	-0.72	-0.63	0.38	-1.42	-2.09	-0.58	1.05	2.17	9.68	5.07
t-stat	-0.37	-0.34	0.23	-0.87	-1.15	-0.30	0.70	1.20	7.28	4.67
SH t-stat	-0.36	-0.33	0.23	-0.82	-1.06	-0.29	0.66	1.10	4.01	3.58
p-value, %	71.71	74.22	82.08	41.37	29.04	77.02	51.11	27.40	0.01	0.07
GRS-F	1.59	2.33	1.62	1.53	1.86	2.32	2.00	1.66	9.33	8.39
p-value, %	4.24	0.06	3.57	5.58	0.99	0.06	0.44	2.90	0.00	0.00
$Q^A(F)$	1.42	1.54	1.68	1.51	1.32	1.67	1.35	0.94	1.87	0.70
p-value, %	10.82	6.64	3.52	7.47	16.22	3.73	14.63	54.18	1.42	83.14
R^2_{LL}	36.12	42.21	37.33	36.09	42.57	42.93	59.08	67.72	70.11	87.82

Note: see Table 1. Source: own research.

Rejecting the hypothetical modes SPEC1 and SPEC2, we decide that a deeper analysis should focus on the pricing application M95FF if penny stocks below 2.0 PLN are excluded. The risk prices γ_{HMLN} and γ_{LMHD} assume values of 1.02% and 0.83% (for monthly periods) with corresponding p-values 0.1% and 0.41%. Although the risk price γ_M assumes an insignificant negative value of -2.09% (with corresponding p-values 29.04%) it does not contradict the ICAPM assumptions (see Fama, 1996, pp. 456 and 463-464). This fact confirms the decisive impact of risk due to *HMLN* and *LMHD* factors. In this case the cross-section determination coefficient R^2_{LL} increases from 36.09% to 42.57%, and elimination of penny stocks below 4.0 PLN or 5.0 PLN significantly deviates from the upper limit 1.0 PLN set by the WSE.

In the case of the classical FF model (if penny stocks below 0.5 PLN are excluded) the intercept γ_0=-3.16 is insignificant on the borderline level 5.76%. Also, only risk premium component γ_{HML}=1.99 is statistically significant (with corresponding p-value=0.05%) for insignificant γ_{SMB}=-0.02 and γ_M=2.75 (with corresponding p-value=96.03%, and p-value=12.97%, respectively).

4.2. Distributions of capital cost of modelled portfolios

The controversial problem of capital cost assessment is the betas estimation method, and the number of monthly estimation periods. It seems appropriate to use linear multivariate regression in accordance with equation 7. However, one can also consider the use of several mono-variable regressions, relative to the examined factors. In the case of commonly used financial applications for betas assessment, the samples with 60 monthly periods were most often applied. However, due to the well-known fact of extending the periods of business cycles from the beginning of the 21st century, it seems appropriate to extend the estimation period to 120 months.

We attempt to estimate the betas, and thus the capital cost, in two approaches. In Approach 1 the betas are estimated on the basis of last 120 months, from period 133 to period 252. In Approach 2, the procedure similar to the one proposed by Zhi Da et al. (2012) is applied, and the betas are estimated using (t-61, t-1) a sixty-month rolling window, with rolled step of one month, using the whole tested period of 252 months.

In Table 4 below we show the statistics of normality tests of bootstrapped capital cost, bootstrapped risk premium and systematic risk components, estimated by the M95FF model, for the portfolio formed on the highest *NUM* and the smallest *DEN* values.

In Figure 1 we show histograms of bootstrapped capital cost estimated in Approach 2 (a), and in Approach 1 (b).

The cost of capital, estimated in Approach 1, does not show normality of distribution. This is clearly confirmed by the results of the four normality tests (see: Table 4). The normality of the risk premium $\widehat{\gamma_{LMHD}}$ cannot be rejected only when using the Shapiro-Wilk and Lilliefors tests (with 5% level of significance), while the hypothesis of normality of $\widehat{\gamma_{HMLN}}$ should be rejected by using any of the used tests.

The distribution of the component $\widehat{\gamma_M}$ is not normal. Normality of the distribution of systematic risk $\widehat{\beta_{1,HMLN}}$, estimated in both approaches, confirms all four tests performed. However, no test performed confirmed the distribution normality of the $\widehat{\beta_{1,LMHD}}$ component, estimated in approach 1. On the other hand, the normal distribution of $\widehat{\beta_{1,LMHD}}$, estimated in Approach 2, is confirmed at the significance level of 0.16 by the Lilliefors test. Normality of the distribution of systematic risk $\widehat{\beta_{1,M}}$, estimated in approaches 1 and 2, also confirm all four tests performed.

It can be concluded that the risk components estimated in Approach 2 have distributions closer to the normal distribution, compared to the risk components estimated in Approach 1. It seems that this results in the normality of the capital cost distribution if the risk components are estimated in Approach 2.

In Table 5 we show the estimated values of the cost of capital, by the classical FF and M95FF models, for 25 model portfolios on the basis of Approach 2.[3] In step 1 of our algorithm, model (2) to estimate the components of systematic risk is used. In step 2, model (3) to estimate the risk premium components is used. In step 3, model (5) is used to estimate current values of betas for capital cost calculation.

[3] The estimated values of the cost of capital for 25 modelled portfolios on the basis of Approach 1, and the MFF93 application (in both approaches) are available from the authors on request.

Table 4. Statistics of normality tests of bootstrapped capital cost, risk premium and systematic risk of portfolio 1, formed on the highest *NUM* and the smallest *DEN*

Parameter	Normality test statistic (p-value, %)			
	Doornik-Hansen	Shapiro-Wilk	Lilliefors	Jarque'a-Bera
Capital cost Approach 1	100.87 (1.24e-020)	0.9973 (2.07e-010)	0.01861 (0)	127.09 (2.53e-026)
Risk premium $\widehat{\gamma_{HMLN}}$	12.625 (0.18)	0.9996 (1.97)	0.0089 (5.00)	13.7557 (0.10)
Risk premium $\widehat{\gamma_{LMHD}}$	6.9690 (3.07)	0.9997 (9.45)	0.0087 (6.00)	7.2862 (2.61)
Risk premium $\widehat{\gamma_M}$	53.5308 (2.38e-010)	0.9988 (6.88e-005)	0.0099 (2.00)	59.1272 (1.45e-0.11)
Systematic risk - Approach 1 $\widehat{\beta_{1,HMLN}}$	2.0549 (35.79)	0.9998 (63.17)	0.0051 (75.00)	1.9348 (38.01)
Systematic risk - Approach 1 $\widehat{\beta_{1,LMHD}}$	8.8843 (1.18)	0.9995 (0.78)	0.0092 (4.00)	9.3097 (0.95)
Systematic risk - Approach 1 $\widehat{\beta_{1,M}}$	5.5185 (6.33)	0.9998 (63.17)	0.0051 (75.00)	1.9348 (38.01)
Capital cost Approach 2	2.2508 (32.45)	0.9998 (59.02)	0.0062 (45.00)	2.1669 (33.84)
Systematic risk - Approach 2 $\widehat{\beta_{1,HMLN}}$	3.5136 (17.26)	0.9998 (40.03)	0.0079 (13.00)	3.4443 (17.87)
Systematic risk - Approach 2 $\widehat{\beta_{1,LMHD}}$	7.0586 (2.93)	0.9996 (2.43)	0.0077 (16.00)	7.1837 (2.75)
Systematic risk - Approach 2 $\widehat{\beta_{1,M}}$	0.2436 (88.53)	0.9998 (71.52)	0.0062 (47.00)	0.2526 (88.13)

Note: The vector components are estimated by the M95FF model. We analyse stock companies registered on the WSE in the period from May 1995 through May 2017 that were showing a positive *BV* and with market prices not lower than 2.00 PLN. The risk premium components are estimated by regression (3) using 252 monthly periods, while betas based on regression (5). In Approach 1 betas are estimated on the basis of last 120 months, from period 133 to period 252. In Approach 2 betas are estimated on the basis of a sixty-month rolling window, with rolled step of one month, using the whole tested period of 252 months. The bootstrap procedure is based on 10000 data resamples. Source: own research.

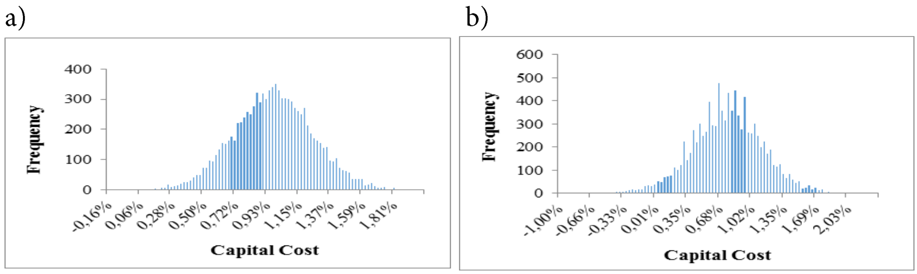

Figure 1. Histograms of bootstrapped capital cost of portfolio 1, formed on the highest *NUM* and the smallest *DEN*: a) Approach 2 - systematic risk components (betas) are estimated using a sixty-month rolling window, with rolled step of one month, using the whole tested period of 252 months, b) Approach 1 - betas are estimated using the last 120 months.

Note: see Figure 1. Source: own research.

Table 5. Percentage values of capital cost of modelled portfolios

Panel A: Classical Fama-French model

I pass: $r_{it} - RF_t = \beta_{i.0} + \beta_{i.M}(RM_t - RF_t) + \beta_{i.HML}HML_t + \beta_{i.SMB}SMB_t + e_{it}$; t=1,…, 252; ∀i=1,…, 25

II pass: $r_{it} - RF_t = \gamma_0 + \gamma_M\widehat{\beta_{i.M}} + \gamma_{HML}\widehat{\beta_{i.HML}} + \gamma_{SMB}\widehat{\beta_{..SMB}} + \varepsilon_{it}$; t=1…..252; i=1….. 25

Average betas: $r_{it} = \propto_i + \beta^t_{i,M}RM_t + \beta^t_{i,HML}HML_t + \beta^t_{i,SMB}SMB_t + e_{it}$; t=1….. 60 : 193…252

$Ccap_i = E(RF) + \widehat{\gamma_0} + \widehat{\beta^{av}_{i,M}}\widehat{\gamma_M} + \widehat{\beta^{av}_{i,HML}}\widehat{\gamma_{HML}} + \widehat{\beta^{av}_{i,SMB}}\widehat{\gamma_{SMB}}$; $\beta^{av}_{i,k} = \frac{1}{193}\sum_{t=1}^{193}\widehat{\beta^t_{i,k}}$

γ_0=-3.51%, SH *t*-stat=-2.35; *BV/MV$_i$* portfolios

CAP portfolios	Low Growth	2	3	4	High Value
	Monthly median values				
	Portfolio 21)	Portfolio 16)	Portfolio 11)	Portfolio 6)	Portfolio 1)
Small	-1.06	-0.32	-0.09	0.22	1.45
	(-1.52÷-0.63)	(-0.69÷0.00)	(-0.46÷0.24)	(-0.15÷0.56)	(0.83÷2.08)
2	-0.35	-0.28	-0.08	0.35	0.62
	(-0.64÷-0.10)	(-0.60÷-0.01)	(-0.32÷0.17)	(0.00÷0.68)	(0.19÷1.03)
3	-0.43	-0.13	-0.27	-0.09	0.62
	(-0.67÷-0.22)	(-0.38÷0.10)	(-0.58÷0.00)	(-0.44÷0.23)	(0.26÷1.00)
4	-0.38	-0.39	-0.41	0.07	0.37
	(-0.60÷-0.17)	(-0.66÷-0.16)	(-0.72÷-0.14)	(-0.15÷0.31)	(0.09÷0.66)
	Portfolio 25)	Portfolio 20)	Portfolio 15)	Portfolio 10)	Portfolio 5)
Big	-0.50	0.13	0.15	0.11	0.90
	(-0.78÷-0.23)	(-0.53÷0.30)	(-0.15÷0.47)	(-0.09÷0.33)	(0.12÷1.64)

Table 5. Percentage values of capital cost of modelled portfolios (cont.)

Panel B: M95FF model

I pass: $r_{it} - RF_t = \beta_{i.0} + \beta_{i.M}(RM_t - RF_t) + \beta_{i.HMLN} HMLN_t + \beta_{i.LMHD} LMHD_t + e_{it}$;
t=1,…, 252;$\forall i$=1,…, 25

II pass: $r_{it} - RF_t = \gamma_0 + \gamma_M \widehat{\beta_{i.M}} + \gamma_{HMLN} \widehat{\beta_{i.HMLN}} + \gamma_{LMHD} \widehat{\beta_{i.LMHD}} + \varepsilon_{it}$

Average betas: $r_{it} = \propto_i + \beta^t_{i,M} RM_t + \beta^t_{i,HMLN} HMLN_t + \beta^t_{i,LMHD} LMHD_t + e_{it}$;
t=1…. 60 : 193…252

$Ccap_i = E(RF) + \widehat{\gamma_0} + \widehat{\beta^{av}_{i,M}} \widehat{\gamma_M} + \widehat{\beta^{av}_{i,HMLN}} \widehat{\gamma_{HMLN}} + \widehat{\beta^{av}_{i,LMHD}} \widehat{\gamma_{LMHD}}$; $\beta^{av}_{i,k} = \frac{1}{193} \sum_{t=1}^{193} \widehat{\beta^t_{i,k}}$

NUM portfolios; γ_0=1.69%; SH t-stat=0.92

Dynamics of increase of financial results

DEN portfolios	Low	2	3	4	High
	Monthly median values				
Small/Cheap	Portfolio 21)	Portfolio 16)	Portfolio 11)	Portfolio 6)	Portfolio 1
	-0.42	-0.19	0.80	0.61	0.97
	(-0.87÷0.04)	(-0.81÷0.44)	(0.39÷1.23)	(0.19÷1.06)	(0.44÷1.5)
2	-1.09	0.00	0.22	0.42	0.54
	(-2.10÷-0.10)	(-0.32÷0.32)	(-0.06÷0.52)	(0.06÷0.77)	(0.25÷0.84)
3	-0.66	-0.47	0.06	0.81	0.37
	(-1.26÷-0.06)	(-0.80÷-0.14)	(-0.18÷0.32)	(0.43÷1.20)	(0.08÷0.70)
4	-1.18	-1.01	0.23	-0.12	-0.08
	(-1.70÷-0.67)	(-1.61÷-0.40)	(-0.06÷0.52)	(-0.53÷0.26)	(-0.35÷0.20)
Big/Priced	Portfolio 25)	Portfolio 20)	Portfolio 15)	Portfolio 10)	Portfolio 5)
	-0.98	-0.97	-0.52	-0.52	-0.58
	(-1.42÷-0.55)	(-1.46÷-0.51)	(-0.97÷-0.12)	(-1.02÷-0.06)	(-0.96÷-0.18)

Note: In Panel A, 25 FF portfolios are investigated. Quintile portfolios are formed on *BV/MV* and *CAP*. In Panel B, 25 M95FF portfolios are investigated. Quintile portfolios are formed on *NUM* and *DEN*. The corresponding 95 confidence intervals appear in brackets. We analysed stock companies registered on the WSE in the period from May 1995 through May 2017 that are showing a positive *BV* and with market prices not lower than 0.5 PLN for the FF model, and 2.00 PLN for the M95FF model. The risk premium components are estimated using 252 monthly periods. The systematic risk components are estimated using a sixty-month rolling window, with rolled step of one month. The lower and the upper limit of the confidence intervals are calculated using the bootstrap distributions with 10000 iterations.

Source: Own research.

Panel A presents the values of capital cost estimated by the classical FF model. The capital cost assumes the positive estimate of 95% confidence interval for portfolios formed on the highest values of *BV/MV* (fifth quintile of *BV/MV*). For four portfolios of the fourth *BV/MV* quintile, the median confidence intervals are also positive. For the second quintile, the median confidence intervals are negative, except for the portfolio with the highest capitalization. On the other hand, the portfolios formed on the lowest *BV/MV* are characterized by the negative estimate of the lower and upper limits of the 95% confidence interval. Changes in the value of capital cost for portfolios with the growing capitalization are less regular. This can be explained by an insignificant non-zero risk premium due to the *SMB* factor. Nevertheless, the median of portfolios 20, 15, 10 and 5, formed on the biggest capitalization, assumes positive values.

The above results seem to be consistent with the Graham and Harvey (2001), who state that large companies more often estimate capital cost by CAPM. On the other hand, if company is seen by investors as a portfolio of current and future projects and by their real options then the returns are influenced by information reaching investors about the possibility of implementing a portfolio of projects with real options. In that case, the dependence of returns on risk factors may be non-linear, despite the fact that returns of projects without real options are consistent with CAPM, and the capital cost of these projects can be correctly estimated.

In our research, the cost of capital is estimated using portfolio market returns, that is, information that may take into account the impact of real options. The values of the estimated capital cost are influenced by all market information, so it can charge the actual capital cost of the company's projects. Then one can examine the impact of additional risk factors or other ICAPM applications. According to Zhi Da et al. (2012) research, the impact of real options on returns leads to price anomalies, which contradict the pricing consistent with CAPM. Therefore, we attempt to estimate the capital cost of the modelled portfolios using other ICAPM applications.

Panel B presents the values of capital cost estimated by the M95FF model. The capital cost assumes the positive estimate of 95% confidence interval for portfolios placed in the upper right corner of Table 5, that is for portfolios formed on the three highest values of *NUM* and three smallest values of *DEN*. Interestingly, there is a monotonous decrease in the cost of capital for portfolios formed at the highest values of *NUM* and diminishing *DEN* values. The capital cost assumes the negative estimate of 95% confidence interval for portfolios placed in the lower left corner of Table 5, that is for portfolios formed on the lowest values of *NUM* and the biggest values of *DEN*. Portfolios with the highest values of *NUM* are portfolios with the highest dynamics of financial results growth. Portfolios with the biggest values of *DEN* are portfolios with the priced stocks in relation to the book value and earning per share.

The portfolios assuming positive values of capital cost (estimated by the FF model) are commonly called value portfolios, and long-term investments in these portfolios generate high returns. On the other hand, the portfolios assuming negative values of capital cost, called growth portfolios, generate small returns (also see: FF, 1992). Similarly, the portfolios assuming positive values of capital cost, estimated by the M95FF model, are the most attractive for investors and generate above average returns (see: Urbański, 2011). However, as mentioned earlier, the estimated capital cost applies to projects with real options. Therefore, you can assume that, taking into account the market hyperactivity, the estimated capital cost according to the above-mentioned procedures is evaluated too high for value portfolios and portfolios formed on high *NUM* and small *DEN*. Similarly, the estimated capital cost is evaluated too low for growth portfolios and portfolios formed on low *NUM* and big *DEN*.

The reasoning presented in this way explains the negative values of the capital cost, estimated on the basis of portfolio market returns, for growth portfolios and portfolios formed on low *NUM* and big *DEN*.

5. Summary and conclusions

In our paper we present a method of estimation of the cost of capital for characteristic portfolios of stocks registered at the Warsaw Stock Exchange. In order to accomplish this, we apply three selected ICAPM applications: the classical Fama-French model (FF), the modified FF model, denoted as M93FF and proposed by Urbanski (2012), and, finally, the M95FF model, which is proposed in this research. Our analysis starts with 595 stocks from which we eliminate the penny stocks with value smaller than 0.50 PLN for FF and smaller than 2.0 PLN for M93FF and M95FF. Our methods allow generating portfolios that are close the multifactor-efficient. In order to estimate the confidence interval for the cost of capital we apply the bootstrap method. The estimated cost of capital, calculated using the market returns, is related to a hypothetical portfolio of investment projects as seen by the external investor. Such a portfolio is a combination of undergoing and planned projects, weighted with selected real options. According to the proposed procedure, the estimated cost of capital may be a valuable indicator for portfolio managers. Moreover, it allows one to estimate the capital returns for investors. However, such an estimate of the capital cost cannot be considered as a benchmark for making decisions regarding new investment projects of stock companies.

Our research leads to the following conclusions related with the estimation of the capital cost:

1) The ICAPM application allows one to estimate the *Ccap* of investment projects of stock companies from the perspective of an external investor.

2) The necessary condition for appropriate estimation of the *Ccap* is precise estimation of the risk premium. Here, the application of ICAPM should generate multifactor-efficient portfolios.
3) Application of the classical FF model and its two modifications (M93FF and M95FF) for stocks coming from the WSE allows one to generate portfolios that are close to multifactor-efficient, provided that the penny stocks are eliminated.
4) The *Ccap* is estimated using two different approaches. In the first approach, the betas are estimated using the most recent 120 months of observations. In the second approach, the betas are estimated using 60-month moving windows that roll with one-month step.
5) The application of the bootstrap method allows one to approximate the distribution of the systematic risk and the risk premium components as well as the distribution of the cost of capital.
6) The estimated *Ccap* is related to the project portfolio and open positions of real options related to these projects.
7) The estimated *Ccap* assumes positive values for value portfolios and portfolios formed on high values of *NUM* and low values of *DEN*.
   a) The *Ccap* of value portfolios varies from 0.37%±0.28% to 1.45±0.62% per month. The average width of the confidence interval for the *Ccap* is about 0.98%.
   b) The *Ccap* of portfolios formed on high *NUM* and low *DEN* varies from 0.37%±0.28% to 0.97%±0.53% per month. The average width of the confidence interval for the *Ccap* is about 0.78%.
8) The estimated *Ccap* takes negative values for growth portfolios and portfolios formed on low values of *NUM* and high values of *DEN*.
   a) The *Ccap* of growth portfolios varies from -0.35%±0.27% to -1.06%±0.45% per month. The average width of the confidence interval for the *Ccap* for such portfolios is about 0.56%.
   b) The *Ccap* of portfolios formed on low *NUM* and high *DEN* varies from -1.18%±0.52% to -0.47±0.33% per month. The average width of the confidence interval for the *Ccap* for such portfolios is about 1.06%.
9) In order to estimate the *Ccap* of stocks without real options one needs the components of the option-adjusted risk premium and option-adjusted systematic risk.

Acknowledgements

This work supported by the National Science Centre, Poland (Research Grant 2015/19/B/HS4/01294) is gratefully acknowledged.

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