CAPM AND COVID-19: EVIDENCE FROM EASTERN EUROPEAN STOCK MARKETS

by

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A thesis submitted in partial fulfillment of the requirements for the degree of

MA in Business and Financial Economics

Kyiv School of Economics

2021

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ACKNOWLEDGMENTS

The author wishes to express the deepest appreciation to all the people, who helped me reach the final goal of this work and supported me along the way. Particularly, to my thesis advisor Professor Olesia Verchenko for the continuous support, valuable advice and inspiring meetings.

A separate word of gratitude goes to my perceptive colleagues from FinPoint, who provided me with necessary access to the data and guided me in navigating Bloomberg termina

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CAPM Capital Asset Pricing model

FFTFM Fama French Three Factor Model

O&G Oil and Gas

WHO World Health Organization

WFH Work from Home

CHAPTER 1. INTRODUCTION

COVID-19 have introduced a new level of uncertainty into countries' economies and financial markets. A new disease was first discovered in Wuhan, China in late 2019 and on March 11th, 2020 was identified as a "global pandemic" by the World Health Organization. More than 90 countries have introduced lockdowns immediately which have led to severe economic and social consequences. On March 15th 2020 financial markets collapsed, Dow Jones Industrial Average fell by 35%, S&P Index have lost 32% and NASDAQ Composite Index droped by 29%. This is the largest stock market crash since the financial crisis 2007-2008. Nevertheless, though the markets recovered quickly, not all industries managed to adapt to new reality. A lot of companies from retail, hospitality, avia, and other industries, which are greatly dependent on human physical interaction have gone bankrupt. Meanwhile, others – e.g. telecomunication, gaming, delivery services and pharmaceuticals succesfully adapted to new social distancing norms and overperformed the market.

Once safe companies for investments have now become risky and volatile, and vice versa. An investor considering which stock to purchase should take into account how sucessful the company is dealing with the pandemic outbreak restrictions and its consequences.

Capital Asset Pricing Model (CAPM) is widely used to measure the expected return on paticular asset. It describes the relationship between the expected retun on the security and the risk associated with it. This model accounts for systematic risk and suggests the compensation to investor in the form of the risk premium. However, such an unexpected phenomenon as COVID-19 outbreak cannot be associated with systematic risk, as nobody unticipated the upcoming crisis and nobody was ready to face it.

There have been numerous extentions introduced to the Capital Asset Pricing Model, in particular by Fama and French in their Three-Factor Model (1992) and Five-Factor Model (2014). They first sugested that when estimating the expected return we should not only account for the systematic risk, but also for the size of market capitalization of the company, value of the stock, profitability of the company and investment intensity.

Pagano, Wagner and Zechner (2020), who were studing the financial markets during COVID-19, were trying to test the impact of pandemic on the asset pricing using three-factor and five-factor CAPM. They were checking the difference between residuals from the estimated models, of COVID-resilient firms versus non-resilient firms. Inspired by their work, in combination with existing literature of extended CAPM, the aim of this study is to add a new extention to the Capital Asset Pricing Model in the form of COVID-19 resilience variable, and test the model in developing countries. In particular – to see how did the influence of basic factors introduced by Fama and French change, as well as to see whether the new variable is statistically significant.

The structure of the paper is the following: Chapter 2 is devoted to the related literature about risk, returns and asset pricing, as well as the impact of COVID-19 on the financial markets; Chapter 3 sugests the methodology to be used in the study; Chapter 4 describes the data and portfolios formation; Chapter 5 offers the results of the study; Chapter 6 summarizes the findings and suggests possible implementation.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

The Capital Asset Pricing model was introduced by Jack Treynor (1962), William Sharpe (1964), John Lintner (1965a,b) and Jan Mossin (1966) independently, developing the prior modern portfolio theory presented by Harry Markowitz. The basic equation to calculate the expected return on the asset is as follows:

$$E(R_i) = R_f + \beta_i{*}(E(R_m) - R_f) \tag{1}$$

where:

$E(R_i)$ = expected return on asset

R_f = risk-free rate

β_i = systematic risk of an asset

$E(R_m)$ = expected return on the market

The equation can also be written as:

$$E(R_i) - R_f = \alpha_i + \beta_i{*}(E(R_m) - R_f) + \varepsilon_i \tag{2}$$

where:

$R_i – R_f$ = expected excess return on an asset

$R_m – R_f$ = expected excess return on the market (risk premium)

α_i = measure of the efficiency of the market

ε_i = random error term

Beta represents the systematic risk of a portfolio. It reflects the volatility of the stock: how does the price of the stock changes in response to the changes in the stock market. Beta can be measured as the covariance of asset relative to the maket.

$$\beta_i = \frac{\text{cov(Ri, Rm)}}{\text{var (Rm)}}$$

Alpha – is a measure of the efficiency of the market. If alpha is equal to 0, then the return earned on the asset is commensurate to the risk taken. If alpha is less then 0, then the return on the asset was too little for the risk taken. If alpha is greater than 0, then the return on the asset was higher than expected according to the risk taken. According to the CAPM theory efficient asset or portfolio will have alpha be equal to zero, i.e. it will offer the highest possible expected return for a certain level of risk.

Originally the CAPM was introduced on the US stock market and later tested by Fama and MacBeth (1973), who first developed the testing methodology. Later other researches expanded the implication of methodology of testing CAPM model on other markets – Eastern European in particular. The fact whether CAPM is applicable to a particular market during a certain period of time is still questionable and is being under study.

Džaja and Aljinović (2013) examined whether the CAPM is an appropriate tool for capital asset valuation on the Central and South-Eastern European Emerging markets. For nine countries under study for the period January 2006 – December 2010 they have discovered that CAPM is not adequate fot pricing capital assets - the model turned out to be not statistically significant.

Czekierda (2006) tested the CAPM on Warsaw Stock Exchange. His results support most of CAPM assumptions about linearity of the relationship between the return on the security and return on the market, and non-systematic risk, and even produce positive slope coefficient (beta), however it was low and insignificant.

In the literature there are numerous extentions of the Capital Asset Pricing Model. The most common and widelly used are the extentions introduced by Fama and French. The researchers argued that the expected return can be solely explained by market beta, and thus developed a Three-Factor CAPM (FFTFM), which also accounts for the size of the company and its book-to-market equity ratio. They have shown that the risk-adjusted returns of companies with small market capitalization usually outperform companies with large market capitalization. Fama and French have also shown that companies with high book-to-market ratio outperform those with low book-to-market ratio, i.e. value stock outperform growth stock. Later, Fama and French (2014) extended their findings to a Five-Factor CAPM introducing two new factors: profitability and investment.

Griffin (2015) examines whether FFTFM are country specific and concludes that indeed, time-series variation can be better explained by the local-specific factors, rather then global ones. There are also quite a lot of studies of emerging markets. For example, Hanauer and Linhart (2015) test for size and value in Latin America, Asia, EMEA and BRIC. They concluded that "the value pattern in emerging markets are more pronounced than in developed markets". They have also discovered that global factors poorly explain the variation in emerging markets.

Bhatt and Rajaram (2014) analyze whether FFTFM is relevant to use for measuring expected returns during crisis, and whether the model captures the systematic risk on the macro level. The researchers found that the size factor has been playing a major role during the crisis periods. However, the value factor has not been very efficient and they assume there may be some other factor to better capture the systematic risk of the firm.

There are already some studies in the existing literature about the impact of COVID-19 outbreak on the capital pricing. The recent paper of Horstmeyer and Vij (2020) show that COVID-19 indeed affected the companies' betas and turned the stocks "upside down". During pre-COVID-19 period, out of more than 2,400 companies trading on NYSE, only 285 companies had negative betas. A negative beta was a common phenomenon for a mining sector and oil extraction – almost half of 285 companies; and pharmaceuticals (only 5%), meaning that while the markets (i.e. S&P 500 Index) were declining, these sectors were growing. However, in 2020 pharmaceuticals composed more than 50% of negative betas companies, while mining sector constituted to only 5%. Furthermore, betas of the WFH companies and tech companies decresed significantly and for some stocks even turned to negative. For example, Zoom beta went down from 1.82 in 2019 to -0.36 in 2020.

In a recent study by Pagano, Wagner and Zechner (2020) devoted to asset pricing during COVID-19 outbreak, the researchers explore whether the disaster risk had been priced in financial markets depending on the companies' resilience to COVID-19 pandemic. They define pandemic resilience as "reliance on technologies and/or organizational structures that are robust to social distancing". Authors account for the factors developed by Fama and French (1992, 2014). According to the results of the study, disaster-resilient companies managed to outperform non-resilient ones.

In this paper we will use the methodology of Fama and MacBeth to test the CAPM on three periods: pre-COVID-19, during COVID-19 and post-COVID-19. Then we will use the methodology of Fama and French (1992, 2014) to test the three-factor CAPM, extended by a fourth factor 'COVID-19 resilience', the creation of which was motivated by the work of Pagano, Wagner and Zechner (2020).

CHAPTER 3. METHODOLOGY

3.1 CAPM Methodology

This section will describe how to test the relationship of risk and return including only one factor – market on the pre-COVID-19 and post-COVID-19 periods. It is based on the methodology developed by Fama and MacBeth (1973), who studied the relationship between average risk and return for NYSE common stocks. Despite Fama-MacBeth methodology implies testing monthly returns, in this section we will apply daily returns or weekly returns, because otherwise we will not have sufficient number of observations.

CAPM is expressed in terms of expected returns (1). However, according to Fama and MacBeth (1973), it must be tested with actual returns, which will give the possibility to evaluate average returns and check the conditions C1-C3 described in Fama-MacBeth, in particular: "(C1) the relationship between the expected return on a security and its risk in any efficient portfolio *m* is linear. (C2) β_i is a complete measure of the risk of security *i* in the efficient portfolio *m;* no other measure of the risk of *i* appears in (1). (C3) In a market of risk-averse investors, higher risk should be associated with higher expected return… Hence, the following equation is suggested as a stochastic generalization of (1):

$$R_i = \gamma_{0t} + \gamma_{1t}\,\beta_i + \gamma_{2t}\,\beta_i^2 + \gamma_{3t}\,s_i + \eta_{it} \qquad (3)$$

where:

R_i – one period return on a security *i* expressed in percentage from preriod $t-1$ to t

γ_{1t} – value of the risk premium, which is the slope of $[E(R_m) - R_f]$ in (1)

β_i^2 – is included to test for linearity

s_i – a measure of risk of a security *i* which was not captured by β_i

η_{it} – a disturbance with zero mean.

On the basis of the equation (3) and conditions C1-C3, the following hypothesis must be tested:

C1 (linearity): $\gamma_{2t} = 0$

C2 (no other systematic non-beta risk): $\gamma_{3t} = 0$

C3 (expected return is positive): $\gamma_{1t} > 0$

In order to avoide measurement error problem, the equation (3) must be tested not on the betas of individual securities, but on the betas of the portfolios, which are formed by ranking betas of individual securities from lowest to highers.

Further is described the speifics of the testing approach, which is the same as suggested by Fama-MacBeth. Assume that *N* – is the total number of securities to be allocated to 20 portfolios, and *int(N/20)* – is the largest integer number less or equal to *N/20*. In our case, *N* is equal to 747, which are to be split into 20 portfolios in the following way. Each of the middle 18 portfolios get *int(N/20)* securities. In our case *int(N/20)* = 37. Each of the first and the last portfolios get *int(N/20) + ½ (N - int(N/20))* securities. As *int(N/20)* is odd, the last portfolio with highest betas gets an additional security, so that in total it has 41 stocks, and the first portfolio has 40 stocks. The process of estimating betas, ranking them, and forming the portfolios is done on the first 4 month of the dataset (04.01.2019 – 31.04.2019). The next four months (07.04.2019 – 27.09.2019) are used to re-estimate β_i for each stock and calculate β_i for each of 20 portfolios by taking the average value of beta of each security in each portfolio and assuming that securities are equally weighted within the portfolio.

As a measure of non-beta risk for each security, Fama-MacBeth use $s(\varepsilon_i)$ – the standard deviation of least squared residuals, which is obtained from running a market model:

$$R_i = \alpha_i + \beta^i R_{mt} + \varepsilon_i \qquad (4)$$

Then, for each weekly returns of 20 portfolios, and for the each weak of the next time period (04.10.2019 – 14.02.2020) a cross-cection regression is run:

$$R_{pt} = \gamma_{0t} + \gamma_{1t}\,\beta_{p,\,t-1} + \gamma_{2t}\,\beta^2_{p,\,t-1} + \gamma_{3t}\,s_{p,\,t-1} + \eta_{pt} \tag{5}$$

where:

$p = 1, 2, 3, \dots, 20$

$\beta_{p,\,t-1}$ – is the average of β_i estimated on 07.04.2019 – 27.09.2019 within each portfolio, from running regression (4)

$\beta^2_{p,\,t-1}$ – is the average of the squared values of β_i

$s_{p,\,t-1}$ – is the average of the standard deviation of residuals estimated on 07.04.2019 – 27.09.2019 within each portfolio, from running regression (4)

The cross-section regression described in (5) is overall run on three periods:

1) 04.10.2019 – 14.02.2020 – pre-COVID-19 period to test the validity of CAPM of Eastern European Markets before the pandemic outbreak

2) 07.04.2020 – 27.11.2020 – during COVID-19 outbreak to observe any changes on the markets in the heat of the pandemic

3) 04.12.2020 – 28.04.2021 – post-COVID-19 period to observe any changes on the markets after the companies have somehow addapted to the new reality

March 2020 and the beginning of April 2020 were the most turbulent months in terms of markets' reaction to quarantine restrictions, so we do not include these two months into any of the observed testing periods as they are not representative.

3.2 Four-Factor CAPM Methodology

This section focuses on testing the relationship of risk and return including three factors introduced by Fama and French (1992) in testing Three-Factor CAPM – market, size and value, extended by a fourth factor – COVID-19 resilience. This section will be based on the methodology developed by Fama and French (1992) in testing Three-Factor CAPM and Fama and French (2014) in testing Five-Factor CAPM.

The basic equation for the FFTFM is:

$$E(R_i) - R_f = a_i + \beta_1 * (E(R_m) - R_f) + \beta_2 * SMB + \beta_3 * HML + \varepsilon_i \tag{6}$$

where:

$E(R_i) - R_f$ = expected excess return on an asset

$E(R_m) - R_f$ = expected excess return on the market (risk premium)

SMB = Small Minus Big, size premium

HML = High Minus Low, value premium

a_i = measure of the efficiency of the market

$\beta_{1,2,3}$ = factor coefficients

ε_i = random error term

A Small Minus Big factor is the average return of the portfolio consisting of small size securities minus the average return on the portfolion consisting of large size securities. High Minus Low factor is the average return of a portfolio consisting of high book-to-market assets minus average returns of low book-to market assets. Fama and French suggest the following equations to construct these two factors:

$$SMB = 1/3(Small\ Low + Small\ Medium + Small\ High) - 1/3(Big\ Low + Big\ Medium + Big\ High)$$

$$HML = \tfrac{1}{2}(Small\ High + Big\ High) - \tfrac{1}{2}(Small\ Low + Big\ Low)$$

In total 6 portfolios are formed on the intersection points of two size groups (Small and Big) and three value groups (Low, Medium and High).

We extend this model further by adding one more variable – COVID-19 resilience. To measure COVID-19 resilience, we refer to the same approach used by Pagano, Wagner and Zechner (2020).

A proxy for resilience was found in Koren and Peto (2020) study. Using data from Occupational Information Network surveys, these authors develop three types of measuring face-to-face interactions: (1) the need for internal physical interaciton and comunication within a firm ('teamwork'); (2) the need for external communication wirh customers ('customers'); (3) the need of "physical proximity to others" ('presence'). 'Teamwork' and 'customers' reflect the percentage of workers in team-work intensive and customer-facing occupations. 'Presence' reflects the percentage of workers, whose job require close physical proximity to others. Then, the first two types are aggregated into one 'communication intensity'. Based on 'communication intensity' and 'presence' Koren and Peto (2020) identify the 'affected share' in percenage for each of the industries. Intuitively, the 'affected share' variable measures by how an industry 'suffered' from the COVID-19 pandemics. Industries, in which this variable is zero, are those that have not been impacted at all, and industries with an 'affected share' of 100 are the most affeted (in comparison to other industries).

Korean and Peto (2020) performed the above classification and identification of the affected share on the United States market. Nevertheless, we can use it for the European market as well, because the negative impact of COVID-19 was quite the same for all industries, moreover, the restrictions of social distancing norms implied by the US and European countries were similar. In our strudy, to identify the 'affected share' in percenage for each of the industries, we obtain NAICS industry codes for each company from Refinitiv workspace. Then, we match the NAICS codes for each industry with respective percentage of affected share estimated by Koren and Peto (2020).

We will name the new factor as Resilient Minus Non-resilient (RMN). To construct the variable, we will split the data by the median into values above 50^{th} percentile and below

50th percentile. RMN will be measured as the difference between average returns on stocks resilient to COVID-19 and average returns on stocks non-resilient to COVID-19.

In order to construct portfolios with more than 2 additional factors (appart from market factor), we refer to another study by Fama and French – "A five-factor asset pricing model". We use the same approach the researchers apply in constructing four factors (+market factor): Size, B/M, profitability, and investment factors. The independent sorts are used to assign stocks into two Size groups, and two or three BE/ME and resilient-non-resilient (RN) groups. The factors are built on the intersection terms of these groups in three different ways (2*3, 2*2 or 2*2*2).

(1) 2*3 sorts. In June of each year t all stocks are ranked on size. The median size is used to split the stocks into two groups: small and big. We also break the stocks into three book-to-market equity groups based on breakpoints for the bottom 30%, middle 40% and top 30% of the ranked values of BE/ME for the stocks. To define book equity, we use the companies' book value of shareholder's equity from the balance sheet for the fiscal year ending of calendar year t-1. Then for BE/ME we divide equity value, by the market equity at the end of December of t-1. As we would define latter, the ranks are almost similar an all years – 2018, 2019 and 2020, we would further use only the ranking based on 2018 data, as the differences in further years are not significant. The decision to sort companies into three BE/ME groups and only two size groups is in line with the evidence that book-to-market equity has a stronger role in average stock terurn, than size, according to Fama and French (1992a). In the same way, we form three resilience groups by spliting the stocks for the bottom 30%, middle 40% and top 30% of the ranked values of the affected share. As this data does not change in time, we perform the ranking only once.
(2) 2*2 sorts and 2*2*2 sorts. The approach for these two sorts is the same as used in the 2*3 sorts. The only difference, is that here we split the stocks based on BE/ME and resilience ranking into only two groups using the median value.

The portfolios are labeled using two or three latters. The first letter always stands for the Size group: small (S) or big (B). In 2*3 sorts and 2*2 sorts, the second letter describes the BE/ME group: high (H), medium (M) or low (L), or the RN group: resilient (R), neutral (N_e) or non-resilient (N_o). In 2*2*2 sorts, the second letter stands for BE/ME group: high (H) or low (L), and the third stands for RN group: resilient (R) or non-resilient (N_o). The final factors are SMB (small minus big), HML (high minus low) and RMN (resilient minus non-resilient).

(1) *<u>2*3 sorts</u> on Size and BE/ME, or Size and RN*

<u>Breakpoints</u>: Size: median, BE/ME: 30th and 70th percentiles, RN: 30th and 70th percentiles

$SMB_{B/M} = (SH + SM + SL)/3 – (BH + BM + BL)/3$

$SMB_{RN} = (SR + SN_e + SN_o)/3 – (BR + BN_e + BN_o)/3$

$SMB = (SMB_{B/M} + SMB_{RN})/2$

$HML = (SH + BH)/2 – (SL + BL)/2$

$RMN = (SR + BR)/2 – (SN + BN)/2$

(2) *<u>2*2 sorts</u> on Size and BE/ME, or Size and RN*

<u>Breakpoints</u>: Size: median, BE/ME: median, RN: median

$SMB = (SH + SL + SR + SN)/4 – (BH + BL + BR + BN)/4$

$HML = (SH + BH)/2 – (SL + BL)/2$

$RMN = (SR + BR)/2 – (SN + BN)/2$

(3) *<u>2*2*2 sorts</u> on Size, BE/ME and RN*

<u>Breakpoints</u>: Size: median, BE/ME: median, RN: median

$SMB = (SHR + SHN + SLR + SLN)/4 – (BHR + BHN + BLR + BLN)/4$

$HML = (SHR + SHN + BHR + BHN)/4 – (SLR + SLN + BLR + BLN)/4$

$RMN = (SHR + SLR + BHR + BLR)/4 – (SHN + SLN + BHN + BLN)/4$

To construct the dependent variable – the left side of equation (7), we will also follow the methodology suggested by Fama and French. We have formed 32 portfolios as follows. As for the right side, we split the dataset by median size breakpoint, measured at the end of June of 2018, and allocate the stocks into two size groups: small and big. Then, inside each size group we use the quartile breakpoints for the stocks ranked based on their book-to market equity values to allocate the stocks into four BE/ME quartiles. Similarly, we use the quartile breakpoints formed on ranking the stocks by their affected share into four resilience groups. We result in 16 portfolios in each size group (small and big), which are built on the intersection of BE/ME and resilience quartiles (4*4). Overall, it is 32 portfolios.

By combining market, size, value and resilience factors on the right side, and forming 32 portfolios on the left side, we form the final equation, which is to be tested using time-series regression:

$$R_i - R_f = a_i + \beta_1 * (R_m - R_f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * RMN + \varepsilon_i \quad (7)$$

The time-series regression for equation (7) is then estimated in two steps:

1) $$R_{it} - R_{ft} = a_i + \beta_{1i} * (R_{mt} - R_{ft}) + \beta_{2i} * SMB + \beta_{3i} * HML + \beta_{4i} * RMN + \varepsilon_i, \quad (8)$$

where:

$i = [1, 2, \ldots, 32]$, t = daily or weekly point of time

2) $$avg(R_{it} - R_{ft}) = c + a_i + d_1 * \beta_{1i} + d_2 * \beta_{2i} + d_3 * \beta_{3i} + d_4 * \beta_{4i}, \quad (9)$$

where:

$avg(R_{it} - R_{ft})$ = is the average return of 32 portfolios minus risk-free rate,

$\beta_{1i}, \beta_{2i}, \beta_{3i}, \beta_{4i}$ = coefficients obtained from Step 1.

Now, the equation (7) can be rewritten as follows:

$$E(Rit) - Rft = ai + \beta 1i * E(Rmt) - Rft + \beta 2i * SMB + \beta 3i * HML + \beta 4i * RMN + \varepsilon i, \quad (10)$$

where:

$E(R_i) - R_f$ = expected excess return on an asset

$E(R_m)$ - R_f = expected excess return on the market = d_1

SMB = d_2, HML = d_3, RMN = d_4

The research goal is to determine whether pandemic resilience factor can be used as an additional explanatory variable to measure expected returns during COVID-19 pandemic period on Eastern European Stock Markets. To prove this, the coefficient in front of RMN factor must be positive and statistically signifiant. Therefore, for this section, the following hypothesis – classical for the FFTFM, but with new resilience factor, must hold: H1: $d_1 > 0$, H2: $d_2 > 0$, H3: $d_3 > 0$, H4: $d_4 > 0$, H5: α_i is not statistically significant.

CHAPTER 4. DATA

The data for this study are daily and weekly returns for all common stocks trading in four Eastern European stock exchanges: Warsaw Stock Exchange (Poland), Moscow Exchange (Russia), Budapest Stock Exchange (Hungary) and Prague Stock Exchange (Czech Republic), during the period of 04.01.2019-28.05.2021. To identify the company's size we use its market capitalization (share price*number of shares outstanding). The value factor is identified as book-to-equity ratio (BE/ME). Market capitalization is used as a proxy for equity value. To measure companies' book value at year t, we use their Total Equity value as of the end of year t-1 from companies' financial statements.

Therefore, from Bloomberg terminal we have collected the data for the total of 930 stocks (Poland – 711, Russia – 174, Hungary – 33, Czech Republic – 12). In order to get into the final sample we will work with, we have applied several filters to the data. First, we keep only companies with positive market capitalization and positive total equity values. The date of incorporation of the company must be before 01.01.2019. Finally, we do not take into companies from banking sector, which is according to the metodolygy proposed by Fama and French. The final dataset consists of 315 securities, and their 608 daily returns.

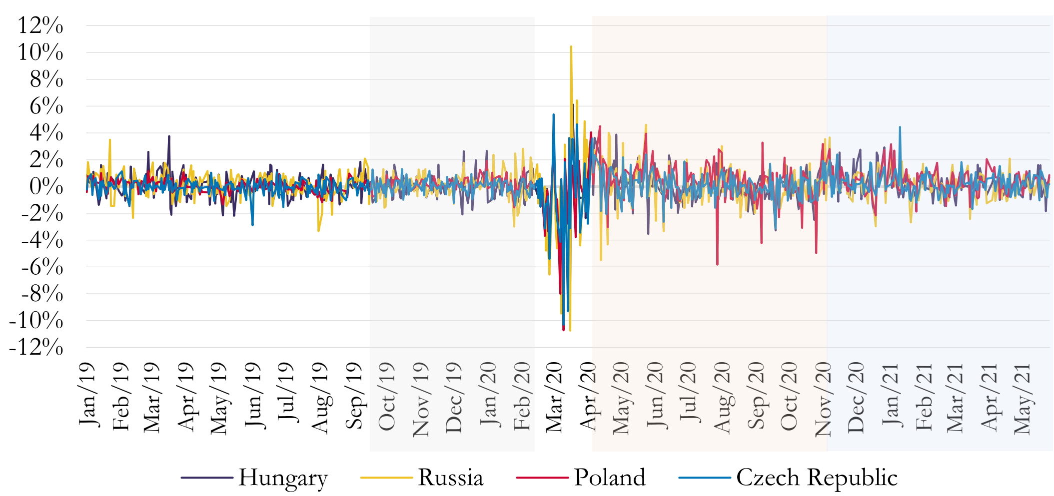
The MSCI Emerging Markets Eastern Europe Index was selected as a proxy for the market return, because it includes the same 4 countries (Poland, Russia, Hungary, and Czech Republic) on which this study is focused. As a proxy for risk-free rate, we use 3-months Germany Government Bond.

From Table 1 we can see that Poland has one of the lowest volatilities (after Czech Republic). Simultaneously, Poland has the largest number of observations (244), while Czech Republic has only 3 stocks. Polish stock exchange had a better absorption capacity of volatility due to its scale and higher diversification. Despite low volatility, Poland has the largest average daily return of 0.15% with its peak average return 4.50% in the post-COVID-19 period. Russia is the second country by the number of stocks – 61. Russia had the highest volatility of 1.51% among all selected countries. Country's stock exchange had also showed the most extreme highest and lowest values of average daily returns, standing at 10.46% max and -10.75% min.

Table 1. Descriptive statistics of simple average daily returns by country

	Hungary	**Russia**	**Poland**	**Czech Republic**
# of observations	7	61	244	3
Mean	0.01%	0.08%	0.15%	0.03%
Median	0.00%	0.11%	0.11%	0.05%
Min	-7.02%	-10.75%	-10.73%	-10.31%
Max	6.16%	10.46%	4.50%	5.38%
St. deviation	1.23%	1.51%	1.14%	1.10%

Figure 1. Distribution of average daily returns of the securities trading on the selected stock exchanges



*Three different colors represent three testing periods used for estimating CAPM model

On Figure 1 we can see the distribution of daily returns for each of four markets. The common trend on all four markets is sharply increased volatility in March 2020, when the lockdown restrictions came into action across the world.

Hungary and Czech Republic are presented with overall of 7 and 3 securities respectively. They both have the lowest average returns, but also the lowest number of stocks, which makes countries' contribution into the model insignificant.

Table 2. Descriptive statistics of 32 portfolios formed on size, book-to-market equity and COVID-19 resilience: 04.01.2019-28.05.2021

	Small Size				**Big Size**			
Resilience* quartiles	**Book-to-market equity (BE/ME) quartiles**							
	Low	2	3	High	Low	2	3	High
	Average of annual averages of firm size (EUR mn)							
Low	11.0	16.9	14.9	14.4	5,631.0	657.6	1,405.7	746.3
2	15.7	24.2	20.5	9.8	3,179.8	2,338.2	4,830.7	629.6
3	18.9	20.5	46.3	11.7	13,369.9	663.0	9,526.5	6,353.8
High	23.7	18.5	11. 5	5.9	1,062.6	587.2	113.6	463.6
	Average of annual BE/ME ratios of firms							
Low	0.4	0.9	1.7	4.3	0.2	0.5	1.3	3.5
2	0.6	1.0	1.7	3.6	0.3	0.8	1.2	2.7
3	0.4	1.0	1.7	3.1	0.5	0.7	1.3	2.4
High	0.4	0.8	1.6	4.7	0.2	0.8	1.2	2.1
	Average portfolios' affected share (%)							
Low	49.9	51.8	49.1	49.9	56.0	54.7	56.9	50.0
2	29.8	28.4	25.9	25.2	35.4	37.2	37.8	40.3
3	15.4	16.4	15.4	17.4	22.8	23.1	22.9	21.6
High	10.2	8.9	8.9	8.6	12.2	14.8	15.5	10.0
	Average of portfolios' returns (%)							
Low	0.18	0.16	0.13	0.16	0.08	0.14	0.07	0.06
2	0.10	0.17	0.21	0.09	0.06	0.09	0.03	0.06
3	0.17	0.17	0.19	0.17	0.04	0.11	0.09	0.10
High	0.26	0.16	0.18	0.21	0.12	0.09	0.11	0.09

*Resilience is represented by the percentage of affected share of each portfolio, meaning that low resilience stands for high affected share

The 32 portfolios presented in Table 4.2 are built on the intersection of size factor, value factor and resilience factor. Companies with small size on average have higher book-to-market ratios, showing that they are undervalued by the market. Also, firms in small size portfolios have on average lower percentage of affected share from COVID-19. At the same time, small portfolios showed much higher average return, than big portfolios. The table also shows that companies which showed lower resilience to COVID-19, they had on average lower returns both in small and big size portfolios, while the companies which showed higher resilience, had higher returns. However, there is no visible pattern related to average portfolio's book-to-market ratio and average return.

Table 3. Descriptive statistics of industries and their affected shares by country

	Total number of firms					Average affected share, %				
	Total	Hungary	Poland	Russia	Czech Republic	**Total**	Hungary	Poland	Russia	Czech Republic
Manufacturing	**96**	3	79	13	1	**25**	21	19	27	35
Information	**41**	1	34	5	1	**39**	47	16	47	47
Utilities	**31**	-	5	25	1	**43**	-	43	43	43
Construction	**31**	-	30	1	-	**39**	-	31	47	-
Professional, Scientific, & Technical Services	**25**	1	24	-	-	**13**	13	13	-	-
Wholesale Trade	**17**	-	17	-	-	**27**	-	27	-	-
Mining	**16**	-	3	13	-	**58**	-	64	52	-
Real Estate Rental & Leasing	**13**	1	11	1	-	**39**	39	40	39	-
Finance & Insurance	**13**	-	12	1	-	**10**	-	10	9	-
Administrative & Support & Waste Management	**11**	-	11	-	-	**36**	-	36	-	-
Retail Trade	**9**	-	9	-	-	**68**	-	68	-	-
Transportation & Warehousing	**7**	1	4	2	-	**48**	43	55	46	-
Health Care & Social Assistance	**2**	-	2	-	-	**65**	-	65	-	-
Accommodation & Food Services	**2**	-	2	-	-	**48**	-	48	-	-
Other Services	**1**	-	1	-	-	**52**	-	52	-	-
Total average						**41**	**33**	**39**	**39**	**42**

Table 3 shows the distribution of the average affected share by industries by coutries. Overall, 96 companies (30% of all firms under reseach) operate in manufacturing industry (includes navigational, measuring, electromedical, and control instruments manufacturing, petroleum refinary, fertilizer manufacturing, ornamental and architectural metal products manufacturing, pharmaceutical and medicine manufacturing, animal slaughtering and processing, etc.). Manufacturing industry showed strong resilience to COVID-19 with only 25% of affected share on average. Information industry is the second popular among selected firms with overal 41 stocks and 39% of average affected share from COVID-19. Sofrware publishers constitute 46% of information industry, while others are: wired and wireless telecommunications carriers, internet publishing and broadcasting and web search portals, television broadcasting, book and newspaper publishers, etc. Utilities and construciton industries both include 31 stocks each. Utilities industry, which is represented by electric power generation, transmission, control and distribution and natural gas distribution, had on average 43% affected share. Construction industry is represented by residential, commercial and institutional buiding construction, highway, street, bridge, power and communication line construction, etc. Overall, finance & insurance industry showed the highest resilience to the pandemic, while retail trade – the lowest. Among countries, Hungary was the most resilient, as all of its four firms operate only in manufacturing and information sector. Firms from Poland are present all industries with most of them operating in manufacturing, information and construction sectors. Russian companies mostly operate in utilities, manufacturing and mining sectors.

Table 4. Descriptive statistics of countries by portfolios

	Size		BE/ME				Resilience			
	Small	**Big**	**Low**	**2**	**3**	**High**	**Low**	**2**	**3**	**High**
	Average, EUR m		**Average, ratio**				**Average, % of affected share**			
Hungary	-	7,792	0.24	-	1.41	1.79	47	41	29	15
Russia	216	373,278	0.30	0.72	1.35	3.32	51	38	22	15
Poland	2,709	50,661	0.35	0.84	1.51	3.42	53	30	19	11
Czech Republic	-	13,513	0.23	0.92	-	-	47	39	-	-
	Average return, %		**Average return, %**				**Average return, %**			
Hungary	-	0.01	0.07	-	-0.01	-0.02	-0.02	-0.01	-	0.07
Russia	0.14	0.06	0.08	0.13	0.06	0.08	0.08	0.06	0.13	0.08
Poland	0.18	0.10	0.18	0.14	0.14	0.12	0.12	0.14	0.14	0.18
Czech Republic	-	0.03	0.02	0.03	-	-	-	-	0.03	0.02

From Table 4 we can see that Russia has firms with much higher market capitalization in big size porfolio, than all other countries. Presumingly, this is because Russia is a huge producer of crude oil and gas having one of the largest O&G companies in the world. Again, we can see that portfolios with small market capitalization firms have higher average returns (Russian and Poland), than firms on average in big size portfolios. Poland has companies with the highest value among all countries, followed by Russia. Yet again, there is no clear pattern between firms' value and return. In Poland, for example, low value companies bring higher returns. This inverse relation is kept in each quartile. Generally, this also works for Hungary, where high value companies broughts negative returns. But this inverse relation doesn't work for Russia, which doesn't have any clear pattern. We can also observe that low resilience firms brought generally lower average return (Hungary and Poland). However, this is not true for Russia.

CHAPTER 5. RESULTS

5.1 CAPM Results

Three testing periods are presented on Figure 1. We have excluded the period with the highest volatility during the peak of the pandemic (March - beginning of April 2020) as it would show not meaningful results.

First testing period is a pre-COVID-19 period. Overall, the period includes 400 observations. Here we would expect to see results, which supports CAPM theory and were highlighted in the Metodology Chapter.

Table 5. Summary results of the cross-section regression (5) built on three time periods

	Pre-COVID-19 04.10.2019 – 14.02.2020		**During COVID-19 07.04.2020 – 27.11.2020**			**Post-COVID-19 04.12.2020 – 28.04.2021**		
Variable	Estimate	Std. Error	Estimate	Std. Error		Estimate	Std. Error	
(Intercept)	0.003	0.002	23.676	12.371	·	-0.007	0.002	**
β_p	-0.001	0.007	-41.030	35.917		0.030	0.006	***
β^2_p	-0.013	0.020	11.473	108.635		-0.078	0.019	***
s_p	0.021	0.062	-558.723	338.784	·	0.327	0.057	***
Observations	400		600			460		

Note: · indicates statistical significance at the 90% confidence level, * 95% confidence level, ** 99% confidence level, *** 99.9% confidence level.

In the first testing period, coefficients in front of β^2_p and s_p are not statistically significant, which is in line with the theory and supports hypothesis C1-C2. However, hypothesis C3 must be rejected, as the coefficient in front of β_p is not statistically different from zero. This result indicates that there is no positive relatioship between the market return and the return on a particular security, which contradicts CAPM theory. However, the initial Capital Asset Pricing model was first developed and tested and proved on the US stock exchange, and there is quite a lot of later studies which had shown that CAPM may not hold on other markets, for example as it was shown in Džaja and Aljinović (2013).

The second testing period is during COVID-19 outbreak. This period includes 600 observations. In this period we would expect to see some changes in β_p, for example we would allow the coefficient to be both positive, negative or not significant at all. We would also expect to see some changes in s_p, assuming that during this period a clear non-systematic risk is present on the markets, which is cannot explained by the market factor. However, we would still expect the relationship between the return on as security and return on the market to be linear. From the results in Table 5 it can be observed that the magnitude of the coefficients is much higher, than in the previous testing period, which can be explained by a much higher volatility of returns after the COVID-19 outbreak and lockdown restrictions which came into force on March 2020, despite we already excluded March. The coefficient at β_p is not statistically significant as well, meaning that the expected return on a security is not explained by the market factor. Coefficient in front of β^2_p is also not statistically significant, meaning that the model linear. Finally, the coefficient in front of s_p is statistically significant at 90% confidence interval. This indicates that there are some other non-systematic risk factors, which are not included into the model. As this testing period is a heat of the COVID-19 outbreak, we may assume that this can be the impact of COVID-19 on the financial markets.

The third testing period is the post-COVID-19 outbreak. This period includes 460 observations. In terms of the results of this cross-section regression, our expectations are the same as expectations for the second testable period. Results indicate that the coefficient in front of β_p is highly statistically significant at 99.9% confidence interval – for this period the average incremental return of β was 3% per week, so that on average associated risk yielded noticable award. At the same time, the coefficient in front of s_p is also highly statistically significant, implying that there is some non-beta risk, which is not systematic and is not explained by the market factor. The linear relatioship between security's return and market return was also confirmed.

5.2 Four-Factor CAPM Results

First, we run the two-step times-series regression for all 4 selected countries on daily returns. As the first step, we estimate slope coefficients described in equation (8), which are presented in Table 6. The results presented in this section refer to 2*2*2 portfolios sorting, as the difference with 2*3 and 2*2 sorts was not meaningful.

Table 6. Estimated results of 32 regressions based on equation (8), 4 countries, daily returns

Resilience* quartiles	**Small Size**				**Big Size**			
	Book-to-market equity (BE/ME) quartiles							
	Low	2	3	High	Low	2	3	High
	β_{i1}							
Low	1.001	1.000	0.998	0.998	1.000	1.000	0.999	1.000
2	1.000	0.999	1.000	1.001	0.999	1.000	0.999	0.999
3	0.997	1.000	1.001	0.999	1.000	0.999	1.000	1.001
High	0.999	0.999	0.999	1.001	0.999	1.000	0.999	0.999
	β_{i1}, Std. error							
Low	0.002	0.002	0.002	0.001	0.001	0.001	0.001	0.001
2	0.002	0.002	0.001	0.002	0.001	0.001	0.001	0.001
3	0.002	0.001	0.001	0.002	0.001	0.001	0.001	0.001
High	0.001	0.002	0.002	0.002	0.001	0.002	0.002	0.002
	β_{i2}							
Low	1.415	1.262	1.394	1.336	0.291	0.489	0.563	0.375
2	1.308	1.640	1.274	1.373	0.263	0.344	0.425	0.289
3	0.933	1.623	1.210	1.355	0.062	0.588	0.358	0.479
High	1.497	1.196	1.635	1.523	0.310	0.173	0.640	0.501
	β_{i2}, Std. error							
Low	0.112	0.135	0.114	0.105	0.076	0.104	0.091	0.078
2	0.176	0.125	0.099	0.110	0.106	0.089	0.079	0.078
3	0.120	0.105	0.104	0.135	0.085	0.091	0.082	0.089
High	0.097	0.116	0.133	0.160	0.086	0.119	0.114	0.118
	β_{i3}							
Low	-0.395	0.419	1.004	1.009	0.273	-0.042	0.336	0.458
2	0.289	-0.099	1.145	1.337	0.067	0.195	0.623	0.619
3	0.093	0.295	0.865	1.153	0.033	0.218	0.627	0.669
High	-0.622	0.266	0.987	1.099	-0.128	-0.302	0.218	0.456
	β_{i3} Std. error							
Low	0.123	0.149	0.125	0.115	0.084	0.114	0.100	0.086
2	0.194	0.138	0.109	0.121	0.117	0.098	0.088	0.086
3	0.132	0.116	0.115	0.148	0.093	0.100	0.091	0.098
High	0.108	0.128	0.147	0.177	0.095	0.131	0.126	0.130
	β_{i4}							
Low	-0.180	0.006	0.360	-0.163	0.352	0.327	0.436	0.188
2	0.161	0.285	0.655	0.684	0.297	0.253	0.172	-0.069
3	0.718	1.375	1.085	1.372	0.122	0.961	0.551	0.895
High	1.389	1.277	1.413	1.331	0.999	1.245	1.101	0.997
	β_{i4} Std. error							
Low	0.101	0.122	0.102	0.094	0.069	0.093	0.082	0.071
2	0.159	0.113	0.089	0.099	0.095	0.080	0.072	0.070
3	0.108	0.094	0.094	0.121	0.076	0.082	0.074	0.080
High	0.088	0.104	0.120	0.145	0.077	0.107	0.103	0.106

The market slopes (β_{i1}) are always close to 1.0 with almost zero standard deviation (at two decimals). The coefficients for SMB factor (β_{i2}) for small size portfolios are higher, than for the big size portfolios. We can say that SMB factor captures the variation in average stock returns, which is missed by market factor and other factors. Regarding HML factor, some slope coefficients for this factor produce negative values, for example for extreme groups of resilience (Low and High) for both small and big firms, and mostly for low value firms. This means, that regardless of firm's resiliency, the stock will produce on average 60% lower return for low value stocks, than for high value stocks. There is also a clear trend for the average expected return to grow (for almost all resilience groups), as the value group increases from Low to High. But this mostly holds for small size portfolios. It is also interesting, that the RMN coefficient gradually increases from low or negative average return in Low resilient groups to greater than 1% in high resilience groups. However, this only works for small size firms.

From Table 7 we can see that from all factors, only SMB factor turned out to be highly statistically significant. This is supported by 0.5066 R^2. The SMB coefficient can be interpreted as follows: companies with small market capitalization yield on average 0.1% higher return, than companies with big market capitalization.

Table 7. Estimated results for equation (9), 4 countries, daily returns

	Estimate	**Std. Error**	**t value**	
Intercept	-0.034	0.075	-0.446	
d_1	0.026	0.075	0.339	
d_2	0.001	0.000	4.292	***
d_3	0.000	0.000	0.616	
d_4	0.000	0.000	1.020	
R^2		0.507		

Note: ˙ indicates statistical significance at the 90% confidence level, * 95% confidence level, ** 99% confidence level, *** 99.9% confidence level.

These results do not fully support all our hypothesis. Mainly, they do not confirm the hypothesis that the resilience factor can be use used as an additional factor in CAPM model to explain expected returns.

Table 8. Estimated results of 32 regressions based on equation (8), 4 countries, weekly returns

Resilience* quartiles	Small Size				Big Size			
	Book-to-market equity (BE/ME) quartiles							
	Low	2	3	High	Low	2	3	High
	β_{i1}							
Low	1.003	1.001	1.000	0.998	1.001	1.001	1.000	1.001
2	1.001	1.000	1.001	1.002	1.001	1.001	1.001	0.999
3	0.998	1.001	1.002	1.000	1.001	1.001	1.001	1.001
High	1.000	1.000	1.000	1.001	1.000	1.001	1.000	1.000
	β_{i1}, Std. error							
Low	0.002	0.002	0.002	0.002	0.001	0.002	0.001	0.001
2	0.002	0.002	0.001	0.002	0.001	0.002	0.002	0.001
3	0.002	0.002	0.002	0.002	0.001	0.001	0.001	0.001
High	0.001	0.002	0.002	0.002	0.001	0.001	0.002	0.002
	β_{i2}							
Low	0.800	0.762	1.178	1.273	-0.066	0.011	0.308	0.006
2	1.527	1.024	0.895	0.591	-0.840	0.010	0.010	0.289
3	0.728	1.191	0.675	0.806	0.065	0.112	0.023	0.015
High	1.218	1.018	1.657	0.853	0.351	0.005	-0.207	-0.207
	β_{i2}, Std. error							
Low	0.291	0.374	0.317	0.281	0.245	0.278	0.246	0.240
2	0.380	0.304	0.246	0.305	0.265	0.282	0.282	0.078
3	0.384	0.331	0.279	0.351	0.232	0.227	0.232	0.236
High	0.271	0.390	0.361	0.457	0.244	0.271	0.312	0.312
	β_{i3}							
Low	-0.402	0.734	0.941	1.476	0.463	0.447	0.366	0.874
2	1.025	-0.145	1.657	1.273	0.301	0.335	0.335	0.619
3	-0.007	0.508	1.175	1.479	0.386	0.330	1.021	0.602
High	-0.042	0.747	0.784	1.751	0.203	0.155	0.763	0.763
	β_{i3}, Std. error							
Low	0.293	0.376	0.319	0.283	0.246	0.280	0.247	0.241
2	0.382	0.306	0.248	0.307	0.266	0.283	0.283	0.086
3	0.386	0.333	0.280	0.353	0.234	0.228	0.233	0.237
High	0.273	0.392	0.362	0.460	0.245	0.272	0.314	0.314
	β_{i4}							
Low	-0.647	-0.600	-0.212	-0.783	-0.051	-0.363	0.003	0.049
2	-0.682	-0.368	0.475	-0.019	-0.305	-0.059	-0.059	-0.069
3	0.251	0.922	0.570	0.889	-0.455	0.352	0.023	0.492
High	0.989	1.084	1.061	1.217	0.480	0.434	0.701	0.701
	β_{i4}, Std. error							
Low	0.233	0.299	0.254	0.225	0.196	0.223	0.197	0.192
2	0.304	0.243	0.197	0.244	0.212	0.225	0.225	0.070
3	0.307	0.265	0.223	0.281	0.186	0.181	0.185	0.189
High	0.217	0.312	0.288	0.366	0.195	0.217	0.250	0.250

For comparison, we also estimated the two-stage time-series regression on weekly returns, instead of daily, as weekly returns are believed to exclude extra so noise in market fluctuation. The results presented in Table 8 are worse, than in Table 6. The pattern is that small companies yield higher returns than big companies does not hold anymore. The trend for increasing average expected return with increasing value and resilience also is not consistent.

Nevertheless, it is still true that small market-cap portfolios have increasing average returns with increasing resilience. However, this does not work for big market-cap companies.

However, the slope coefficients, presented in Table 9 turned out to be not statistically significant, with very low R^2 = 0.043. The all also have negative direction, which contradicts CAPM theory, and our assumption for COVID-19 resilience factor.

Table 9. Estimated results for equation (9), 4 countries, weekly returns

	Estimate	**Std. Error**	**t value**
Intercept	2.301	3.212	0.716
d_1	-2.356	3.210	-0.734
d_2	-0.004	0.005	-0.689
d_3	-0.001	0.006	-0.139
d_4	-0.002	0.005	-0.426
R^2		0.043	

Note: $^{\cdot}$ indicates statistical significance at the 90% confidence level, * 95% confidence level, ** 99% confidence level, *** 99.9% confidence level.

As a matter of robustness check, we decided to exclude from the observed sample stock returns collected from Moscow stock exchange. There are several reasons for this decision. Russia has enormous natural oils and gas reserves. Most large companies operating on Moscow stock exchange are O&G companies, which drive the market behavior and makes the greatest contribution to country's economy overall. Therefore, economy's great dependence on oil makes it very vulnerable to the volatility of global oil prices, which are also subject to political tensions with OPEC and other O&G producers. We are worried, that factors would distort the results of CAPM model, which is unlikely to hold on this market.

Table 10. Estimated results of 32 regressions based on equation (8), 3 countries, daily returns

	Small Size				**Big Size**			
Resilience* quartiles	**Book-to-market equity (BE/ME) quartiles**							
	Low	2	3	High	Low	2	3	High
	β_{i1}							
Low	0.501	0.500	0.501	0.500	0.500	0.501	0.500	0.500
2	0.500	0.499	0.500	0.500	0.500	0.500	0.500	0.500
3	0.499	0.500	0.500	0.500	0.502	0.500	0.500	0.501
High	0.500	0.501	0.500	0.501	0.501	0.500	0.500	0.500
	β_{i1}, Std. error							
Low	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
2	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
3	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
High	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	β_{i2}							
Low	0.730	0.744	0.280	0.724	-0.293	-0.228	-0.128	-0.083
2	0.661	0.451	0.632	0.717	-0.425	-0.242	-0.245	-0.045
3	1.089	0.842	0.645	0.645	0.444	0.368	0.145	-0.255
High	1.095	0.730	1.275	1.051	0.197	0.366	0.248	-0.096
	β_{i2}, Std. error							
Low	0.110	0.135	0.121	0.106	0.085	0.086	0.067	0.076
2	0.167	0.088	0.089	0.098	0.102	0.075	0.091	0.080
3	0.113	0.089	0.105	0.105	0.185	0.106	0.113	0.080
High	0.109	0.110	0.127	0.143	0.118	0.111	0.138	0.104
	β_{i3}							
Low	-0.922	-1.034	0.249	0.594	-0.315	-0.426	-0.047	0.273
2	-0.578	0.129	0.795	0.978	-0.272	-0.088	-0.012	0.325
3	-0.221	0.134	0.748	0.748	0.427	0.213	0.551	0.315
High	-0.712	-0.922	1.029	0.948	0.185	0.139	0.228	0.113
	β_{i3}, Std. error							
Low	0.117	0.144	0.129	0.113	0.091	0.092	0.071	0.081
2	0.177	0.093	0.095	0.105	0.108	0.108	0.108	0.108
3	0.121	0.095	0.111	0.111	0.197	0.113	0.120	0.086
High	0.117	0.117	0.136	0.153	0.125	0.118	0.147	0.110
	β_{i4}							
Low	0.120	0.059	-0.071	0.122	0.106	0.128	0.096	0.101
2	-0.028	0.107	0.086	0.126	0.116	0.160	0.129	0.111
3	0.234	0.162	0.213	0.213	-0.101	-0.135	0.261	0.162
High	0.204	0.120	0.221	0.189	-0.097	-0.056	-0.037	-0.078
	β_{i4} Std. error							
Low	0.016	0.020	0.018	0.016	0.013	0.013	0.010	0.011
2	0.025	0.013	0.013	0.015	0.015	0.011	0.014	0.012
3	0.017	0.013	0.015	0.015	0.027	0.016	0.017	0.012
High	0.016	0.016	0.019	0.021	0.017	0.016	0.020	0.015

From Table 10 it is clear that the market factor has decreased twice from 1.0 to 0.5, with also lower standard deviation of 0.001. The SMB coefficient is now almost always negative for big size portfolios – especially with high value. In small size portfolios, it is also evident that the SMB coefficient increases with resiliency for all value groups. The HML coefficient is negative for low value companies in small size groups for all resilience levels, while in big portfolios – only for low resilience groups. It is interesting, that RMN factor in big size portfolios is negative for high resilient firms regardless of firm's value.

Table 11 shows that the SMB factor is still highly statistically significant. It implies, that firms with small market capitalization yield 0.1% higher average return, than companies with big market capitalization. Intriguingly the RMN factor is now statistically significant at 90% confidence level. This means that our hypothesis that companies which are resilient to the pandemic, outperform non-resilient ones. Yes, resilient firms yield 0.1% higher average return, than non-resilient. Overall, this model has higher explanatory power with 58.9% R^2, than the one estimated for all countries including Russia on daily returns, with 50.7% R^2.

Table 11. Estimated results for equation (9), 3 countries, daily returns

	Estimate	**Std. Error**	**t value**	
Intercept	-0.022	0.065	-0.337	
d_1	0.029	0.130	0.220	
d_2	0.001	0.000	5.168	***
d_3	-0.000	0.000	-0.993	
d_4	0.001	0.001	1.965	.
R^2	0.589			

Note: . indicates statistical significance at the 90% confidence level, * 95% confidence level, ** 99% confidence level, *** 99.9% confidence level.

Shortly about HML factor. Both from the descriptive statistics, and estimated regressions there was no clear behavior in this factor in explaining returns, especially on the cross section with other factors. In all models this factor was not statistically significant, and the hypothesis that high value companies tend to outperform low values companies was not supported. Fama and French (2014) have faced with the redundancy of this HML factor in building five-factor model. They have proved, that when adding profitability and investment factors to the CAPM model, BE/ME factor becomes redundant. This could be a potential possible explanation of non-significant value factor in our asset pricing tests.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

The Capital Asset Pricing Model was tested on Eastern European Stock Echanges. Despite there are plenty of studies, which had proven that CAPM does not always hold, we have evidenced some arguments for using CAPM model in these markets in both one-factor CAPM and four-factor CAPM.

The results of one-factor CAPM regression estimated on three different time periods, are summarized in the table below:

Table 12. Summary of thre CAPM model for three data periods (weekly data)

	Pre-COVID-19 (04.10.2019 – 14.02.2020)	**During COVID-19 (07.04.2020 – 27.11.2020)**	**Post-COVID-19 (04.12.2020 – 28.04.2021)**
C1 (linearity)	Passed	Passed	Failed
C2 (no other systematic non-beta risk)	Passed	Failed	Failed
C3 (expected return is positive)	Failed	Failed	Passed

According to the first testing period, the Capital Asset Pricing Model was not fully supported by the empirical data from the Eastern European Markets. Despite the results confirmed the assumptions about linearity and absence of any other non-systematic risk, the relation between the expected return of a particular security and the return of the market turned out to be not statistically significant. In the future study it is recommended to expand the time frame for the pre-COVID-19 period to include more observations and capture more variations of the market.

What is important, the results of the CAPM on the second and third testing periods have shown that there is some non-systematic risk, which is not captured by only the market factor. As the second and the third testing periods are during COVID-19 outbreak, we may relate the existance of the non-systematic risk to the risk caused by the pandemic, which was also further tested in this research.

We have evidenced some patterns in average returns related to size and resilience on Easten European stock markets. The four-factor CAPM model built on stock returns from four countries – Poland, Hungary, Russia and Czech Republic, showed that only size factor is significant in explaining average stock returns.

After we excluded Russia from the sample, the new four-factor CAPM model has shown better results and had higher explanatory power. It evidenced, that small size companies yield 0.1% higher daily returns, than big companies, and that high resilient firms yield 0.1% higher return, than non-resilient ones. This confirms two out of four main hypothesis presented in Chapter 3.2. It was proved in the research, that in the post-COVID era resilience factor can be added to CAPM to help explain expacted average returns on stock markets. Intuitively, as Hungary and Czech Republic have little number of observations, this makes our results applicable primarily to Poland, which constituted the main sample.

At the same time, the value factor, which assumed that high value companies tend to outperform low value companies, was not supported by the results of the model. The possible explanation for this was offered earlier by Fama and French (2014), who called the HML factor as "redundant", when to the CAPM model are added two other factors – profitability and investment. Or maybe, the value of the company is no longer an important measure of expexted returns during pandemic periods.

The subject for further research is to combine the size and COVID-19 resilience factors with other factors, suggested in Fama and French (2014) – in particular profitability and investments. It would be intresting to check whether the value factor also becomes 'redundand' after adding two new variable, tested on the European Emerging market, and in combination with COVID-19 factor.

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