In times of regional geopolitical turmoil – Why do some equity funds perform better than others?

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Abstract

In times of regional geopolitical turmoil – why do some investment portfolios, equity funds, perform better than others? Is it simply luck, the effects of systematic risk or do factors such as investment styles and managerial skills play a significant part in the performance of a fund?

As financial markets often reflect the macro environment, much of the previous year’s fluctuations of Eastern European stocks can be seen to derive from a number of geopolitical events; from the 2013 summer clashes between the Turkish police and opposing parties to the current issue concerning Russia and Ukraine. Needless to say, these events have affected return on equity in their regions and created a distressed environment for investors and equity fund managers investing in Eastern Europe.

This thesis aims to explore how the aforementioned macroeconomic events impact the market and thus the portfolios of asset managers. The thesis also intends to provide aspects of eventual investment strategies that are more preferable than others under such circumstances, in order to mitigate the subsequent risks.
I geopolitiskt turbulenta tider – varför presterar vissa aktiefonder bättre än andra?

Sammanfattning

I tider av geopolitiskt tumult – hur kommer det sig att vissa investeringsportföljer, aktiefonder, presterar bättre än andra? Är det ren tur, effekten av systematisk risk eller spelar faktorer så som investeringsstilar och förvaltningsförmåga en signifikant roll i en fonds avkastning?

Eftersom finansiella marknader ofta reflekterar makromiljön, kan man urskilja att mycket av de föränderligheter östeuropeiska aktier upplevde förra året tycks härstamma från ett antal geopolitiska händelser; så som förra sommarens sammandrabbningar mellan turkisk polis och demonstranter till den aktuella krisen gällande Ryssland och Ukraina. Det säger sig själv att händelserna har påverkat avkastningen på bland annat aktieinvesteringar i regionen och således skapat en orolig miljö för investerare och fondförvaltare som investerar i Östeuropa.

Denna uppsats ämnar utforska dessa makroekonomiska händelsers påverkan på marknaden och således fondförvaltarnas investeringsportföljer – fonder. Uppsatsen ämnar även bidra med aspekter för eventuella investeringsstrategier som är att föredra över andra under geopolitiskt oroliga omständigheter i syfte att minimera efterföljande risker.
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1 Introduction

1.1 Background

In 2013, Eastern Europe was the scenery of a number of geopolitical events with substantial consequences on the social, political and economic environment. The crises sent stock markets sliding and consequently affected investors, asset managers and equity funds.

In March 2013 the Northern part of Eastern Europe started to display recovery from the long-term recession and harsh economical situation following the 2008 financial crisis and the recent Eurozone crisis. The West developed better than the South and it was foremost the Baltic region and Poland that during 2013-2014 started to show acceptable GDP-growth and decreasing unemployment. Both the Central and Southern parts of Eastern Europe had suffered severely from the Eurozone crisis, but started slowly to move from recession as investments turned upwards with improving credit possibilities [1].

However, at the end of the second quarter of 2013, an environmentalist protest in Istanbul sparked what in months proceeding was to become a series of protests and violence. The turmoil in Turkey commenced in late May with the Turkish police’s intense response to a peaceful protest in the Turkish capital. The police force’s violent reaction triggered a growing opposition and public rage towards the government’s actions. Like a wildfire, spreading to neighboring cities, the Turkish summer of 2013 was a set for violent clashes between police and demonstrators.

In the end of 2013 – Ukraine became a geopolitical hot spot. The crisis, involving Ukraine and Russia, origins from conflicting pro-Western and pro-Eastern opinions. This caused violent protests in late November 2013 when the pro-Russian and former Ukrainian President Viktor Yanukovych announced the neglect of a trade agreement with the European Union to instead seek closer ties with Russia [2].

The protests became a trigger for the following events in Ukraine – including violent clashes between the protesting opposition and military, a new political government, and a Russian annexation of Crimea. It became a global issue of concern, troubling several political bodies and countries like the European Union, United Nations, NATO and the United States.

Eastern European securities, i.e. equity stocks, have been severely affected by the instability and this has been reflected on the financial markets, by sharp losses on stock exchanges, regional stock indices as well as record falls in local currencies [3] [4].

To summarize, from 2013 to early 2014, there had been a gradual economic recovery in Eastern Europe, but due to the geopolitical turmoil, like the crises in Turkey, Ukraine and Russia, its financial markets became an uncertain and volatile environment for many of its investors.
1.2 Research Question

How can investors hedge themselves in volatile times, like the ones aforementioned – is there a way, and if so, which strategies, investment styles and managerial skills have best effect on equity returns and how do macroeconomic factors affect them?

We will in our thesis explore these issues by analyzing the fund performance of different Eastern European equity funds by employing a structural interpretation of multiple linear regression analysis. Performing the Ordinary Least Squared estimation (OLS) and different statistical tests, we will regress fund performances on a number of carefully chosen covariates, which fund managers often use to motivate fund fees and define as active management. This mathematical approach will enable us to investigate which factors, strategies and styles of investment allocations are significant and how the macroeconomic environment affects them.

Our study of Eastern European stock portfolios consists of Eastern European equity funds. As they mainly consist of company stocks, their value is thus the price that the market imposes on them. We have chosen this economically and geopolitically diverse frontier market as it has throughout the time frame for our data collection been exposed to several geopolitical events, as introduced earlier.

The thesis has chosen to limit observations by studying the rolling fund performance development of Eastern European funds from 21 March 2013 to 21 March 2014. These include about a hundred different funds - Turkish, Russian, Baltic and purely Eastern European funds as well as mixtures of these fund categories (see Appendices Table 10). The impact they have had on regional investments brings out an interesting discussion on how macroeconomic factors affect asset management.

1.3 Purpose & Aim

The purpose of every fund is to generate return on its investments. This thesis therefore evaluates fund performance through portfolio strategies and investment styles that incorporate factors like allocation strategies and holding weightings, while also allowing for predictability in fund risk loadings and benchmark returns. It contributes to the analysis of funds’ behavior during crises, which there seems to be a lack of in literature. Asset managers motivate the fees they induce through for example stock-picking, unique market experience and other strategies they have to achieve positive returns on their investments.

There have been numerous studies of fund performance and their correlation with different investment styles. But the question of which funds perform better than others in geopolitical crises is more seldom investigated, as well as their direct effect on short-term equity returns [5, page 1]. Therefore, this thesis contributes to studies exploring if there is any value added from active fund management in distressed times and the macroeconomic linkages between return and geopolitical turmoil. Our results will therefore hopefully provide an insight for investors and fund managers looking for ways to mitigate risks caused by geopolitical instability.

By creating a mathematical model, using the principles of linear regression, we explore the above-mentioned and discuss how certain geopolitical events and macroeconomic factors impact the covariates of our model.
2 Mathematical theory

To be able to analyze our data and provide groundwork for our research question we employed the theories behind multiple linear regression analysis. This is a statistical technique that estimates the relationship between a set of covariates, i.e. explanatory variables, and a dependent variable.

2.1 Multiple Regression Analysis

The linear regression model is defined as

\[ y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_n x_{in} + \epsilon_i, \quad i = 1, \ldots, j \quad (1) \]

Equation (1) can also be written in matrix form:

\[ \mathbf{y} = \mathbf{X}\beta + \epsilon \]

\( \mathbf{Y} \) is a column vector consisting of our 101 observations of each fund’s 12-month rolling fund performance. \( \mathbf{X} \) is a matrix including our covariates in rows corresponding to the observations \( y_i \), i.e.

\( \mathbf{X}_i = (1 \ x_{i1} \ x_{i2} \ x_{i3} \ldots \ x_{in}) \), where 1 is the coefficient for the intercept and \( x_{i1} \) to \( x_{in} \) our \( n \) covariates whose effect on the fund performance we want to analyze.

The regression estimates the coefficients \( \beta \) of the regression equation \( \mathbf{y} = \mathbf{X}\beta + \epsilon \), where

\[ \beta = \left( \begin{array}{c} \beta_0 \\ \vdots \\ \beta_n \end{array} \right) \]

are the coefficients corresponding to the explaining variables \( x_{i1} \) and \( \epsilon = \left( \begin{array}{c} \epsilon_0 \\ \vdots \\ \epsilon_n \end{array} \right) \) are the error terms for the different observations.

The different mathematical methods, which are used in this study, are given below.

2.1.1 Ordinary Least Squares

When estimating values for the coefficients, \( \beta \)'s, for a set of covariates, the Ordinary Least Squares (OLS) estimation is commonly used. This estimation of the \( \beta \)'s minimizes the sum of squared residuals, \( |\epsilon|^2 \), associated with the regression equation. This is done by solving the normal equations \( \mathbf{X}^t\epsilon = 0 \), where \( \epsilon = \mathbf{y} - \mathbf{X}\beta \) [6, page 20].

The Ordinary Least Square (OLS) methodology assumes that the residuals \( \epsilon_i \) are independent of each other in each observation i.e. \( E(\epsilon|\mathbf{X}) = 0 \) and \( E(\epsilon\epsilon'|\mathbf{X}) = \sigma^2 \mathbf{I} \). These two last properties assume that the errors are serially uncorrelated and homoscedastic – i.e. all observations have the same variance. These properties, which in a way imply unrealistic simplifications, will be discussed later in our thesis. Among other themes, the issue concerning heteroscedasticity will be discussed. Another assumption of OLS is that the error terms are approximately \( \sim N(0, \sigma^2) \) [6, pages 18-19].
The coefficient for the equation which satisfies the above, is obtained from the normal equations:

\[ \beta = (X'X)^{-1}X'Y \]  

(2)

This equation can be interpreted as linear, and implies that the OLS is said to be BLUES (Best Linear Unbiased EStimator). Each estimate, \( \hat{\beta}_i \), explains how much a unit change of its corresponding covariate, \( x_i \), has on fund performance, \( y_i \), ceteris paribus.

When employing the method of multiple linear regression, one needs to carefully choose the covariates that are used. The covariates are to explain the model, and if they are not relevant, the error term will be large and the model will fail to be explanatory [7, page 345].

There are two “types” of covariates: Standard- and Dummy-variables [7, page 313],

- **Standard** – Variables of this type are given its real value, e.g. when we regress the returns of different funds on its NAV, the NAV would be a standard covariate with its value given in million SEK.
- **Dummy** – Dummy variables, sometimes referred to as indicator variables, are binary variables taking either the value 1 or 0 [7, page 315]. For instance, when we regress the returns of our funds on their investment-style, “Growth”, “Value” or “Mix”, we employ dummy variables. If one of the funds has an investment style incorporating purely growth stocks, it will have a 1 as covariate for “Growth” and 0 for the two other covariates “Value” and “Mix”. However, in our initial model we leave “Growth” as a benchmark in order to mitigate risks of linear dependency. It seems natural that if “Mix” = 0 and “Value” = 0, then it implies that “Growth” = 1.

### 2.2 Model Validation and Improvement

To be able to validate the significance of our initial model and, if needed, improve it, we will need to apply a few statistical tests and theories. This is reviewed in the following section.

#### 2.2.1 Hypothesis Testing

Hypothesis testing is used to compare and analyze a certain set of parameters. When comparing statistical models and identifying which to prefer, one can employ different tests. One test is the Student’s t-test, which can be used for testing if two sets of data are significantly different from one another. Our thesis, however, employs the F-test, which is preferred when comparing a higher number of estimates.

#### 2.2.1.1 The F-statistic

The F-test can be used to test the different \( \beta \)-values’ significance to our regression model. This corresponds to testing the hypothesis that \( \hat{\beta}_1 = \hat{\beta}_2 = ... = \hat{\beta}_r = 0 \), that is testing if a certain set of covariates have no significance to our dependent variable. Assuming that the error terms are normally distributed, there exists an exact test, which test the hypothesis,

\[ F = \frac{n-k-1}{r} \left( \frac{\sum \hat{e}^2}{\hat{\sigma}^2} - 1 \right) \in F(r, n - k - 1) \]  

(3)
where $\mathbf{e}$ denotes the residuals from the unrestricted regression, and $\mathbf{e}^*$ the residuals from the restricted model where $\beta_1 = \beta_2 = \ldots = \beta_r = 0$ [6, page 24].

The null hypothesis, $H_0 : \beta_1 = \beta_2 = \ldots = \beta_r = 0$, is rejected if $F$ is larger than the critical $F$-value [8, page 137]. This will generate a $p$-value, the probability $\Pr(X > F)$ where $F$ has the distribution of (3). If the $p$-value is under a chosen significance level (often $5\% - 10\%$), one can reject that the excluded covariates do not have any significant effect on the dependent variable [8, page 137]. In our thesis we employ a significance level of $5\%$. The $F$-statistic is used in order to verify the significance of our regression model’s covariates.

### 2.2.2 $R^2$

$R^2$, or the coefficient of determination, measures the “goodness of fit” of the data points on the statistical model $Y = \mathbf{X} \beta$. That is, $R^2$ is the fraction of the sample variance, which is explained by the least squares fit [7, page 354]. The $R^2$ is the percentage of the response variable that is explained by the linear model, which ranges from 0 to 100%, where 100% implies that the model explains all variability of the data around its mean.

$$R^2 = 1 - \frac{\text{Sum of squared residuals}}{\text{Total sum of square}} = \frac{SS_{\text{tot}}}{SS_{\text{res}}}$$

(4)

In (4), $SS_{\text{tot}} = \sum(y_i - \bar{y})^2$, the total sum of squares (proportional to the sample variance) and $SS_{\text{res}} = \sum(y_i - f_i)^2$, the sum of squared residuals, also called the residual sum of squares. It is of importance not to be too fixated on the $R^2$ value, as a low $R^2$ value does not necessarily imply a bad model [9].

As the formula above states, the $R^2$ value cannot decrease while adding an additional covariate; therefore the adjusted $R^2$ value is a better criterion. It takes the number of parameters in the regression into account, and adjusts the $R^2$ accordingly. Therefore, the adjusted $R^2$ can decrease if an additional covariate only explains a small proportion of the unexplained variance [7, page 355].

### 2.2.3 BIC-criterion

In order to find the model with best significance possible, the BIC-test (Bayesian Information Criterion, AKA the Schwartz test) may be used. One chooses the model that minimizes $n \cdot \ln(\tilde{e}^2) + (k + 1) \cdot \ln(n)$, where $k$ is the number of covariates including the intercept and $n$ is the number of observations. We can use the BIC to judge our model and see if removing each regression’s covariate, with the highest $p$-value, improves the model [10].

Studies often argue over which one of the BIC-value or the $F$-value, when reducing regression models, is the most explanatory. They often give indications of similar results and we use them both in this thesis, as they are a good compliment to each other.
2.3 Errors

Major key assumptions of linear regression is that the model is homoscedastic, errors are independent and that there is a lack of multicollinearity. In this section we go through errors that violate the aforementioned key assumptions, and how to reduce their impact in order to improve the model.

2.3.1 Multicollinearity

Multicollinearity occurs when the intercept is linearly dependent with some other covariate. This happens if you employ the regression with every dummy variable, without excluding ones that would cause linear dependency. A typical sign of multicollinearity is that the standard deviations for some coefficients are particularly high [6, page 30].

An example of a way to detect multicollinearity is by using a statistic called the Variance Inflation Factor (VIF) [11, page 200]. A VIF is a test that estimates how much the variance of a coefficient is increased due to linear dependency. It is obtained by running a regression of a coefficient on the remaining variables. For each obtained $R^2$, the VIF is then calculated through $\frac{1}{1-R^2}$. As a general rule, a VIF larger than 10 indicates a potential issue of multicollinearity [7, page 409].

One way to eliminate multicollinearity is to employ the regression without one of the dummy coefficients. Then the intercept will not longer be linearly dependent with the coefficients.

2.3.2 Endogeneity

When we perform the regression, one problem that might occur is the case with endogeneity. A covariate is endogeneous if it correlates with the error term in the regression model. If endogeneity occurs, it may be that the covariates estimated by OLS are biased. This means that the expected value and the exact value of the parameter might not be the same.

Endogeneity can occur due to different factors. Below follows some of the most common [6, page 30].

Measurement errors
Measurement errors cause endogeneity because it causes correlation between the independent variables and error terms. On the other hand, unbiased measurement errors in the dependent variable do not cause endogeneity; it instead just adds a component to the error term.

Missing covariates
If the regression is missing some relevant covariates, the error term will try to “explain” this. It is therefore critical to identify as many relevant covariates possible when performing regression.

Simultaneity
Simultaneity causes endogeneity because the dependent variable not only is explained by the covariates, but can also explain the covariates. This happens with simple demand and supply models.
Sample Selection Bias

Sample selection bias may cause endogeneity when the selection of data is not randomly chosen. If the sample selection is not random, it may be so that it correlates with an unmeasured covariate that is explained by the error term.

If the situation with endogeneity occurs, it can be solved using instrumental variables and the 2SLS instead of OLS. The 2SLS is a 2-step regression, called “Two Stage Least Squares”.

The 2SLS procedure is as follows:

First identify covariates that could be explained by the remaining covariates (which are correlated with the error term) but themselves uncorrelated with the error term. These covariates, called *instrumental variables*, are then used to make a predicted value of the original covariate. This is the first stage [12].

Then the predicted values go into the original equation instead of the ones that correlate with the error terms. The new values are then used in the linear regression model. Since the predicted values are uncorrelated with the error term, the new model is optimal. This is the second stage and explains the procedure’s name – the 2 Stage Least Squares [12].

2.3.3 Heteroscedasticity

Heteroscedasticity occurs when the error terms do not have constant variance. As mentioned earlier, the OLS assumes that $E(e|X) = 0$ and that $E(ee'|X) = I \sigma^2$. This signifies that the variance of the error term is constant. If the error terms do not have constant variance, they are said to be heteroscedastic. This means that every error term has a unique variance, i.e. $E(e_i|X) = 0$ and $E(e_i^2|X) = \sigma_i^2$ [6, page 33].

When the error terms are heteroscedastic there are several ways to reduce its impact. Below follows a few [6, page 34].

Reformulate the model

One way to reduce heteroscedasticity is by transforming the variables of the model mathematically, taking the logarithm of the model and adding explanatory variables.

Using White’s consistent variance estimator

If the variances of the error terms are not constant, hence not fulfilling $E(ee'|X) = I \sigma^2$, one can use a consistent estimator for the covariance matrix to help remove such invariances. The estimator is as follows: $\text{Cov}(\hat{\beta}) = (X'X)^{-1} \cdot \left( \sum_{i=1}^{n} e_i^2 x_i' x_i \right) \cdot (X'X)^{-1} (\beta)$. The regression is still performed using OLS (2), but the standard errors are estimated through the formula above. Under normal conditions the standard error, also called the estimate of standard deviation, $SE(\hat{\beta}_j)$ is the $j$th diagonal element of $\sqrt{\text{Cov}(\hat{\beta})} = (X'X)^{-1} s^2$, where $s^2 = \frac{1}{n-k-1} |\varepsilon|^2$ [6, page 23].

If one might suspect the existence of differing residual variance one can use White’s estimate.

Bootstrap

Bootstrapping is a process of resampling data. When resampling the data, bootstrapping creates new estimates each time, and the estimates become more accurate. In bootstrapping, confidence intervals for the coefficients can be created [6, page 36].
3 Method and Model

When conducting the study, we first performed the initial full multiple regression analysis with a carefully set of chosen covariates presented below. Then, by performing stepwise statistical tests, we reduced the initial model and eliminated insignificant variables. We also verified the appropriateness of our Final Model using several analytical tools and models.

3.1 Data Collection

In accordance with inputs from interviews with fund managers and fund specialists, as well as different academic studies, we obtained a unique set of covariates. The interviewees were portfolio managers and risk analysts from three different asset management firms specializing in Russia, Turkey, Eastern Europe and other emerging and frontier markets. The conducted interviews provided us with aspects on ways geopolitical crises affect equity markets as well as quantitative and qualitative insights in the different investing styles they employ in their management. The conclusions from interviews, together with statements from experts and studies of earlier research and literature, resulted in the set of covariates presented next. We chose a larger set of covariates against a higher number of observations for our data set in order to reduce risks of obtaining high error terms in our regression.

Data for fund performances were obtained as the rolling return from 21 March 2013 to 21 March 2014. The data range comes from funds classified by Morningstar, an investment resource specialized in fund investing, as Eastern European funds. We also considered all valuations in Swedish Krona to reduce impacts of foreign exchange fluctuations. Time frame was chosen to one year in order to reduce eventual impacts of seasonal variations as a yearly cycle is observed.

To collect the data for our covariates, we used financial software and analytical tools like Bloomberg, Trustnet and Morningstar. Bloomberg, Trustnet and Morningstar provide a large database with fund facts, but they do not tell every detail about how the fund has allocated its investments. Therefore fund fact sheets, annual reports and interviewees helped complete the picture of the fund’s investments.

In total, 123 observations of individual fund performances were collected with 36 covariates in total and 33 covariates when excluding variables to mitigate linear dependency. Due to some funds lacking specific information, and hence data for certain covariates, we reduced the observations to a total number of 101, whom all had complete information about each covariate.

3.2 Variables

3.2.1 Dependent Variable

When performing the regression, we chose the compounded return of the fund as our dependent variable, \( y \). The return of the fund is compounded from one year backward (21 March 2014) to 21 March 2014. It is hence the 12-month rolling return as it concerns the funds’ change in its Net Asset Value (NAV) from the 21 March 2013 to 21 March 2014.
The fund’s NAV is the total value of the funds assets and liquid capital, excluding liabilities and fees and including eventual receivables. The return of a fund is the NAV, and any income generated, divided by the original amount of the investment. Fees and other liabilities for the fund are subtracted from the NAV. This is in our model measured in percent, %, and data was taken from Morningstar’s database.

### 3.2.2 Covariates

**Fund fee**

The fund fee is the compensation investors pay, for the fund management of their invested capital. This is measured as a percentage of total asset value of each investor’s holdings and is also referred to as the expense ratio. This is measured in percent, %, in our model and fees were taken from Morningstar’s database.

**Net Asset Value**

As mentioned earlier, the fund’s Net Asset Value (NAV) is the total value of the funds assets and liquid capital, excluding liabilities and fees and including eventual receivables. It is important as it tells one about the size of the fund and in a sense depicts how liquid it is and its market value. Big investors often choose to invest in larger funds, and therefore decrease the risk of influencing the fund too much in case of a withdrawal of capital. One could expect that perhaps small funds in terms of NAV might risk having a disadvantage when markets hits rocky road, as they often do in geopolitical turmoil. This is because their NAV is more vulnerable to sudden redemptions of fund shares than larger funds [13].

Important to point out, is that this covariate is a measure of a fund’s size whereas the dependent variable is a measure of a fund’s performance, even though the dependent variable contains NAV values for the determination of its value.

The covariate is demonstrated in SEK of millions, i.e. the value 42,000,000 is specified as 42, and data was taken from Morningstar’s database.

**Age**

The age of a fund is an interesting instrument that can be an indicator of different aspects of a fund - for instance that the knowledge of the market becomes greater over time. Earlier studies state that the age of investment funds could play a role in deciding performance since younger funds may face significant higher costs in their start-up period. Other evidence shows that more mature funds have a competitive advantage as they possess a deeper knowledge and therefore perform better [14, page 35]. However, there also exist contradicting studies that show the reverse relation, stating that younger funds may benefit more from fortunate stock picks as they tend to be smaller than older funds [14, page 35].

The variable is defined as the number of years from the fund’s inception date until 21 March 2014, and data was taken from Morningstar’s database.
Standard Deviation
In our study the standard deviation quantifies the variation of the fund's performance from its average. A low standard deviation implies that performance is rather regular and that the portfolio is less volatile. If a fund’s performance varies heavily, it has a high standard deviation and therefore larger volatility. The fund has then high performance during certain periods and lower during other. For statistical data with observations of the return $x_i$, the standard deviation, $s$, is defined as $s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n}(x_i - \bar{x})^2}$ [15, page 482].

We measure the standard deviation for the same 12 months as our performance and in the same unit, and data was provided by individual funds’ balance sheets and Morningstar’s database.

Allocation strategy: Proportion of equity in different countries
Although there are a lot of Eastern European funds that have a high proportion of Russian stocks, there are some funds that do not invest in Russia, such as Swedbank Eastern Europe Equity and Nordea New Emerging Markets. In order to measure and analyze the impact of allocation in regards to which countries the fund chooses to invest its equities in, we regress on the country weights of the portfolio, hence we can analyze the macroeconomic aspects of investment styles and the link between stock market development and economic developments. This can depict the effect of contagion from sources of geopolitical turmoil to other countries’ stock markets and the effect of stock performances.

Eastern European states are considered to be different according to different institutions. Summing up expert definitions from the UN and the CIA one can include Albania, Austria, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Lithuania, Macedonia, Moldova, Montenegro, Poland, Romania, Russia, Serbia, Slovakia, Georgia, Slovenia and Ukraine [16] [17]. Our study also includes Turkey and Greece, which in some definitions are considered Eastern European. The funds we consider contain at least some percentage of these countries. As funds often contain a certain percentage of cash, this was also included as a covariate.

This covariate is measured in percent, where variables for every country contained its percentage weighting, and information was obtained from individual funds’ fact sheets as well as from Morningstar and Trustnet’s databases.

Allocation strategy: Company size
Another set of covariates in our study is the portfolio weightings of Large Cap, Mid Cap and Small Cap companies. This refers to the company sizes of the fund investments where Large Cap companies are defined as larger traded company stocks whose stock value makes up 70% of the total stock value of the stock market, medium sized companies makes up 20% and Small Cap 10%.

This is thus a category made out of three covariates - large, medium and small. This is measured as a percentage of how much the fund has of each investment type, and information was provided by Morningstar.

Investment style: Valuation style
Using the Morningstar Stylebox we differentiate each fund’s “investment style” according to their portfolio model and choice of company stocks. Styles are divided into the categories “Growth”, “Mix” or ”Value”. Morningstar does this using historical measures of the companies’

We employ dummy variables for these investment styles. A company can either invest in value-companies, growth companies, or a mix between them. Important to note is that two variables are employed in the regression to avoid linear dependency.

**Investment diversification: Sector weights**

Different fund managers have different strategies when allocating the pool of investor capital into the stock market. Investing in a number of different market sectors is a common diversification strategy. If the management knows its markets and regions well, investment allocation can be rewarded in financial upswings, or in financial jargon *bull markets*.

In our model we use three different industry sectors, which Morningstar specifies as - Cyclical, Dynamical and Stable. Cyclical sectors include companies and industries that work within commodities, cyclical consumer goods, finance and real estate. Dynamical sectors are telecommunication services, energy, industrials and technology. Stable sectors are stable consumer goods, health care and community beneficial.

This was measured in percentage and only two covariates where included in the model, leaving the third one as benchmark reference, to mitigate linear dependency. Information was provided by Morningstar.

**Investment diversification: Stock holdings**

A common way of spreading risk is by increasing the variation of holdings. Here we include a covariate measuring the total amount of different company stock holdings. However, funds can be extremely diversified but still hold the majority of its capital in a very few companies. Therefore we also included a covariate measuring the percentage of how much of the fund’s capital is invested in the fund’s ten largest investments. This information was provided by Trustnet, Morningstar and the fund’s individual balance sheet.

**Benchmark index**

The benchmark index is a standard against which the performance of an equity fund can be measured. The index aims to replicate the considered market by holding similar proportions, market-capitalizations, as the simulated market [19]. Our model uses benchmark indices such as MSCI EM Europe, MSCI Turkey and MSCI Russia depending on the funds equity holdings. This is a good way of measuring how well, and if, the fund performs better than the overall market. If fund $j$’s benchmark index is MSCI EM Europe NR USD, the other benchmark indices’ covariates, e.g. MSCI Turkey and MSCI Russia, are set to 0. We included this covariate in our model to see if fund managers should replicate its underlying market during geopolitical crises or not.

The benchmark index performance is measured in percentage and covers the same time frame as the fund performances. Data for enabling the calculation of this covariate was provided by Bloomberg, Morningstar and completed with information from individual fund fact sheets.
### 3.2.3 Initial Model

Table 1 gives the reader a clear overview and summarize of our model. The covariates Large Cap, Growth and Dynamical were excluded in the regression in order to mitigate linear dependency. In that way, these covariates are left as benchmarks.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Explanation</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y_{it}$</td>
<td>12-month fund performance</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{1it}$</td>
<td>Fund Fee</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{2it}$</td>
<td>Net Asset Value</td>
<td>Million SEK</td>
</tr>
<tr>
<td>$x_{3it}$</td>
<td>Age</td>
<td>Years</td>
</tr>
<tr>
<td>$x_{4it}$</td>
<td>Standard Deviation</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{5it}$</td>
<td>Small Cap</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{6it}$</td>
<td>Mid Cap</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{7it}$</td>
<td>Large Cap</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{8it}$</td>
<td>Mix</td>
<td>Dummy, 1 or 0</td>
</tr>
<tr>
<td>$x_{9it}$</td>
<td>Value</td>
<td>Dummy, 1 or 0</td>
</tr>
<tr>
<td>$x_{10it}$</td>
<td>Growth</td>
<td>Dummy, 1 or 0</td>
</tr>
<tr>
<td>$x_{11it}$</td>
<td>Cyclical</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{12it}$</td>
<td>Stable</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{13it}$</td>
<td>Dynamical</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{14it}$</td>
<td>Company Stock Holdings</td>
<td>Number</td>
</tr>
<tr>
<td>$x_{15it}$</td>
<td>% in 10 largest holdings</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{16it}$</td>
<td>Austria</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{17it}$</td>
<td>Bulgaria</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{18it}$</td>
<td>Croatia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{19it}$</td>
<td>Cyprus</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{20it}$</td>
<td>Czech Rep.</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{21it}$</td>
<td>Estonia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{22it}$</td>
<td>Georgia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{23it}$</td>
<td>Greece</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{24it}$</td>
<td>Hungary</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{25it}$</td>
<td>Kazakhstan</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{26it}$</td>
<td>Latvia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{27it}$</td>
<td>Lithuania</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{28it}$</td>
<td>Poland</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{29it}$</td>
<td>Romania</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{30it}$</td>
<td>Russia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{31it}$</td>
<td>Serbia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{32it}$</td>
<td>Slovenia</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{33it}$</td>
<td>Turkey</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{34it}$</td>
<td>Ukraine</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{35it}$</td>
<td>% of cash in portfolio</td>
<td>Percent, %</td>
</tr>
<tr>
<td>$x_{36it}$</td>
<td>Benchmark index performance</td>
<td>Percent, %</td>
</tr>
</tbody>
</table>
4 Results

4.1 Initial Model

In the first regression we left the covariates *growth holdings, large-cap holdings* and *dynamical company stocks* as benchmarks to mitigate linear dependence and multicollinearity. Our first regression on fund performance, including our initial covariates, resulted in the $\beta$-values (coefficients), standard errors and p-values depicted in Table 2.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>p-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>18.32</td>
<td>11.42</td>
<td>0.1134</td>
</tr>
<tr>
<td>Fee</td>
<td>-0.111</td>
<td>1.167</td>
<td>0.9245</td>
</tr>
<tr>
<td>Value</td>
<td>0.777</td>
<td>2.399</td>
<td>0.7468</td>
</tr>
<tr>
<td>Mix</td>
<td>2.451</td>
<td>2.364</td>
<td>0.3036</td>
</tr>
<tr>
<td>% of Mid Cap</td>
<td>0.014</td>
<td>0.063</td>
<td>0.8256</td>
</tr>
<tr>
<td>% of Small Cap</td>
<td>-0.091</td>
<td>0.049</td>
<td>0.6797</td>
</tr>
<tr>
<td>% of Cyclical</td>
<td>-0.162</td>
<td>0.079</td>
<td>0.0449</td>
</tr>
<tr>
<td>% of Stable</td>
<td>-0.277</td>
<td>0.110</td>
<td>0.0143</td>
</tr>
<tr>
<td>SD</td>
<td>0.209</td>
<td>0.145</td>
<td>0.1520</td>
</tr>
<tr>
<td>NAV</td>
<td>-0.001</td>
<td>0.001</td>
<td>0.5457</td>
</tr>
<tr>
<td>Age</td>
<td>-0.278</td>
<td>0.100</td>
<td>0.0071</td>
</tr>
<tr>
<td># of stock holdings</td>
<td>0.027</td>
<td>0.018</td>
<td>0.1400</td>
</tr>
<tr>
<td>% in 10 biggest</td>
<td>0.059</td>
<td>0.091</td>
<td>0.5145</td>
</tr>
<tr>
<td>% of Austria</td>
<td>0.412</td>
<td>0.226</td>
<td>0.0724</td>
</tr>
<tr>
<td>% of Bulgaria</td>
<td>-0.564</td>
<td>0.962</td>
<td>0.5595</td>
</tr>
<tr>
<td>% of Croatia</td>
<td>3.916</td>
<td>1.608</td>
<td>0.0173</td>
</tr>
<tr>
<td>% of Cyprus</td>
<td>-0.629</td>
<td>0.461</td>
<td>0.0766</td>
</tr>
<tr>
<td>% of Czech Rep.</td>
<td>0.166</td>
<td>0.401</td>
<td>0.6793</td>
</tr>
<tr>
<td>% of Estonia</td>
<td>1.019</td>
<td>0.634</td>
<td>0.1187</td>
</tr>
<tr>
<td>% of Georgia</td>
<td>-0.082</td>
<td>0.514</td>
<td>0.8733</td>
</tr>
<tr>
<td>% of Greece</td>
<td>-0.203</td>
<td>0.166</td>
<td>0.2259</td>
</tr>
<tr>
<td>% of Hungary</td>
<td>0.449</td>
<td>0.446</td>
<td>0.3177</td>
</tr>
<tr>
<td>% of Kazakhstan</td>
<td>-0.469</td>
<td>0.419</td>
<td>0.2662</td>
</tr>
<tr>
<td>% of Latvia</td>
<td>-3.557</td>
<td>1.481</td>
<td>0.0114</td>
</tr>
<tr>
<td>% of Lithuania</td>
<td>-0.278</td>
<td>0.292</td>
<td>0.3446</td>
</tr>
<tr>
<td>% of Poland</td>
<td>-0.088</td>
<td>0.119</td>
<td>0.4627</td>
</tr>
<tr>
<td>% of Romania</td>
<td>0.221</td>
<td>0.348</td>
<td>0.5268</td>
</tr>
<tr>
<td>% of Russia</td>
<td>-0.289</td>
<td>0.081</td>
<td>0.00063</td>
</tr>
<tr>
<td>% of Serbia</td>
<td>-0.949</td>
<td>0.598</td>
<td>0.1173</td>
</tr>
<tr>
<td>% of Slovenia</td>
<td>0.608</td>
<td>0.422</td>
<td>0.1539</td>
</tr>
<tr>
<td>% of Turkey</td>
<td>-0.394</td>
<td>0.087</td>
<td>0.00003</td>
</tr>
<tr>
<td>% of Ukraine</td>
<td>0.579</td>
<td>0.374</td>
<td>0.1266</td>
</tr>
<tr>
<td>% of Cash</td>
<td>-0.291</td>
<td>0.163</td>
<td>0.0781</td>
</tr>
<tr>
<td>Benchmark</td>
<td>0.317</td>
<td>0.106</td>
<td>0.00397</td>
</tr>
</tbody>
</table>

As we can see from Table 2, plenty covariates have a high p-value, indicating that they do not significantly add value to the model, and that the model therefore may be able to be reduced.
Table 3 - Initial Model Statistics

<table>
<thead>
<tr>
<th>R</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.95851</td>
<td>0.91875</td>
<td>0.87873</td>
<td>4.41874</td>
</tr>
</tbody>
</table>

Table 3 shows some statistics from the regression. As covered in the second chapter, the appropriateness of a regression model can be explained by the $R^2$. In our initial model we obtained a $R^2$ of 0.91875. This means that our initial model explains 91.875% of the variation of the dependent variable. We can also see that the adjusted $R^2$ has a very decent value of 0.8787.

### 4.2 Verification of the Initial Model

However well the fit the initial model happened to be, the initial regression resulted in numerous ineffective covariates (see Table 2). In order to evaluate the appropriateness of the initial regression model, the model fit, we employed a set of techniques called regression diagnostics [20, p 188]. This enabled us to illustrate the model fit with the three figures in the section that follows. We also calculated the \textit{Variance inflation factor} (VIF) for the regression coefficients. The verification of the Initial Model aims to examine if the regression model violates key assumptions of linear regression. Here we investigate if the model contains the errors described in section 2.4, i.e. if the model violates assumptions of being homoscedastic, errors are not independent and if there is a presence of multicollinearity.

#### 4.2.1 Effectiveness Plots

**Residuals versus Fitted**

![Figure 1 - Initial Model Residuals vs Fitted](image)

Figure 1 represents the residuals plotted against the predicted values. The residuals are the best estimates of the error terms of the regression. They represent what the model does not explain by its estimates and covariates. When performing a linear model regression, one assumption is that the variability of the residuals will not change over the range of the dependent variable. If that would be the case, the plot would show an obvious pattern such as a systematic relationship between the residuals and the fitted values [20, page 190]. This does not apply to our case and we therefore draw the conclusion that the variability of the residuals does not change over time.
Normal Q-Q

Figure 2 - Initial Model Normal Q-Q

Figure 2 is the Normal Quantile-Quantile-plot of the standardized residuals against values that would be expected under normality. It illustrates how well the errors follow a normal distribution. As the OLS-regression performed assumes normality, the error terms should be normally distributed [20, page 190]. This is something that needs to hold for the normality assumption in order for the regression model to be accurate. As we see in the plot, some of the errors deviate from the straight line, and thus not fully follow a normal distribution. This is something that will be investigated further in the reduced model.

Scale-Location

Figure 3 - Initial Model Scale-Location

Figure 3 should prove homoscedasticity if the regression model has met the constant variance assumption [20, page 190]. This is the Scale-Location graph, and is similar to the plot of Figure 1. Instead it uses the square root of the residuals in the y-axe. It can be used to confirm homoscedasticity, a critical assumption when performing linear regression. If the Scale-Location plot does not show any observable pattern, i.e. forming a random band around a horizontal line, it indicates homoscedasticity [20, page 190]. As we can see in the plot, all the dots are scattered randomly over the graph and we can therefore confirm an indication of homoscedasticity.
4.2.2 The VIF-test

A VIF-test conducted on our variables resulted in Table 4:

<table>
<thead>
<tr>
<th>Covariate</th>
<th>VIF</th>
<th>Covariate</th>
<th>VIF</th>
<th>Covariate</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fee</td>
<td>1.65</td>
<td>% in 10 biggest</td>
<td>3.32</td>
<td>% of Latvia</td>
<td>53.19</td>
</tr>
<tr>
<td>Value</td>
<td>7.41</td>
<td>% of Austria</td>
<td>3.31</td>
<td>% of Lithuania</td>
<td>22.88</td>
</tr>
<tr>
<td>Mix</td>
<td>7.22</td>
<td>% of Bulgaria</td>
<td>2.26</td>
<td>% of Poland</td>
<td>12.41</td>
</tr>
<tr>
<td>Mid Cap</td>
<td>5.35</td>
<td>% of Croatia</td>
<td>14.31</td>
<td>% of Romania</td>
<td>18.35</td>
</tr>
<tr>
<td>Small Cap</td>
<td>5.91</td>
<td>% of Cyprus</td>
<td>1.82</td>
<td>% of Russia</td>
<td>49.50</td>
</tr>
<tr>
<td>Cyclical</td>
<td>6.03</td>
<td>% of Czech Rep.</td>
<td>7.20</td>
<td>% of Serbia</td>
<td>12.84</td>
</tr>
<tr>
<td>Stable</td>
<td>3.82</td>
<td>% of Estonia</td>
<td>88.50</td>
<td>% of Slovenia</td>
<td>6.61</td>
</tr>
<tr>
<td>SD</td>
<td>4.30</td>
<td>% of Georgia</td>
<td>2.38</td>
<td>% of Turkey</td>
<td>37.74</td>
</tr>
<tr>
<td>NAV</td>
<td>1.39</td>
<td>% of Greece</td>
<td>1.69</td>
<td>% of Ukraine</td>
<td>5.77</td>
</tr>
<tr>
<td>Age</td>
<td>1.62</td>
<td>% of Hungary</td>
<td>6.05</td>
<td>% of cash</td>
<td>2.72</td>
</tr>
<tr>
<td># of stock holdings</td>
<td>4.81</td>
<td>% of Kazakhstan</td>
<td>6.45</td>
<td>Benchmark</td>
<td>4.42</td>
</tr>
</tbody>
</table>

We see that the VIF-values fluctuate a lot. The lowest is 1.39 whereas the largest is 88.50. As mentioned earlier, the common critical VIF-value is 10 [20, pages 409], and if all VIF-values are lower than this, it indicates that there is small, or no, redundancy among the explanatory variables of the model. This is not true in our regression and indicates multicollinearity among our covariates. This implies that the model needs to be reduced.

As we have seen in the analysis of the results above, the full model is effective, but not perfect, and is in need of reduction, something that the p-values and the VIF-test confirm. The reduction of our initial model is presented in the next section.

4.3 Reducing the Model

To create a final model, with only significant covariates, we reduced covariates with low significance according to the F-test and its resulting p-values, and by employing the stepwise Bayesian Information Criterion (BIC).

We started by calculating the BIC-value for each model, and reduced the model one covariate at a time. As presented in second chapter,

\[ BIC = n \cdot \ln(\hat{\sigma}^2) + (k + 1) \cdot \ln(n) \]  \( (5) \)

For each new and reduced model, a new OLS-regression was performed on the remaining covariates. We eliminated the covariate with the highest insignificant p-value. We stopped the process of model reduction when we found a minimum value of the estimated BIC.
As Table 5 shows, we reduced the model by removing 19 of the 33 covariates. When we removed Cyprus, the BIC-value grew larger, which allowed Cyprus to be a part of the reduced model.

### 4.4 Final Model

A regression performed on the significant covariates from above tests resulted in Table 6 presenting the coefficients of the reduced model’s covariates, standard errors and p-levels. The p-values (in the table referred to as p-levels) were extracted from the formula for the F-statistic (3). As before, we rejected the significance of the estimated coefficient if the p-value exceeded the significance level of 5%.
As we can see in Table 6, some coefficients have a negative value, and thus impact negatively on the performance of the fund. For example, 1% more of Austrian holdings implies a 0.449% increase in fund return. An important finding is that all covariates are significant at, at least, a 1% level. This indicates high significance.

The reduced and Final Model became after the above procedure:

\[
\text{Performance} = (6.996) + (\text{Small cap}) \cdot (0.176) + (\text{Standard Deviation}) \cdot (0.324) - (\text{Age}) \cdot (0.279) + (\text{Number of stock holdings}) \cdot (0.033) + (\text{Austria}) \cdot (0.450) + (\text{Croatia}) \cdot (4.767) - (\text{Cyprus}) \cdot (0.839) + (\text{Estonia}) \cdot (0.761) - (\text{Latvia}) \cdot (3.123) - (\text{Russia}) \cdot (0.228) - (\text{Serbia}) \cdot (1.021) + (\text{Slovenia}) \cdot (0.872) - (\text{Turkey}) \cdot (0.397) + (\text{Benchmark performance}) \cdot (0.264)
\]

**4.4.1 Verification of the Final Model**

In order to test whether our model violates basic linear regression assumptions, the VIF-test and effectiveness plots were once again conducted. As in section 4.2, we investigated if the model contained the errors described in section 2.4. That is, if the model violates assumptions of being homoscedastic, errors are not independent and there is a presence of multicollinearity.

**4.4.1.1 The F-test**

To confirm the Final Model’s preciseness, we employed an F-test to test if the \( \beta \)'s that were removed in the previous section truly were insignificant. Here we denote the set of removed \( \beta \)-values as \( \beta^* \), and tested the hypothesis,

\[ H_0: \beta^* = 0, \text{ against } H_A \neq 0. \]

The sum of squared residuals, \( SSE \), from the full model was 1308.19 and from the reduced model, 1741.65. Using formula (3) with the required values \( r=19 \), \( k=33 \) and \( n=101 \), resulted in a F-value of 1.168. This in turn generated a p-value of 0.31. As it is a significantly high value, we cannot reject the hypothesis that all the \( \beta \)-values are equal to zero and it therefore indicates that the covariates removed from the BIC-test are not significant.
4.4.1.2 The VIF-test

A VIF-test performed on the reduced model resulted in Table 7.

<table>
<thead>
<tr>
<th>Country</th>
<th>Small Cap</th>
<th>SD</th>
<th>Age</th>
<th># of stock holdings</th>
<th>Austria</th>
<th>Croatia</th>
<th>Cyprus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latvia</td>
<td>2.22</td>
<td>3.42</td>
<td>1.18</td>
<td>1.21</td>
<td>1.43</td>
<td>8.85</td>
<td>1.10</td>
</tr>
<tr>
<td>Estonia</td>
<td>8.35</td>
<td>13.62</td>
<td>4.35</td>
<td>4.38</td>
<td>2.61</td>
<td>7.99</td>
<td>3.43</td>
</tr>
</tbody>
</table>

As Table 7 illustrates, the VIF-test for all the covariates except Latvia is below 10. We also see that Estonia is close to 10. This may indicate that they correlate with each other, which can be explained by their close geographical placement. This was confirmed by running a regression without Latvia, which resulted in a VIF-value of 3.5 for Estonia, but a worse fit of the data. We have therefore kept Latvia in our final model, since it is still a highly significant covariate.

4.4.1.3 Bootstrap

A bootstrap was performed in order to obtain a better accuracy of the estimated coefficients. To achieve a well-defined resampling, the bootstrap was performed with 10,000 resamples. Table 8 is a table of the bootstrapped estimates using a 90% confidence interval. The column Bootstrapped CI contains the intervals where 90% of the estimated estimates lie between, and the Bootstrapped Estimate in the second column is the median of the samples’ estimates.

<table>
<thead>
<tr>
<th>Covariate</th>
<th>Estimate</th>
<th>Bootstrapped Estimate</th>
<th>Bootstrapped CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>6.996</td>
<td>7.024</td>
<td>(0.313 , 15.264)</td>
</tr>
<tr>
<td>% of Small Cap</td>
<td>-0.176</td>
<td>-0.177</td>
<td>(-0.224 , -0.088)</td>
</tr>
<tr>
<td>SD</td>
<td>0.324</td>
<td>0.322</td>
<td>(0.123 , 0.608)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.279</td>
<td>-0.248</td>
<td>(-0.475 , -0.157)</td>
</tr>
<tr>
<td># of stock holdings</td>
<td>0.033</td>
<td>0.014</td>
<td>(-0.038 , 0.062)</td>
</tr>
<tr>
<td>% of Austria</td>
<td>0.449</td>
<td>0.447</td>
<td>(0.024 , 1.231)</td>
</tr>
<tr>
<td>% of Croatia</td>
<td>4.767</td>
<td>4.929</td>
<td>(1.601 , 12.507)</td>
</tr>
<tr>
<td>% of Cyprus</td>
<td>-0.839</td>
<td>-0.784</td>
<td>(-2.250 , -0.302)</td>
</tr>
<tr>
<td>% of Estonia</td>
<td>0.761</td>
<td>1.169</td>
<td>(-0.135 , 1.386)</td>
</tr>
<tr>
<td>% of Latvia</td>
<td>-3.123</td>
<td>-1.595</td>
<td>(-5.526 , 8.686)</td>
</tr>
<tr>
<td>% of Russia</td>
<td>-0.228</td>
<td>-0.219</td>
<td>(-0.288 , -0.179)</td>
</tr>
<tr>
<td>% of Serbia</td>
<td>-1.021</td>
<td>-1.179</td>
<td>(-2.914 , -0.099)</td>
</tr>
<tr>
<td>% of Slovenia</td>
<td>0.872</td>
<td>0.782</td>
<td>(0.094 , 2.488)</td>
</tr>
<tr>
<td>Benchmark</td>
<td>0.264</td>
<td>0.283</td>
<td>(-0.044 , 0.758)</td>
</tr>
</tbody>
</table>

As we can see from the confidence intervals estimated with the bootstrapping technique (Bootstrapped CI), there are four estimates that fluctuate between positive and negative. # of stock holdings, % of Estonia, % of Latvia and Benchmark. Drawing a conclusion, this means that it is to certain extent unclear whether or not they have a positive effect on the funds’ performance or not.
Apart from the estimates mentioned earlier, the bootstrapped estimates do not differ significantly from the original estimates. This implies that the estimates are relatively stable. In all, original estimates from the Final Model regression did not differ notably from the bootstrapped estimates.

4.4.1.4 Effectiveness Plots

We verified the effectiveness of the reduced model by employing the equivalent plots to the ones employed to validate the Initial Model.

**Residuals versus Fitted**

![Figure 4 - Final Model Residuals vs Fitted](image)

From Figure 4, the Residuals vs. Fitted-plot, we see that the residuals still do not form any obvious pattern. This implies that our reduced model captures the systematic variance present in our data. If it were to show evidence of a curved relationship we might have to add quadratic terms to our regression [20, page 190].

**Scale-Location**

![Figure 5 - Final Model Scale-Location](image)

From the Scale-Location plot, Figure 5, we still do not seem to have any observable pattern, simply a randomly scarred band of data around the horizontal lines. This confirms indications of homoscedasticity in our model.
Figure 6 shows that the errors follow the normal distribution, as they since they all seem to track a straight line following a 45 degrees angle. For normality all points should fall on this angle [20, pages 189-194].

The Normal Q-Q-plot has improved from the full model, which implies that the p-values may be more accurate in this model. This stems from the fact that we have removed a number of covariates that initially may have had a slightly incorrect p-value.

To verify that the residuals truly follow a normal distribution we plotted them in a new figure, Figure 7, against a normal distribution curve.

From Figure 7, we see that the standardized residuals follow a normal distribution quite satisfactory. There is a peak around -0.5, which indicates that it is following a rather weak positive skewed normal distribution. To be certain, White’s consistent variance estimator was applied and it resulted in Figure 8 over the standardized residuals:
As we can see from Figure 8, the standardized residuals are now more uniformly allocated around the peak, which still is located around -0.5. Since the skewness only is weak, we can conclude that the p-values are fairly accurate. An explanation of why the standardized residuals not fully follow a normal distribution may be because of our quite narrowly chosen data set with only 101 variables. If the model would consist of more data points, the standardized residuals would probably more accurately follow a normal distribution.

### 4.4.1.5 $R^2$

In addition to the verification the previous sections have provided, running the regression on our Final Model obtained the $R^2$ statistics presented in Table 9:

<table>
<thead>
<tr>
<th>R</th>
<th>$R^2$</th>
<th>Adjusted $R^2$</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.94436</td>
<td>0.89183</td>
<td>0.87422</td>
<td>4.50019</td>
</tr>
</tbody>
</table>

As we can see from Table 9, the $R^2$ is still satisfactory, with an explaining value of 89.18%. This means that even though having reduced the model by 19 explanatory variables, it still has explanatory significance in explaining the data points. An interesting observation is also that the adjusted $R^2$ has not decreased significantly.

### 4.4.2 Analysis of Covariates in the Final Model

Below, we briefly explain the reduced model’s resulting coefficients ($\beta$-values). A more in depth analysis of the macroeconomic linkage between our findings, specific to country weightings and the geopolitical conditions during the analyzed time period, is found in the succeeding chapter which is specific to the department of Industrial Engineering & Management. According to the results of our bootstrapped confidence interval, some coefficients in the Final Model, Benchmark performance, Latvian holdings, Estonian holdings and Number of stock holdings, varied from negative to positive values. We have therefore chosen to analyze these partly according to their estimated $\beta$-values from the Final Model, Table 6, and also according to the bootstrapped confidence intervals from Table 8.
Concerning the remaining covariates we analyze their estimates according to their estimates from the Full Model as they are fully verified and significant covariates, completely fulfill the assumptions of multiple linear regression and their coefficients do not range from negative to positive values.

**Market weightings - Small cap**

Regarding the covariates that reflect the fund managers stock-picking styles, there exists research that investigate what kind of investment portfolios prove better than others in recessionary markets [21, page 3]. In our model we employed the Morningstar categorization of mutual equity funds regarding company sizes.

Our results of a negative $\beta$-value for holding small cap companies coincide with earlier findings; small cap funds earn higher returns than large cap funds in bullish times but that the pattern changes during contractions of the financial markets when small cap companies earn significantly higher negative returns [21]. Investors are better off strategically shifting equity from small cap to large cap stocks during contractions [21, page 3]. A contraction is in this case the bullish and unstable market experienced during the time frame for this study.

To quickly react to geopolitical and sudden events, like the Russian annexation of Crimea, funds which quickly are able to sell or short risky assets are better equipped for volatile periods than other funds and thus protect the NAV from falling to heavily. Small cap companies are much less liquid, especially in financially distressed times, as they may trade less frequently [22]. The negative estimate obtained in the Final Model supports this. Small cap stocks involve higher risks than securities of larger companies. Prices of such investments are often more volatile than prices of large capitalization stocks [23].

**Standard Deviation**

The positive correlation between volatility and fund performance over our 12-month time frame is consistent with previous studies such as Markowitz’s modern portfolio theory. Taking higher risks, which a higher standard deviation partly implies, enables investors to receive higher return [24]. Research shows that managers who take big bets have better luck of outperforming the overall market [25]. Throughout our thesis we discuss how fund managers should decrease the risk of losses in their investment portfolios. Our interpretation of the positive correlation between standard deviation and fund performance is that there are some more volatile holdings that have generated large positive returns in the funds. A proposal for further research would be to identify these stocks.

**Age**

Age is negatively correlated with the fund performance. A rise of one year of the fund’s age implies a decrease of 0.27% in fund return during a 12-month period. The result coincides with a study made in 2001 by Otten and Bams that showed that younger funds performed better than mature ones as they tend to be smaller and thus benefit more from fortunate stock picks [14, page 35].

**Number of stocks holdings**

The number of stock holdings, different company allocations, obtained a bootstrapped confidence interval of estimate varying from -0.0375 to 0.0624. The estimate median was positive (0.0139068) implying that the more investments fund managers had in their portfolios the less exposed they were to significant drops of one of their company holdings.
By spreading investments over a range of companies reduces risk [26]. An undiversified portfolio can be rewarding in bullish times but can under bearish market conditions, like those under geopolitical turmoil, be painful for investors. However spreading holdings decreases risk. This contradicts somewhat with the result of our Standard Deviation-estimate, which was positive. One implication of a positive estimate for standard deviation is that the higher the risk fund managers takes, the more rewarding the return. However, bearing in mind that the Number of stock holdings bootstrapped estimate also included negative values, this coincides with our positive value of the Standard Deviation-coefficient. As our estimate for the standard deviation covariate was positive it could be an explanation of how it supports the negative part of the estimate interval for Number of stock holdings.

Country weightings (Austria, Croatia, Cyprus, Estonia, Latvia, Russia, Serbia, Slovenia, Turkey)

Country weightings as covariates will be thoroughly analyzed and discussed in the fifth chapter, but we will briefly go through a few key points.

Austria, Croatia, Estonia and Slovenia all had positive betas in our Final Model. That is, a percentage increase of stock holdings in these countries corresponded to an increase in the 12-month fund performance. A common factor for these countries is that they are all members of the European Union. The 2013 enlargement of the EU saw Croatia join the economic and political union. Interestingly enough the beta of holding Croatian stocks is significantly high (4.67). A conclusion you can draw from this is that transparency and the financial safety net that the EU brings about, creates investor confidence during tense political periods. Our results prove that holdings within the EU are a safe haven during distressed market conditions.

Negative correlation with fund performance was held for stock holdings in Russia, Latvia, Serbia, Cyprus and Turkey. Russia and Turkey were for the time frame of our data extremely exposed to the crises and market fluctuations. It is therefore not a surprising result. As mentioned earlier, remaining analysis of the resulting coefficients for country holdings will be presented in the next chapter.

From the bootstrapping results, Estonia and Latvia contained an estimate interval ranging from negative to positive. This can be explained by the fact that they are neighboring countries and might influence each others’ financial markets and fluctuations.

Benchmark performance

The coefficient for a fund portfolio’s benchmark index performance can be seen as a rough estimate of the funds sensitivity to market movements. The coefficient we obtained in our final model was 0.264. This gives an indication of how the fund moves in these special geopolitical conditions compared to the market. A beta of 0.264 is quite low which means that its performance is not significantly tied to the stock market. It indicates that the fund’s return is expected to perform 73.6% worse than the market during bull markets but 73.6% better during bear markets, nevertheless negative. However, as its estimates’ bootstrap confidence interval ranging from negative to positive we can conclude that depending on the funds’ underlying benchmark (MSCI Turkey, MSCI Russia, etc.) it either is slightly negatively correlated or positively correlated with fund performance. But as the bootstrap estimate (mean) was roughly 0.282 and the Final Model estimate 0.264, and its bootstrap confidence varied from a very low negative number (-0.0440) to a very high positive number (0.7575) we can conclude that our aforementioned analysis is accurate, the covariate positively correlates with fund performance.
This further implies that active management - not replicating an underlying index - during geopolitical turmoil is beneficiary as it hedges against the massive drops in its holdings’ values that would occur if it contained the same weightings as the benchmark index.

4.5. Final remarks

The model’s benchmarks – factors we did not explicitly include in our regression as it would lead to linear dependency - were large cap, growth, and dynamical stock holdings. As the intercept is positive (6.996) we assume that at least one of these variables positively correlates with the fund performance during the 12-month period.

Surprisingly enough, cyclical stock holdings, which include equity in commodities, are not a significant factor in our final model. Oil, gas, gold and grain experienced a sharp price increase during the 12-month period due to uncertainties in supply. This was especially due to the Ukraine-Russia crisis, the threat of sanctions and Russia raising prices of its gas export [27]. What more, one primary effect of geopolitical events on stock markets is their impact on the production and delivery of oil [28, page 3]. The cyclical sector however also comprises of stocks in financial services, which experienced a massive drop during the time frame, hence affecting the significance of the β-value [29].
5 Discussion & Analysis

Clearly, there are a number of macroeconomic variables and external factors that affect stock returns in geopolitical turmoil. In this chapter we specifically analyze those derived from our Final Model’s country allocation-covariates, with the help from our mathematical results and research. We will also suggest ways fund managers could hedge against the potential risks incurred from geopolitical instability. Throughout the chapter we will embed key principles of macroeconomics for clarification and justification of our analysis. This chapter of our thesis is specific to the department of Industrial Engineering & Management as it incorporates the elements of its tuition.

5.1 Direct Linkages Between Macroeconomic Variables and Market Returns

Eastern European mutual equity funds are portfolios of Eastern European equity, company shares listed on Eastern European stock exchanges. Their value is the price that the market imposes on them and geopolitical events are often reflected in their valuation. Understanding the linkage between the macroeconomic environment, financial markets and price fluctuations is hence a competitive tool for asset managers in optimizing their fund portfolio [30].

A common financial effect of a geopolitical crisis is lower confidence among investors. This is further accelerated by Western Media. Even though underlying businesses are doing well in regards to actual earnings the market punishes stock prices as a fear and perception of the events may lead the companies to do less than expected. International investors heavily influence the performance of, for instance, Russian equities as they hold nearly three fourths of the free float [31]. This vastly reduces the efficiency of the market in periods of very high or low risk.

Reduced investing appetite often leads to capital flight, meaning a rapid outflow of money and assets from the country in crisis and a devaluation of its assets. A consequence of swift capital outflow is a rapid devaluation of the floating local exchange rate against other currencies or a forced depreciation if the exchange rate is fixed [2]. Funds with securities denominated in, or receiving revenues in the affected currency, take hit. Adverse changes in currency exchange rates relative to the Swedish Krona, which our data collection of funds are denominated in, may erode or reverse any potential gains from the fund’s investments in securities denominated in a foreign currency or may widen existing losses [23].

In attempt to retain money in the country, sovereigns tend to raise interest rates, and bond yields often rise as the risk of credit default increases. This can affect equity as investors instead seek return through fixed income, such as safe-haven assets like treasury bonds, instead of equity investments. This causes difficulties in companies finding finance for their businesses and growth hence lowering corporate earnings [32].

The fear of defaults, as well as impact from credit rating institutes and media have great influence in investor confidence and risk-taking. For example, when rating’s agency Moody’s warned Turkey about the risks it faced by ongoing protests, the leading Turkish index fell an additional 1.7% [33].
The Final Model shows clear evidence of this as we found that holding Turkish equity had negative impact on fund performances. Further downgrades from agencies like Moody’s is a reputational risk fund managers need to bear in mind during geopolitical turmoil as the market reacts more strongly to rating downgrades than to rating upgrades. Studies suggest downgrades and negative outlook announcements have an adverse impact on equity returns [34].

Eastern European economic experts believe that the events in Ukraine, during the time frame for our data collection, have affected the Russian economy. The increased political unsteadiness started weighing in on Russia’s credit rating in the end of 2013 and Russia experienced heavy capital flight [32]. It is interesting that more capital left Russia in the first quarter of 2014 than in the whole year of 2013 [35]. Russian investments had substantial impact on overall return in our Final Model; for every 1 percent invested in Russian equity fund performance backed 0.22788%.

The risk of contagion, in other words, the fear of investor’s is spreading to neighboring countries, can be depicted in the negative correlation of Latvian holding on fund performance which is found in it’s Final Model estimate. Experts believe that the unrest in Ukraine and Russia could spread to neighboring countries. One of these is Latvia where 25 % are ethnic Russians [36].

The school of macroeconomics emphasizes a lot of importance on international trade. Today import and export constitute an increasingly higher proportion of a country’s Gross Domestic Product (GDP) [37, page 363] – a key measure in macroeconomics. It is estimated as the market value of goods and services produced in an economy for a certain period [37, pages 18-19].

International trade means inflow of capital across countries and hence increases welfare. For some companies and sectors, for instance those who operate in gas and oil, the Ukraine-Russia is particularly important. Several countries in Eastern Europe are highly dependent of Russian exports and Ukraine’s pipelines for gas exports [38]. For instance, Belarus’ economy is highly dependent on energy imports from Russia [39], and Poland receives 60% of its gas from Russia [40]. Rising gas prices and sanctions on Russian companies due to the crisis, has threatened international trade. Several European countries depend on Russian energy and hence should affect the equity market of those countries as it lowers prospects of growth. This is however not particular evident in our Final Model. It can be explained by the fact that the rise in economic situation in Germany and the West compensated partly for the lower Russian demand. With the stabilization of the Eurozone and bank systems in 2013, several economies in Eastern Europe gained support from Western countries’ growth [1].

Clearly, geopolitical turbulence dampens the investment willingness of investing in affected regions. In conclusion, we see strong linkages and correlation between geopolitical events and their effect on directly affected countries. Our mathematical model shows this and research coincide with our findings.
5.2 Index of Economic Freedom

The Index of Economic Freedom is an annual guide published by The Wall Street Journal and the Washington think thank The Heritage Foundation [41]. It covers ten freedoms – from property rights to entrepreneurship – in 186 countries where the countries of our Final model are included. With the help of it, we intend to find other measures to understand the countries’ estimates (β-values) from our Final Model. Our findings for these countries are summarized in Table 11 in the Appendices.

The index measures economic freedom based on quantitative and qualitative factors including property rights, freedom from corruption, fiscal freedom, labor freedom, monetary freedom and trade freedom, investment freedom and financial freedom. These factors incorporate ways of measuring the fundamentals of economic growth and prosperity. There are great benefits of economic freedom to society such as healthier societies, cleaner environments, greater per capita wealth, human development, democracy, and poverty elimination. It allows goods and capital to move more freely and supports labor and more liberal societies [41].

The economic freedom within the categories is graded on a scale from 0 to 100 [41].

We have summarized the ratings in Figure 9, where the dark-grey staples signify the average rating values of our positive β-countries (Austria, Croatia, Estonia and Slovenia) whereas the light-grey staples are the average ratings of negative β-countries (Cyprus, Latvia, Russia, Serbia and Turkey) from our Final Model.

![Figure 9 – Ratings of Economic Freedom](image)

Interestingly enough, all countries with positive β-values in our Final Model had, according to the index, better overall economic freedom than the countries with negative β. The diagram above considers ratings in fiscal, business, monetary, trade, investment and financial freedom. Their GDP per Capita was in average higher and unemployment rate lower. In conclusion, these findings signal that economical freedom in the scenery of geopolitical instability give positive returns.
5.3 The Impact of Political and Financial Bodies

5.3.1 The European Union

In this section we examine the effects of Western and Eastern polarization on our equity funds. Our study provides a platform for investigating the short-run relationship among investments and macroeconomic variables like exports, economic growth and political stability as well as the influence from Russia. Many of the Eastern European countries our model examines, and fund portfolios partly invest in, are former countries of the Soviet Union [42].

Some of these countries have during the past years become more “westernized” and joined the European Union, whilst some have remained more Russian-friendly. How does this political polarization affect investments – do EU-friendlier country’s equities perform better? One macroeconomic aspect of our results can help us investigate if investors in Eastern Europe would gain from the so-called Enlargement of the European Union.

Politically Turkey’s prospects for joining the European Union has been negatively impacted as EU foreign ministers agree on postponing further EU membership talks with Turkey due to the government’s handling of the protests [43]. Another potential candidate is Serbia. However, none of these were during our time frame members and interestingly enough they are included in our reduced model with negative correlation with fund performance.

So, how does European integration affect the stock markets?

According to research:

“Integrated stock markets generate better opportunities for international investors by eliminating country specific risks and let them diversify their portfolios across countries. A larger pool of funds other than the limited local financing will be available for corporations. Integrated stock markets decrease the cost of capital. Hence, the number of productive investments increases, which flourishes the economic growth. In an economic environment where better risk-sharing opportunities exist, households will be able to smooth their consumption more efficiently.” [44, page 1]

Also, funds that invest in markets with transparent financial institutes, like those within the European Union, avoid risks as frozen assets, failing trades and other trade settlement risks.

As mentioned in the previous section, international trade contributes to welfare – especially in financially coarse times. This is due the fact that the EU facilitates trade within its borders and thus, indirectly, growth as trade helps to strengthen businesses. One mean of facilitation is lower tariffs and quotes between member states. This often reflects in the businesses’ listed company stocks, leading to the conclusion that there must be a correlation between being a EU-member and equity market performances. This is another explanation why EU member states in our Final Model obtained positive β’s.

Considering what we have mentioned above and that the recent EU-member Croatia had a significantly positive correlation with fund performance – we can conclude that holding equity in countries with EU-memberships seems to be a good hedge in geopolitical turmoil.
5.3.2 The Federal Reserve Bank

One important macroeconomic principle concerns monetary policy. These are actions central banks take that affect the flow and supply of money [37, page 290]. One of these actions is quantitative easing (QE). This is a monetary stimulus that involves a central bank purchasing bonds and market securities to help revive investment sentiments.

After benefiting greatly from the US Federal Reserve’s (Fed) quantitative easing program, many Central and Eastern European financial markets were deeply affected when the financial body announced its plans of tapering its QE program in May 2013. After having performed very well due to this, investors began to get nervous of the future. The so-called quantitative easing program produced rising exports and boosted growth and trade balances [45].

Several countries that have negative beta in the Final Model were highly dependent on external monetary stimulus. Experts agree that tapering affects emerging markets like Eastern Europe [46]. Turkey was one of the countries most vulnerable to the Fed’s tapering program because of its particular dependency on the availability of foreign capital to keep its markets emerging. Equity markets, especially Russia and Turkey, was hit hard by Fed’s talks of tapering and triggered investors selling off assets in several emerging markets [47].
6 Further Research

This thesis can help asset managers, and other types of investors, identify weak and/or rewarding investment allocations and styles in geopolitical turmoil. However, due to a slightly limited quantity of data, our findings should not be perceived as valid truth, but as a guideline when evaluating an investment portfolio. As this thesis aimed to provide aspects and linkages between the macroeconomic events and equity returns caused by geopolitical turmoil, there exists some areas of study that were excluded in our exploration of the studied theme.

The mathematical model that has been used in this thesis to investigate how different factors affect fund performances is multiple linear regression. The error terms from our results appear to be normal-distributed but we cannot say with full certainty that they are. Therefore, further research could be to analyze this data with more generalized linear models, like the logistic regression, and see if the result is consistent with this thesis’.

To make an even more accurate model, research could be expanded to investigate other geographical areas with similar tense geopolitical climate, i.e. Latin America, and compare the results with our thesis’ findings. This would increase the legitimacy of our results, and give investors and fund managers a stronger and more verified base of support in identifying critical factors during geopolitical turmoil.

Furthermore, it would be of interest to conduct an even more global study of equity funds and omit covariates that represent country allocations. Instead a dummy variable would be used to indicate if the fund invests in geopolitically troubled regions or not.

A different approach to our research question could be to analyze the funds performance over time, using a time series analysis. A possible approach could be to use an autoregressive integrated moving average (ARIMA) model. This would possibly generate a better picture of how the geopolitical turmoil has affected the funds’ performances over time.

Another interesting area to further research would be to analyze the persistency of the funds. Is it the same funds that perform well every year, or is it different during geopolitical turmoil? Frennberg and Hansson conducted a study of the persistency of stocks for Swedish stocks in 1995 [48]. The authors found that if a stock performed well the previous season it would be more likely to do so the next season. An up-to-date study in this subject considering Eastern European equity funds would provide good knowledge for investors in how to hedge themselves in times of geopolitical turmoil.

We have in our model identified qualitative variables aimed to add explanatory value to the analysis. There are off course several more qualitative variables that can be investigated in future research. These can for example be variables that explain the profile of the fund manager. Some examples of qualitative covariates include variables that rate the merits of fund manager – for instance if they have received recognition from the industry, the amount of years the fund manager has been active in the business and how many years the fund manager has managed the fund. We believe that the fund manager has significant influence in how the fund performs, as it is he or she who decides the portfolio model.
7 Conclusion

Our thesis has shown several of the direct effects and results of geopolitical turbulence that can help fund managers to mitigate short-term potential losses which often leads to investors withdrawing capital from the fund. A common finding is that negative returns are more likely to be accompanied by fund outflows [51, page 15] - a risk that all fund managers want to reduce.

Our study is relevant as the emerging markets, where Eastern Europe is included, will become even more economic important. It has since the 1990s hurled investors and asset managers to their markets [49, page 7]. There is a constant evolvement of geopolitical risks - both threats and opportunities. Portfolio managers need to manage investing under uncertainties and geopolitical turmoil. By recognizing how investments behave under such circumstances and the macroeconomic linkages to stock prices, fund managers are more likely to have better performing portfolios than others [28, page 2/12].

As commonly known – with reward comes risk. Many of the regions of emerging markets have experienced hefty market fluctuations due to geopolitical instabilities from time to time. As the Turkish protests and Ukraine-Russia crisis were taking place – Latin American equity of the emerging market Venezuela suffered due to similar political instability [50]. Our findings of influencing factors can be applied to other markets’ investment portfolios as well.

We have in our thesis combined “hard knowledge” with “soft knowledge” – using mathematical theories and models to understand soft variables like the political and social interaction with equity returns. By using mathematical statistical theories, which are commonly used in financial studies, we explored a less researched area. This area considers the direct impacts of geopolitical turmoil on equity funds, and we investigated it by examining the 12-month performances of different Eastern European equity funds. Regressing fund performance on a set of investment styles and fund characteristics and validating significance, resulted in a reduced model that fund managers in similar markets and geopolitical circumstances can use in their future portfolio management. Needless to say, our thesis examines only a portion of the wide-ranging area of investment management and market analysis. It can however provide means for further studies and as a resource for investment managers in markets similar to the ones analyzed throughout our thesis.
8 References


### 9 Appendices

#### Table 10 – Fund Collection

<table>
<thead>
<tr>
<th>Funds 1-34</th>
<th>Funds 35-68</th>
<th>Funds 69-101</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aberdeen Global Eastern European Eq A2</td>
<td>Evli Russia B</td>
<td>Pictet Eastern Europe-R EUR</td>
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<td>FIM Russia</td>
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<td>Pioneer Fds Emerg Eur+Med Eq A</td>
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<td>RAM (Lux) Sys European Equities</td>
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<td>Russian Prosperity Fund (Lux)</td>
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