The Influence of Climate and Macroeconomic Covariates on Adverse Market Events: Evidence from the European Stock Market

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Abstract

This research paper analyzes the relationship between macroeconomic and climate covariates and extreme events in the European stock market. The research analyzed 01-01-2000 - 25-05-2022 for 6 market indices: DAX, CAC 40, FTSE MIB, IBEX 35, AEX, and FTSE 100. The study aims to answer three subquestions: 1) What are the most important driving factors for modeling extreme risks in the market? 2) Has the inclusion of climate factors had a significant beneficial effect? Furthermore, 3) To what extent does a climate agreement affect financial market risk? The research found that covariates have significantly affected market risk for all market indices, with statistically accurate VaR models constructed for some market indices when including both climate and macroeconomic covariates. However, the ES models were unsuitable for use in this research setting. Furthermore, the results suggest that omitting the climate variables increases the model fit to the data, indicating that macroeconomic covariates are more informative than climate covariates. Finally, the study found that the Paris climate agreement has a risk-reducing effect on almost all market indices.

Keywords: Extreme events, POT approach, European stock market, macroeconomic covariates, climate variables, VaR models, Paris climate agreement.

Contents

1 Introduction

The increasing concerns about the impacts of climate change have led to an increase in interest in analyzing the relationship between climate covariates and various economic sectors. (IPCC, 2014) The stock market is a good indicator of a country's economic status. This market is susceptible to extreme events like natural disasters and pandemics. These events have been more frequent and intense due to the changing climate over the last decades. (World Health Organization, 2021). This research aims to analyze the relationship between macroeconomic and climate covariates and extreme events in the stock market in Europe.

The financial crisis in 2008 and COVID-19 have shown that natural disasters can significantly affect the economy and society. (World Health Organization, 2021) Considering this, it is essential to understand the drivers behind this to create policies and strategies to mitigate the drivers' impacts. Therefore, the main question that this research tries to answer is, 'Do climate and macroeconomic covariates contain important information in predicting extreme adverse market events in Europe?' The emphasis is on the climate variables. However, including macroeconomic variables in the research makes the methodology more complete and applicable to stakeholders. If these extreme events can be predicted more precisely, this will benefit multiple stakeholders—for example, the insurance industry, banks, and policymakers. It brings multiple benefits if the extreme risks can be estimated more precisely when the covariates are included. The insurance industry, whose business model revolves around risks, can benefit if new models are developed that predict the risk pattern more precisely. Moreover, banks can also benefit from improved risk models. Improved models can, for example, more accurately predict how much a bank's minimum capital requirement is. Banks should adhere to the Basel III framework requirements for the minimum capital requirement. (King and Tarbert, 2011). Finally, policymakers could use the found results to their benefit. If they could adjust their policies to change the most influential macroeconomic and climate covariates, they could mitigate the possibility of an adverse risk event.

The first subquestion is: 'What are the most critical driving factors (covariates) for modeling the extreme risks in the market?' The answer will form the foundation of the research. The second subquestion is: 'Has the inclusion of the climate factors in the process a significant beneficial effect?' This question will analyze the importance of the climate covariates and test whether their inclusion can significantly improve existing models. Finally, the third question is: 'To what extent does a climate agreement affect financial market risk?' If climate agreements impact risk measurement, these agreements effectively adjust policy. As a reference point, we take the Paris Climate Agreement (United Nations Framework Convention on Climate Change, 2015) signed on the 12th of December, 2015.

This research is scientifically relevant because it analyses new relationships between climate covariates and market indices. Climate research is a relatively new topic since the Intergovernmental Panel on Climate Change (IPPC) was founded in 1988 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP) to assess and provide climate research for policymakers. This research will contribute to climate research by discovering new relations between various (climate) covariates and extreme adverse risks in the European stock market. These new relationships will provide more insights into the processes and point out new directions for further research.

The results suggest that covariates help construct VaR models. The estimations allow for the construction of statistically accurate VaR models. Furthermore, it is found that omitting the climate variables increases the model fit to the data, which indicates that macroeconomic covariates are more informative than climate covariates. Finally, it is also found that the Paris climate agreement has a risk-reducing effect on almost all the different market indices.

The research is built up as follows, first, the current literature will be discussed in Section 2. Secondly, the data that is used is analyzed in Section 3. Third, the methodology is described in Section 4, and the results are shown in Section 5. Finally, the thesis is concluded in Section 6.

2 Literature

This section will review and synthesize the relevant literature on the research topic. Moreover, it will state where this research will support and extend the existing literature. Specifically, this section will focus on three areas of literature: risk measurement, macroeconomic analysis, and economic climate research. By reviewing and synthesizing these different areas of literature, this section aims to establish a solid theoretical foundation for the study and to identify potential avenues for further investigation.

2.1 Risk Measurement and Extreme Value Theory (EVT)

The Peaks-over-Threshold (POT) is a widely used approach for modeling extreme events in various fields. The POT procedure assumes that exceedances above a certain threshold can be modeled differently than the entire dataset. One of the most influential papers that demonstrated the effectiveness of the POT approach is by Davison and Smith (1990). Their research estimated parameters with this model in the field of river flows and on nuclear power sites. This research will apply this methodology to financial returns in combination with implementing macroeconomic and climate covariates. Chavez-Demoulin and Embrechts (2004) first investigated the inclusion of covariates into the modeling of financial return tails and Chavez-Demoulin et al. (2016). Both papers form the foundation for the methodology of this research. Moreover, their developed methods form a significant basis to expand further to model financial risk's tails more efficiently.

Different risk measures will be used to assess the risk measurement of the different models that will be developed. In the field of risk management, there are a few widely used risk measures. James et al. (2021) try to forecast the Value-at-Risk (VaR) and Expected Shortfall (ES) in the US stock market in combination with the POT and specific covariates. According to Philippe (2001), these risk measures are still widely used in current systems. The Basel II framework, developed by the Basel Committee on Banking Supervision, is the most important recommendation for international banking. (Lind, 2005). In their proposals, these measures are more efficiently used to calculate risks for the minimum capital requirement. The international adoption of the measures suggests that these risk measures are reliable and used widely in the professional world. This research will add a method with different covariates to the current literature to estimate the VaR and ES, which could lead to a more optimal way to estimate risks in the market.

2.2 Macroeconomic Covariates and Stock Market Returns

There is much research on the relationship between macroeconomic covariates and stock market returns. All these papers are a basis for this research because all known relations could play a role in the connection between extreme market observations and macroeconomic covariates. Most research focused on developed economies which is suitable for this research since the target regions are developed regions in Europe. The paper by Sirucek (2012) tested relations between the stock market in the US and macroeconomic variables. The report found significant relations between two major stock indices in the US and industrial production, interest rate, inflation, oil price, production price index, unemployment, and money supply. These relations form a reasonable basis for the macroeconomic covariates used in this research. In addition, Humpe and Macmillan (2009) found similar ties in the US and Japanese economies. The US has a relationship between the stock market and industrial production, the consumer price index, money supply, and long-term interest rate. In Japan, there is a relationship between stock prices, industrial production, and money supply. The mentioned papers agreed on the relationship between the stock market returns and industrial production, the interest rate, and the money supply. These statements can also be supported by earlier research which found relations between major international stock indices and real oil price, real consumption, real money, and real output (Cheung and Ng, 1998). The reason behind the stock market growth was studied in earlier research by Chen (1991). This paper analyzed that there are relations between the investment opportunities in the market and the macroeconomy. Especially production growth rate, default premium, term premium, short-term interest rate, and market dividend-price ratio played a significant role. If these investment opportunities are favorable, this will lead to average growth in the market and a positive return on the stock indices.

Jin and Guo (2021) found that the relations between the stock market and the macroeconomic variables are much weaker for emerging markets. This is mainly due to external factors such as irrational market sentiments. Maghyereh (2002) found fragile relations in the emerging market of Jordan between exports, foreign reserves, interest rate, inflation, industrial production, and the stock market. This shows similar factors to mature markets but is much less robust.

Some papers find no existing relations between certain macroeconomic variables and stock market indices. Filis (2010), for example, found no direct connection between industrial production and the stock market in Greece. Since Greece is a southern European country, this finding may have the same conclusion in this paper for some of the sample regions. Moreover, Gay Jr et al. (2008) found no significant relationship between selected macroeconomic variables and the leading stock indices of the BRIC (Brazil, Russia, India, and China) economies. However, this might be due to excluding other domestic or international variables in the research.

Combining all the conducted research between the macroeconomic covariates and the stock market indices in different markets will lead to an extensive basis for choosing variables in this research. Moreover, it provides insights into future results to find specific differences and similarities between countries and regions.

2.3 Climate Covariates and Stock Market Returns

Climate research is a field of science which gained more attention in recent decades. The problems and challenges of the changing climate are becoming increasingly apparent. An increasing area of literature investigates the relationship between climate change and its driving factors. Therefore researchers have also increased attention to the implications of these changes on the financial markets, recognizing the risk and opportunities related to these climate factors.

Venturini (2022) performed a literature study on the relationship between climate change, risk factors, and stock returns. In the paper, three main points are made which are related to this research. First, the response to climate risk factors has increased over the years. Recent periods react more strongly to these risks, emphasizing the recent increase in climate change concern in the market. The most used climate factors are temperature anomalies and drought. These two risk factor classes will form the basis for the climate covariate selection.

Secondly, more research is needed on the relationship between asset returns and climate risk factors. New studies clarifying relations can be used to improve climate models. Moreover, in the future, extreme events are more likely to happen due to climate change, giving more data points to enhance the models again.

The last point made by Venturini (2022) is that many individual firms cannot adapt to climate change. However, there are also solutions proposed to this problem. The leading answer is that investors prefer 'green' assets over other assets, which automatically will shift the market towards a more sustainable economy. This process will make individual firms more capable of adapting to climate change.

Finally, there is also climate (finance) research which also uses the same risk measurement techniques. For example, Silva et al. (2016) use climate covariates within the POT model to model the risk of floods in Brazil. Applying the POT with climate covariates provides an inspirational basis for this research. This concludes contemporary climate research and gives a broad foundation to build on and extend the current literature.

3 Data

In the research, two types of data are used. The first type is the market indices for different regions, and the second is the covariates. Moreover, the covariates can also be divided into macroeconomic and climate-related categories.

3.1 Market indices

Six different regions are selected for this research. First, the biggest economies in the European Union in terms of GDP are chosen, and the United Kingdom is added to this list. Germany, France, Italy, Spain, the Netherlands, and the United Kingdom are the countries. The biggest and most well-known index is selected as the market proxy for the corresponding country. These are the DAX (Germany), CAC40 (France), FTSE MIB (Italy), IBEX35 (Spain), AEX (the Netherlands), and the FTSE100 (United Kingdom). The exact definition and composition of each index are given in Appendix A.1. The period is from 01-01-2000 until 25-05-2022. This period contains the financial crisis and also the COVID-19 crisis. However, the exact role of the climate crisis is unknown. The market index closing prices are retrieved from the Google Finance database and transformed into weekly negative log returns to show the weekly losses. Weekly losses are used to match the covariate data better. In total, we have 1169 weekly losses from six different market indices. The descriptive statistics of the market index losses are shown in Table 1.

Table 1: Descriptive Statistics of the Weekly Index Losses in Percentages (%)

Index	# Losses	Mean	St. Dev	Min	Q1	Median	Q3	Max
DAX	526 (45.0%)	-0.062	3.21	-14.94	-1.84	-0.37	1.58	24.35
CAC 40	530 (45.3%)	-0.0053	3.01	-12.43	-1.75	-0.25	1.49	25.05
FTSE MIB	538 (46.0%)	0.045	3.30	-19.36	-1.84	-0.27	1.66	26.52
IBEX 35	544 (46.5%)	0.024	3.16	-12.48	-1.74	-0.27	1.76	23.83
AEX	521 (44.6%)	-0.001	3.01	-13.58	-1.61	-0.24	1.44	28.75
FTSE 100	537 (45.9%)	-0.012	2.44	-12.58	-1.32	-0.20	1.21	23.63

Table 1 shows that the indices have much in common. For example, they all have almost the same number of losses in the research period. However, there are some noticeable differences. The main difference is that the means of nearly all indices are negative. Only the FTSE MIB and the IBEX 35 have a positive mean for the losses. Moreover, the highest loss in the period is from the AEX, with a log loss of 28.75%. The final observation is that FTSE 100 is more stable than the other indices with a lower standard deviation, highest minimal loss, and lowest maximal loss. In contrast, the amount of losses equals the rest.

Next, we examine the presence of autocorrelation, which is the serial dependence of the index returns (or losses). The autocorrelation will be tested in two ways, the first is an autocorrelation plot, and the second way is the Ljung-Box test for autocorrelation. (Ljung and Box, 1978) The Ljung-Box test statistic is shown below.

$$Q = n(n+2)\sum_{k=1}^{h}\frac{\hat{\rho}_k^2}{n-k},$$

Here n is the total sample size of the time series, ρ_k is the sample autocorrelation at lag k, and h is the total number of lags tested in the test. The test statistic Q is Chi-squared distributed ($Q \sim \chi^2_{(h)}$) under the null hypothesis that the time series is independently distributed. Autocorrelation is not only tested in the time series of losses but also in the time series of absolute losses and also the squared losses time series. These last two will indicate volatility clustering in the indices, a common element in the time series of stock returns. Volatility clustering means that periods with high volatility will follow after each other. The same holds for periods with low volatility.

Table 2: Ljung-Box test statistics for 30 lags

Index	Losses	Absolute Losses	Squared Losses
DAX	47.667**	718.31***	291.65***
CAC 40	52.663***	655.87***	192.07***
FTSE MIB	58.347***	640.6***	181.8***
IBEX 35	41.152*	508.4***	178.87***
AEX	52.207***	805.99***	180.61***
FTSE 100	75.397***	503.34***	190.75***

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 2 shows that the losses have autocorrelation. Moreover, the pattern becomes even stronger for the absolute and squared losses. This is a commonly seen phenomenon. This image is also clear from the autocorrelation plots, which can be found in Figure 4 in Appendix A.1. This Figure shows the same results. The autocorrelation pattern in the regular, absolute, and squared losses indicates that the data is undoubtedly serial-dependent.

3.2 Covariates

The second main element of the research is the class of covariates. A covariate is a variable that can influence an outcome or a not directly significant process. Two different types of covariates are used in this research paper. The first type is macroeconomic covariates, and the second is climate covariates.

3.2.1 Macroeconomic Covariates

Macroeconomic covariates depend on or measure the macroeconomic environment in different aspects. Therefore, based on Section 2, a set of covariates is selected. The covariates are the industrial production, the consumer price index as a proxy for inflation, the unemployment rate, the short-, middle- and long-term interest rates, the producer price index, the imports, the exports, and three sentiment indicators for each country. Moreover, for many covariates, two values are used. The first is the country-specific value, and the second is the European average. All the different macroeconomic covariates are retrieved from Eurostat, which is the official statistical office of the European Union.

There are 128 individual macroeconomic covariates used in the research. These are spread over the six countries used in this research. The exact definitions and explanations for all the different covariates are given in the appendix. Most macroeconomic data is only available monthly. Since the index data is available weekly, the macroeconomic covariate data is interpolated into weekly data. So, the monthly value is used for all 4 (or 5) weeks. Moreover, the units of all covariates are different. This is why all the covariates are standardized, meaning all covariates are demeaned and divided by the standard deviation. The descriptions of all the standardized macroeconomic covariates are in section C.1 of the appendix.

3.2.2 Climate Covariates

This section will outline the different climate covariates. The main challenge in selecting climate covariates is that each country does not have one national-level climate variable. For example, the maximum temperature may differ between places within the same country. Therefore the covariate values of the weather station closest to the market are chosen. These cities are Frankfurt (DAX), Paris (CAC 40), Milan (FTSE MIB), Madrid (IBEX 35), Amsterdam (AEX), and London (FTSE 100). Moreover, the data is not available from one data source.

There are three separate data sources: NASA (National Aeronautics and Space Administration), POWER (Prediction Of Worldwide Energy Resources) earth program, the Copernicus database, and the IMF database. These databases can be seen as reliable since they are globally well-known institutions. The NASA data contains four types of covariates: Solar Fluxes, Temperature, Humidity/Precipitation, and Wind/Pressure. The Copernicus database, which is European Union's earth observation program, provides other climate and energy indicators for this database. Finally, the IMF database contains indicators about the impact of economic activity on climate change.

The total dataset consists of 28 climate covariates available for each country. Moreover, all the individual data is standardized, like the macroeconomic covariate data. Finally, the data is matched to the weekly observations of the returns dataset. The same procedure as for the macroeconomic covariates is used. A complete list of all the individual covariates, abbreviations, and explanations is given in the appendix. So the index data, the macroeconomic covariates, and the climate covariates are the complete dataset used in this research.

The descriptions of the different climate covariates are shown in Appendix C.2. Moreover, the corresponding abbreviations can be found in this section.

3.2.3 Multicollinearity

A problem that can arise in the data set is multicollinearity between the different covariates, especially in the dataset where the covariates are directly or indirectly related. For example, the wind speed at 10 meters is associated with the wind speed at 50 meters. Multicollinearity is a statistical phenomenon that occurs when two or more explanatory variables in a regression model are highly correlated (Hair et al., 1998). This can cause problems in the model interpretation, as the coefficients of the correlated variables may be unstable and difficult to interpret. One way to detect multicollinearity is to use variance inflation factors (VIFs).

To calculate VIFs, a separate regression model is fit for each explanatory variable, with all of the other explanatory variables as predictors (Hair et al., 1998). The VIF for a particular explanatory variable is then calculated as the reciprocal of the tolerance, which measures the degree to which that variable is correlated with the other variables in the model. A VIF value of 1 indicates no multicollinearity, while a value greater than 1 indicates the presence of multicollinearity. It is generally recommended to consider removing variables with VIF values above five from the model. (Neter et al., 1996) This method will be used to test the chosen covariates on multicollinearity, resulting in a set of independent covariates for the methodology.

4 Methodology

The methodology used in this research consists of three main steps. The first step is the POT method which analyses the extreme events in the market. The method fits a Generalized Pareto distribution to observations above a certain threshold. The second step is covariate selection. This part introduces the covariates to model the Generalized Pareto distribution (GPD) parameters. Moreover, here is also determined which covariates are the most influential for the extreme risk observations. In the final step, the models with the covariates are used to estimate different risk measures. These risk measures are then tested against known and used benchmark models. As a benchmark, the historical simulation and non-dynamic POT method are used. These tests determine if the inclusion of the covariates can significantly benefit the traditional risk measurement in Europe. Furthermore, there is also tested if including climate variables has a significant beneficial effect. Finally, there also tested if the role of covariates has changed after the Paris Climate Agreement, signed on December 12, 2015.

4.1 Peaks-over-Threshold approach

The POT approach is an extreme value theory(EVT) technique. This concept, developed by Smith (1984), tries to model threshold exceedances in i.i.d data. (McNeil et al., 2015) The POT procedure in this research makes three assumptions:

- Exceedances above a certain threshold occur in time according to a homogeneous Poisson process.
- Excess amounts above the threshold are i.i.d. and independent of exceedance times.
- The distribution of excess amounts is GPD.

Since the assumptions require i.i.d. data, the market index loss data must be adjusted. This is because the index data has a significant degree of autocorrelation, shown in section 3. The filtration technique developed by McNeil and Frey (2000) is used to overcome the problem of autocorrelation in the data to make the data suitable for the POT approach. This method uses the residuals after an appropriate GARCH model is fitted to the index losses. In this research, like in McNeil and Frey (2000), an AR(1) process with GARCH(1,1) (generalized autoregressive conditional heteroskedasticity) model is fitted to the losses of the indices using the quasi maximum likelihood approach. The GARCH(1,1) model is originally introduced by Bollerslev (1986). The AR(1) process with the GARCH(1,1) model is defined as follows,

$$\begin{aligned} L_t &= \mu_t + \sigma_t Z_t \\ \mu_t &= \mu + \phi(L_{t-1} - \mu_{t-1}) \\ \sigma_t^2 &= \alpha_0 + \alpha_1(L_{t-1} - \mu_{t-1})^2 + \beta\sigma_{t-1}^2, \end{aligned} \tag{1}$$

where L_t is a market index loss at time t, $t \in \{1, ..., n\}$, μ_t and σ_t^2 are the conditional mean and variance, respectively, and $\alpha_0 > 0, \alpha_1 > 0, \beta > 0$ and $\beta + \alpha_1 < 1$. The underlying distribution of Z_t is the student's t-distribution with κ degrees for freedom. κ will be estimated as a variable in the model. After fitting the model to the market index data, the residuals series Z_t should approximately be i.i.d. Thus, the residuals will be used in the POT because these series do not violate the assumptions of the POT approach.

The residuals of the fitted model are used in the POT procedure in the same procedure and with the same notation as in McNeil et al. (2015). As mentioned, the POT approach aims to model exceedances above a certain threshold. These exceedances are denoted as $\tilde{Z}_1, ..., \tilde{Z}_p$ where the number of losses that exceed the threshold is p. $\tilde{Z}_1, ..., \tilde{Z}_p$ are residuals from the GARCH model that exceed threshold u. Further, $\tilde{X} = \tilde{Z} - u$ where $\tilde{X}$ are the excesses above the threshold. As mentioned in the assumptions, the POT approach in this research fits these excesses to the Generalized Pareto Distribution (GPD) if the threshold is chosen sufficiently high. The GPD is one of the most widely used distributions in the POT procedure. (Davison and Smith, 1990) This is the case because the GDP can take a wide range of tail shapes. The GPD includes both the exponential and Pareto distributions as special cases and can also model heavy-tailed or light-tailed distributions, depending on the data. The distribution function of the GPD is,

$$G_{\xi,\beta}(x) = \begin{cases} 1 - (1 + \xi x/\beta)^{-1/\xi}, & \xi \neq 0, \\ 1 - exp(-x/\beta), & \xi = 0, \end{cases} \tag{2}$$

where $\beta > 0$, and $x \geq 0$ if $\xi \geq 0$ and $0 \leq x \leq -\beta/\xi$ if $\xi < 0$. Moreover, the distribution specifies the parameters ξ and β as the shape and scale parameters, respectively. The GPD is fitted on the data using a maximum likelihood to obtain parameter estimates.

The next part of the methodology is estimating the intensity parameter of the occurrences of the exceedances. If the assumptions hold, it means that occurrences of the residuals that exceed the threshold follow a homogeneous Poisson distribution with λ as the intensity parameter. Furthermore, the excesses $X_1, ..., X_p$ are asymptotically independent of the exceedance time and the number of exceedances p in this process.

As mentioned before, a suitable threshold is needed in the POT approach. This is the case because of a bias-variance trade-off. If the threshold is too high, there will be too few observations in the extreme dataset. This can lead to too-small sample size and a high variance in the estimate of the tail distribution. This can result in an unreliable assessment of the tail risk and may lead to overfitting or underestimation of the tail risk. Conversely, if the threshold is too low, there will be too many observations in the extreme dataset. This will increase the bias. Three rules of thumb and one graphical method are used to find a suitable threshold in this research. Each market index will get its POT threshold. For quick threshold setting, a few rules of thumb can be used. They can give an immediate indication of an applicable threshold. Three primary rules of thumb are frequently used in extreme value research (Scarrott and MacDonald, 2012). The first is the 90th percentile rule, which is used by DuMouchel (1983) for example. The second rule of thumb often used is $k = \sqrt{n}$, where the k-th largest observation is used as a threshold. This rule is used by Ferreira et al. (2003), for example. The last rule of thumb regularly used was introduced by Loretan and Phillips (1994). The threshold is the k-th largest observation where $k = n^{2/3}/log(log(n))$. These rules of thumb do not contain information about the structure within the dataset, which is why a graphical method is also used to determine a sufficient threshold. This method is a mean residual life plot. The mean of the excesses for each threshold is plotted in a mean residual life plot. When the plot shows a linear trend, a sufficient threshold can be estimated. The threshold will be chosen as the moment that the graph becomes linear. These are all the different methods to find the best suitable threshold in the POT approach. The optimal threshold is chosen by combining the information from the 90th percentile and the mean residual life plot. The other heuristics give an indication of whether the selected threshold is a reasonable choice.

4.2 Covariates

This section introduces covariates to the previously explained POT approach. This dynamic POT procedure is introduced by Chavez-Demoulin et al. (2016), and the key concept is to let the parameters of the POT approach depend on the different covariates. In our case, the parameters in the POT approach are going to be dependent on macroeconomic and climate covariates. In the dynamic POT procedure, there are three different parameters, which are $\lambda(t)$ in the Poisson arrival distribution and $\xi(t)$ and $\beta(t)$ in the generalized Pareto distribution at every time point t depending on covariates. The covariates, both climate and macro-economic, are in the vector $c = (c_1, ..., c_q)$, where q is the number of covariates that correspond to the specific market index. The method that will be used to estimate the parameters on the covariates is the penalized maximum (log-)likelihood. This is also used to overcome overfitting problems when the procedure has too many covariates. The method will be explained in more detail in section 4.3.1.

4.2.1 Dynamic Poisson process

As mentioned before, the occurrences of exceedances above the threshold follow a Poisson process. If we let the parameters depend on the covariates, this becomes a non-homogeneous Poisson process because the intensity parameter $\lambda(t)$ varies over time t. The intensity parameter will be modeled using a generalized additive model. In generalized additive models (GAM) (Hastie and Tibshirani, 1986), the linear response variable depends on a linear, smooth function of covariates. In the case of the intensity parameter, the function is,

$$\lambda(t) = exp(\phi_{\lambda,0} + c_1(t)\phi_{\lambda,1} + ... + c_q(t)\phi_{\lambda,q}) \tag{3}$$

where $\phi_{\lambda,0}$ is the estimated constant and $\phi_{\lambda,1}, ..., \phi_{\lambda,q}$ are the estimated coefficients for the different covariates. Depending on the different covariate coefficient estimates, this leads to a different intensity parameter for each time point. The GAM model will be estimated using a penalized log-likelihood.

The likelihood function of the Poisson process is defined as follows,

$$L_\lambda(\lambda(t)) = \exp\Big(-\int_0^n \lambda(t)dt\Big)\prod_{i=1}^{p}\lambda(t), \tag{4}$$

for $t \in 1, ..., n$ where n is the sample size, and where $\lambda(t)$ is, in this case, the additive model defined in equation (3). In the optimization process, the function that will be optimized is the $log(L_\lambda(\lambda(t)))$, which transforms the multiplication of the $\lambda(t)$ into a summation of $log(\lambda(t))$. Moreover, the integral also transforms into a summation because we assume that $\lambda(t)$ is constant between time point t and $t+1$ for every t. The log-likelihood function of the Poisson process is defined as follows,

$$\ell_\lambda(\lambda(t)) := log(L_\lambda(\lambda(t))) = \sum_{i=1}^{p} log(\lambda(t)) - \sum_{t=1}^{n}\lambda(t) \tag{5}$$

Moreover, a penalty function will be introduced for the covariate selection for the penalization. This will be explained in section 4.3.

4.2.2 Dynamic Generalized Pareto Distribution

The parameters $\xi(t)$ (shape) and $\beta(t)$ (scale) are modeled to be dependent on the covariates in the generalized Pareto distribution. However, the parameters must be reparameterized due to the simultaneous fitting procedure. This is needed because of the convergence of the fitting procedure, which is explained in Chavez-Demoulin (1999). The reparameterization is as follows, following Chavez-Demoulin et al. (2016), $\nu(t) = log((1+\xi(t))\beta(t))$, where automatically follows that $\beta(t) = \frac{exp(\nu(t))}{1+\xi(t)}$. Furthermore, the reparameterization is only accurate if $\xi(t) > -1$. Now we can set up the general additive models for the penalized log-likelihood, shown below.

$$\begin{aligned} \xi(t) &= \phi_{\xi,0} + c_1(t)\phi_{\xi,1} + ... + c_q(t)\phi_{\xi,q}, \\ \nu(t) &= \phi_{\nu,0}c_1(t)\phi_{\nu,1} + ... + c_q(t)\phi_{\nu,q}. \end{aligned} \tag{6}$$

Again, the same notation is used as in equation (3). These models indicate that the parameters depend linearly on the chosen covariates and include a constant. The likelihood function for the optimization of the parameters in the distribution is,

$$L_{\xi,\beta}(\xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p) = \prod_{i=1}^{p} g_{\xi(t_i),\beta(t_i)}(\tilde{X}_{t_i}), \tag{7}$$

where $t_i \in 1, ..., p$, are the time points where the residuals exceed the thresholds. For the optimization, the log-likelihood is used, which is shown below.

$$\ell_{\xi,\beta}(\xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p) = \sum_{i=1}^{p} \log(g_{\xi(t_i),\beta(t_i)}(\tilde{X}_{t_i})), \tag{8}$$

where,

$$\log(g_{\xi(t_i),\beta(t_i)}(\tilde{X}_{t_i})) = \begin{cases} -\log(\beta(t_i)) - (1 + 1/\xi(t_i))\log(1 + \frac{\xi(t_i)\tilde{X}_{t_i}}{\beta(t_i)}), & \text{if } \xi(t_i) \neq 0 \text{ and } 1 + \frac{\xi(t_i)\tilde{X}_{t_i}}{\beta(t_i)} > 0, \\ -\log(\beta(t_i)) - \frac{\tilde{X}_{t_i}}{\beta(t_i)}, & \text{if } \xi(t_i) = 0, \\ -\infty, & \text{otherwise.} \end{cases} \tag{9}$$

The optimization of this function will give the estimated coefficients (ϕ_ξ and ϕ_ν) for the different covariates for the parameters of the distribution.

4.2.3 Likelihood estimation

Due to the asymptotic independence between the exceedance time, the number of exceedances, and the excesses, as stated by the assumptions of the approach, the log-likelihood can be split into two independent marginal log-likelihoods. This procedure of splitting the likelihoods is shown below,

$$L(\lambda(t), \xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p) = L_\lambda(\lambda(t)) \cdot L_{\xi,\beta}(\xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p) \tag{10}$$

which means for the log-likelihood that,

$$log(L(\lambda(t), \xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p)) = \ell_\lambda(\lambda(t)) + \ell_{\xi,\beta}(\xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p). \tag{11}$$

In practice, this means that the intensity parameter can be estimated separately from the parameters in the GPD, which is computationally less intensive.

4.3 Model Selection

4.3.1 Model Regularization

A lot of different individual covariates are used in this research. This leads to a lot of different models that can be evaluated. A strategic approach is needed to look efficiently at the best models. The method that will be used here is the penalized likelihood approach. The penalized likelihood approach tries the optimize the "bias-variance" trade-off in the models by implementing regularization. Because as said before, a simple model is preferred over a more complex model, but without a significant increase in the variance. Regularization techniques are applied to the log-likelihood function in equation (11), ensuring that only significant informative covariates are added to the log-likelihood function. The general form of the penalized likelihood is as follows,

$$\ell(\lambda(t), \xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p)) = \ell_\lambda(\lambda(t)) + \ell_{\xi,\beta}(\xi(t), \beta(t); \tilde{X}_1, ..., \tilde{X}_p)) - \sum_j \tau_j ||\phi_j||_r^r. \tag{12}$$

The last term, $\sum_j \tau_j ||\phi_j||_r^r$ is the penalization term for the specific parameter $j \in \{(\lambda), (\beta, \xi)\}$. So we have one specific for the Poisson likelihood and one for the GPD likelihood. τ_j is the regularization term and $||.||_r^r$ is the L_r norm of ϕ_j. An L_r norm (Euclidean norm) is defined as $||\phi_j||_r^r = \sum_{i=1}^q |\phi_{j,i}|^r$. The log-likelihood is penalized for the number of parameters in the model. In the research, three different types of regularization will be used: the Ridge penalization, the LASSO penalization, and the Elastic-Net penalization. The Ridge penalization (or Tikhonov regularization), introduced and developed by Tikhonov (1943); Phillips (1962), is a regularization technique that takes multicollinearity into account. It uses an L_2 norm in the log-likelihood function in equation (12). The second regularization technique is the LASSO (least absolute shrinkage and selection operator) penalization. LASSO penalization was first introduced and developed by Santosa and Symes (1986); Tibshirani (1996). This method uses a L_1 norm in the optimization function in the penalty term, which is the absolute value. The difference between Ridge and Lasso penalization is that LASSO penalization can shrink some covariates to zero, which is impossible in the Ridge penalization. However, LASSO cannot deal well with multicollinearity. The last method that is introduced is the ElasicNet penalization. This method combines both Ridge and LASSO. (Zou and Hastie, 2005) It includes both a L_1 and L_2 norm in the log-likelihood function. The penalization term, in this case, becomes $\alpha \sum_j \tau_j ||\phi_j||_1^1 + (1 - \alpha) \sum_j \tau_j ||\phi_j||_2^2$, where we choose $\alpha = 0.5$. The ElasticNet penalization tries to combine the strengths of Ridge and LASSO penalization. These three regularization techniques optimize the "bias-variance" trade-off in the models by selecting the right amount of parameters.

The penalized likelihood is unable to exclude covariates from the equation. It is only able to shrink the estimated coefficients toward zero. That is why covariates with an estimated coefficient smaller than 0.001 are excluded from the results and are treated as insignificant.

Regularization term selection A grid search is performed to find the best regularization term τ_j. There are two different regularization terms, one for the Poisson process likelihood and one for the GPD likelihood. The grid search is performed over a logarithmically spaced range: $\tau_j \in \{1, 10, 100\}$. The grid search is performed with the Lasso regularization for the DAX market index. Due to their computational intensiveness, the same regularization terms are used for all the market indices. The optimal regularization term for the Poisson process and the GPD estimation is 1 in this setting after 10000 and 100000 likelihood optimization iterations, respectively. However, the likelihoods did not converge within the iterations. This is why a more restrictive regularization term is chosen. That is why the second best option 10 is chosen as the regularization term for the Poisson process and the GPD likelihood estimation.

4.3.2 Model Criteria

In Section 3, it is shown that there are a lot of individual covariates, so we have a lot of potential models which are interesting to research. The best-performing model needs to be selected out of all the potential models. Criteria are needed to choose the best models from all the possible models. In this research, three commonly used criteria for model selection are used. The first one that is used is the Akaike information criterion (AIC), (Akaike, 1998; Mills and Prasad, 1992) $AIC = 2k - ln(\hat{L})$, where k is the number of estimated 'significant' covariates and $\hat{L}$ is the value of the likelihood. The lower the AIC, the better the model, but this only can be used to rank the models. It does not give an absolute indication of how good the model is. Looking at the definition of the AIC, it protects against over- and underfitting; it covers the under-fitting by the likelihood value and over-fitting by including the number of parameters k. The second criterion is the Bayesian (Schwarz) information criterion (BIC). (Schwarz, 1978) The BIC is defined as, $BIC = kln(n) - 2ln(\hat{L})$, where again k is the number of estimated 'significant' covariates, n is the sample size ($n \gg k$) and $\hat{L}$ is the value of the likelihood. Moreover, here applies that a lower BIC is better but can only be used to rank models. Like the AIC, also the BIC controls for both over- and underfitting. However, there is a slight difference between these information criteria in the penalty term. The difference in performance, as indicated by Vrieze (2012), is that the AIC generally performs better when n is finite. However, the best solution is to check both criteria, often leading to the same model.

The criterion for model evaluation is a goodness-of-fit test, which is the likelihood-ratio or Wilks test. (Wilks, 1938) the test statistic is,

$$\Lambda_{LR} = -2\left[\frac{L(\theta_1)}{L(\theta_2)}\right],$$

or for the log-likelihoods, the test statistic becomes,

$$\lambda_{LR} = -2(\ell(\theta_1) - \ell(\theta_2)),$$

where $L(\theta_1)$ and $\ell(\theta_1)$ are the likelihood and log-likelihood of the more parsimonious model, respectively. The parameters θ_1 and θ_2 indicate the parameter spaces of the models. The test statistic λ_{LR} is (asymptotically) chi-squared distributed with p degrees of freedom under the null hypothesis that the parsimonious model is the better performing model ($\lambda_{LR} \sim \chi^2_p$, where p is the difference in the number of parameters). This only holds if the models are nested, which is the case in the research. Moreover, the degree of freedom is equal to the difference in the number of parameters in the models. These three selection criteria are used to determine which model is preferred for estimation compared to another model.

4.4 Risk and Performance Measures

The last step is to move from the optimized models to estimate the financial risk for the different indices. In Chavez-Demoulin et al. (2016), the most well-known risk measures are used for the different models. The first one is the most used risk measure, which is the Value-at-Risk (VaR). (Philippe, 2001) The VaR measure is adopted worldwide by banks and was agreed upon in the Basel II Accord framework. This framework contains international banking recommendations for laws and regulations which the Basel Committee on Banking Supervision issues. (Yetis, 2008) The Value-at-Risk is formally defined as,

$$VaR_\alpha(X) = -\inf\{x \in \Re : F_X > \alpha\} = F_Y^{-1}(1-\alpha).$$

Alternatively, in words, VaR_α is defined as the threshold where the probability of a loss larger than VaR_α is only $(1-\alpha)$. Besides the VaR, the Expected Shortfall (ES) (or conditional Value at Risk (CVaR)) is also used as a risk measure. This measure is the average loss when the VaR level is exceeded.(Rockafellar et al., 2000) The ES, compared to the VaR, takes more care of the distribution of the losses. This might, in some cases, give more insight into the risks of a market.

$$\begin{aligned} \widehat{VaR}_\alpha^Z(t) &= u + \frac{\hat{\beta}(t)}{\hat{\xi}(t)}\left(\left(\frac{1-\alpha}{1-e^{-\hat{\lambda}(t)}}\right)^{-\hat{\xi}(t)} - 1\right) \\ \widehat{ES}_\alpha^Z(t) &= \begin{cases} \frac{\widehat{VaR}_\alpha^Z(t)+\hat{\beta}(t)-\hat{\xi}(t)u}{1-\hat{\xi}(t)}, & \text{if } \hat{\xi}(t) \in (0,1), \\ \infty, & \text{if } \hat{\xi}(t) \geq 1 \end{cases} \end{aligned} \tag{13}$$

Where the VaR and ES are transformed back from the residuals to the index losses by the following formulas,

$$\begin{aligned} \widehat{VaR}_\alpha^L(t) &= \hat{\mu}_t + \hat{\sigma}_t \cdot \widehat{VaR}_\alpha^Z(t) \\ \widehat{ES}_\alpha^L(t) &= \hat{\mu}_t + \hat{\sigma}_t \cdot \widehat{ES}_\alpha^Z(t) \end{aligned} \tag{14}$$

The $\hat{\mu}_t$ and $\hat{\sigma}_t$ are the estimated values from the GARCH model in equation 1. These estimated models will be statistically tested against benchmark models to see which models perform significantly better.

4.4.1 Benchmark models

The next thing to consider is a benchmark model to compare to the found models in the research. The first benchmark model to be considered is the historical simulation approach. The historical simulation approach for the VaR uses past data. It takes the value which satisfies the requested VaR condition. This value will be the VaR over time. This benchmark's strength is that it is nonparametric; it does not need a pre-specified distribution. The second benchmark model used is the Peaks-over-Threshold method without the covariates. The Poisson and Generalized Pareto distribution parameters will be estimated without any covariates. The rest of the methodology will be the same as the dynamic method. This will give insights into the impact that the covariates have. This method can also be repeated for the expected value. These two benchmark models test if the optimal dynamic covariate model performs significantly better.

4.4.2 Model Performance

Statistical tests are needed to determine which VaR model outperforms the others. Kupiec et al. (1995) has developed two tests for Value-at-Risk models. The first one is the proportion of failing (POF) test which tests whether the confidence level is statistically equal to the exceedance rate of the VaR level. The test statistic, a special likelihood ratio test, is defined as in equation (15).

$$LR_{POF} = -2\log\left(\frac{\alpha^{n-x_e}(1-\alpha)^{x_e}}{(1-\frac{x_e}{n})^{n-x_e}(\frac{x_e}{n})^{x_e}}\right) \sim \chi_1^2, \tag{15}$$

n is the number of observations, x_e is the number of observations exceeding the VaR level, and α is the confidence level. Under the null hypothesis, the VaR model is accurate, so the exceedance rate equals the confidence level. The second test by Kupiec et al. (1995) is the time until the first failure test (TFF). This test examines whether or not the observed time until the first exceedance of the VaR level is equal to the expected time. The test statistic is almost equal to the previous statistic,

$$LR_{TFF} = -2\log\left(\frac{\alpha^{t_{e,1}-1}(1-\alpha)}{(1-\frac{1}{t_{e,1}})^{t_{e,1}-1}(\frac{1}{t_{e,1}})}\right) \sim \chi_1^2, \tag{16}$$

where the notation is the same as before, except for $t_{e,1}$, which is the time of the first VaR exceedance. Both tests backtest the VaR models on the dataset's theoretical and observed behavior. Another test that backtests an estimated Value-at-Risk is the VaR duration test by Christoffersen and Pelletier (2004). This test evaluates whether or not the VaR exceedances are independent of each other, which is the case in an adequate VaR model. The test is built up as follows: first, we need to define $d_i = t_{e,i} - t_{e,i-1}$ ($t_{e,i}$ is the time of the ith VaR exceedance) which is the duration between two VaR exceedances. Then, since d_i are independent under the null hypothesis, they need to be distributed with a memoryless distribution. The only continuous memoryless distribution is the exponential distribution. This distribution has the density:

$$f(d) = p\exp(-pd) \tag{17}$$

This means that under the null hypothesis of a correct specified VaR model, there needs to hold that the VaR level α is equal to p. A likelihood ratio test again tests this. These are all the methods to analyze the models on their performance.

4.5 Influence of Climate Covariates

We employ the dynamic POT method to evaluate the influence of climate covariates. However, we only consider macroeconomic covariates as input covariates. We determine the coefficients for the covariates and then construct the Value-at-Risks and Expected Shortfall. Additionally, we conduct the same tests as previously to ascertain whether the climate covariates have a favorable impact.

4.6 Impact of Climate Agreements

Finally, the impact of the Paris climate agreement is estimated. A typical before-after analysis is used to assess the impact. This is a standard method to examine the effect of an intervention on a particular outcome variable. The intervention, in this case, is the signing of the Paris climate agreement. In this method, a dummy variable is constructed to assess the impact. The dummy variable will be 0 for the periods before the climate agreement, and 1 after the agreement was signed. So, in formula form:

$$D_{Paris} = \begin{cases} 1, & \text{in the period after } 12/12/2015. \\ 0, & \text{in the period before } 12/12/2015. \end{cases}$$

We add this variable to the set of existing covariates and proceed with the dynamic POT approach. The other covariates in the model will serve as control variables to address possible endogeneity in this setting. The coefficient estimated for the dummy variable will indicate how the agreement influences the different parameters in the model. The difference in risk between the period before and after the climate agreement can be constructed using the estimated coefficients and equation (13). This indicates how the Paris climate agreement has impacted the risk measures in this setting.

5 Results

5.1 Threshold Determination

Table 3 shows the thresholds for the different market indices based on the rules and heuristics stated before. Moreover, the table shows the chosen threshold for the rest of the methodology based on the decision rule. The DAX has the highest chosen threshold, and the FTSE 100 has the lowest. The pattern in the chosen thresholds generally corresponds to Table 1. A higher standard deviation in the losses indicates more variability in the data, so a higher point is needed to classify an observation as an extreme observation.

Table 3: Threshold selection based on different decision rules

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
90th percentile	0.039	0.036	0.039	0.039	0.032	0.027
$\sqrt{n}$	0.066	0.057	0.065	0.062	0.061	0.048
$\frac{n^{2/3}}{log(log(n))}$	0.053	0.050	0.053	0.053	0.050	0.039
mean residual life plot	0.040	0.035	0.039	0.030	0.029	0.025
Chosen Threshold	0.040	0.036	0.039	0.035	0.030	0.026

5.2 Dynamic Peaks-over-Threshold

First, the results of the dynamic POT approach are examined. Covariates are introduced in this approach. The results for the different market indices are presented per market index. In the main section of this research, the DAX market index is shown, while the rest of the results are presented in the Appendix. All figures and tables are given per market index in Appendix B.1 (Table 16) - B.5 (Table 28). Table 4 shows the estimated coefficients for the different regularization methods per covariate. The general pattern for the market indices is that the Lasso and ElasticNet regularization methods are the most restrictive. It shrinks coefficients more strongly toward zero compared to the Ridge regularization.

Here, an economic explanation will be given of the sign of the coefficients. The first thing to remember is that we work with standardized covariates. This means that the covariates are 0 for their average value in the research period. The coefficient of the constant can be interpreted as the geometric mean for the $\hat{\lambda}(t)$ parameter and as the arithmetic mean for the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameters. This is because the covariates depend linearly on parameters $\hat{\xi}(t)$ and $\hat{\nu}(t)$ but also depend linearly on $log(\hat{\lambda}(t))$. So, the covariate coefficient estimates for $\hat{\xi}(t)$ and $\hat{\nu}(t)$ can directly be seen as the increase (decrease) magnitude of the corresponding parameter if the covariate increases (decreases) by one unit. However, the covariate coefficient estimates for $\hat{\lambda}(t)$ can be seen as the increase (decrease) magnitude of the $log(\hat{\lambda}(t))$ if the covariate increases (decreases) by one unit.

Furthermore, an increase in the $\hat{\lambda}(t)$, $\hat{\xi}(t)$, and $\hat{\nu}(t)$ parameters lead to an higher estimated VaR. Combining this notion with the explanation of the coefficients it can be determined that an increase of covariates with a positive coefficient lead to a higher estimated VaR. Moreover, a decrease in this covariate leads subsequently to a lower estimated VaR. This is the opposite for covariates with a negative coefficient.

The model that best fits the criteria specified beforehand is selected along with its corresponding regularization method. For instance, the Lasso method was chosen as the model for the $\hat{\lambda}(t)$ parameter in the DAX market index. Similarly, the CAC 40, IBEX 35, and FTSE 100 also adopted the Lasso regularization method. However, the ElasticNet regularization proved optimal for the FTSE MIB, while the Ridge regularization was best suited for the AEX. These optimal models surpassed other regularization methods by producing lower AIC (and BIC) scores. Additionally, for the DAX, CAC 40, and the FTSE 100 market indices, the goodness-of-fit test statistic indicated that the null hypothesis could be rejected, meaning the more parsimonious model is preferred. In this case, this was the model with the Lasso regularization. Furthermore, the IBEX 35, AEX, and FTSE MIB had the same conclusion as the model based on the AIC. Their optimal method based on the AIC also outperformed the others in terms of log-likelihood value.

The first thing to notice regarding the coefficient estimates for the $\hat{\lambda}(t)$ parameter is that the covariate with the highest magnitude for the DAX market index is the Long rate in the Euro area followed by the SCI. The Long rate has a positive coefficient and the SCI has a negative coefficient. This is also the case for the FTSE MIB market index. More similarities can be found between market indices. For example, the AEX and CAC 40 share a large negative coefficient for the unemployment rate percentage change. In contrast, there are also differences between the market indices. For example, the coefficients for the producer price index percentage change are negative for the AEX and IBEX 35 market indices, while they are positive for all other indices. Moreover, the minimum wind speed at 10 meters has a positive coefficient for all indices except for the FTSE MIB. Moreover, there are also differences in which covariates are considered significant for the model. For example, the Imp TV (Change) Euro area is only in the models for the DAX and AEX market indices.

Table 5 shows estimation results for the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameters for the DAX market index. The same general pattern can be seen for these parameters as for the $\hat{\lambda}(t)$ parameter. The Lasso and ElasticNet regularization methods are the most restrictive, and Ridge is the least restrictive. For the DAX market index, the ElasticNet method is optimal in this setting. Since it the lowest AIC criterion, this is also the case for the CAC 40, FTSE MIB, IBEX 35, and the FTSE 100 market indices. Only the AEX has the Lasso regularization as the optimal method. These model choices are also supported by the goodness-of-fit likelihood ratio test since this tests conclude that the same regularization methods are optimal for the different market indices. These results are presented in Tables 17, 20, 23, 26 and 29.

In the dynamic POT approach estimation for the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameters there are also similarities and differences between market indices. For example, the Imp TV (Change) Euro area covariate is included in the models for the $\hat{\xi}(t)$ parameter for all the market indices except for the IBEX 35 market index. There are also a lot of differences in coefficient signs between market indices. To highlight one, the CLD covariate has a positive sign for the $\hat{\xi}(t)$ parameter for all market indices except for the FTSE MIB market index.

From these differences in significant covariates, it is quite apparent that the impact of a covariate is heavily reliant on the country and the type of regularization technique that is executed. This is primarily due to the fact that each country possesses its own distinct economic characteristics, institutional frameworks, climate patterns, and political landscape, all of which can play a crucial role in determining the relation between the covariates and the potential market risk. Therefore, it is possible for different countries to have completely different coefficients assigned to the same covariate, underscoring the noteworthy impact that regional variations can exert on market projections.

Table 4: Dynamic POT for DAX index describing the $\hat{\lambda}(t)$ parameter in different regularisation methods

	Lasso	Ridge	ElasticNet
Constant (Intercept)	-2.293 (0.097)	-2.067 (0.079)	-2.122 (0.084)
IP (Change) EU28	-0.034 (0.099)	-0.036 (0.090)	-0.053 (0.099)
IP (Change)	0.001 (0.016)	-0.102 (0.111)	0.039 (0.121)
HICP (Change) Euro area	0.058 (0.099)	0.214 (0.106)	0.116 (0.096)
HICP (Change)		-0.147 (0.101)	-0.016 (0.105)
Unemp (Change) EU	-0.005 (0.174)	-0.031 (0.095)	
Unemp (Change)		-0.049 (0.122)	-0.121 (0.109)
PPI (Change) EU28	-0.070 (0.134)	-0.075 (0.097)	
PPI (Change)	0.019 (0.133)	0.093 (0.095)	0.049 (0.108)
Long rate Euro area	0.464 (0.161)	0.304 (0.117)	0.371 (0.115)
Exp TV (Change) Euro area	0.022 (0.095)	0.019 (0.142)	-0.017 (0.114)
Imp TV (Change) Euro area	0.153 (0.116)	0.004 (0.137)	0.091 (0.101)
CCI Euro area		0.047 (0.092)	
ICI	-0.010 (0.150)	-0.051 (0.112)	-0.082 (0.124)
RCI	0.098 (0.186)	-0.136 (0.114)	0.158 (0.132)
SCI	-0.405 (0.160)		-0.285 (0.130)
PS	0.122 (0.111)	0.197 (0.089)	0.158 (0.095)
WS10M	0.115 (0.136)	-0.014 (0.103)	0.007 (0.116)
CLOUD_AMT	0.070 (0.125)	0.316 (0.111)	0.169 (0.116)
T2M_RANGE	-0.029 (0.136)	0.019 (0.100)	0.122 (0.101)
WS10M_MAX		0.094 (0.101)	0.025 (0.113)
WS10M_MIN	0.019 (0.086)	0.190 (0.069)	0.114 (0.075)
PRECTOTCORR_SUM	0.006 (0.112)	0.039 (0.091)	0.092 (0.098)
CDD EU	0.093 (0.101)	0.047 (0.120)	0.039 (0.132)
CDD		0.131 (0.100)	0.096 (0.114)
Solar	0.052 (0.126)	0.137 (0.119)	-0.037 (0.117)
Hydro		0.047 (0.108)	
CLD	-0.136 (0.104)	-0.081 (0.086)	-0.146 (0.087)
Log-likelihood value	-403.65	-420.63	-414.09
AIC	851.31	885.27	876.18
BIC	962.72	996.67	997.71

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA, then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Table 5: Dynamic Peak-over-Threshold for DAX index describing the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameter for different regularisation methods

	Lasso		Ridge		ElasticNet	
	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	0.231 (0.267)	-3.161 (0.458)	0.586 (0.156)	-2.315 (0.160)	0.590 (0.203)	-2.633 (0.209)
IP (Change) EU28	0.049 (0.407)	-0.108 (0.536)	-0.022 (0.153)	-0.011 (0.169)	0.005 (0.194)	0.015 (0.014)
IP (Change)	0.079 (0.440)	0.204 (0.561)	0.041 (0.145)	-0.015 (0.155)	0.041 (0.172)	
HICP (Change) Euro area	0.006 (0.045)		0.064 (0.162)	0.059 (0.177)	0.044 (0.229)	
HICP (Change)	0.121 (0.302)	0.174 (0.281)	-0.028 (0.148)			0.024 (0.189)
Unemp (Change) EU	0.028 (0.183)	-0.004 (0.520)	-0.085 (0.179)	-0.013 (0.170)	0.022 (0.176)	0.001 (0.208)
Unemp (Change)	-0.040 (0.909)	-0.006 (2.247)		-0.098 (0.172)	0.004 (0.202)	0.060 (0.018)
PPI (Change) EU28	0.027 (0.533)	-0.027 (0.935)	0.032 (0.149)	0.093 (0.191)		
PPI (Change)	0.010 (0.305)	0.222 (0.682)	0.085 (0.158)	0.102 (0.162)	0.123 (0.317)	0.003 (0.184)
Long rate Euro area	0.300 (0.692)	0.008 (1.566)	-0.029 (0.170)	-0.232 (0.161)	0.002 (0.029)	-0.139 (0.188)
Exp TV (Change) Euro area	0.042 (0.977)		0.107 (0.169)	-0.147 (0.172)		-0.110 (0.192)
Imp TV (Change) Euro area	-0.124 (0.663)	-0.384 (1.029)	-0.129 (0.169)	-0.049 (0.173)	-0.009 (0.203)	0.010 (0.213)
CCI Euro area	-0.192 (0.114)	-0.020 (0.324)	0.059 (0.152)	0.016 (0.175)	0.044 (0.199)	0.217 (0.014)
ICI	0.282 (NA)	0.154 (0.323)	0.120 (0.154)	0.253 (0.155)	0.008 (0.208)	
RCI	0.031 (0.732)	0.024 (1.073)	0.131 (0.169)	0.318 (0.169)		0.101 (0.190)
SCI	-0.053 (0.446)	-0.053 (0.586)	0.058 (0.155)	0.095 (0.177)	0.115 (0.214)	0.039 (0.225)
PS	0.022 (0.183)	0.041 (1.049)	-0.060 (0.156)	-0.062 (0.163)	-0.010 (0.175)	0.001 (0.194)
WS10M	-0.012 (0.785)		-0.041 (0.175)	-0.038 (0.173)	0.233 (0.256)	0.140 (0.025)
CLOUD_AMT	-0.008 (0.155)	0.001 (0.018)	0.055 (0.150)	0.216 (0.166)	0.022 (0.222)	0.128 (0.198)
T2M_RANGE	0.039 (0.327)	0.413 (0.990)	-0.051 (0.161)	0.168 (0.170)		0.175 (0.178)
WS10M_MAX	0.054 (0.560)	0.013 (0.639)	0.047 (0.153)	0.139 (0.183)	-0.007 (0.224)	0.199 (0.224)
WS10M_MIN	0.066 (0.374)		0.080 (0.151)	-0.023 (0.177)	-0.049 (0.185)	-0.245 (0.215)
PRECTOTCORR_SUM	-0.006 (0.637)	0.357 (0.443)	0.120 (0.154)	0.130 (0.161)	0.196 (0.262)	0.024 (0.182)
CDD EU	0.394 (0.658)	0.041 (0.566)	-0.050 (0.178)	-0.012 (0.174)		-0.002 (0.180)
CDD	0.029 (0.387)	0.003 (0.845)	0.018 (0.172)	-0.186 (0.184)	0.029 (0.245)	-0.004 (0.238)
Solar	-0.205 (0.335)		0.060 (0.167)	0.017 (0.169)	0.106 (0.207)	0.310 (0.014)
Hydro	0.282 (0.830)		0.098 (0.172)	0.207 (0.185)	0.050 (0.235)	
CLD	-0.293 (0.184)		0.108 (NA)	0.448 (0.181)	0.018 (NA)	0.153 (0.219)
Log-likelihood value	213.57		219.21		219.30	
AIC	-329.14		-330.42		-348.61	
BIC	-81.00		-56.97		-120.73	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA, then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Finally, in the optimal models for the $\hat{\lambda}(t)$, $\hat{\xi}(t)$ and $\hat{\nu}(t)$ ($\hat{\beta}(t)$) parameters the climate covariates have a significant enough coefficient to be contained in the model. So in the dynamic POT method, the climate covariates affect all the market indices. These models for the parameters will be used in constructing the VaR and ES.

5.3 Benchmark models

Now the benchmark models are considered. The parameters λ, ξ, and β do not depend on covariates in these two models. In Tables 6 and 7, the estimates are shown for the historical simulation (HS) Value-at-Risk and Expected Shortfall, respectively. It can be seen that the Value-at-Risk estimates are almost equal between the different market indices. However, the FTSE 100 has the lowest VaR and ES for all levels. The highest ES is estimated for the FTSE MIB for all levels. The rest of the market indices are estimated to be similar. The historical simulation method provides constant level estimates for the VaR and ES for the entire period.

Table 6: Historical simulation Value-at-Risk

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
VaR 90	0.036	0.035	0.037	0.038	0.033	0.025
VaR 95	0.050	0.049	0.050	0.050	0.048	0.037
VaR 99	0.091	0.087	0.095	0.081	0.093	0.070

Table 7: Historical simulation Expected Shortfall

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
ES 90	0.060	0.057	0.064	0.059	0.058	0.045
ES 95	0.078	0.073	0.083	0.075	0.077	0.060
ES 99	0.133	0.129	0.154	0.130	0.134	0.108

Table 8 shows the estimation results of the POT approach without covariate dependence. The AEX and DAX market indices are estimated to have almost the same tail distribution because the estimated ξ and β parameters are nearly the same. The other market indices do not have a tail distribution that is close to another tail distribution. Moreover, all the indices have almost the same estimated λ parameter, which is the intensity parameter for threshold exceedances. Only the IBEX 35 market index has a higher parameter. The log-likelihood, AIC, and BIC for the model evaluation are also shown in the table.

Table 8: Estimated POT benchmark model without covariate dependence

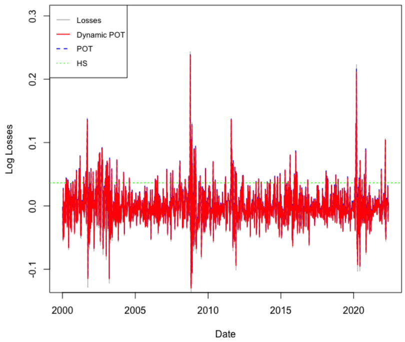
	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
ξ	0.216	0.322	0.308	0.209	0.217	0.376
	(0.106)	(0.121)	(0.118)	(0.090)	(0.100)	(0.132)
β	0.019	0.015	0.018	0.017	0.019	0.012
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Log-Likelihood	312.29	344.89	315.51	416.03	378.69	389.80
AIC	-620.58	-685.77	-627.03	-828.05	-753.37	-775.61
BIC	-610.46	-675.64	-616.90	-817.92	-743.25	-765.48
λ	0.098	0.102	0.100	0.124	0.118	0.110
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Log-Likelihood	-379.36	-390.89	-386.30	-447.64	-432.86	-411.01
AIC	760.72	783.78	774.60	897.28	867.72	824.02
BIC	758.72	781.78	772.60	895.28	865.72	822.02

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid.

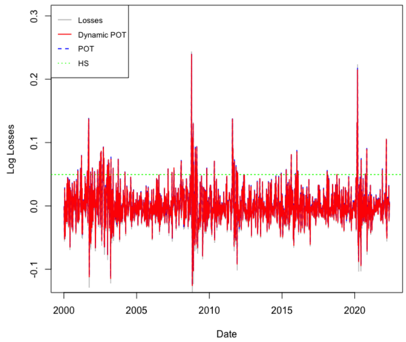
5.4 Risk Measures

Figure 1 shows the estimated VaR for different probability levels. The chosen probability levels are often used in risk measurement. The general pattern is visible in the figure since a higher probability level needs a higher VaR estimation. Moreover, it can be seen that the dynamic POT approach is very close to the non-dynamic POT approach for the VaR. Only for the 99% probability level VaR, a slight deviation is noticeable for the DAX market index. This picture is visible for all the different market indices. The historical simulation is a constant line by construction. So, from the visual presentation, the standard POT approach and dynamic POT are very close in performance for the VaR. Statistical tests are used to examine their accuracy.

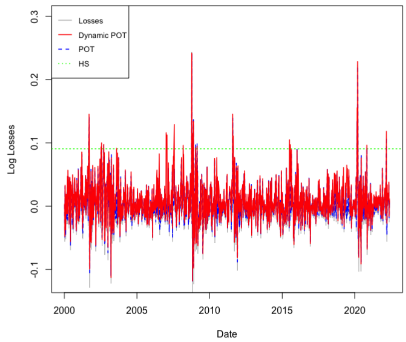
Figure 1: Value-at-Risk for the DAX market index



(a) Value-at-Risk at the 90% probability level



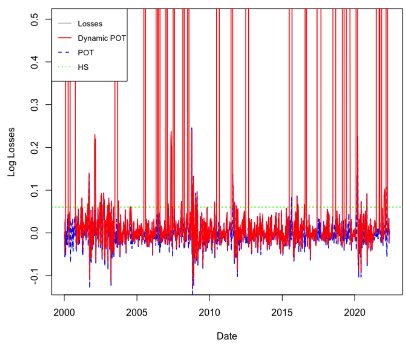
(b) Value-at-Risk at the 95% probability level



(c) Value-at-Risk at the 99% probability level

The ES estimated with the dynamic POT approach, shown in Figure 2, is not informative. The $\hat{\xi}(t)$ is sometimes estimated to be above 1. According to the definition used in (13), the ES is estimated to be ∞ in this case. Only the 90% probability level is shown, because this is the case for all the probability levels for all the market indices. Therefore the ES is not used in further analysis.

Figure 2: Expected Shortfall at the 90% probability level for the DAX market index



5.4.1 Model Accuracy

This section discusses the statistical tests for the VaR models. The first test that was performed was the Kupiec POF test. The test's null hypothesis is that the VaR model is accurate in terms of exceedance proportion according to its probability level. The significance level of the test is equal to the probability level of the estimated VaR models. Table 9 shows the estimated test statistics. The historical simulation VaR does not reject the null hypothesis by construction. Some dynamic VaR models are statistically accurate in terms of their exceedance proportion. Namely, the CAC 40, AEX, and FTSE 100 at the 90% probability level. The FTSE MIB at the 95% probability level and the AEX at the 99% probability level. Moreover, for the non-dynamic POT models, none of the VaR models is statistically accurate. It can be concluded that the historical simulation models are preferred according to this test. However, for some market indices, the dynamic POT models can also be used.

Table 9: Kupiec Proportion of Failing (POF) test

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
HS VaR 90	0.000	0.000	0.000	0.000	0.000	0.000
HS VaR 95	0.005	0.005	0.005	0.005	0.005	0.006
HS VaR 99	0.008	0.008	0.008	0.008	0.008	0.009
Dynamic POT VaR 90	59.113*	0.956	13.955*	3.312*	1.637	0.937
Dynamic POT VaR 95	22.076*	29.117*	1.698	27.232*	13.749*	18.971*
Dynamic POT VaR 99	16.561*	15.561*	24.187*	16.561*	0.008	12.382*
POT VaR 90	180.352*	165.294*	165.294*	165.294*	156.128*	160.445*
POT VaR 95	80.022*	71.338*	67.393*	75.536*	75.536*	84.751*
POT VaR 99	12.399*	12.399*	12.399*	12.399*	12.399*	12.382*

*: The null hypothesis (H_0) of an accurate VaR model is rejected

Table 10 shows the result of the second VaR test. The null hypothesis is the same as the previous test, but in terms of time until the first VaR exceedance. Moreover, again the significance level is used that corresponds to the probability level of the estimated model. Evidently, if the VaR has no exceedance, then the model is not accurate. The table shows that all VaR models for the 99% probability level are statistically accurate according to the corresponding significance level of the test. However, compared to the previous test in Table 9, not all historical simulation VaR models are accurate. Furthermore, more dynamic POT VaR models are statistically accurate compared to the non-dynamic POT models. The preferred model differs per probability level for each market index.

Table 10: Kupiec Time until First Failure (TFF) test

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
HS VaR 90	0.083	4.605*	0.083	4.605*	4.605*	2.043
HS VaR 95	1.214	5.991*	3.973*	0.000	1.214	3.321
HS VaR 99	0.016	0.013	0.013	0.013	0.013	0.013
Dynamic POT VaR 90	0.207	3.153*	0.128	1.208	0.207	2.043
Dynamic POT VaR 95	1.214	3.973*	3.973*	3.973*	7.672*	2.011
Dynamic POT VaR 99	4.145	0.013	4.145	4.145	4.145	4.129
POT VaR 90	12.183*	12.183*	12.183*	12.183*	12.183*	12.183*
POT VaR 95	4.053*	4.053*	4.053*	4.053*	4.053*	38.524*
POT VaR 99	4.145	4.145	4.145	4.145	4.145	4.129

*: The null hypothesis (H_0) of an accurate VaR model is rejected

Finally, the last test is the VaR duration test, which tests whether the VaR exceedances are independent. Also in this test, the significance level corresponds with the probability level of the estimated VaR model. VaR models with no exceedances cannot be tested with this test. Table 11 shows that most VaR models do not have independent VaR exceedances. None of the historical simulation models have independent exceedances. However, for a few POT approach models the null hypothesis is not rejected at the corresponding significance level. Most notably is that for all market indices, the non-dynamic POT models for the 95% probability level have statistically independent VaR exceedances.

Table 11: Value-at-Risk duration test

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
HS VaR 90	0.015*	0.056	0.011*	0.018*	0.009*	0.023*
HS VaR 95	0.000*	0.000*	0.000*	0.008*	0.000*	0.009*
HS VaR 99	0.003*	0.029*	0.002*	0.003*	0.025*	0.005*
Dynamic POT VaR 90	0.002*	0.923	0.000*	0.000*	0.260	0.004*
Dynamic POT VaR 95	0.096	0.021*	0.000*	0.000*	0.000*	0.088
Dynamic POT VaR 99	1**	1**	0.000*	1**	0.000*	0.016*
POT VaR 90	0.031*	0.049*	0.002*	0.003*	0.002*	0.010*
POT VaR 95	0.238	0.307	0.092	0.134	0.098	0.059
POT VaR 99	0.016*	0.016*	0.016*	0.016*	0.016*	0.016*

*: The null hypothesis (H_0) that the VaR exceedances are independent is rejected. **: The VaR model did not have enough exceedances to evaluate the test statistic.

Various tests are used to evaluate the effectiveness of VaR models, with each test emphasizing a distinct feature. To draw a comprehensive conclusion about their performance and accuracy, all tests must be considered, including the null hypotheses. The combined results indicate that there is no definitive winner among the models. The model of choice depends on the market index and its accuracy. However, it can be concluded that the dynamic POT, which takes into account climate covariates, performs just as well as the non-dynamic POT VaR model with respect to accuracy.

5.5 Influence of Climate covariates

Table 12 shows the estimation results from the dynamic POT approach with the same penalization methods chosen for the VaR construction. In the case of the DAX market index, these were Lasso penalization for the $\hat{\lambda}(t)$ and the ElasticNet penalization for the $\hat{\xi}(t)$ and $\hat{\nu}(t)$. The climate covariates were excluded from this estimation. The same model performance measures are used to see if the model without climate covariates outperforms the original dynamic POT estimation approach. The likelihood, AIC, and BIC criterion of the $\hat{\lambda}(t)$ parameter all favor the model without climate covariates. The same conclusion holds for the estimation of the $\hat{\xi}(t)$ and $\hat{\beta}(t)$ parameters. This indicates that including the climate covariates lowers the model fit for the DAX market index. This conclusion holds for all the market indices based on the criteria. So, for all the market indices, the influence of climate variables is not beneficial for the model's overall fit. It is more optimal only to include the macroeconomic covariates in the model.

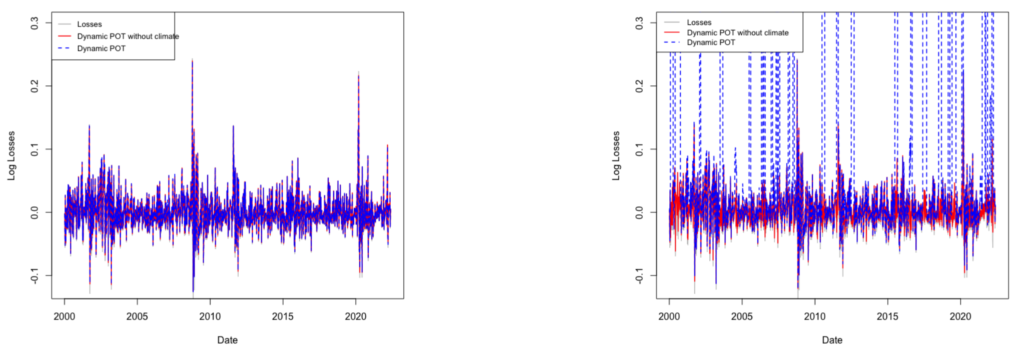
Table 12: DAX coefficient estimates without climate covariates

	$\hat{\lambda}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	-2.286 (0.094)	0.478 (0.192)	-2.984 (0.172)
IP (Change) EU28	-0.029 (0.105)	-0.002 (0.039)	0.023 (0.189)
IP (Change)	-0.074 (0.134)	0.143 (0.169)	-0.003 (0.228)
HICP (Change) Euro area	0.057 (0.101)		0.022 (0.251)
HICP (Change)	-0.069 (0.147)		0.009 (0.184)
Unemp (Change) Euro area		0.123 (0.199)	-0.036 (0.170)
Unemp (Change)		0.010 (0.227)	0.021 (0.215)
PPI (Change) EU28	-0.237 (0.118)	-0.008 (0.180)	-0.068 (0.304)
PPI (Change)	-0.011 (0.125)	0.087 (0.282)	0.095 (0.232)
12m rate Euro	0.354 (0.131)	0.006 (0.169)	
Exp TV (Change) Euro area	0.070 (0.126)	0.007 (0.235)	-0.070 (0.014)
Imp TV (Change) Euro area			
CCI Euro area	-0.009 (0.125)	0.001 (0.024)	-0.005 (0.016)
ICI		0.047 (0.198)	0.113 (0.145)
RCI	-0.110 (0.110)	0.010 (0.241)	0.121 (0.192)
SCI		0.096 (NA)	
Log-likelihood	-395.98	230.22	
AIC	813.96	-408.43	
BIC	869.66	-276.77	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA, then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Figure 3 shows the constructed VaR estimations based on the estimation results without including the climate covariates. According to the VaR estimation in the figure, including the climate covariates does not seem to have a significant influence. The performance appears graphically very similar, valid for all market indices. However, the ES estimation can still not be used in this setting. This is because the $\hat{\xi}(t)$ is still estimated to be above 1 for some points in the period, both with and without climate covariates. This is why the ES is also not analyzed further without climate covariates. Therefore, although the inclusion of climate covariates seems to lower the model's fit, no significant differences are visible between the models graphically.

Figure 3: Value-at-Risk and Expected Shortfall without Climate covariates



(a) Value-at-Risk at the 95% probability level

(b) Expected Shortfall at the 95% probability level

5.5.1 Model Accuracy

Table 13 shows the results of the statistical test to assess the statistical accuracy and assumptions for the estimated VaR models. The tests have the same null hypotheses as in Tables 9-11. Also, in these tests, the significance level corresponds to the probability level of the estimated VaR models. Here we only evaluated the VaR models for the 95% probability level. The results in Table 13 show that the VaR model for the CAC 40 market index is the only statistically accurate model in terms of failing proportion. The FTSE MIB market index was the only accurate model for the model with climate covariates. Moreover, the Kupiec TFF test results differ if the climate covariates are not included. Of all the models considered, only the estimated VaR model for the FTSE 100 market index has independent VaR exceedances. These results show that omitting the climate covariates does not automatically increase the statistical accuracy of the dynamic POT VaR models.

Table 13: Model performance test results

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
POF test	14.696*	3.002	12.591*	33.156*	29.117*	35.250*
TFF test	3.973*	4.053*	3.973*	0.692	1.214	4.053*
Duration test	0.001*	0.000*	0.000*	0.019*	0.009*	0.187

*: The null hypothesis (H_0) of the test is rejected

5.6 Impact of Climate agreements

Table 14 shows the estimated coefficients for the climate agreement dummy variable and the corresponding performance measures. In the previous section, it was concluded that including the climate covariates decreases the model fit. Therefore, the impact of the climate agreement dummy on the VaR will be examined.

Using the climate dummy's coefficients, we can evaluate the difference in estimated VaR for the different market indices. The inclusion climate agreement dummy variable decreases the fit of the models compared to the dynamic POT models with climate covariates.

Table 14: Climate agreement dummy variable coefficient estimates for the different parameters

	DAX	CAC 40	FTSE MIB	IBEX 35	AEX	FTSE 100
$\hat{\lambda}(t)$	0.001 (0.017)	0.000 (0.010)	0.000 (0.014)	-0.133 (0.475)	-0.240 (0.190)	-0.099 (0.187)
$\hat{\xi}(t)$	0.265 (NA)	0.028 (NA)	0.028 (NA)	0.000 (0.068)	-0.004 (NA)	0.000 (0.295)
$\hat{\nu}(t)$	-0.165 (0.189)	-0.120 (0.014)	-0.200 (0.251)	-0.203 (0.110)	-0.003 (0.010)	-0.034 (0.451)
Log-likelihood $\hat{\lambda}(t)$	-406.86	-422.64	-416.12	-476.47	-450.46	-445.28
AIC $\hat{\lambda}(t)$	855.73	885.28	878.23	1002.95	958.92	946.56
BIC $\hat{\lambda}(t)$	962.07	986.56	994.70	1129.54	1105.77	1088.33
Log-likelihood ($\hat{\xi}(t)$, $\hat{\nu}(t)$)	221.74	244.09	228.16	328.92	291.19	275.54
AIC ($\hat{\xi}(t)$, $\hat{\nu}(t)$)	-345.48	-400.18	-358.32	-565.85	-490.38	-459.07
BIC ($\hat{\xi}(t)$, $\hat{\nu}(t)$)	-97.35	-177.37	-110.18	-332.91	-257.44	-226.17

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA, then the estimated standard error is negative, which is impossible.

From equation (13), it can be determined that the parameters have a positive correlation with the estimated VaR. An higher $\hat{\lambda}$, $\hat{\xi}$ and $\hat{\beta}$ all lead to an higher estimated VaR.

For the DAX market index, the estimated VaR at the 95% probability level after the signing of the climate agreement, when the dummy variable is 1, is 0.032 higher compared to the period before the climate agreement. However, for this value, it is assumed that the covariates are at their mean value and $\hat{\lambda}(t)$ is scaled to unity. This equals that $\hat{\xi}$ and $\hat{\nu}$ are equal to their intercept value and $\hat{\lambda}(t) = 1$. This ensures we do not get an invalid value in (13). The values for the CAC 40, FTSE MIB, IBEX 35, AEX, and FTSE 100 are -0.025, -0.038, -0.063, -0.009, and -0.015, respectively. So, only for the DAX, the risk increases after the climate agreement. For the other market indices, the estimated VaR at the 95% probability level decreases. This indicates that the climate agreement is estimated to have a risk-decreasing effect on 5 of the 6 market indices.

6 Conclusion and Discussion

In conclusion, this thesis researched if climate and macroeconomic covariates could be used to predict better market risk for six different market indices in Europe. (DAX, CAC 40, FTSE MIB, IBEX 35, AEX and FTSE 100) A dynamic POT approach estimates parameters in the Poisson process and GPD distribution as a linear relation of the different covariates. We used a penalized likelihood approach for the estimation. Furthermore, different regularization methods were used to restrict the number of parameters added to the model, and the best method was selected. Finally, we estimate VaR and ES models as risk measures. Various tests are used to assess the accuracy and performance of the models. This procedure was used to answer the research questions.

This study's findings suggest that covariates significantly affect estimated market risk for all market indices, with statistically accurate VaR models constructed for some market indices when including climate and macroeconomic covariates. However, the ES models were unsuitable for use in this research setting. Notably, excluding climate covariates improved model fit for all the different climate covariates, indicating that the macroeconomic covariates were more informative than the climate covariates. However, the omission of the climate covariates did not automatically increase the statistical accuracy of the VaR models.

The discrepancy between the initial expectation about the climate covariates and the evidence from the data could be due to several reasons. One important reason is that the chosen covariates may not be good indicators for large-scale climate impacts. Moreover, climate covariates alone may not capture the indirect effects of climate impacts on market risk, and additional factors may need to be considered to understand the relationship entirely.

Finally, an analysis was conducted on the Paris climate agreement's influence, revealing a decrease in risk for 5 out of 6 markets. The signing of the agreement resulted in a lower estimated VaR at the 95% probability level for all the selected market indices except for the DAX market index. This discovery reinforces the importance of signing the agreement, as it leads to a lower estimated VaR for most markets. It is undeniable that the Paris climate agreement had a positive effect on market risk in this particular context.

6.1 Limitations and Potential Improvements

There are a few things that could be improved in this research. The first limitation is that this research is limited to this data period and market indices. The results are limited to the context of this research and thus have low external validity.

The second limitation is that some assumptions made in the research might need to be revised or be more complex. For example, the parameters in the Poisson process and GPD distribution depend only linearly on the different covariates. However, this assumption may not hold since the real effect is not linear.

Another limitation of the research is that the covariates used in the models are not tested for stationarity within the scope of the study. Stationarity can lead to biased and unreliable results. Therefore, the covariates' potential non-stationarity might affect the results' validity. Additional research could address the potential stationarity of the covariates and incorporate appropriate methods to address non-stationarity if necessary.

The final limitation is the uncertainty in the data. There are two main limitations in the data selection. The first is that we matched the data frequency to weekly observations. This might remove some of the information that is present in the data. The second is that there may be more informative variables than the data used in this research. These variables may contain more information and are more critical in the linear relation with the parameters.

Furthermore, other assumptions might need to be more relaxed or realistic. Finally, these assumptions need more research to assess if they are valid within the scope of the study.

6.2 Future Research

Future research in this area could address the limitations of this study by exploring the use of alternative data frequencies. For example, using daily or intra-day data may provide more detailed information on the relationship between covariates and market risk, which may help improve the accuracy of risk prediction models. Additionally, future research could consider alternative covariates that may be more informative than the climate and macroeconomic variables considered in this study. For example, social and political factors may significantly drive market risk and could be incorporated into the modeling approach.

Another area for future research is to utilize more sophisticated modeling approaches that allow for more flexible and realistic parameterizations. For example, non-linear relationships between the covariates and market risk may be more appropriate than the linear relationships assumed in this study. Additionally, machine learning algorithms and deep learning techniques may offer a more flexible and powerful approach to modeling complex relationships between covariates and market risk.

Finally, further research could investigate the impact of other climate-related events and policies on market risk. For example, the effect of extreme weather events such as hurricanes, floods, and droughts on market risk may be significant and should be considered in future studies. Furthermore, other climate policies, such as carbon taxes, renewable energy subsidies, and emissions trading schemes, significantly impact market risk and should be explored. By considering these factors, future research could provide a more comprehensive understanding of the relationship between climate and market risk, which may have important implications for risk management and policy-making.

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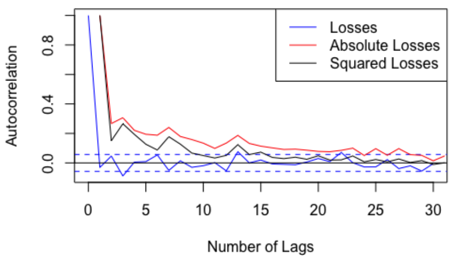
A Appendix 1: Market Index Description

A.1 Stock Indices Description

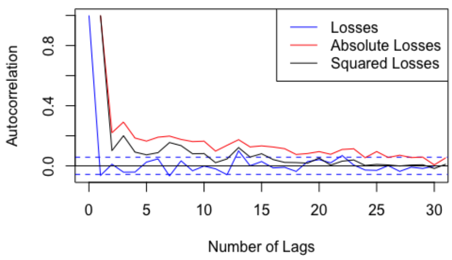
Table 15: Indices Description

Indices	Data Period	Place of origin	Definition
DAX	03/01/2000-25/05/2022	Germany, Frankfurt am Main	A market index that consists of 40 major German blue chip companies trading on the Frankfurt Stock Exchange
CAC 40	03/01/2000-25/05/2022	France, Paris	A market index that represents a capitalization-weighted measure of the 40 most largest stocks on the Euronext Paris
IBEX 35	03/01/2000-25/05/2022	Spain, Madrid	A market cap weighted index containing the 35 most liquid stocks traded on Bolsa de Madrid
FTSE MIB	03/01/2000-25/05/2022	Italy, Milan	A market index that consists of the 40 most liquid stocks on the Borsa Italiana
AEX	03/01/2000-25/05/2022	the Netherlands, Amsterdam	A market index that contains 25 of the most liquid stocks\ traded on the Euronext Amsterdam
FTSE 100	03/01/2000-25/05/2022	United Kingdom, London	A market index that contains the 100 largest (market cap) companies traded on the London Stock Exchange

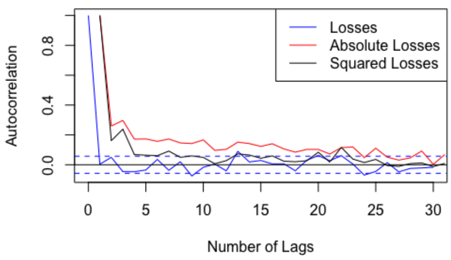
Figure 4: Autocorrelation plots for the different Indices



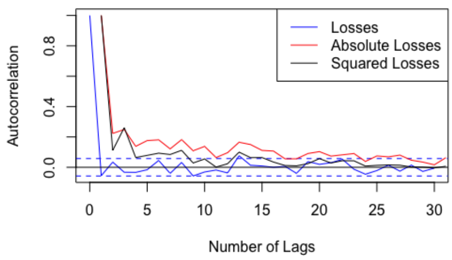
(a) DAX



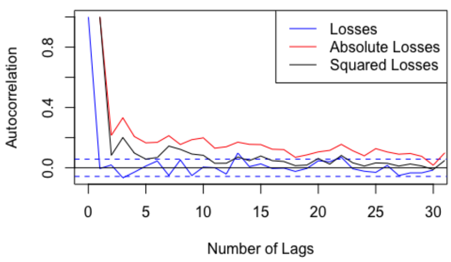
(b) CAC 40



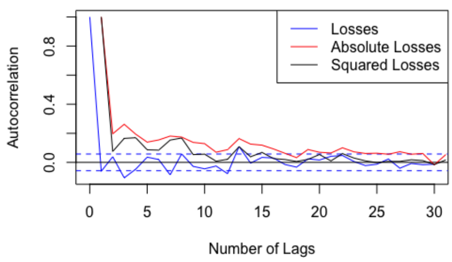
(c) FTSE MIB



(d) IBEX 35



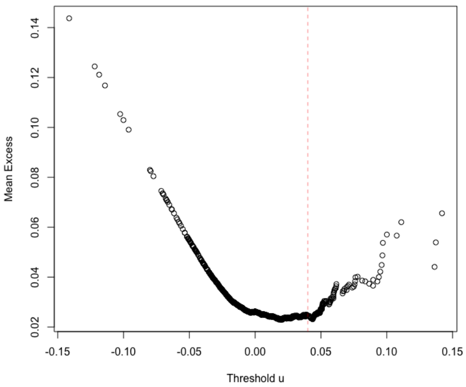
(e) AEX



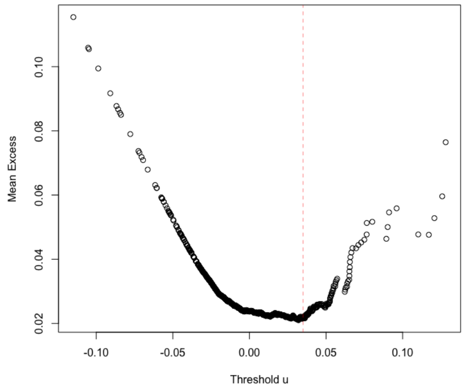
(f) FTSE 100

A.2 Threshold Selection

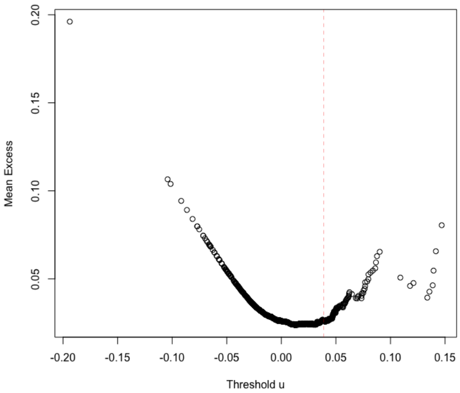
Figure 5: Mean Residual Life plots



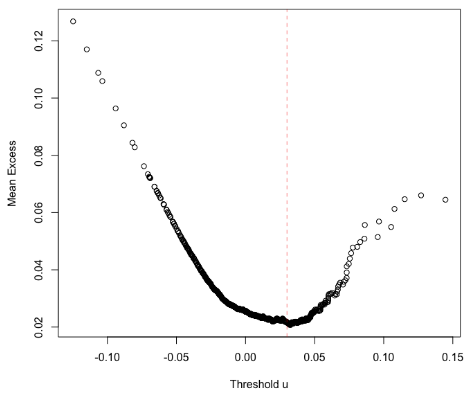
(a) DAX



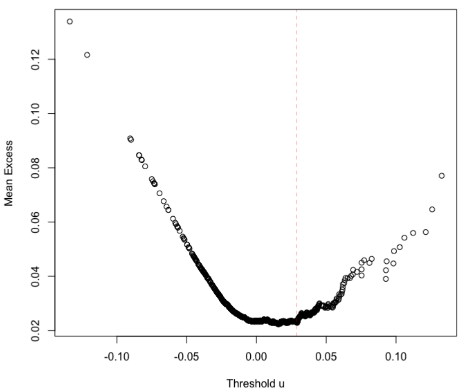
(b) CAC 40



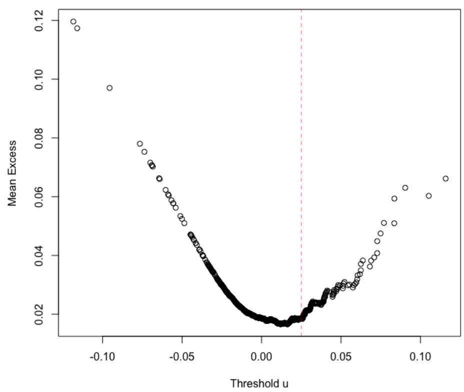
(c) FTSE MIB



(d) IBEX 35



(e) AEX



(f) FTSE 100

B Appendix 2: Results Market Indices

B.1 Methodology results CAC 40

Table 16: Dynamic POT for CAC index describing the $\hat{\lambda}(t)$ parameter in different regularisation methods

	Lasso	Ridge	ElasticNet
Constant (Intercept)	-2.235 (0.093)	-2.009 (0.076)	-2.119 (0.083)
IP (Change)	0.017 (0.113)	0.011 (0.091)	0.078 (0.098)
HICP (Change) Euro area	0.003 (0.095)	0.185 (0.117)	0.081 (0.093)
HICP (Change)		-0.084 (0.112)	-0.241 (0.100)
Unemp (Change)	-0.326 (0.109)	-0.203 (0.089)	
PPI (Change) Euro area	-0.083 (0.120)	0.034 (0.127)	-0.121 (0.153)
PPI (Change)	0.009 (0.133)	-0.122 (0.128)	0.021 (0.154)
Imp TV (Change) Euro area		0.020 (0.101)	-0.080 (0.115)
CCI	-0.184 (0.165)	-0.154 (0.115)	-0.224 (0.134)
ICI	-0.024 (0.127)	-0.125 (0.098)	-0.010 (0.113)
RCI	0.004 (0.123)	0.020 (0.094)	0.029 (0.107)
PS	0.005 (0.116)	0.126 (0.092)	0.154 (0.097)
WS10M	0.005 (0.116)	0.147 (0.104)	0.053 (0.121)
CLOUD_AMT	0.069 (0.133)	0.213 (0.105)	0.163 (0.113)
T2M_RANGE	0.016 (0.123)	-0.090 (0.096)	0.008 (0.105)
WS10M_MAX	0.032 (0.133)	0.109 (0.099)	0.114 (0.110)
WS10M_MIN	0.025 (0.091)	0.044 (0.075)	0.136 (0.079)
PRECTOTCORR_SUM	-0.090 (0.117)	-0.077 (0.092)	0.001 (0.021)
ALLSKY_SFC_SW_DWN	0.221 (0.146)	0.228 (0.111)	0.161 (0.124)
CDD	0.014 (0.103)	0.167 (0.073)	0.119 (0.079)
Hydro	0.130 (0.106)	0.065 (0.087)	0.057 (0.096)
CLD	0.341 (0.140)	0.087 (0.098)	0.027 (0.111)
CO2		0.224 (0.106)	0.259 (0.122)
ND-GAIN	0.224 (0.173)	0.145 (0.114)	0.082 (0.134)
ND-GAIN (change)	0.456 (0.152)	0.306 (0.108)	0.297 (0.125)
Log-likelihood value	-420.60	-429.21	-426.52
AIC	885.21	902.43	901.04
BIC	996.62	1013.83	1022.57

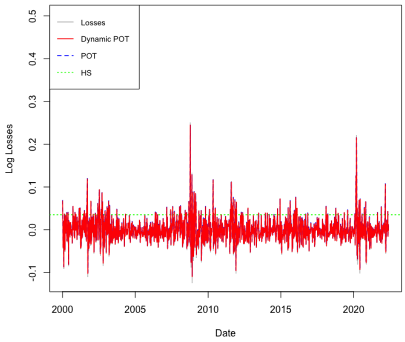
Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Table 17: Dynamic Peak-over-Threshold for CAC 40 index describing the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameter for different regularisation methods

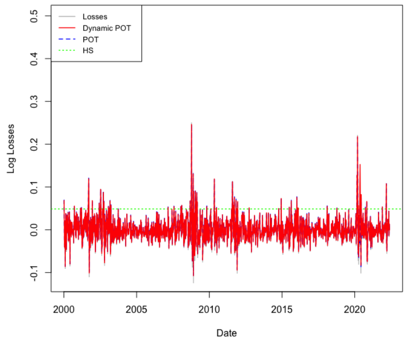
	Lasso		Ridge		ElasticNet	
	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	1.178 (0.440)	-3.141 (0.424)	0.653 (0.153)	-2.672 (0.166)	0.900 (0.222)	-2.848 (0.251)
IP (Change)	0.001 (0.017)	-0.096 (0.162)	-0.056 (0.102)	-0.053 (0.159)	0.070 (0.333)	0.004 (0.193)
HICP (Change) Euro area	-0.016 (0.142)		0.051 (0.155)	0.057 (0.144)	0.006 (0.409)	-0.001 (0.146)
HICP (Change)	0.361 (0.386)		0.094 (0.161)	0.035 (0.182)	-0.014 (0.254)	0.020 (0.015)
Unemp (Change)		0.083 (0.380)	0.041 (0.149)	0.140 (0.178)	0.007 (0.667)	
PPI (Change) Euro area	0.016 (0.292)	0.001 (0.018)	0.136 (0.155)	0.181 (0.158)		0.015 (0.204)
PPI (Change)	-0.110 (0.352)	0.004 (0.157)	0.047 (0.166)	0.113 (0.185)		0.044 (0.249)
Imp TV (Change) Euro area	-0.058 (0.176)	-0.020 (0.187)	-0.021 (0.146)	-0.015 (0.173)	0.161 (0.229)	-0.006 (0.387)
CCI	0.162 (0.359)	-0.198 (0.327)	-0.002 (0.167)	0.111 (0.158)	0.004 (0.313)	0.020 (0.209)
ICI		-0.004 (0.282)	0.169 (0.149)	-0.018 (0.171)	0.031 (0.339)	-0.016 (0.254)
RCI	0.116 (0.405)	0.004 (0.317)	-0.017 (0.112)	0.066 (0.160)	0.001 (0.024)	-0.002 (0.193)
PS	-0.036 (0.557)	0.116 (0.389)	0.019 (0.145)	0.238 (0.158)	0.001 (0.022)	0.222 (0.167)
WS10M	0.067 (NA)	0.002 (0.032)	0.015 (0.171)	-0.086 (0.175)		-0.007 (0.181)
CLOUD_AMT	0.201 (0.356)	0.234 (0.297)	-0.013 (0.164)	-0.067 (0.163)		0.269 (0.014)
T2M_RANGE	0.215 (0.296)		0.046 (0.147)	0.279 (0.173)	0.199 (0.474)	
WS10M_MAX	0.615 (NA)	0.164 (NA)	-0.010 (0.164)	0.041 (0.171)	-0.002 (0.034)	0.012 (0.200)
WS10M_MIN	-0.019 (0.274)	0.064 (0.182)	-0.079 (0.110)	-0.127 (0.161)	0.046 (0.199)	0.116 (0.014)
PRECTOTCORR_SUM	-0.083 (0.421)	0.370 (0.314)	-0.098 (0.165)	0.266 (0.140)	-0.018 (0.298)	
ALLSKY_SFC_SW_DWN	0.338 (0.372)	0.038 (0.372)	0.056 (0.163)	-0.103 (0.162)	0.256 (0.298)	0.002 (0.018)
CDD	0.014 (0.191)	-0.013 (0.307)	0.050 (0.174)	-0.101 (0.181)	0.027 (0.291)	
Hydro		-0.126 (0.380)	-0.057 (0.143)	-0.072 (0.182)		-0.023 (0.030)
CLD	0.045 (0.527)		0.080 (0.157)	0.028 (0.168)	0.051 (0.391)	0.065 (0.259)
CO2	0.003 (0.466)	-0.007 (0.426)	-0.044 (0.154)	-0.155 (0.180)	0.009 (0.323)	-0.005 (0.260)
ND-GAIN	0.520 (0.603)	0.065 (0.524)	0.088 (0.180)	0.063 (0.171)	0.078 (0.244)	0.138 (0.210)
ND-GAIN change	0.300 (0.618)	-0.130 (0.448)	-0.002 (NA)	-0.229 (0.173)	-0.148 (NA)	-0.160 (0.232)
Log-likelihood value	237.09		236.77		243.59	
AIC	-388.18		-373.55		-405.17	
BIC	-170.43		-120.35		-197.55	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

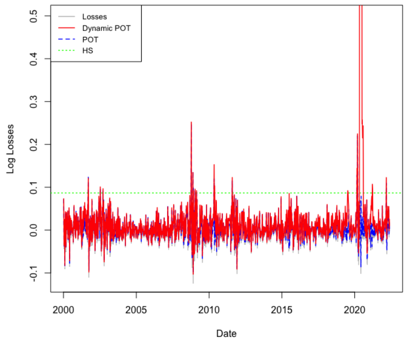
Figure 6: Value-at-Risk for the CAC 40 market index



(a) Value-at-Risk at the 90% probability level



(b) Value-at-Risk at the 95% probability level



(c) Value-at-Risk at the 99% probability level

Figure 7: Expected Shortfall at the 90% probability level for the CAC 40 market index

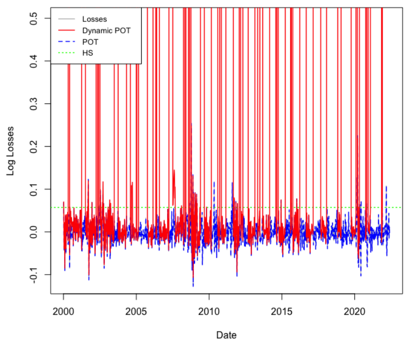
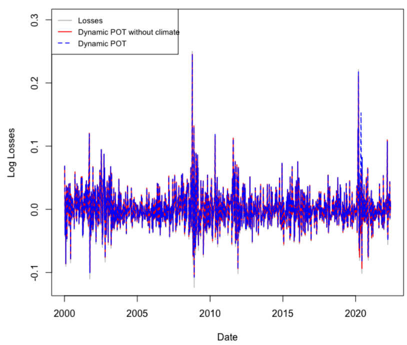


Table 18: CAC 40 coefficient estimates without climate covariates

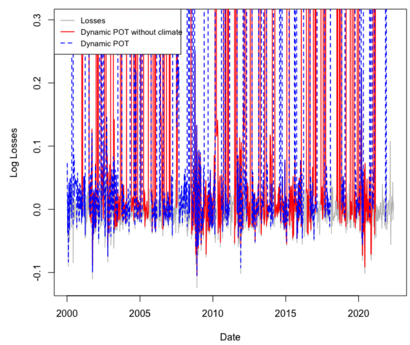
	$\hat{\lambda}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	-2.440 (0.108)	0.924 (0.058)	-2.958 (NA)
IP (Change) EU	-0.261 (0.119)	0.084 (NA)	-0.002 (0.145)
IP (Change) Euro area	0.213 (0.310)	-0.106 (0.201)	0.003 (NA)
IP	0.023 (0.161)	0.017 (NA)	
IP (Change)	-0.016 (0.247)	0.012 (0.129)	
HICP (Change) Euro area	0.001 (0.015)		-0.054 (0.014)
HICP (Change)	0.036 (0.105)	0.309 (NA)	0.275 (0.177)
Unemp (Change) EU	0.016 (0.214)	-0.033 (0.148)	-0.056 (0.078)
PPI (Change) Euro area		0.057 (NA)	0.004 (0.174)
PPI (Change)	0.118 (0.214)	-0.011 (NA)	0.111 (NA)
Long rate Euro area	0.534 (0.152)		-0.063 (0.172)
Exp TV (Change) Euro area	-0.110 (0.158)	0.054 (NaN)	
Imp TV (Change) Euro area		-0.010 (0.238)	-0.075 (0.014)
CCI	-0.156 (0.117)		-0.110 (0.165)
ICI		0.268 (NA)	0.204 (0.147)
RCI	-0.007 (0.121)	-0.011 (NA)	
Log-likelihood	-425.96	243.62	
AIC	877.93	-437.24	
BIC	943.76	-310.64	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Figure 8: Value-at-Risk and Expected Shortfall without Climate covariates



(a) Value-at-Risk at the 95% probability level



(b) Expected Shortfall at the 95% probability level

B.2 Methodology results FTSE MIB

Table 19: Dynamic POT for FTSE MIB index describing the $\hat{\lambda}(t)$ parameter in different regularisation methods

	Lasso	Ridge	ElasticNet
Constant (Intercept)	-2.263 (0.096)	-2.029 (0.077)	-2.124 (0.083)
IP Euro area	-0.003 (0.103)	0.121 (0.100)	0.003 (0.104)
IP (Change) Euro area		-0.149 (0.138)	
IP (Change)		0.121 (0.110)	-0.101 (0.118)
HICP (Change) EU		0.186 (0.118)	0.018 (0.142)
HICP (Change)		-0.134 (0.116)	-0.037 (0.132)
Unemp (Change)	-0.046 (0.095)	0.071 (0.096)	0.002 (0.101)
PPI (Change) EU28		-0.096 (0.087)	-0.057 (0.098)
PPI (Change)	0.389 (0.130)	0.023 (0.097)	0.004 (0.110)
Long rate		0.223 (0.113)	0.206 (0.111)
Exp TV (Change) Euro area	-0.003 (0.245)	-0.121 (0.149)	-0.015 (0.113)
Imp TV (Change) Euro area	-0.013 (0.242)	0.065 (0.139)	
CCI	-0.014 (0.135)	-0.060 (0.116)	-0.003 (0.135)
RCI		-0.097 (0.109)	
SCI	-0.006 (0.131)	-0.057 (0.115)	-0.142 (0.115)
PS	0.133 (0.142)	0.034 (0.104)	0.002 (0.112)
WS50M	0.006 (0.147)	0.011 (0.118)	-0.006 (0.122)
CLOUD_AMT	0.117 (0.143)	0.066 (0.105)	0.040 (0.112)
T2M_RANGE	0.012 (0.106)	-0.014 (0.088)	
WS10M_MAX	-0.002 (0.020)	0.029 (0.090)	
WS10M_MIN	0.101 (0.121)	-0.105 (0.087)	-0.003 (0.093)
WS50M_MIN		0.080 (0.090)	0.013 (0.099)
PRECTOTCORR_SUM		0.042 (0.099)	0.083 (0.105)
CDD	0.085 (0.156)	0.019 (0.117)	
Solar	0.142 (0.166)	0.104 (0.114)	0.160 (0.122)
Hydro	0.138 (0.119)	0.075 (0.097)	
Wind	0.266 (0.175)	0.081 (0.118)	0.111 (0.133)
CLD	0.204 (0.108)	0.167 (0.089)	0.068 (0.091)
CO2	-0.040 (0.104)	-0.026 (0.113)	-0.004 (0.120)
ND-GAIN (change)	-0.001 (0.017)	0.058 (0.120)	
Log-likelihood value	-417.77	-424.49	-415.76
AIC	877.54	890.97	875.53
BIC	983.88	997.31	986.93

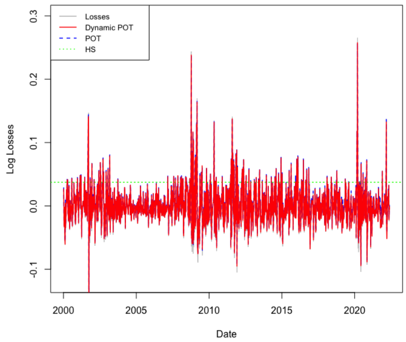
Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Table 20: Dynamic POT for FTSE MIB index describing the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameter in different regularisation methods

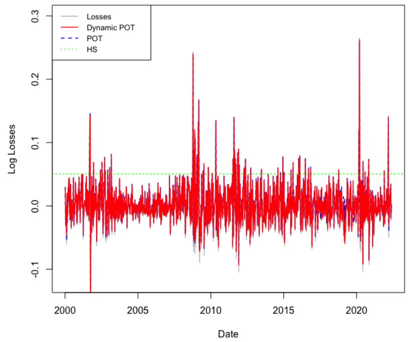
	Lasso		Ridge		ElasticNet	
	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	0.812 (0.738)	-2.922 (0.427)	0.612 (0.151)	-2.457 (0.177)	0.598 (0.178)	-2.750 (0.015)
IP Euro area	-0.017 (0.408)	-0.018 (0.363)	0.192 (0.133)	0.076 (0.161)	0.003 (0.176)	
IP (Change) Euro area	0.014 (0.802)	-0.003 (0.601)	-0.012 (0.105)	-0.027 (0.185)		0.001 (0.016)
IP (Change)		-0.038 (0.566)	0.035 (0.003)	0.059 (0.187)	0.065 (0.204)	-0.012 (0.022)
HICP (Change) EU	-0.150 (0.246)	-0.054 (0.376)	0.053 (0.155)	0.153 (0.253)	0.003 (NA)	
HICP (Change)	0.090 (0.464)	-0.075 (0.424)	-0.014 (0.138)	0.046 (0.174)		0.146 (0.014)
Unemp (Change)	0.219 (0.667)		0.089 (0.136)	-0.102 (0.172)	0.111 (0.160)	-0.063 (0.113)
PPI (Change) EU28	0.650 (0.416)	-0.094 (0.446)	0.110 (0.132)	-0.028 (0.172)	0.130 (0.094)	-0.013 (0.213)
PPI (Change)	-0.088 (0.570)	0.004 (0.601)	0.026 (0.172)	0.089 (0.169)	-0.008 (0.361)	0.018 (0.176)
Long rate	-0.290 (0.290)	0.002 (0.020)	-0.174 (0.148)	-0.234 (0.179)		-0.052 (0.216)
Exp TV (Change) Euro area	0.025 (1.007)		0.030 (0.159)	-0.023 (0.181)	0.067 (0.186)	0.070 (0.198)
Imp TV (Change) Euro area	0.046 (0.771)	0.001 (0.020)	0.023 (0.157)	0.181 (0.188)	0.018 (0.209)	0.044 (0.239)
CCI	-0.019 (0.766)		0.133 (0.157)	0.271 (0.185)	0.179 (0.214)	0.101 (0.217)
RCI	0.068 (1.020)	-0.129 (0.557)	0.128 (0.168)	0.354 (0.184)	0.098 (0.206)	0.343 (0.206)
SCI	0.073 (0.237)		0.052 (0.157)	0.081 (0.176)	0.090 (0.220)	
PS	-0.214 (0.585)		0.133 (0.148)	0.375 (0.178)		0.127 (0.016)
WS50M	-0.227 (0.748)	0.002 (0.035)	-0.066 (0.148)	0.139 (0.174)		0.186 (0.176)
CLOUD_AMT	0.275 (0.988)	0.048 (0.886)	0.124 (0.135)	0.021 (0.177)	0.037 (0.175)	-0.090 (0.208)
T2M_RANGE	0.399 (0.577)	0.002 (0.289)	-0.034 (0.145)	-0.013 (0.173)	0.106 (0.203)	0.006 (0.199)
WS10M_MAX	0.132 (0.635)		0.004 (0.109)	0.005 (0.199)	0.030 (0.148)	0.048 (0.243)
WS10M_MIN	-0.066 (0.874)	-0.225 (0.527)	0.045 (0.108)	-0.028 (0.167)		0.006 (0.209)
WS50M_MIN	0.358 (0.674)	0.441 (0.479)	-0.004 (0.119)	-0.040 (0.16)	0.002 (0.028)	-0.120 (0.165)
PRECTOTCORR_SUM	0.029 (1.179)	0.076 (0.316)	0.035 (0.139)	-0.098 (0.173)	0.112 (0.185)	
CDD		0.007 (1.410)	0.094 (0.153)	0.067 (0.174)	-0.022 (0.209)	
Solar	-0.365 (0.738)	-0.204 (0.525)	0.083 (0.151)	0.089 (0.187)	-0.004 (0.241)	0.025 (0.014)
Hydro	0.190 (0.520)	-0.003 (0.326)	-0.024 (0.134)	-0.084 (0.191)	-0.026 (0.214)	-0.123 (0.235)
Wind	0.021 (0.631)	0.022 (0.486)	0.026 (0.140)	-0.103 (0.168)	-0.008 (0.279)	-0.011 (0.160)
CLD	-0.040 (0.259)	0.106 (0.230)	-0.151 (0.141)	-0.041 (0.180)	-0.025 (0.192)	0.131 (0.217)
CO2	-0.415 (0.583)	-0.009 (0.487)	0.072 (0.150)	-0.008 (0.182)	0.032 (0.202)	0.038 (0.207)
ND-GAIN (change)	1.009 (0.828)	0.133 (0.639)	0.099 (NA)	0.028 (0.169)		0.015 (0.208)
Log-likelihood value	180.51		224.27		228.27	
AIC	-257.02		-328.53		-360.54	
BIC	6.30		-24.70		-117.47	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

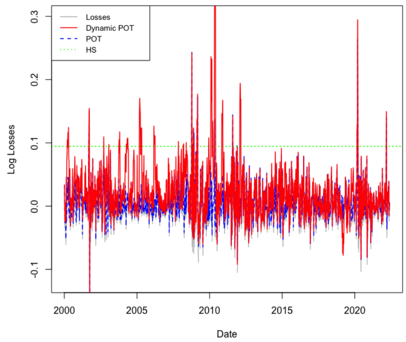
Figure 9: Value-at-Risk for the FTSE MIB market index



(a) Value-at-Risk at the 90% probability level



(b) Value-at-Risk at the 95% probability level



(c) Value-at-Risk at the 99% probability level

Figure 10: Expected Shortfall at the 90% probability level for the FTSE MIB market index

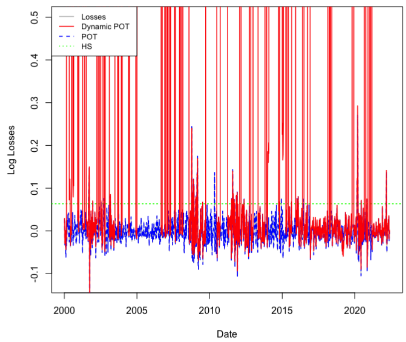
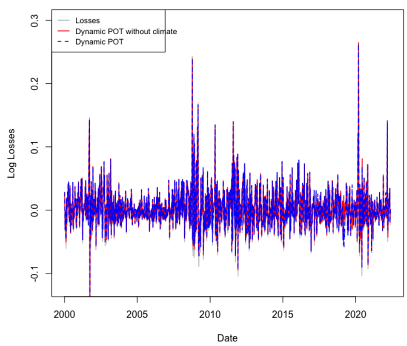


Table 21: FTSE MIB coefficient estimates without climate covariates

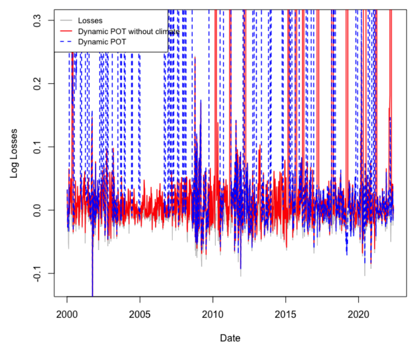
	$\hat{\lambda}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	-2.096 (0.082)	0.365 (0.198)	-2.821 (0.014)
IP (Change) EU28	0.073 (0.093)	0.062 (0.109)	0.163 (0.194)
IP (Change) Euro area	-0.005 (0.170)	-0.020 (0.192)	-0.007 (0.186)
IP (Change)	-0.172 (0.145)	0.181 (0.223)	0.049 (0.279)
HICP (Change) EU	-0.029 (0.136)	0.132 (0.184)	0.404 (0.360)
HICP (Change)	0.082 (0.124)	0.186 (0.137)	0.223 (0.201)
Unemp (Change) EU	-0.188 (0.118)	0.020 (0.173)	
Unemp (Change)	0.231 (0.110)	0.018 (0.085)	-0.114 (0.014)
PPI (Change) EU28	-0.003 (0.095)	0.058 (0.113)	-0.010 (0.177)
PPI (Change)	0.493 (0.123)	-0.105 (0.129)	-0.387 (0.206)
Long rate		-0.022 (0.198)	-0.108 (0.224)
Exp TV (Change) Euro area	-0.029 (0.183)	-0.015 (0.169)	0.040 (0.200)
Imp TV (Change) Euro area	0.083 (0.170)	0.144 (0.194)	0.237 (0.229)
CCI	0.058 (0.100)	0.035 (0.164)	0.108 (0.235)
ICI	-0.271 (0.119)	0.028 (0.163)	0.136 (0.159)
RCI	0.252 (0.117)	0.038 (0.167)	0.125 (0.154)
SCI	-0.184 (0.144)		
Log-likelihood	-425.17	222.95	
AIC	882.34	-383.90	
BIC	963.37	-226.92	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Figure 11: Value-at-Risk and Expected Shortfall without Climate covariates



(a) Value-at-Risk at the 95% probability level



(b) Expected Shortfall at the 95% probability level

B.3 Methodology results IBEX 35

Table 22: Dynamic POT for IBEX 35 index describing the $\hat{\lambda}$ parameter in different regularisation methods

	Lasso	Ridge	ElasticNet
Constant (Intercept)	-2.031 (0.083)	-1.920 (0.074)	-1.931 (0.076)
IP (Change) EU 28	-0.052 (0.087)	-0.036 (0.077)	
IP (Change) Euro area	0.008 (0.106)	-0.049 (0.122)	-0.002 (0.028)
IP (Change)		0.123 (0.103)	0.168 (0.098)
HICP (Change) EU	0.070 (0.111)	0.005 (0.080)	0.021 (0.081)
Unemp (Change) EU		0.088 (0.089)	0.010 (0.095)
PPI (Change) Euro area	-0.012 (0.101)	-0.070 (0.123)	-0.021 (0.097)
PPI (Change)	-0.001 (0.018)	-0.002 (0.119)	
DtD rate Euro	0.007 (0.127)	0.115 (0.096)	0.040 (0.103)
Exp TV (Change) Euro area	0.003 (0.115)	-0.110 (0.148)	-0.417 (0.166)
Imp TV (Change) Euro area		0.096 (0.138)	0.287 (0.163)
RCI Euro area	-0.005 (0.129)	-0.056 (0.100)	-0.009 (0.107)
RCI	-0.024 (0.112)	-0.070 (0.106)	-0.124 (0.115)
PS	0.117 (0.124)	0.051 (0.100)	
QV2M	0.079 (0.117)	-0.067 (0.105)	0.039 (0.094)
WS10M	0.111 (0.121)	0.043 (0.105)	0.108 (0.082)
CLOUD_AMT	0.286 (0.141)	0.214 (0.111)	0.201 (0.113)
T2M_RANGE	0.022 (0.107)	-0.001 (0.099)	
WS10M_MAX	-0.025 (0.112)	0.016 (0.095)	
WS10M_MIN	0.070 (0.122)	0.060 (0.078)	
WS50M_MIN		0.099 (0.120)	
PRECTOTCORR_SUM		0.078 (0.101)	0.003 (0.102)
CDD EU	0.196 (0.110)	0.186 (0.097)	0.169 (0.098)
Hydro	-0.230 (0.107)	-0.009 (0.085)	
CLD		-0.261 (0.092)	-0.186 (0.092)
CO2	0.053 (0.151)	0.030 (0.090)	0.090 (0.096)
ND-GAIN		0.143 (0.110)	0.041 (0.122)
Log-likelihood value	-470.93	-474.31	-476.08
AIC	981.85	988.62	990.16
BIC	1083.13	1089.90	1086.37

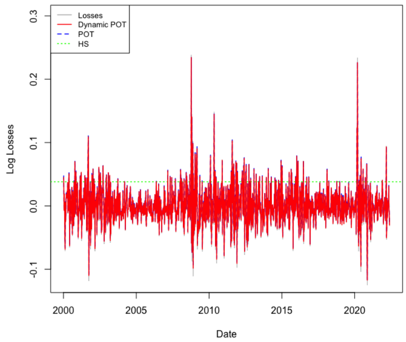
Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Table 23: Dynamic POT for IBEX 35 index describing the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameter in different regularisation methods

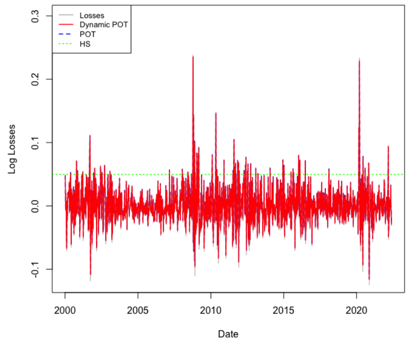
	Lasso		Ridge		ElasticNet	
	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	0.827 (1.768)	-3.240 (0.730)	0.486 (0.147)	-2.881 (0.157)	0.792 (0.227)	-2.871 (0.236)
IP (Change) EU 28	0.017 (2.068)	0.033 (0.235)	0.032 (0.143)	-0.130 (0.157)	0.261 (0.209)	0.006 (0.195)
IP (Change) Euro area		0.059 (1.084)		0.105 (0.154)		
IP (Change)	-0.091 (0.704)	0.003 (0.322)	-0.112 (0.143)	-0.209 (0.168)	-0.038 (0.250)	
HICP (Change) EU	0.130 (1.159)	0.144 (0.519)	0.078 (0.142)	0.022 (0.168)	0.100 (0.204)	
Unemp (Change) EU	0.058 (0.333)	-0.047 (0.434)	-0.099 (0.132)	-0.198 (0.164)		-0.103 (0.014)
PPI (Change) Euro area	-0.312 (0.311)		0.114 (0.162)	0.078 (0.164)	0.002 (0.058)	0.024 (0.148)
PPI (Change)	0.104 (0.356)	0.040 (0.400)	0.063 (0.157)	0.103 (0.174)	-0.001 (0.023)	
DtD rate Euro	0.144 (1.142)	0.003 (0.433)	-0.017 (0.140)	-0.099 (0.169)	0.020 (0.188)	
Exp TV (Change) Euro area	0.014 (1.556)	-0.170 (1.218)	0.054 (0.172)	-0.043 (0.159)	0.004 (0.203)	
Imp TV (Change) Euro area	0.073 (2.440)		-0.074 (0.159)	0.006 (0.181)		0.004 (0.014)
RCI Euro area	0.326 (0.458)	0.002 (0.024)	0.161 (0.139)	0.148 (0.183)	0.007 (0.232)	0.026 (0.151)
RCI	0.143 (0.713)	-0.050 (0.436)	0.091 (0.150)	0.147 (0.171)	0.024 (0.230)	0.030 (0.201)
PS		0.131 (0.372)	0.169 (0.160)	0.273 (0.171)		0.343 (0.207)
QV2M	-0.143 (0.743)	0.160 (0.506)	-0.008 (0.149)	0.147 (0.163)	-0.075 (0.263)	0.078 (0.162)
WS10M	0.029 (0.858)	0.187 (0.685)	0.022 (0.137)	-0.054 (0.170)	0.143 (0.217)	0.157 (0.208)
CLOUD_AMT		-0.161 (0.517)	0.028 (0.145)	-0.167 (0.162)	0.001 (0.021)	
T2M_RANGE	-0.005 (0.589)	-0.057 (0.666)	-0.056 (0.128)	0.146 (0.176)	0.060 (0.231)	0.248 (0.015)
WS10M_MAX	0.015 (0.929)		-0.014 (0.155)	0.158 (0.174)	-0.044 (0.256)	0.082 (0.209)
WS10M_MIN	0.055 (0.981)		-0.160 (0.089)	-0.117 (0.157)	-0.006 (0.248)	0.005 (0.180)
WS50M_MIN	0.714 (0.551)	-0.002 (0.334)	0.042 (0.139)	-0.206 (0.166)	0.119 (0.247)	-0.038 (0.180)
PRECTOTCORR_SUM	0.027 (0.797)	-0.069 (1.900)	0.125 (0.174)	0.117 (0.178)		
CDD EU	-0.001 (0.014)	0.008 (1.266)	0.045 (0.153)	-0.017 (0.162)	0.002 (0.249)	-0.005 (0.014)
Hydro	0.232 (1.886)		-0.016 (0.128)	-0.039 (0.168)	0.153 (0.232)	-0.002 (0.196)
CLD	-0.001 (0.015)	0.156 (0.256)	0.163 (0.155)	0.414 (0.155)	0.007 (0.204)	0.244 (0.179)
CO2	0.041 (2.257)		0.028 (0.152)	-0.078 (0.172)	0.016 (0.223)	-0.087 (0.207)
ND-GAIN		-0.062 (1.291)	0.129 (NA)	0.005 (0.151)	0.114 (NA)	0.005 (0.189)
Log-likelihood value	311.90		309.62		312.95	
AIC	-535.80		-513.23		-543.89	
BIC	-312.99		-244.85		-336.27	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

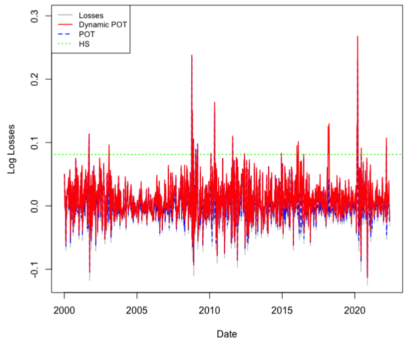
Figure 12: Value-at-Risk for the IBEX 35 market index



(a) Value-at-Risk at the 90% probability level



(b) Value-at-Risk at the 95% probability level



(c) Value-at-Risk at the 99% probability level

Figure 13: Expected Shortfall at the 90% probability level for the IBEX 35 market index

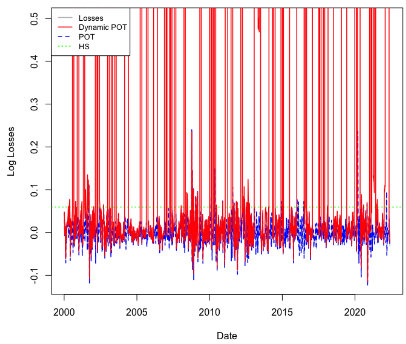
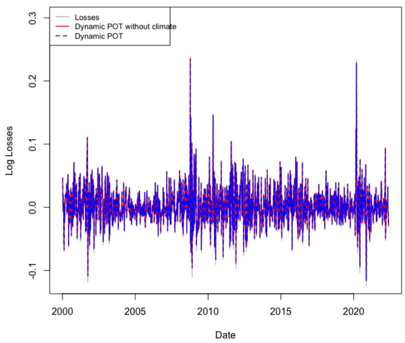


Table 24: IBEX 35 coefficient estimates without climate covariates

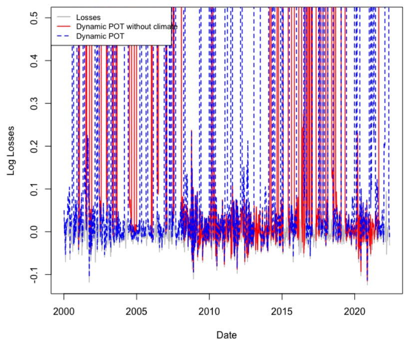
	$\hat{\lambda}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	-1.964 (0.080)	0.820 (0.212)	-2.979 (0.179)
IP (Change) EU28	-0.020 (0.083)	0.159 (0.149)	0.008 (0.174)
IP Euro area	0.073 (0.162)		0.282 (0.149)
IP (Change) Euro area		-0.008 (0.139)	
IP	-0.118 (0.090)	0.288 (0.226)	0.160 (0.014)
IP (Change)	0.048 (0.114)	-0.006 (0.190)	-0.110 (0.194)
HICP (Change) Euro area	0.020 (0.168)	0.196 (0.217)	
HICP (Change)	-0.130 (0.166)	0.017 (0.238)	0.078 (0.014)
Unemp (Change) EU	-0.001 (0.016)	0.007 (0.173)	
PPI (Change) Euro area	0.087 (0.099)	0.035 (0.220)	-0.004 (0.014)
PPI (Change)		0.003 (0.208)	0.017 (0.215)
Long rate	0.261 (0.096)	-0.006 (0.228)	0.035 (0.203)
Exp TV (Change) Euro area	-0.196 (0.149)	-0.001 (0.027)	0.094 (0.185)
Imp TV (Change) Euro area	0.003 (0.123)		0.005 (0.210)
RCI		0.253 (0.203)	0.178 (0.204)
SCI Euro area	-0.186 (0.117)	0.003 (NA)	-0.021 (0.186)
Log-likelihood	-469.64	313.39	
AIC	965.29	-572.77	
BIC	1031.12	-436.05	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Figure 14: Value-at-Risk and Expected Shortfall without Climate covariates



(a) Value-at-Risk at the 95% probability level



(b) Expected Shortfall at the 95% probability level

B.4 Methodology results AEX

Table 25: Dynamic POT for AEX index describing the $\hat{\lambda}(t)$ parameter in different regularisation methods

	Lasso	Ridge	ElasticNet
Constant (Intercept)	-2.015 (0.084)	-1.977 (0.076)	-2.022 (0.080)
IP (Change) EU28	-0.123 (0.088)	-0.117 (0.080)	-0.041 (0.084)
IP Euro area	0.014 (0.080)	0.041 (0.092)	0.103 (0.097)
IP (Change)		0.020 (0.073)	0.031 (0.078)
HICP (Change) Euro area	0.024 (0.108)	-0.036 (0.092)	0.031 (0.099)
HICP (Change)	0.184 (0.105)	0.103 (0.090)	0.092 (0.096)
Unemp (Change)	-0.005 (0.090)	-0.112 (0.096)	-0.092 (0.107)
PPI (Change) Euro area	-0.002 (0.164)	-0.025 (0.122)	0.032 (0.143)
PPI (Change)	-0.173 (0.152)	-0.065 (0.112)	-0.059 (0.130)
Long rate Euro area	0.201 (0.121)	0.142 (0.108)	0.219 (0.118)
Exp TV (Change) Euro area	0.142 (0.095)	0.040 (0.132)	0.054 (0.094)
Imp TV (Change) Euro area	-0.118 (0.092)	0.069 (0.133)	
CCI		-0.180 (0.098)	-0.005 (0.106)
ICI Euro area		-0.200 (0.110)	-0.336 (0.124)
RCI	0.228 (0.096)	0.099 (0.113)	0.035 (0.129)
PS		0.100 (0.087)	0.135 (0.093)
QV2M	0.013 (0.171)	0.020 (0.126)	0.205 (0.135)
RH2M	0.002 (0.141)	0.002 (0.112)	0.170 (0.126)
WS10M	0.057 (0.145)	0.122 (0.117)	0.111 (0.131)
CLOUD_AMT	0.006 (0.097)	0.014 (0.103)	0.099 (0.114)
T2M_RANGE		0.042 (0.089)	0.168 (0.091)
WS10M_MAX	-0.022 (0.116)	-0.068 (0.100)	-0.039 (0.109)
WS50M_MIN	0.106 (0.078)	0.079 (0.073)	0.095 (0.077)
PRECTOTCORR_SUM	0.301 (0.101)	0.116 (0.093)	0.140 (0.102)
CDD EU	0.004 (0.131)	0.043 (0.117)	
CDD	0.022 (0.123)	-0.055 (0.101)	-0.006 (0.097)
CLD		-0.068 (0.090)	
ND-GAIN		0.079 (0.105)	0.177 (0.117)
Log-likelihood value	-455.43	-452.10	-459.18
AIC	952.86	946.19	968.36
BIC	1059.20	1052.54	1094.95

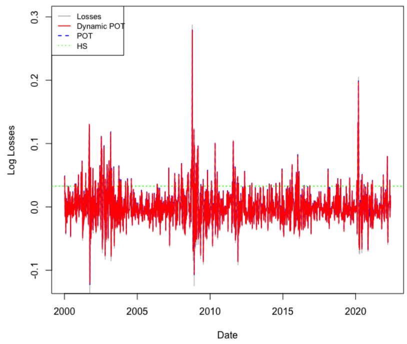
Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Table 26: Dynamic POT for AEX index describing the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameter in different regularisation methods

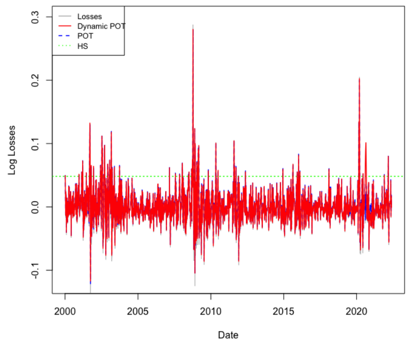
	Lasso		Ridge		ElasticNet	
	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	0.315 (NA)	-3.504 (0.070)	0.584 (0.145)	-2.697 (0.149)	0.452 (0.188)	-3.088 (0.185)
IP (Change) EU28	-0.007 (NA)	-0.078 (0.095)	0.080 (0.108)	0.134 (0.159)	0.008 (0.205)	0.034 (0.185)
IP Euro area	-0.108 (0.023)	-0.008 (0.227)	0.141 (0.124)	0.282 (0.156)	-0.011 (0.304)	0.054 (0.181)
IP (Change)	0.025 (0.166)	0.125 (0.159)	-0.036 (0.062)	-0.037 (0.167)	-0.071 (0.163)	-0.055 (0.216)
HICP (Change) Euro area	-0.020 (0.136)	0.002 (0.241)	0.095 (0.096)	0.127 (0.123)		
HICP (Change)		0.059 (0.214)	-0.146 (0.114)	-0.019 (0.169)		0.202 (0.014)
Unemp (Change)	-0.026 (0.196)	-0.054 (0.261)	0.211 (0.142)	0.059 (0.153)	0.040 (0.209)	-0.002 (0.138)
PPI (Change) Euro area	-0.093 (NA)	-0.193 (NA)	0.184 (0.158)	-0.040 (0.171)	0.126 (0.271)	-0.080 (0.032)
PPI (Change)	-0.075 (NA)	-0.010 (NA)	0.029 (0.154)	0.012 (0.176)	-0.009 (0.272)	0.003 (0.229)
Long rate Euro area	0.154 (0.266)	0.018 (0.224)	0.130 (0.136)	-0.115 (0.169)		-0.246 (0.238)
Exp TV (Change) Euro area	-0.048 (0.216)	0.055 (0.162)	0.044 (0.132)	-0.208 (0.179)	0.055 (0.322)	-0.163 (0.200)
Imp TV (Change) Euro area	0.299 (0.019)	0.162 (0.268)	-0.112 (0.152)	0.001 (0.169)	-0.159 (0.299)	-0.028 (0.259)
CCI	0.181 (0.172)		0.126 (0.141)	0.280 (0.163)	0.194 (0.195)	0.243 (0.244)
ICI Euro area			-0.016 (0.119)	0.208 (0.162)	0.021 (0.199)	-0.002 (0.224)
RCI	0.005 (0.352)		0.138 (0.131)	-0.054 (0.159)		-0.024 (0.206)
PS	0.263 (0.256)	0.015 (0.378)	0.055 (0.143)	0.106 (0.163)	0.021 (0.197)	0.136 (0.185)
QV2M	0.016 (0.180)	-0.012 (0.396)	0.048 (0.145)	-0.104 (0.167)	0.002 (0.029)	0.003 (0.212)
RH2M	0.005 (0.337)	0.064 (0.402)	0.020 (0.127)	0.174 (0.171)	-0.031 (0.234)	0.041 (0.202)
WS10M	-0.018 (0.203)	-0.367 (0.270)	-0.096 (0.130)	-0.214 (0.173)	-0.090 (0.182)	-0.156 (0.219)
CLOUD_AMT	0.003 (0.309)		0.117 (0.131)	0.129 (0.183)		0.075 (0.210)
T2M_RANGE	0.069 (0.141)	-0.229 (0.125)	0.189 (0.131)	0.070 (0.168)	0.113 (0.193)	0.041 (0.164)
WS10M_MAX		0.086 (0.174)	0.098 (0.151)	-0.061 (0.160)	0.085 (0.215)	0.055 (0.215)
WS50M_MIN	0.144 (NA)		-0.071 (0.122)	-0.081 (0.168)		-0.001 (0.218)
PRECTOTCORR_SUM	0.198 (0.781)	0.143 (0.160)	-0.116 (0.090)	-0.060 (0.147)	-0.013 (0.279)	0.036 (0.023)
CDD EU		-0.029 (0.439)	-0.018 (0.163)	0.205 (0.173)	0.002 (0.034)	0.065 (0.235)
CDD	0.452 (NA)	0.514 (NA)	0.014 (0.181)	0.172 (0.174)	-0.002 (0.295)	0.110 (0.198)
CLD	-0.043 (0.322)	0.015 (0.351)	0.144 (0.138)	0.202 (0.189)	0.010 (0.184)	
ND-GAIN	0.027 (0.206)	0.001 (0.015)	0.211 (NA)	0.008 (0.180)	0.222 (NA)	0.009 (0.016)
Log-likelihood value	293.74		278.96		289.99	
AIC	-493.49		-445.91		-483.98	
BIC	-255.48		-162.33		-240.91	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

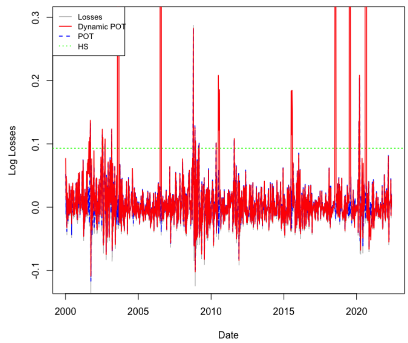
Figure 15: Value-at-Risk for the AEX market index



(a) Value-at-Risk at the 90% probability level



(b) Value-at-Risk at the 95% probability level



(c) Value-at-Risk at the 99% probability level

Figure 16: Expected Shortfall at the 90% probability level for the AEX market index

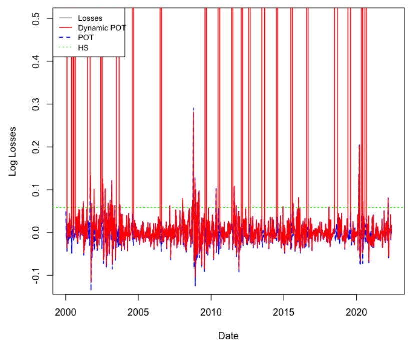
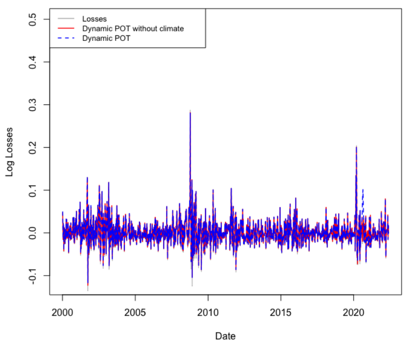


Table 27: AEX coefficient estimates without climate covariates

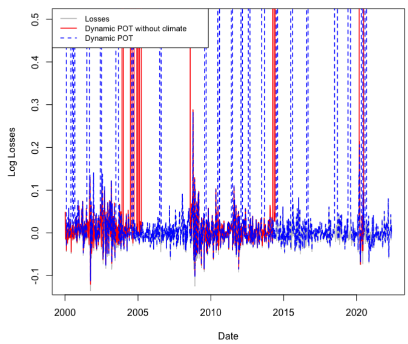
	$\hat{\lambda}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	-1.968 (0.076)	1.059 (NA)	-3.159 (NA)
IP (Change) EU28	-0.191 (0.081)	0.032 (NA)	-0.024 (NA)
IP Euro area	0.070 (0.089)	0.370 (NA)	0.172 (NA)
IP (Change) Euro area	0.003 (0.109)	-0.042 (NA)	-0.152 (NA)
IP (Change)	0.049 (0.070)	0.002 (0.021)	0.006 (NA)
HICP (Change) Euro area	0.002 (0.088)	-0.045 (0.531)	-0.011 (0.128)
HICP (Change)	0.018 (0.087)	-0.067 (0.363)	-0.006 (0.429)
Unemp (Change)	-0.057 (0.089)	0.055 (0.227)	0.002 (0.28)
PPI (Change) EU28	-0.071 (0.098)	-0.008 (0.229)	0.032 (0.256)
PPI	-0.004 (0.093)	-0.080 (NA)	-0.159 (0.194)
PPI (Change)	-0.092 (0.108)	0.012 (0.265)	
Long rate Euro area	0.141 (0.092)	-0.466 (NA)	-0.412 (0.01)
Exp TV (Change) Euro area	0.108 (0.144)	0.111 (NA)	-0.046 (NA)
Imp TV (Change) Euro area	-0.028 (0.136)	0.001 (0.018)	
CCI	-0.161 (0.105)	-0.065 (NA)	-0.009 (0.010)
RCI	0.185 (0.111)	-0.021 (NA)	0.013 (0.342)
SCI Euro area	-0.223 (0.104)	0.230 (NA)	0.009 (NA)
Log-likelihood	-455.93	298.54	
AIC	945.85	-533.07	
BIC	1031.94	-371.03	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Figure 17: Value-at-Risk and Expected Shortfall without Climate covariates



(a) Value-at-Risk at the 95% probability level



(b) Expected Shortfall at the 95% probability level

B.5 Methodology results FTSE 100

Table 28: Dynamic POT for FTSE 100 index describing the $\hat{\lambda}(t)$ parameter in different regularisation methods

	Lasso	Ridge	ElasticNet
Constant (Intercept)	-2.178 (0.089)	-1.979 (0.075)	-2.063 (0.081)
IP (Change) EU27	-0.172 (0.139)	0.019 (0.100)	-0.039 (0.105)
IP	0.060 (0.126)	-0.083 (0.108)	-0.134 (0.124)
IP (Change)		-0.008 (0.103)	0.073 (0.111)
HICP (Change) EU	0.095 (0.109)	0.072 (0.106)	0.048 (0.11)
HICP (Change)	-0.037 (0.145)	-0.012 (0.096)	0.019 (0.106)
Unemp (Change) EU		-0.179 (0.110)	-0.054 (0.128)
PPI (Change) EU27		0.015 (0.088)	
PPI (Change)	0.038 (0.146)	-0.038 (0.085)	
Exp TV (Change)		0.061 (0.111)	
Imp TV (Change)	-0.033 (0.116)	-0.078 (0.091)	
CCI	0.011 (0.120)	0.012 (0.098)	0.095 (0.111)
ICI	-0.141 (0.137)	0.049 (0.111)	-0.028 (0.126)
RCI EU27	0.004 (0.140)	-0.004 (0.113)	0.087 (0.126)
RCI	-0.031 (0.135)	-0.159 (0.106)	-0.204 (0.118)
PS	0.064 (0.128)	0.134 (0.101)	0.106 (0.110)
QV2M	-0.004 (0.149)	-0.037 (0.116)	
WS10M	0.173 (0.145)	0.220 (0.109)	0.156 (0.099)
CLOUD_AMT	0.140 (0.109)	0.035 (0.087)	0.052 (0.095)
T2M_RANGE		0.018 (0.097)	-0.034 (0.106)
WS10M_MAX	0.015 (0.133)	-0.078 (0.105)	
WS50M_MIN	0.028 (0.094)	-0.003 (0.083)	-0.002 (0.086)
PRECTOTCORR_SUM	0.055 (0.133)	0.101 (0.101)	0.052 (0.110)
ALLSKY_SFC_SW_DWN	0.064 (0.135)	0.015 (0.116)	0.022 (0.123)
CDD EU		0.147 (0.102)	0.131 (0.099)
CLD	0.018 (0.092)	0.059 (0.077)	0.043 (0.083)
ND-GAIN change	0.219 (0.111)	0.301 (0.099)	0.265 (0.113)
Log-likelihood value	-440.82	-446.32	-442.59
AIC	925.63	936.64	927.18
BIC	1037.02	1048.02	1033.50

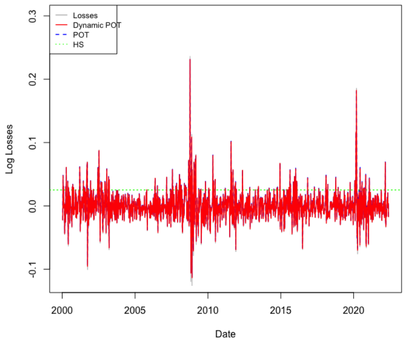
Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Table 29: Dynamic POT for FTSE 100 index describing the $\hat{\xi}(t)$ and $\hat{\nu}(t)$ parameter in different regularisation methods

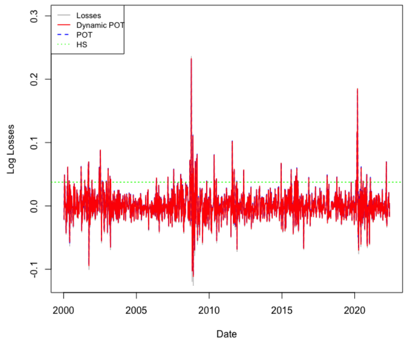
	Lasso		Ridge		ElasticNet	
	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	1.059 (1.026)	-3.502 (0.414)	0.720 (0.156)	-2.832 (0.166)	0.738 (0.211)	-3.205 (0.164)
IP (Change) EU27	-0.002 (0.053)	-0.335 (0.272)	0.143 (0.175)	0.149 (0.160)	0.017 (0.269)	
IP	0.351 (0.663)	0.211 (0.501)	-0.023 (0.186)	0.140 (0.287)	0.162 (0.238)	0.036 (0.014)
IP (Change)			0.009 (0.179)	-0.128 (0.183)	0.234 (0.221)	
HICP (Change) EU	0.098 (0.268)	-0.185 (0.305)	0.166 (0.182)	0.070 (0.172)	0.075 (0.200)	0.015 (0.014)
HICP (Change)	0.092 (0.430)		-0.007 (0.172)	0.059 (0.173)		0.009 (0.220)
Unemp (Change) EU	0.012 (0.464)		0.035 (0.172)	0.074 (0.162)		-0.102 (0.132)
PPI (Change) EU27	-0.012 (0.293)	-0.006 (0.264)	-0.047 (0.160)	-0.043 (0.177)	-0.005 (0.183)	
PPI (Change)	0.198 (0.203)		0.049 (0.156)	-0.056 (0.162)	0.036 (0.249)	-0.029 (0.014)
Exp TV (Change)	0.251 (0.400)	0.005 (0.385)	0.038 (0.188)	-0.004 (0.163)		0.108 (0.187)
Imp TV (Change)	-0.020 (NA)	0.011 (0.150)	0.018 (0.151)	0.121 (0.185)	0.054 (0.150)	0.028 (0.234)
CCI	-0.173 (NA)	-0.157 (0.258)	0.012 (0.164)	0.010 (0.173)	-0.010 (0.216)	0.079 (0.217)
ICI	0.002 (0.166)	0.011 (0.333)	0.036 (0.184)	0.059 (0.173)		-0.052 (0.197)
RCI EU27	0.002 (NA)	-0.046 (NA)	0.013 (0.176)	-0.093 (0.169)	0.038 (0.198)	-0.012 (0.217)
RCI	-0.066 (0.303)	-0.048 (0.350)	0.075 (0.171)	0.012 (0.176)	0.152 (0.234)	0.013 (0.215)
PS	0.285 (0.626)	0.022 (0.397)	0.012 (0.180)	0.160 (0.165)	0.208 (0.247)	0.237 (0.216)
QV2M	0.529 (0.643)	0.002 (0.042)	0.161 (0.171)	0.080 (0.176)	0.083 (0.220)	-0.011 (0.218)
WS10M	0.113 (0.510)	0.112 (0.441)	0.080 (0.174)	0.038 (0.175)	0.015 (NA)	0.004 (0.226)
CLOUD_AMT	0.567 (0.247)	0.124 (0.255)	0.018 (0.166)	0.073 (0.177)	0.170 (0.329)	0.003 (0.214)
T2M_RANGE	-0.017 (0.012)	0.041 (0.271)	0.043 (0.178)	0.334 (0.172)	0.141 (0.131)	0.295 (0.144)
WS10M_MAX	0.278 (0.586)	0.046 (0.483)	0.106 (0.166)	0.150 (0.160)		0.016 (0.217)
WS50M_MIN	0.186 (0.399)	0.068 (0.349)	-0.192 (0.162)	0.069 (0.183)		0.164 (0.214)
PRECTOTCORR_SUM	-0.002 (1.148)	0.028 (0.485)	-0.003 (0.169)	0.148 (0.236)	-0.073 (0.195)	0.069 (0.137)
ALLSKY_SFC_SW_DWN	0.044 (0.715)	-0.015 (0.234)	0.117 (0.176)	-0.008 (0.173)	0.122 (0.247)	0.016 (0.208)
CDD EU	0.129 (0.352)		0.046 (0.182)	-0.072 (0.191)	0.089 (0.225)	
CLD	-0.008 (NA)	0.057 (NA)	0.032 (0.162)	-0.123 (0.170)	0.113 (0.161)	
ND-GAIN change	-0.282 (0.528)	0.006 (0.330)	-0.028 (NA)	-0.196 (0.159)	0.034 (NA)	-0.007 (0.014)
Log-likelihood value	274.95		265.26		280.40	
AIC	-453.90		-422.51		-474.79	
BIC	-210.87		-149.11		-257.08	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

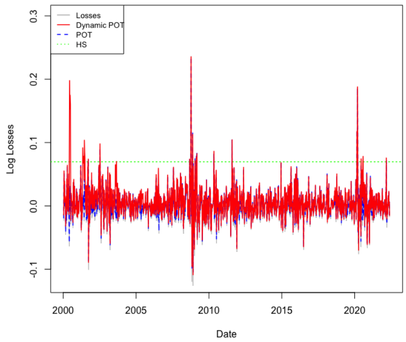
Figure 18: Value-at-Risk for the FTSE 100 market index



(a) Value-at-Risk at the 90% probability level



(b) Value-at-Risk at the 95% probability level



(c) Value-at-Risk at the 99% probability level

Figure 19: Expected Shortfall at the 90% probability level for the FTSE 100 market index

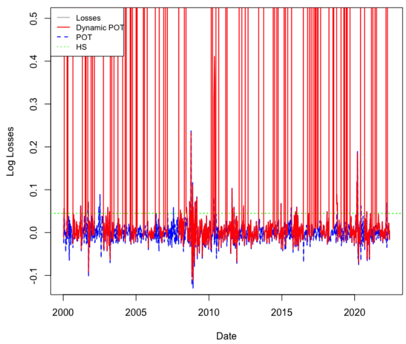
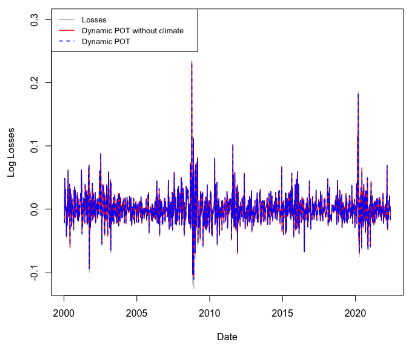


Table 30: FTSE 100 coefficient estimates without climate covariates

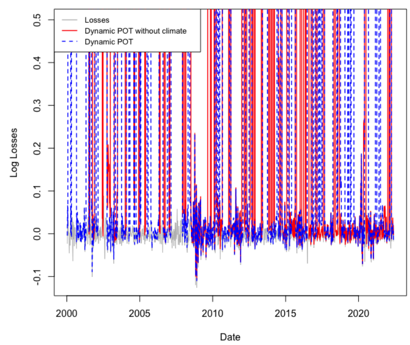
	$\hat{\lambda}(t)$	$\hat{\xi}(t)$	$\hat{\nu}(t)$
Constant (Intercept)	-2.137 (0.086)	0.920 (0.221)	-3.143 (0.250)
IP (Change) EU27	-0.003 (0.110)	0.066 (0.144)	-0.036 (0.178)
IP (Change)	0.050 (0.118)	-0.018 (0.241)	-0.014 (0.123)
HICP (Change) EU	0.026 (0.128)	0.004 (0.266)	0.021 (0.215)
HICP (Change)	-0.065 (0.120)		
Unemp (Change) EU		0.148 (0.184)	
PPI (Change) EU27	-0.040 (0.101)	0.070 (0.244)	
PPI (Change)		0.120 (0.230)	-0.052 (0.014)
DtD rate	0.121 (0.110)	0.118 (0.216)	0.115 (0.186)
Long rate EU27	0.029 (0.119)		
Exp TV (Change)		0.175 (0.257)	0.365 (0.014)
Imp TV (Change)		-0.011 (0.182)	-0.230 (0.222)
CCI		0.005 (0.227)	0.013 (0.188)
ICI	-0.018 (0.112)	0.010 (0.260)	0.024 (0.187)
RCI	-0.174 (0.106)	0.097 (0.232)	-0.037 (0.201)
SCI EU27		0.028 (NA)	-0.025 (0.197)
Log-likelihood	-431.84	280.80	
AIC	883.68	-509.61	
BIC	934.31	-377.97	

Note: The standard errors in this table were calculated using the Hessian matrix, which assumes normally distributed errors and valid regularization assumptions. If these assumptions are not met, the standard errors are not valid. If the standard error is NA then the estimated standard error is negative, which is impossible. The term (Change) refers to the percentage change of the covariate in relation to the previous period.

Figure 20: Value-at-Risk and Expected Shortfall without Climate covariates



(a) Value-at-Risk at the 95% probability level



(b) Expected Shortfall at the 95% probability level

C Appendix 3: Covariates Description

C.1 Macroeconomic Covariates

Table 31: Macroeconomic Covariate description

Covariates	Abbreviation	Data Regions	Data Type	Description
Industrial Production	IP	EU, Euro area, DE, FR, ES, IT, NL, UK	Index & Percentage change on previous period	A business cycle indicator which measures monthly changes in the price-adjusted output of industry
Inflation	HICP	EU, Euro area, DE, FR, ES, IT, NL, UK	Index & Percentage change on previous period	This measures the changes over time in the prices of consumer goods and services acquired by households
Unemployment Rate	Unemp	EU, Euro area, DE, FR, ES, IT, NL, UK	Percentage change on previous period	This is the number of people unemployed as a percentage of the labor force.
Producer Price Index	PPI	EU, Euro area, DE, FR, ES, IT, NL, UK	Index & Percentage change on previous period	A business-cycle indicator showing the development of transaction prices for the monthly industrial output of economic activities.
Short Interest Rates	-	Euro area, UK	Day-to-day rate, 1 month, 3 months, 6 months, 12 months	Rates on money markets for different maturities
Long Interest Rate	-	EU, Euro area, DE, FR, ES, IT, NL, UK	Government bond rate	Rates on money markets for the corresponding government bond.
Total Export Value	Exp	Euro area, UK	Index & Percentage change on previous period	The total value of goods and services that are exported by a country or a group of countries.
Total Import Value	Imp	Euro area, UK	Index & Percentage change on previous period	The total value of goods and services that are imported by a country or a group of countries.
Consumer Confidence Indicator	CCI	EU, Euro area, DE, FR, ES, IT, NL, UK	Index	A measure of the overall sentiment and perception of consumers in a specific country or a group of countries.
Economic Sentiment Indicator	ESI	EU, Euro area, DE, FR, ES, IT, NL, UK	Index	A measure of the overall sentiment and perception of businesses and consumers about the current and future economic situation in a specific country or a group of countries.
Industrial Confidence Indicator	ICI	EU, Euro area, DE, FR, ES, IT, NL, UK	Index	A measure of the sentiment and perception of businesses in the industrial sector regarding the current and future economic conditions, production expectations, and order books.
Retail Confidence Indicator	RCI	EU, Euro area, DE, FR, ES, IT, NL, UK	Index	A measure of the sentiment and expectations of businesses in the retail sector regarding their assessment of the current economic situation, their expectations for the future, and their retail sales outlook.
Services Confidence Indicator	SCI	EU, Euro area, DE, FR, ES, IT, NL, UK	Index	A measure of the sentiment and perception of businesses in the services sector regarding the current and future economic conditions, demand for services, employment expectations, and business situation.

C.2 Climate Covariates

Table 32: Climate Covariate description

Covariates	Abbreviation	Data Regions	Data Type	Description
All Sky Insolation Clearness	ALLSKY_KT	DE, ES, FR, IT, NL, UK	Index	A fraction representing clearness of the atmosphere and the all-sky insolation that is transmitted through the atmosphere to strike the surface of the earth divided by the average of top of the atmosphere total solar irradiance incident.
All Sky Insolation Incident on a Horizontal Surface	ALLSKY_SFC_SW_DWN	DE, ES, FR, IT, NL, UK	Index	The total solar irradiance incident (direct plus diffuse) on a horizontal plane at the surface of the earth under all sky conditions. An alternative term for the total solar irradiance is the "Global Horizontal Irradiance" or GHI.
Cooling degree days	CDD	EU, DE, ES, FR, IT, NL	Index	The severity of the heat in a specific time period taking into consideration outdoor temperature and average room temperature.
Heating degree days	HDD	EU, DE, ES, FR, IT, NL	Index	The severity of the cold in a specific time period taking into consideration outdoor temperature and average room temperature.
Climate-related disasters frequency	CLD	DE, ES, FR, IT, NL, UK	Number of disasters	Total number of climate disasters related to drought, extreme temperatures, flood, landslides, storms and wildfires
Daylight Cloud Amount	CLOUD_AMT	DE, ES, FR, IT, NL, UK	Percentage	The average percent of cloud amount during the temporal period.
Co2 Emissions	CO2	DE, ES, FR, IT, NL, UK	Millions of metric tons	CO2 Emissions Embodied in Production
Hydropower generation reservoirs	Hydro	DE, ES, FR, IT, NL, UK	MW	Amount of watts generated by hydropower reservoirs
Notre Dame Global Adaptation Index	ND-GAIN	DE, ES, FR, IT, NL, UK	Index, change on previous period	The ND-GAIN Country Index summarizes a country's vulnerability to climate change and other global challenges in combination with its readiness to improve resilience.
Precipitation	Precipitation	DE, ES, FR, IT, NL, UK	Meters	Depth of rainwater accumulated on a flat, horizontal and impermeable surface per unit area during a given time period.
Precipitation Corrected (Sum)	PRECTOTCORR (SUM)	DE, ES, FR, IT, NL, UK	Meters	The bias-corrected average (sum) of total precipitation at the surface of the earth in water mass.
Surface pressure	PS	DE, ES, FR, IT, NL, UK	kPa	Surface pressure
Humidity	QV2M, RH2M	DE, ES, FR, IT, NL, UK	g/kg, %	Absolute Humidity at 2 meters high, Relative Humidity at 2 meters high
Solar photovoltaic power generation	Solar	DE, ES, FR, IT, NL, UK	MW	Amount of watts generated by solar panels
Temperature	T2M, T2M_MAX, T2M_MIN, T2M_RANGE, T2MDEW,	DE, ES, FR, IT, NL, UK	C	Temperature at 2 meters, maximum, minimum, range, and Dew/Frost Point
Wind power generation onshore	Wind	DE, ES, FR, IT, NL, UK	MW	Onshore wind power generation
Wind speed	WS10M, WS50M, WS10M_MIN, WS10M_MAX, WS50M_MIN, WS50M_MAX	DE, ES, FR, IT, NL, UK	m/s	Wind speed at 10 meters, 50 meters, max and min for both heights