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THE IMPACT OF EQUITY TAIL RISK ON EUROPEAN MARKETS

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Abstract

I apply a dynamic equity tail risk variable to equity and government bond returns in Europe, understanding how investors react upon an increase in market uncertainty, departing from a risk aversion premise. I show that tail risk has predictive power for market returns, but less significantly than in the US. Nevertheless, the cross-sectional analysis provides evidence that investors demand a higher return from stocks that co-move more with tail risk, and the government bond analysis demonstrates that the yield-to-maturity of safer bonds decreases upon an increase in equity tail risk, a sign of investors' flight to safety, in uncertain times.

Keywords: Tail Risk; Risk Aversion; Equity Markets; Government Bonds.

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Introduction

We find ourselves in a highly unstable macroeconomic environment. Coming off the Covid-19 pandemic, the disruption in supply chains and the huge stimulus delivered by Central Banks and governments worldwide, which boosted demand everywhere, many signs of uncertainty arose. The war in Ukraine aggravated and escalated the situation. We now see inflation values not observed for decades, like Germany reaching values last seen in 1951. This is making Central Banks, Governments, Investors and Consumers feel anxious about the future. Recessions in many European countries have been forecasted for 2023 and we observe bear markets in many geographical regions. Predicting the next events is extremely hard and looking for clues is part of the mission of this Work Project.

Left tail risk - the main focus of this report - is defined generally as the probability of an investment having returns more than three standard deviations to the left of its mean being higher than what we observe in a normal distribution set up. The higher this probability, the higher the uncertainty, that is, the higher the risk. The key thing about it is that tail events are very rare and hard to predict, creating big impacts on markets.

The centrepiece of this Work Project will then be to investigate the impact of extreme events in the stock market on future returns, in equity and sovereign debt markets, something essential for all economic agents. By learning from past events and how markets reacted upon an increase in tail risk, can we predict what will happen? Is tail risk really useful when studying equity markets' returns? The argument is that investors seek higher returns when risk increases, so the impact should be there. The question is how big of an impact can we observe. In the case of sovereign debt, the intuition is that investors should seek safer assets when risk increases, something that is possible to achieve with government bonds.

The first point that needs to be verified is whether tail risk is a good indicator of equity returns. There is a large literature pointing in that direction, for example Bollerslev, Todorov and Xu (2015) or Gao, Song and Lu (2015), which look at tail risk premium and equity returns. This led me to investigate deeper, that is, to look for a better measure of tail risk, which is an important challenge. How can one study the impact of extreme events when extreme events are itself rare? Some methods seem to directly try to solve this issue, by setting-up time-varying measures of tail risk. Nevertheless, for reasons to be detailed below, I will follow Kelly and Jiang's (2014) approach. In their paper, they find that stocks with high loadings on past tail risk, based on the S&P500 index, have an excess return of 5.4pp higher than stocks with low tail risk, a demonstration of the demand for risk reward. What I intend to add to their approach is: 1- see whether similar results can be found in the European stock market, which became relevant since the Great Recession started in 2008, when the linkage between the US and European markets deviated (Gil-Alana, Orlando and Caporale 2016); and 2- observe if equity tail risk has any impact on European government bonds.

The computed time dynamic tail risk variable for this Work Project seems to identify correctly high uncertainty events. Nevertheless, what is relevant is to see whether the variable has any predictive power, which is indeed confirmed. The AR(1) model estimated for the estimated tail index series has a coefficient of 0.41, yet it displays worse self-predictive power than seen in Kelly and Jiang (2014) for the US. This weaker result also reflects on how the variable predicts market returns. Using the STOXX 600 index as a European market benchmark, an increase in tail risk by one standard deviation increases, in a univariate model, the forward 5-year annualized return by 1.46pp. Yet, the results are statistically insignificant for the 1-year forward return and are statistically significant only at the 10% level for the 2-year forward return, while showcasing a negative coefficient for the 1-month annualized return. In comparison with the most successful and commonly used variables to analyse market returns, tail risk is still able to outperform a few of them, however in a less significant manner than Kelly and Jiang (2014) show, again. Still, when controlling for other variables, it was possible to find models with high predictive power, namely the combination of tail risk and German 2-year Yield-to-Maturity as regressors for the 5-year forward return, with an R-squared of 49%. However, the out-of-sample performance of the variable is poor and seems to provide little value added in any investment strategies.

Nevertheless, the cross-sectional analysis goes in line with our hypothesis that investors demand higher compensation for stocks that are riskier, that is, that co-move with tail risk. Stocks that co-move the most have an extra 2.1pp excess returns, in relation to the Fama-French 3-Factor (FF3) model than stocks that co-move the less, i.e., that can be used to hedge risk. As for government bonds, when we use control variables, an increase in tail risk is associated with a decrease in the yield-to-maturity (YTM), as investors demand more government bonds - safer assets - and require a lower YTM. We observe that this behaviour depends on whether investors see those assets as a safe heaven, since this effect is stronger in Germany and statistically insignificant in Italy.

Literature Review

The idea of obtaining return for risk is one of the pillars of most investing strategies. Traditionally, this risk is looked at from the returns' variance perspective. More recently, there has been an increasing interest for the study of downside risk, that is, financial risk associated with losses - left tail risk. Value-at-risk (VaR) is probably the most used concept within this reality, which quantifies the extent of possible financial losses over a specific time frame. Risk-averse investors deeply care about losses and will try to minimize the VaR, meaning that they will prefer thinner tails, but research has found that equity tail risk is actually heavier than what normal distributions showcase (Nicolau and Rodrigues 2019).

This should imply that investors change their strategies to avoid tail risk, which must be priced in the market. For instance, Moore et al. (2013) show the homogeneity of cross-section returns when faced with a certain tail risk. We wish, however, to have a strong time-varying measure of tail risk, something a lot more rare in the literature.

The Kelly and Jiang Approach

In many papers, a measure implicit in short-maturity options of the stock market is used to compute time-varying equity tail risk, such as, Bollerslev, Todorov and Xu (2015) or, alternatively, methods from high frequency-data, such as Bollerslev and Todorov (2011). Although the results are strong, Kelly and Jiang (2014) argue that their approach fits any setting which has a large cross-sectional sample available, while other approaches have several data limitations, such as shorter sample horizons or the impossibility to use low-frequency data – corresponding to the type of data we have. As data for Europe is harder to access from an academic perspective, the method I will use should assure the soundness of the model. Verifying whether they are right or not about their methodology being more easily used in a different time span and market samples is also an objective of this work.

Another reason for using their approach comes from the good results in the paper. They find relevant results for the S&P500 market, seeing that the coefficient of the auto-regressive model of tail risk is 0.93, meaning that tail risk is precise in estimating future extreme events itself, pointing in the direction of a good asset price indicator. Also, the hypothesis that tail risk itself reflects on market returns is not rejected, with results supporting this idea, whether they control for other variables, or not. Some of the predictors used to limit any unwanted noise in their model are the ones in Goyal and Welch's paper[1], which I will also analyse. These are relevant as they are referred very often by academia or

[1] Welch, I., & Goyal, A. (2008). A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. Review of Financial Studies, 1455-1508.

investment strategies. Regardless, they find that as tail risk increases, excess market returns also increase, a typical investment result – higher risk demands higher return. A further reason for this result is that assets that hedge against tail risk – bad state of the economy – are valuable, more expensive, hence generate lower returns. They observe it by sampling stocks according to their tail risk beta and looking at the average returns. Besides, the results seem very solid even out-of-sample, indicating a strong predictive power of the variable.

Furthermore, their methodology has brought a new, exciting perspective to this reality, incentivizing new research to be conducted around it.

Tail Risk

Kelly and Jiang (2014) observed that obtaining tail risk dynamics from the univariate time series – for instance, GDP - is not possible due to the rarity of extreme events in these short series. To solve this issue, they pursued a panel based method that uses several individual firms´ stock information – in their case, the S&P500 index - **extracting from the sample common variation in tail risk**. By using several firms, they increase their sample substantially, which allows them to look at rare events in a more precise way. Doing so is possible because they assume that firm-level tail distributions have similar behaviour. I will follow a similar approach, but within a European stock market index - STOXX Europe 600.

The keyway of looking at tail risk in this Work Project is to look at the probability of a set of returns falling below a certain threshold, which unlike in the general definition of tail risk, can be flexible in the model to be used. That probability of returns falling below a threshold behaves according to a Power Law, which allows to explore non-linear relationships between phenomena. Throughout this Work Project, I assume, just like in Kelly and Jiang (2014) that the lower tail distribution of asset *i*, is:

$$P\left(R_{i,t+1} < r \,\middle|\, R_{i,t+1} < u_t \text{ and } F_t\right) = \left(\frac{r}{u_t}\right)^{-a_i/\lambda_t} \quad (1)$$

where u_t stands for the minimum threshold imposed by the modeler and F_t the available information. Any change to these parameters changes the model to be used and therefore its results. The essential part of equation (1), just like in any Power Law, is its superscript: $-a_i$ $/\lambda_t$, the tail index. The numerator of the superscript represents the firm-level impact on the lower tail risk distribution, while the denominator shows the common tail risk dynamics, precisely what we wish to compute and will use in our models. As r is smaller than u_t and a_i/λ_t is larger than zero, it is assured that the referred probability lies between 0 and 1. A large value of λ_t leads to fat tails, hence more tail risk – higher probability of extreme results.

The underlying assumption in this model is that the tail risk of individual firms behaves in similar ways, which is possible to conclude by observing high correlation values between λ_t in models that are run for specific industries. To estimate λ_t, I follow Kelly and Jiang (2014) in using Hill's approach (Hill 1975). By using daily stock information, I compute a separate monthly tail risk variable, to be used in the final regressions. Details on the equation and methodology are provided below.

Government Bonds Market

The link between fixed income markets and stock markets is something deeply analysed by academia, especially in times of crisis. For example, Connolly, Stivers and Sun (2005) observe that stock market uncertainty has important impacts on the bond markets and Hartmann, Straetmans and De Vries (2004) find that, actually, a contagion between the stock and bond markets is as likely as a flight to safety. What is rarer is the use of equity tail risk in bond prices. Yet, this link between equity tail risk and fixed income markets has also been explored. For instance, Rubin and Ruzzi (2020) observe that Treasury Prices, in the US, increase when the perception of equity tail risk is higher, because investors demand more bonds, running away from risky assets. They also extend their results to government bonds in Europe. In the European case, in Italy for example, this relation is non-existent, perhaps because Italian government bonds are hardly seen as safer assets, something I explore as well. Nonetheless, equity tail risk is found in all cases using the S&P 500 index.

What I intend to add to this finding is the use of Kelly and Jiang's method to calculate time-varying equity tail risk and the focus on the European market. Rizzo and Rubin (2020) performed their research using Bollerslev, Todorov and Xu's (2015) approach to tail risk we mentioned above, with short-maturity options of the stock market but to my knowledge, the application of Kelly and Jiang´s estimator of equity tail risk is something that has not been done. Ultimately, do investors really run for government bonds when tail risk increases? Does this finding depend on which method we use, or the location focused on?

But how can we look at returns in fixed income and its dynamics? Many papers use a complex estimated term structure model from Gaussian regressions, where the pricing factors are crucial to explain yields. They explore combination of yields, decomposing them into interest rates expectations and risk premium that investors require for having such a long-term investment. Most use several principal components of yields as risk factors, such as level, slope or curvature of the yield curve (Litterman and Scheinkman 1991) and run cross-section models with it. Others have implemented more pricing factors, with some variations and found similar results (Adrian, Crump and Moench 2013). However, several papers have found that bond excess returns are observed outside yield curves and its components. For example, Ludvigson & Ng (2009) found that real and inflation factors have important forecasting power regarding government bonds, even past the power in information of forward rates and yield spreads. This is what Rizzo and Rubin (2020) pursued in their paper, a variable originated in the stock market, namely equity tail risk**,** that has no impact on direct yield dynamics. I will maintain the approach of avoiding using combination of yields, as the main purpose of the analysis is to see whether one of the pricing factors of bonds can be found in stock markets. I will, however, simplify their approach of bond returns, using simply the YTM of the bonds – a proxy for returns required by investors - as the dependent variable and equity tail risk as one of the regressors.

It is frequently argued that YTM is weak in measuring what is truly earned by investors. In other words, it is a "myth" that YTM measures the rate of return of a bond. This would point to a limitation in my model. However, it has been defended that YTM is always earned regardless of how coupons are allocated (Cebula and Yang 2008), as they differentiate YTM from the realized compounded yield (RCY) - the rate of return from holding the bond plus investing the coupon payments when received. They claim that YTM is equal to RCY only when all payments are reinvested at the same rate as the initial YTM and that the two concepts got mixed over the years by many individuals. This would imply that YTM is in fact a good measure of the true rate of return of holding a bond until maturity, with no restrictions. Moreover, YTM is a good measure to use when comparing securities with different characteristics, such as in our case. It is important to remember that the objective of this part of the Work Project is to see whether stock market tail risk using Hill's estimator is seen to explain part of the dynamics in the government bond market in any way. That is, to see if equity tail risk influences the return in government bonds required by investors. Details on term structures should be developed in future studies of this reality.

Methodology – Hill's estimator

Power law type tail behaviour of equity returns is not something unusual, see Mandelbrot (1963). What is new is the key parameter of the power law, the tail index, changing with time, i.e., a time-varying power law. As mentioned before, a dynamic tail risk variable is hard to compute due to the rarity of extreme events in short-samples. Kelly and Jiang (2014) count on the commonality of tail risk of individual firms to overcome this limitation. They pool all daily returns within a month, of all stocks in S&P500 index indiscriminately, which allows the sample size to increase, while reducing sampling noise.

Going back to equation (1), that is how it is assumed tail distribution to behave and using Hill's approach, from the cross-section, we can estimate the monthly λ_t. The inference method is based on conditional likelihood describing the tail behaviour, crucial for when we do not know the tail threshold. Following Kelly and Jiang (2014), Hill's estimator is:

$$\lambda_t{}^{Hill} = \frac{1}{K_t} \sum_{k=1}^{kt} ln \frac{R_{k,t}}{u_t} \qquad (2)$$

where $R_{k,t}$ is the kth daily return, in the month t, that falls below the extreme limit u_t, set by the user - fifth percentile in Kelly and Jiang (2020). K_t is the number of observations within a month whose returns fall below u_t, which should be set appropriately. Furthermore, u_t is the threshold that marks the beginning of the tail of the distribution and in my empirical application I set it to 0.005. One should notice however that Hill's estimator does not yield us the true common tail risk component that we wish to compute. But it gives us a perfectly correlated estimator of it, thoroughly demonstrated in Kelly and Jiang (2014). Therefore, I use the estimator as is in the following regressions.

Using Hill's estimator, I am able compute the time-varying tail risk variable. I run the model with the real returns and then with the residual returns from the FF3 model (Fama and French 1993), to avoid part of the bias involved. That bias would arise from dependence among returns which is largely diminished by removing some of the common factors. Using the residuals allows us then to focus on the individual behaviours of stocks. There were other concerns in Kelly and Jiang's model, for instance the effect of cross-sectional volatility heterogeneity on estimates. However, they find that results are not impacted whether they use volatility-standardized or raw results, so we will ignore this situation. Volatility dynamics is also not a concern from a contamination position, as I allow the threshold to change in each period, letting the model take these dynamics into consideration.

Data

The data for this Work Project has been in its majority extracted from Bloomberg. Remembering the need for a big sample, to be able to study rare events, I extracted the daily (trading days) stock price of the largest 100 firms[2] of the STOXX Europe 600 index from the first trading day of 2000 until the last trading day of September 2022. The data starts in 2000 as I wanted to look at the results since the creation of the Euro Area, and most data is only consolidated from 2000 onwards. With this information, I calculate the daily returns and compute the monthly time-varying tail risk variable. The prices of the securities are in different currencies, which does not influence the return, so any currency exchange will be ignored for simplicity reasons. The residuals from the FF3 model will be needed, and this data was extracted from the Kenneth R. French Data Library. The sample for the FF3 data has around 200 less days than the stock information. For that reason, when computing the tail risk from the residuals, the sample will be slightly shorter.

The monthly price of the STOXX 600 Europe index has also been obtained and transformed into returns. This will allow me to see if tail risk can predict market returns. Furthermore, I also extracted the monthly stock price – to be transformed into monthly returns as well – plus the trailing 12-month earnings-per-share (EPS) and the price-to-book value (P/B) of the same firms. This data will be used to run models with more covariates. In most cases, the EPS and P/B are announced only quarterly/semesterly. To solve this issue, I use the same values for the three/six months of the quarter/semester. This should not be a

[2] See annex 1.

big concern as these firms' fundamentals will only be used in some versions of the model to control part of the variations in return and verify the existence of any hidden bias.

Lastly, to look at the impact on government bonds, I selected three countries, with different characteristics: France, Germany and Italy. I extracted the monthly YTM of the 10-year, 5-year and 2-year sovereign bonds of these countries. To control part of the variation in the YTM, I also use the monthly 6-month Euribor rate, the S&P credit rating of the countries and the Euro Area YoY inflation rate. These are supposed to show reflections and behaviours from investors when faced with a certain economic and financial reality.

Hypothesis

My hypothesis is that investors are indeed tail risk averse and seek compensation for it, and that extra compensation can be priced with our time-varying tail risk measure in the European market. My second hypothesis is that when facing an increase of tail risk in equity markets, investors look to minimize their risk. First, they seek assets that hedge against it. Secondly, they seek government bonds. Therefore, when risk increases, more investors should seek more bonds, which will lead to a fall in YTM.

Methodology and Discussion of Results

The Predictive Power of Tail Risk

I started by estimating the time-varying tail risk variable, using the daily returns and the residuals of each stock from the FF3 regression. To obtain the residuals, I performed a simple linear regression with the FF3 data. Using these two approaches allows me to avoid dependence of returns across firms if that dependence is detected. We observe that the results do not differ substantially, a sign that the concern with bias can be relaxed, as the variation and peaks in tail risk occur in the same periods. Nonetheless, tail risk from the FF3 residuals will be used as the standard variable and be solely referenced as tail risk in future references.

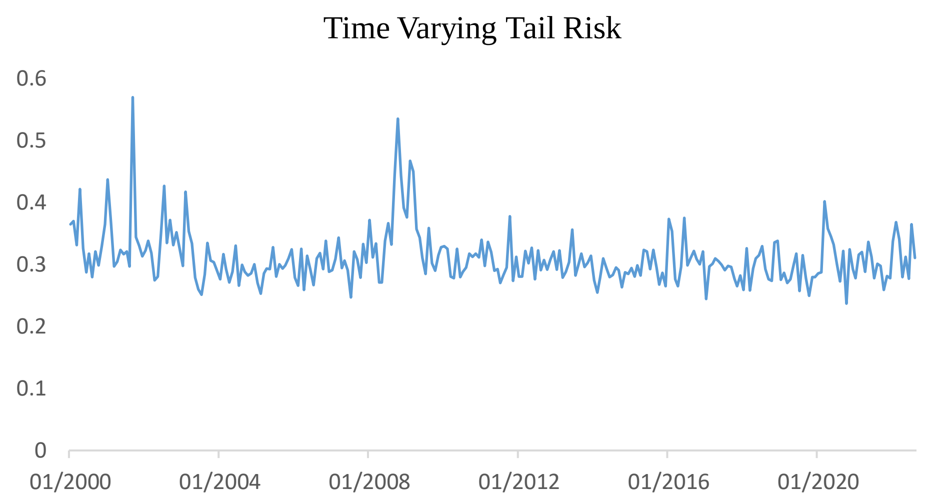

Figure 1 – Time Varying Tail Risk, using residuals from the FF3 regression

Going deeper in the plot analysis, it is possible to identify 3 major peaks in tail risk from 2000 to 2022 – remember that large λ_t represent fat tails, hence more risk - corresponding to the Dot-Com Bubble, the Great Recession and the Covid-19 pandemic. This gives a hint that the computed variable correctly identifies times of more uncertainty and risk in the market. Interestingly, 2016 seems to be a period of high uncertainty as well. This demonstrates the European side of our data as 2016 was the year in which the Brexit vote took place and uncertainty rose tremendously.

Following Kelly and Jiang (2014), I proceed with the analysis of the predictive power of this variable. Therefore, I computed the autoregressive model of the monthly tail risk variable, with a one time period lag. The results show that there is indeed time dependence in the tail risk with an autoregressive parameter estimate of 0.41, with a p-value of 0.0[3]. This means that tail risk is not a random walk, something vital to allow it to be used to estimate

[3] See annex 3

returns. Still, the time dependence seems to be less persistent than what was observed in the case of Kelly and Jiang (2014), who obtained an estimate of 0.93 for the US.

Tail Risk and Market Returns

The time dependence observed led me to the next step: assess the impact of equity tail risk on market returns. In order to do so, a market returns variable is needed. Therefore, I computed several time periods returns of the STOXX 600 index, to be used as a European market proxy. It is true that tail risk is not computed from all 600 firms in the group. Nevertheless, the 100 selected firms should be a good measure of the overall risk for the specific market, as they not only do they represent all sectors in the market but also, they are the most capitalized ones, representing a higher weight in the index.

Investors will not see tail risk the same way for all investing horizons, therefore I used the 1-month, 1-year, 2-year and 5-year annualised returns to identify such differences. The longer the time horizon, the shorter the sample size gets, as forward data is needed. For example, in the case of the of the 2-year forward returns, we can only reach September 2020. Using different time periods will then give us a hint on the horizon of tail risk's impact.

Below, in Figure 2, it is possible to observe the co-movement of the monthly tail risk and the reference 2-year forward return of the market index. In the graph, it is possible to identify a certain pattern in the way both variables change, although not very obvious. To a certain extent, it is observable that as tail risk increases, the 2-year forward return increases, a sign that investors will demand higher return for the increase in risk. This is especially identifiable in the 2008 financial crisis. For other periods, the effect seems less obvious.

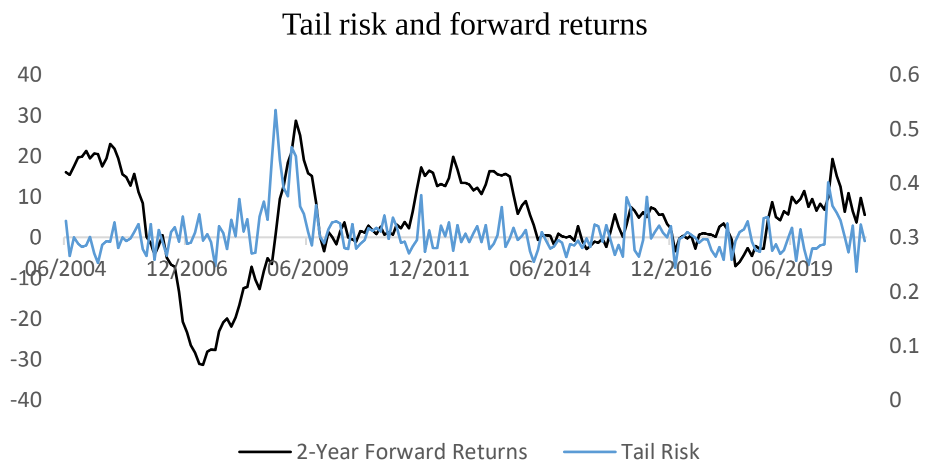

Figure 2 – Time series of tail risk and forward 2-year market return

Computing the univariate model with tail risk as the independent variable, I was able to observe the impact that tail risk has on the returns of the market and the difference of results according to length of periods. One adjustment that had to be made to the regression was the use of Newey-West standard errors (West and Newey 1987). This not only controls for heteroskedasticity in errors but also for autocorrelation. Autocorrelation comes from the fact that when computing 1-year returns, for example, we will have overlapping data in 11 months, for 2-year returns there is overlapping data for 23 months, and so on, due to the monthly nature of data.

The results are interesting, as seen in table 1 below. The coefficients for the 1-month, 1-year, 2-year and 5-year annualised returns, with the standardized monthly tail risk, are -8.3, 2.38, 1.62 and 1.46 with p-values of 0.03, 0.18, 0.07 and 0.0, respectively. Two things stand-out. The first is that the results are statistically significant for the 1-monh and 5-year returns but are only significant for the 2-year forward return at the 10% significance level and insignificant for the 1-year return. In the reference paper, all coefficients seem to be statistically significant, at any significance level. This may be due to the fact that we have different sample periods. Mine only focus on the last 2 decades, a period full of events that had major impacts in the stock market in a very short sample size, for the good and the bad. This contaminates the annualized returns. For instance, when computing the 2-year forward return in 2019, those values will be influenced by the Covid-19 pandemic and there will be some noise. In Kelly and Jiang (2014), they have a larger sample period, with crisis more dispersed, relatively. When looking at the 1-month and 5-year returns, that noise would be limited because in the first case, that effect would never come to exist and in the second case, the effect would be overtaken. The second thing that stands out from the results is that tail risk is associated with different behaviours according to the investment horizon. In a 1-month period, the returns are 8.3pp lower when tail risk increases by one standard deviation. For larger investment horizons, an increase in tail risk is associated with an increase in market return. This shows investors' first reaction in running away from the risky assets overshadowing everything else and pushing prices to go down for a while. As that first instinct passes, the risk aversion mirrors a demand for excess return. In the 5-year horizon, with a p-value of 0.0, as tail risk increases by one standard deviation, the market return is associated with 1.46pp extra annual returns. This is in line with our hypothesis.

1 month		1-year		2-year		5-year	
beta	p-value	beta	p-value	beta	p-value	beta	p-value
-8.28	0.03	2.38	0.18	1.62	0.07	1.46	0.00

Table 1 – Univariate regression results with market forward returns as the dependent variable and tail risk as the regressor

Robustness

To conclude on the fitness of tail risk as a robust estimator, I computed univariate models with other variables – see table 2 below - attempting to use the same variables as in Goyal and Welch (2008). Due to data limitations, I chose the 6 most significant variables and adjusted them. Namely: 1- the 6-month Euribor as a proxy for the risk-free rate; 2- an equal weight average EPS of the 100 firms in sample to have an overall market earnings measure; 3- equal weight average P/B of the 100 firms in sample to have an overall book value measure; 4- the YTM on 2-year German bonds to replicate Treasury Bills for Europe; 5- the YTM on 10-year German bonds to replicate long-term yield; 6- inflation in Euro Area. In Kelly and Jiang (2014), only the dividends-to-price ratio revealed to be comparable to tail risk's performance. My conclusions go partly in the same direction. I focused the comparison on the 5-year investment horizon, the one with more statistically significant results. Recalling that the variables with the best performance in the reference paper were selected, tail risk still outperforms 2 of them. Still, the models of the 6-month EURIBOR, the equal weight average EPS, the German 2-year YTM and the Germany 10-year YTM models have larger R-squared and bigger coefficients in absolute terms, whilst also being statistically significant. So, tail risk is still one of the best variables in explaining market returns in the European context, although not being a clear front-runner.

	5-year	
	beta	p-value
Equal_WeightP/B	1.06	0.07
Equal_WeightEPS	-4.06	0.00
YTMGermany2year	-1.85	0.00
YTMGermany10year	-1.24	0.00
Euribor	-1.51	0.00
Inflation	0.83	0.03

Table 2 – Univariate regression results with 5-year forward returns as the dependent variable and the adjusted Goyal and Welch variables as the regressors

To follow on this reasoning, I proceeded to develop bivariate models with tail risk next to all the adjusted Goyal and Welch variables. Any significant change to the coefficient of tail risk would point out to weak robustness in the variable. By looking at the table 3 below, it is possible to observe that the robustness of tail risk is solid, especially for the largest investment horizon. However, tail risk becomes statistically insignificant for the 1-month horizon at the 5% level, when put together with the 6-month Euribor, Germany 2-

year YTM or inflation. For the 5-year horizon, the coefficients become even higher, meaning that there is negative bias being captured by tail risk in the univariate models, which strengthens the hypothesis that investors are risk-averse and that upon an increase in tail risk, the return required is even higher than what the univariate model showcases. When looking at the R-squared of the models, in the same figure, for the 5-year period, it is possible to observe that tail risk, combined with other variables, demonstrates a very high level of predictability, reaching 49%, when put together with the German 2-year YTM, the highest value. The German 2-year YTM itself only generates an R-squared of around 30%, meaning that tail risk adds a significant predictive power to this bivariate model. Comparably, in Kelly and Jiang's paper, the best bivariate model has an R-squared of 54%, a model that puts dividend-price ratio next to tail risk.

	1 month			5-year		
	beta	R^2	p-value	beta	R^2	p-value
Univariate	-8.30	0.02	0.00	1.46	0.09	0.00
Equal_WeightP/B	-8.52	0.03	0.03	1.48	0.11	0.00
Equal_WeightEPS	-8.05	0.03	0.04	1.76	0.30	0.00
YTMGermany2year	-7.60	0.03	0.05	2.03	0.49	0.00
YTMGermany10year	-7.88	0.02	0.05	1.87	0.25	0.00
Euribor	-7.03	0.03	0.08	2.35	0.42	0.00
Inflation	-7.04	0.05	0.07	1.64	0.13	0.00

Table 3 – Bivariate regression results with forward returns as the dependent variables and tail risk as the common regressor alongside adjusted Goyal and Welch variables

In summary, these results allow me to conclude that tail risk is in fact a useful variable to study market returns in-sample, especially when put together with other variables that control other aspects of the economy.

I proceeded to explore the out-of-sample power of this variable. As stated by Goyal and Welch, most variables traditionally used behave poorly out-of-sample. If robust results are found, this improves the argument that tail risk is a good variable to use in equity market returns analysis. To analyse the robustness of tail risk out-of-sample, I use the first 120 months of the sample to compute the univariate tail risk's coefficient on the STOXX 600 index return. With the results of the regression and knowing the 121st tail risk value, I predict the market return in that same month. This market return is annexed to the previous 121 and the same computation is performed for the 122nd period. This process is repeated several times until reaching the last observation. In the end, I run a regression between the real market returns and the returns predicted using the procedure described above (out-of-sample), for which a coefficient and a R-squared can be computed. A high R-squared means that tail risk has success in estimating returns and that our tail risk variable can be used successfully in investment strategies. The process was executed for all time horizons and the remaining 6 variables used in-sample as well to have a performance comparison benchmark.

By looking at the results in table 4 below, it is possible to conclude that the R-squared from the regressions when estimating returns using tail risk is very low. It has a very poor predictive power especially for the 1-month and 5-year maturities, the time horizons that performed the best in-sample. This is an indication that using tail risk for making investment strategies for European market returns may not be the most advisable situation, going against the results of the reference paper.

	1-month		1-year		2-years		5-years	
	Beta	R^2	Beta	R^2	Beta	R^2	Beta	R^2
Tail Risk	10.09	0.00	-19.78	0.09	-0.55	0.08	1.79	0.02
Equal_WeightP/B	17.25	0.00	-0.10	0.02	1.89	0.07	-1.54	0.27
Equal_WeightEPS	14.53	0.00	3.54	0.00	3.01	0.15	2.29	0.00
YTMGermany2year	-58.91	0.01	-23.54	0.02	-19.25	0.13	-10.57	0.17
YTMGermany10year	-72.86	0.02	-20.67	0.06	-22.16	0.48	-6.66	0.11
Euribor	-44.59	0.00	-14.63	0.01	-24.89	0.13	-14.87	0.14
Inflation	9.64	0.02	-6.53	0.13	5.98	0.02	3.13	0.00

Table 4 – Out-of-sample results for different forward returns and variables – regression results between real and predicted returns

These findings come, to some extent, in line with Goyal and Welch (2008). They argue in their paper that results in the past tend to lose clarity when different data, time horizons and geographies are used. When they verified whether the widely accepted variables in the market, such as dividend-earnings ratios, would have been helpful for investors to use in their strategies, they conclude they would not have. This does not mean that tail risk is useless for market analysis. The truth is that interesting results were still found as we discussed above. Tail risk still outperforms some variables, and in this Work Project, we are comparing it with top variables in the referenced paper. What the results have shown so far is that results do not look as outstanding as they did in Kelly and Jiang (2014). It is then important to have a certain scepticism and avoid making absolute statements with it.

Cross-Sectional Analysis

After the market wide analysis proving to have similar but weaker results in Europe, we turn to cross-section returns, observing how each firm´s returns in our sample behave with tail risk. The objective is to identify if risk aversion reflects itself on individual returns as observed in the US. If investors are risk-averse, stocks with higher coefficients, riskier in times of uncertainty, will have prices more heavily discounted, hence higher returns. On the opposite side, firms with lower coefficients will be valuable in times of crises, as the co-movement is less similar. Since investors can use these stocks as hedges, they are extremely valuable, leading to higher prices, and so lower future returns.

To observe that, I first run the univariate regression of stock returns with tail risk for the 100 firms, without taking into account the last 120 months of the sample. I perform the same analysis with bivariate regressions adding EPS and P/B as controls. Then, I sort firms according to their coefficient, creating 5 portfolios, equally distributed. The first portfolio with the 20 firms that showcase a higher correlation with tail risk, the second portfolio with the second 20 largest coefficient, and so on, calculating the portfolios' equal weight returns. I leave the last 120 observations of the sample outside of the regression to avoid overlapping results. That is, I use the first 12 years of the sample to identify which stocks co-move the most with tail risk and then use the following 10 years to test this idea of risk aversion. Following this reasoning, the 1st portfolio would have higher returns, followed by the 2nd portfolio, until reaching the 5th portfolio. With this in mind, I computed the portfolios' Alpha, relating to the FF3 model, which allows me to see which portfolios offer higher excess returns relative to the FF3 benchmark.

Unsurprisingly, in the univariate analysis, the 1st portfolio is the one with the highest Alpha, with 2.8pp, followed by the 3rd portfolio, with 1.8pp, the 2nd portfolio with 1.5 pp, the 4th with 1.3pp and the 5th with 0.7 – see table 5. Our reasoning failed only with the second and third portfolio. Yet, these stocks are less clearly used in risk-aversion/taking strategies, which can make it harder to observe an explicit risk-aversion, especially in a univariate model. What stands out is that the 1st portfolio's Alpha is nearly 2.1pp higher than the 5th, going in line with our hypothesis. Furthermore, the average return sits at 2.7pp for the 1st portfolio, the highest among the 5. The remaining portfolios have less indicative average returns. When repeating the same procedure using the stocks' coefficients from the bivariate regression (putting EPS and P/B with tail risk) to create the portfolios, similar results can be found, but in an even more evident way. In fact, the Alpha decreases perfectly as we go from the 1st portfolio to the 2nd portfolio, to the 3rd, to the 4th and to the 5th. This is because the coefficient with tail risk in the univariate regression was capturing the effect of EPS and P/B on stock returns. As we isolate further the effect of tail risk, our hypothesis of cross-sectional results for risk-aversion becomes even clearer. In summary, investors seek higher return from stocks that co-move the most with tail risk and require lower returns from stocks that can be used as a hedge.

	Univariate	Bivariate
P1	2.78	2.65
P2	1.49	1.86
P3	1.80	1.41
P4	1.25	1.28
P5	0.71	0.83

Table 5 –Portfolio´s excess return, relatively to the FF3 benchmark

Yet again, the results seem less strong than in the US, as the excess return was 4.2pp for the highest quintile portfolio relatively to the lowest quintile portfolio, which can also be a reflection of different investing cultures in the different geographies.

Government Bonds

As the hypothesis that investors demand compensation for tail risk is to a certain point verified, and as we observe that investors do indeed minimize risk by using hedge stocks, we turn now to the hypothesis of the search for safer securities, that is government bonds. Remember the hypothesis is that investors will look for bonds when equity tail risk increases, making its price increase, lowering the YTM.

The univariate regression of Germany, France and Italy, at the 2-year, 5-year and 10-years YTM with tail risk shows exactly the opposite, with positive coefficients for the 9 regressions and a p-value of 0.0, highly statistically significant – results in table 6. The YTM of government bonds actually increases as equity tail risk rises. Does this mean that the flight-to-safety idea does not hold? Not necessarily. Investors take several variables into account when investing in government bonds. The way equity markets behave is not the only one, meaning that the univariate models might have severe hidden bias.

Therefore, it is crucial to make this analysis in bivariate models. When using both the 6-month Euribor and inflation as covariates, the results seem to support our hypothesis. The use of the Euribor and inflation will capture investors views on the state of the economy which of course influences the YTM. For example, the increase in inflation and future inflation expectations will decrease the value of future cash-flows, leading investors to require a higher return. With bivariate models, I try to further isolate solely the effect of equity markets' behaviour on bond markets – see results in table 6 below. For Germany, the tail risk's coefficient is negative for all three maturities, decreasing in absolute terms as maturity increases. Furthermore, the p-value is higher, the higher the maturity we use for the regressions – 10-year model not statistically significant. For France, similar results are verified but the 5-year maturity model is also statistically insignificant. This shows that the effect of equity tail risk is stronger and statistically significant in shorter maturities as investors see government bonds as a short-term escape from equity risk, rather than a long-term escape. For Italy, the coefficient is negative for 2-year and 5-year maturity and positive for the 10-year one, but the results are not statistically significant, not even for the shortest maturity, in line with what Rubin and Ruzzi run into in their paper. This is because Italy is seen, for Europe standards, as a country with high credit risk and when equity markets run into recessions, Italy is not seen as a go to safe option.

	10-year		5-year		2-year	
	beta	p-value	beta	p-value	beta	p-value
Germany (univariate)	0.42	0.00	0.42	0.00	0.39	0.00
France (univariate)	0.41	0.00	0.42	0.00	0.39	0.00
Italy (univariate)	0.33	0.00	0.37	0.00	0.38	0.00
Germany (bivariate)	-0.05	0.28	-0.07	0.05	-0.10	0.00
France (bivariate)	-0.02	0.70	-0.05	0.15	-0.09	0.00
Italy (bivariate)	0.09	0.60	0.01	0.90	-0.04	0.29
Italy (credit rating controlled)	0.03	0.59	0.01	0.91	-0.04	0.28

Table 6 – Tail Risk coefficient on government bonds' YTM, in different models

Investors will rather look at countries like Germany and France that offer much better guarantees of safe returns. Additionally, the coefficients are higher, in absolute terms, for Germany than for France, as German bonds seem to be pursued more by investors upon an increase in uncertainty, a reflection of the better credit rating. I tried running the same regressions for Italy, using a dummy variable for when the S&P credit rating was seen as moderate credit risk or below (BBB+, BBB and BBB-, etc), grades that Germany and France never achieve, as to isolate the credit risk. The result is that tail risk remains statistically insignificant. The effect is not found, as equity tail risk seems not represent itself in bad credit rating bond markets.

These regressions prove once again that investors will look for safer assets when equity tail risk increases and government bonds fall within that pool of safe assets. In the future, it would be interesting to use this equity tail risk measure in more technical bond pricing model, including it in the term structures and, eventually, investment strategies.

Conclusion

Intuitively, having a dynamic measure of tail risk is essential for asset pricing. This is because investors are risk averse and want to minimize the losses coming from their investments, reflecting itself on market dynamics. The need for a dynamic measure comes from the intense volatility that markets showcase, something univariate static models cannot easily overcome. Using a dynamic tail risk variable capable of explaining behaviours in equity markets and sovereign bond market was the scope of this Work Project, with an emphasis on Europe. Although, having a good dynamic tail risk variable is complex, the literature review pointed us to the method developed by Kelly and Jiang (2014). From daily cross-sections of stock price information, they are able to extract a common monthly tail risk variable, which is then used in univariate and bivariate regression models, both in-sample and out-of-sample, demonstrating extremely good results for the US market.

By mirroring their methodology to the European market, the evidence demonstrates that investors are indeed risk averse, seeking compensation for it, as I observe that tail risk has predictive power in the market. However, one can conclude that results are not as strong, and in some cases as statistically significant, as the ones observed in the US market. Nevertheless, the cross-section analysis produced strong results, going in line with our hypothesis, with the stocks that co-move the most with tail risk generating excess results, in relation to FF3 benchmark, of 2.1pp higher that stocks that hedge against tail risk.

Lastly, the analysis of the impact of equity markets on government bonds markets, through the dynamic equity tail risk, provided evidence that investors, when faced with an increase in uncertainty in the stock market, seek safer assets, such as Government Bonds, increasing its demand, pushing down the YTM. This impact is stronger for Germany, the safest country in analysis and was statistically insignificant in Italy, a country where investors do not look at, regarding a flight-to-safety strategy.

This Work Project provided weaker results that the ones of Kelly and Jiang (2014). One can argue that it is because we are making the analysis in a different geography where market, investing and even regulatory dynamics are different, leading to different reactions in the market upon an increase in uncertainty. Moreover, the use of a different time span, with different events, can easily change the results, *ceteris paribus*, as so many papers have shown. Nonetheless, the weaker results might also come from data limitations we have. The sample period is much shorter than the one of Kelly and Jiang (2104) and despite efforts by many European agencies, the European market stills lags the US market in terms of cohesion. This fragmentation increases the difficulty of having a good wide market benchmark. In the future, when there is more available and generalized data, the same tests should be run again. Other interesting analysis could still be performed on this topic, like the use of dynamic tail risk in more complex bond pricing models as to understand whether such a variable can be used in investment strategies.

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Appendix

Annex 1 – 100 firms of the STOXX 600 index used in the Work Project

LVMH Moet Hennessy Louis Vuitton SE; AstraZeneca PLC; Diageo PLC; BP PLC; Rio Tinto PLC; British American Tobacco PLC; Mercedes-Benz Group AG; UBS Group AG; Heineken NV; Atlas Copco AB; Anglo American PLC; BASF SE; ING Groep NV; Sika AG; Volvo AB; STMicroelectronics NV; Capgemini SE; Prudential PLC; BAE Systems PLC; Hexagon AB; Holcim AG; Nokia Oyj; DNB Bank ASA; Wolters Kluwer NV; CRH PLC; Swisscom AG; Assa Abloy AB; Skandinaviska Enskilda Banken AB; Telefonaktiebolaget LM Ericsson; Telefonica SA; Nibe Industrier AB; ArcelorMittal SA; Sandvik AB; UPM-Kymmene Oyj; Repsol SA; Tesco PLC; Endesa SA; Kerry Group PLC; Legal & General Group PLC; Swedbank AB; Swedish Match AB; Koninklijke Philips NV; Aviva PLC; Antofagasta PLC; ASM International NV; Fortum Oyj; Jeronimo Martins SGPS SA; Norsk Hydro ASA; Stora Enso Oyj; Akzo Nobel NV; Bunzl PLC; Croda International PLC; Rentokil Initial PLC; Smith & Nephew PLC; Segro PLC; Acciona SA; WPP PLC; Svenska Cellulosa AB SCA; Spirax-Sarco Engineering PLC; Elisa Oyj; Pearson PLC; Rolls-Royce Holdings PLC; ACS Actividades de Construccion y Servic; St James's Place PLC; SKF AB; Holmen AB; Smiths Group PLC; Kongsberg Gruppen ASA; TOMRA Systems ASA; Skanska AB; Trelleborg AB; Beijer Ref AB; Kingfisher PLC; Axfood AB; Getinge AB; SSAB AB; Centrica PLC; Persimmon PLC; Flughafen Zurich AG; Weir Group PLC/The; Harbour Energy PLC; Eurazeo SE; Saab AB; Leonardo SpA; Georg Fischer AG; Wartsila OYJ Abp; Barratt Developments PLC; Aalberts NV; BE Semiconductor Industries NV; Taylor Wimpey PLC; Hiscox Ltd; Storebrand ASA; Securitas AB; Spectris PLC; Arcadis NV; Electrolux AB; Siegfried Holding AG; AIXTRON SE; TietoEVRY Oyj; Avanza Bank Holding AB

Annex 2 – Computed dynamic Tail Risk

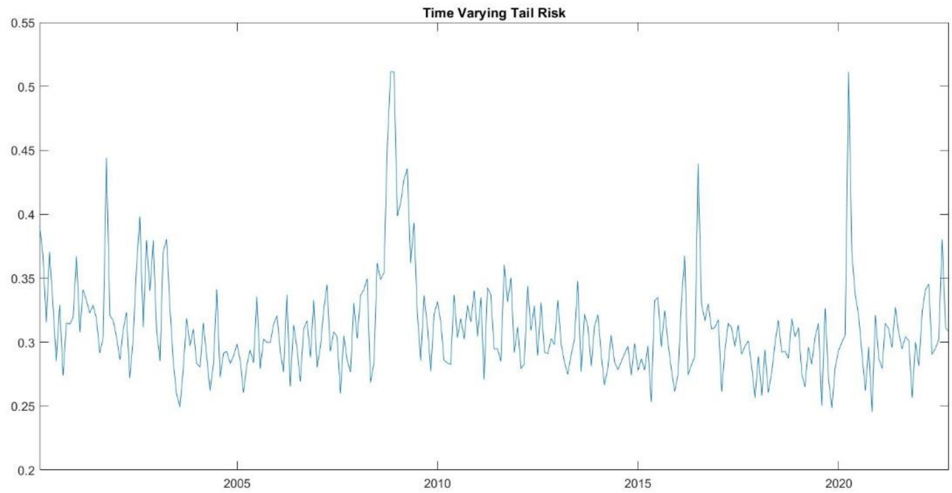

Figure 3- Time Varying Tail Risk, using absolute returns

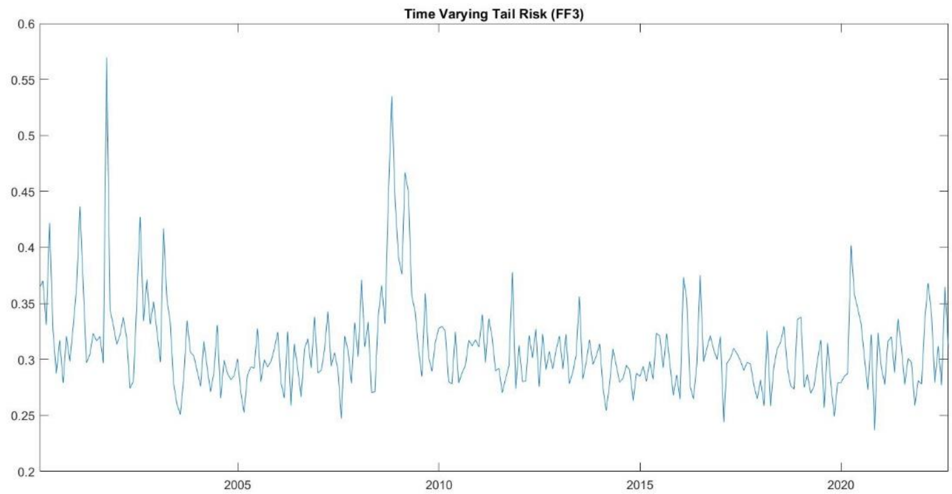

Figure 4 – Time Varying Tail Risk, using residuals from the FF3 regression

Annex 3 – AR(1) results

```
. var Raw, lags(1/1)

Vector autoregression

Sample: 2000m3 thru 2022m9                      Number of obs     =        271
Log likelihood =   518.5163                     AIC               =  -3.811928
FPE            =   .0012943                     HQIC              =  -3.801254
Det(Sigma_ml)  =   .0012753                     SBIC              =  -3.785344

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
Raw                  2     .035844   0.2161   74.72527   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
         Raw | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Raw          |
         Raw |
         L1. |    .463146   .0535777     8.64   0.000     .3581356    .5681564
             |
       _cons |   .1666706   .0167968     9.92   0.000     .1337495    .1995917
------------------------------------------------------------------------------
```

Figure 5 – AR(1) of computed monthly tail risk using raw returns

```
. var Residuals, lags(1/1)

Vector autoregression

Sample: 2000m3 thru 2022m8                      Number of obs     =        270
Log likelihood =   496.7186                     AIC               =  -3.664582
FPE            =   .0014997                     HQIC              =  -3.653878
Det(Sigma_ml)  =   .0014777                     SBIC              =  -3.637927

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
Residuals            2     .038584   0.1692   54.98049   0.0000
----------------------------------------------------------------

------------------------------------------------------------------------------
   Residuals | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
Residuals    |
   Residuals |
         L1. |   .4097773   .0552642     7.41   0.000     .3014616    .5180931
             |
       _cons |   .1828909   .0173041    10.57   0.000     .1489756    .2168062
------------------------------------------------------------------------------
```

Figure 6 – AR(1) of computed monthly tail risk using residuals from FF3

Annex 4 – Univariate models for different periods, with tail risk as regressor

Linear regression

STOXXmonthly	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-8.284	3.864	-2.14	0.033	-15.900	-0.668	**
Constant	15.733	3.855	4.08	0.000	8.134	23.331	***

Mean dependent var	15.733	SD dependent var	57.523
R-squared	0.021	Number of obs	219.000
F-test	4.596	Prob > F	0.033
Akaike crit. (AIC)	2394.756	Bayesian crit. (BIC)	2401.534

**** p<0.01, ** p<0.05, * p<0.1*

Table 7 – Regression of annualized monthly market return with tail risk

Regression with Neweyâ€“West standard errors

STOXXyear	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	2.380	1.763	1.35	0.178	-1.095	5.854	
Constant	4.835	3.299	1.47	0.144	-1.669	11.338	

Mean dependent var	4.801	SD dependent var	16.919
Number of obs	210.000	F-test	1.822

**** p<0.01, ** p<0.05, * p<0.1*

Table 8 – Regression of annual market return with tail risk, adjusted for Newey –West standard errors

Regression with Neweyâ€“West standard errors

STOXX2years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	1.620	0.895	1.81	0.072	-0.145	3.386	*
Constant	3.524	2.862	1.23	0.220	-2.121	9.169	

Mean dependent var	3.524	SD dependent var	11.435
Number of obs	198.000	F-test	3.275

**** p<0.01, ** p<0.05, * p<0.1*

Table 9 – Regression of annualized 2-year forward market return with tail risk, adjusted for Newey –West standard errors

Regression with Neweyâ€“West standard errors

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	1.460	0.347	4.21	0.000	0.775	2.146	***
Constant	2.416	1.755	1.38	0.171	-1.051	5.883	
Mean dependent var		2.476	SD dependent var			5.210	
Number of obs		163.000	F-test			17.719	

*** p<0.01, ** p<0.05, * p<0.1*

Table 10 – Regression of annualized 5-year forward market return with tail risk, adjusted for Newey –West standard errors

Annex 5 – Univariate models for different periods, with alternative Goyal and Welch adjusted variables as regressors

Linear regression

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Equal_WeightPB	1.063	0.577	1.84	0.067	-0.077	2.203	*
Constant	-0.049	1.429	-0.03	0.973	-2.872	2.774	
Mean dependent var		2.476	SD dependent var			5.210	
R-squared		0.021	Number of obs			163.000	
F-test		3.394	Prob > F			0.067	
Akaike crit. (AIC)		1000.289	Bayesian crit. (BIC)			1006.477	

*** p<0.01, ** p<0.05, * p<0.1*

Table 11 – Regression of annualized 5-year forward market return with P/B, adjusted for Newey –West standard errors

Linear regression

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Equal_WeightEPS	-4.055	0.675	-6.01	0.000	-5.389	-2.722	***
Constant	13.366	1.850	7.22	0.000	9.713	17.019	***
Mean dependent var		2.476	SD dependent var			5.210	
R-squared		0.183	Number of obs			163.000	
F-test		36.093	Prob > F			0.000	
Akaike crit. (AIC)		970.719	Bayesian crit. (BIC)			976.907	

*** p<0.01, ** p<0.05, * p<0.1*

Table 12 – Regression of annualized 5-year forward market return with EPS, adjusted for Newey –West standard errors

Linear regression

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
YTMGermany2year	-1.854	0.209	-8.86	0.000	-2.268	-1.441	***
Constant	4.793	0.425	11.27	0.000	3.953	5.633	***

Mean dependent var	2.476	SD dependent var	5.210
R-squared	0.328	Number of obs	163.000
F-test	78.511	Prob > F	0.000
Akaike crit. (AIC)	938.947	Bayesian crit. (BIC)	945.134

*** p<0.01, ** p<0.05, * p<0.1*

Table 13 – Regression of annualized 5-year forward market return with German 2-year YTM, adjusted for Newey –West standard errors

Linear regression

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
YTMGermany10year	-1.240	0.268	-4.62	0.000	-1.770	-0.710	***
Constant	5.392	0.739	7.30	0.000	3.933	6.850	***

Mean dependent var	2.476	SD dependent var	5.210
R-squared	0.117	Number of obs	163.000
F-test	21.369	Prob > F	0.000
Akaike crit. (AIC)	983.375	Bayesian crit. (BIC)	989.563

*** p<0.01, ** p<0.05, * p<0.1*

Table 14 – Regression of annualized 5-year forward market return with German 10-year YTM, adjusted for Newey –West standard errors

Linear regression

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
monthEuribor	-1.513	0.227	-6.66	0.000	-1.962	-1.064	***
Constant	4.838	0.507	9.54	0.000	3.836	5.840	***

Mean dependent var	2.476	SD dependent var	5.210
R-squared	0.216	Number of obs	163.000
F-test	44.298	Prob > F	0.000
Akaike crit. (AIC)	964.071	Bayesian crit. (BIC)	970.258

*** p<0.01, ** p<0.05, * p<0.1*

Table 15 – Regression of annualized 5-year forward market return with 6-month EURIBOR, adjusted for Newey –West standard errors

Linear regression

STOXX5years	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Inflation	-0.833	0.383	-2.17	0.031	-1.589	-0.076	**
Constant	3.830	0.742	5.16	0.000	2.365	5.295	***

Mean dependent var	2.476	SD dependent var	5.210
R-squared	0.029	Number of obs	163.000
F-test	4.729	Prob > F	0.031
Akaike crit. (AIC)	998.971	Bayesian crit. (BIC)	1005.159

**** p<0.01, ** p<0.05, * p<0.1*

Table 16 – Regression of annualized 5-year forward market return with inflation, adjusted for Newey –West standard errors

Annex 6 – Comparison between univariate and bivariate model's results

	1 month			5-year		
	beta	R^2	p-value	beta	R^2	p-value
Univariate	-8.30	0.02	0.00	1.46	0.09	0.00
Equal_WeightP/B	-8.52	0.03	0.03	1.48	0.11	0.00
Equal_WeightEPS	-8.05	0.03	0.04	1.76	0.30	0.00
YTMGermany2year	-7.60	0.03	0.05	2.03	0.49	0.00
YTMGermany10year	-7.88	0.02	0.05	1.87	0.25	0.00
monthEuribor	-7.03	0.03	0.08	2.35	0.42	0.00
Inflation	-7.04	0.05	0.07	1.64	0.13	0.00

Table 17 – Tail Risk coefficients in univariate and bivariate models, with the respective covariables, for the 1-month and 5-year annualized forward returns

Annex 7 – Out-of-sample analysis

	1-month		1-year		2-years		5-years	
	Beta	R^2	Beta	R^2	Beta	R^2	Beta	R^2
Tail Risk	10.09	0.00	-19.78	0.09	-0.55	0.08	1.79	0.02
Equal_WeightP/B	17.25	0.00	-0.10	0.02	1.89	0.07	-1.54	0.27
Equal_WeightEPS	14.53	0.00	3.54	0.00	3.01	0.15	2.29	0.00
YTMGermany2year	-58.91	0.01	-23.54	0.02	-19.25	0.13	-10.57	0.17
YTMGermany10year	-72.86	0.02	-20.67	0.06	-22.16	0.48	-6.66	0.11
monthEuribor	-44.59	0.00	-14.63	0.01	-24.89	0.13	-14.87	0.14
Inflation	9.64	0.02	-6.53	0.13	5.98	0.02	3.13	0.00

Table 18 – Regression results between predicted returns, out-of-sample, and real returns

Annex 8 – Cross-sectional analysis. Portfolio created from univariate model's coefficients. Analysis of portfolios' equal weight excess return, in relation to the FF3

Linear regression

P1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	-0.112	0.107	-1.04	0.298	-0.325	0.101	
SMB	-0.002	0.179	-0.01	0.990	-0.356	0.352	
HML	-0.124	0.125	-0.99	0.325	-0.372	0.124	
Constant	2.780	0.447	6.22	0.000	1.894	3.666	***

Mean dependent var	2.668	SD dependent var	4.721
R-squared	0.019	Number of obs	120.000
F-test	0.739	Prob > F	0.531
Akaike crit. (AIC)	717.761	Bayesian crit. (BIC)	728.911

**** p<0.01, ** p<0.05, * p<0.1*

Table 19 – Regression results for the portfolio composed by the 20 firms with the highest tail risk beta

Linear regression

P2	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	0.292	0.131	2.23	0.028	0.032	0.552	**
SMB	-0.119	0.218	-0.54	0.588	-0.551	0.314	
HML	-0.002	0.153	-0.01	0.991	-0.305	0.301	
Constant	1.487	0.546	2.72	0.007	0.405	2.569	***

Mean dependent var	1.797	SD dependent var	5.834
R-squared	0.041	Number of obs	120.000
F-test	1.657	Prob > F	0.180
Akaike crit. (AIC)	765.798	Bayesian crit. (BIC)	776.948

**** p<0.01, ** p<0.05, * p<0.1*

Table 20 – Regression results for the portfolio composed by the second 20 firms with the highest tail risk beta

Linear regression

P3	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	0.182	0.103	1.76	0.081	-0.023	0.386	*
SMB	-0.086	0.172	-0.50	0.618	-0.426	0.255	
HML	0.021	0.120	0.17	0.862	-0.218	0.260	
Constant	1.804	0.430	4.19	0.000	0.952	2.656	***

Mean dependent var	1.995	SD dependent var	4.557
R-squared	0.026	Number of obs	120.000
F-test	1.042	Prob > F	0.377
Akaike crit. (AIC)	708.369	Bayesian crit. (BIC)	719.518

*** *p<0.01, ** p<0.05, * p<0.1*

Table 21 – Regression results for the portfolio composed by the third 20 firms with the highest tail risk beta

Linear regression

P4	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	0.498	0.092	5.41	0.000	0.316	0.680	***
SMB	0.015	0.153	0.10	0.921	-0.288	0.319	
HML	0.049	0.107	0.45	0.652	-0.164	0.261	
Constant	1.251	0.383	3.26	0.001	0.492	2.011	***

Mean dependent var	1.777	SD dependent var	4.539
R-squared	0.220	Number of obs	120.000
F-test	10.882	Prob > F	0.000
Akaike crit. (AIC)	680.837	Bayesian crit. (BIC)	691.987

*** *p<0.01, ** p<0.05, * p<0.1*

Table 22 – Regression results for the portfolio composed by fourth the 20 firms with the highest tail risk beta

Linear regression

P5	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	1.173	0.095	12.37	0.000	0.985	1.361	***
SMB	0.093	0.158	0.59	0.557	-0.220	0.405	
HML	0.245	0.111	2.22	0.028	0.026	0.464	**
Constant	0.706	0.395	1.79	0.076	-0.076	1.487	*

Mean dependent var	1.936	SD dependent var	6.577
R-squared	0.606	Number of obs	120.000
F-test	59.540	Prob > F	0.000
Akaike crit. (AIC)	687.760	Bayesian crit. (BIC)	698.910

*** *p<0.01, ** p<0.05, * p<0.1*

Table 23 – Regression results for the portfolio composed by the fifth 20 firms with the highest tail risk beta

Annex 9 – Cross-sectional analysis. Portfolio created from bivariate model's coefficients. Analysis of portfolios' equal weight excess return, in relation to the FF3

Linear regression

P1	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	-0.022	0.122	-0.18	0.857	-0.264	0.220	
SMB	0.004	0.203	0.02	0.983	-0.399	0.407	
HML	-0.002	0.142	-0.01	0.989	-0.284	0.280	
Constant	2.651	0.509	5.21	0.000	1.643	3.658	***

Mean dependent var	2.628	SD dependent var	5.320
R-squared	0.000	Number of obs	120.000
F-test	0.011	Prob > F	0.998
Akaike crit. (AIC)	748.661	Bayesian crit. (BIC)	759.811

*** *p<0.01, ** p<0.05, * p<0.1*

Table 24 – Regression results for the portfolio composed by the 20 firms with the highest tail risk beta, in bivariate models

Linear regression

P2	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	0.140	0.103	1.36	0.177	-0.064	0.344	
SMB	-0.089	0.172	-0.52	0.606	-0.429	0.251	
HML	-0.149	0.120	-1.24	0.219	-0.387	0.090	
Constant	1.860	0.430	4.33	0.000	1.009	2.711	***

Mean dependent var	2.017	SD dependent var	4.556
R-squared	0.028	Number of obs	120.000
F-test	1.121	Prob > F	0.343
Akaike crit. (AIC)	708.056	Bayesian crit. (BIC)	719.206

**** p<0.01, ** p<0.05, * p<0.1*

Table 25 – Regression results for the portfolio composed by the second 20 firms with the highest tail risk beta, in bivariate models

Linear regression

P3	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	0.232	0.102	2.28	0.024	0.031	0.434	**
SMB	-0.069	0.169	-0.41	0.685	-0.404	0.266	
HML	-0.012	0.119	-0.10	0.920	-0.247	0.223	
Constant	1.413	0.424	3.33	0.001	0.574	2.252	***

Mean dependent var	1.660	SD dependent var	4.530
R-squared	0.044	Number of obs	120.000
F-test	1.766	Prob > F	0.157
Akaike crit. (AIC)	704.745	Bayesian crit. (BIC)	715.895

**** p<0.01, ** p<0.05, * p<0.1*

Table 26 – Regression results for the portfolio composed by the third 20 firms with the highest tail risk beta, in bivariate models

Linear regression

P4	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	0.651	0.101	6.43	0.000	0.450	0.851	***
SMB	-0.013	0.168	-0.08	0.939	-0.346	0.320	
HML	0.078	0.118	0.66	0.510	-0.156	0.311	
Constant	1.277	0.421	3.03	0.003	0.443	2.110	***

Mean dependent var	1.962	SD dependent var	5.196
R-squared	0.282	Number of obs	120.000
F-test	15.197	Prob > F	0.000
Akaike crit. (AIC)	703.275	Bayesian crit. (BIC)	714.425

**** p<0.01, ** p<0.05, * p<0.1*

Table 27 – Regression results for the portfolio composed by the fourth 20 firms with the highest tail risk beta, in bivariate models

Linear regression

P5	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MktRF	1.031	0.097	10.66	0.000	0.840	1.223	***
SMB	0.068	0.161	0.42	0.675	-0.251	0.387	
HML	0.274	0.113	2.43	0.017	0.051	0.498	**
Constant	0.828	0.403	2.06	0.042	0.030	1.626	**

Mean dependent var	1.907	SD dependent var	6.188
R-squared	0.537	Number of obs	120.000
F-test	44.757	Prob > F	0.000
Akaike crit. (AIC)	692.693	Bayesian crit. (BIC)	703.843

**** p<0.01, ** p<0.05, * p<0.1*

Table 28 – Regression results for the portfolio composed by the second 20 firms with the highest tail risk beta, in bivariate models

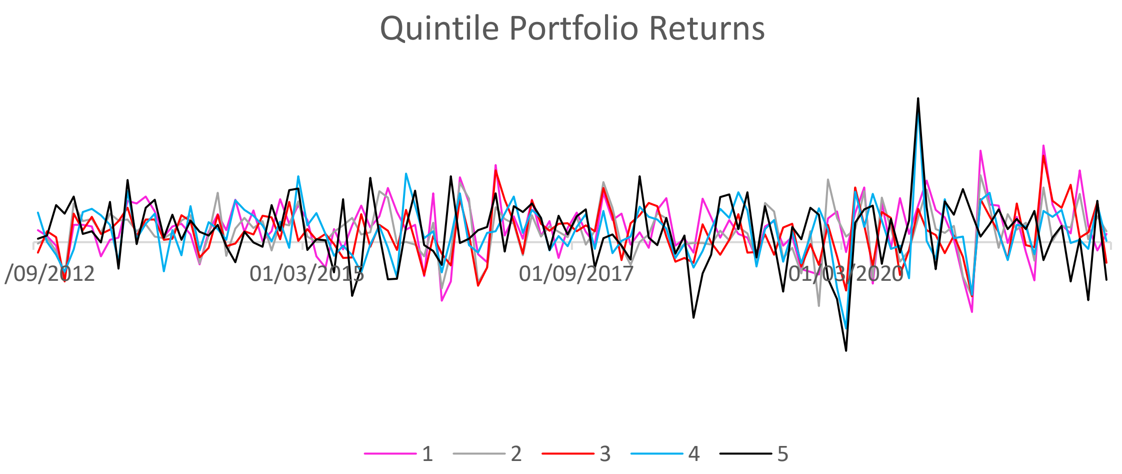

Figure 7 – Portfolios' excess return distribution

Annex 10 – Impact of tail risk on government bonds – univariate models

Linear regression

Germany10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.415	0.100	4.14	0.000	0.218	0.612	***
Constant	2.255	0.112	20.21	0.000	2.035	2.474	***

Mean dependent var	2.302	SD dependent var	1.884
R-squared	0.060	Number of obs	272.000
F-test	17.177	Prob > F	0.000
Akaike crit. (AIC)	1102.640	Bayesian crit. (BIC)	1109.852

**** p<0.01, ** p<0.05, * p<0.1*

Table 29 – Regression results of German 10-year YTM with equity tail risk

Linear regression

Germany5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.419	0.102	4.11	0.000	0.218	0.620	***
Constant	1.692	0.114	14.89	0.000	1.468	1.915	***
Mean dependent var		1.740	SD dependent var			1.917	
R-squared		0.059	Number of obs			272.000	
F-test		16.879	Prob > F			0.000	
Akaike crit. (AIC)		1112.553	Bayesian crit. (BIC)			1119.764	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 30 – Regression results of German 5-year YTM with equity tail risk

Linear regression

Germany2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.387	0.100	3.88	0.000	0.191	0.583	***
Constant	1.281	0.111	11.54	0.000	1.062	1.499	***
Mean dependent var		1.325	SD dependent var			1.868	
R-squared		0.053	Number of obs			272.000	
F-test		15.092	Prob > F			0.000	
Akaike crit. (AIC)		1099.947	Bayesian crit. (BIC)			1107.158	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 31 – Regression results of German 2-year YTM with equity tail risk

Linear regression

France10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.413	0.094	4.39	0.000	0.228	0.598	***
Constant	2.557	0.105	24.43	0.000	2.351	2.763	***
Mean dependent var		2.604	SD dependent var			1.774	
R-squared		0.067	Number of obs			272.000	
F-test		19.290	Prob > F			0.000	
Akaike crit. (AIC)		1067.927	Bayesian crit. (BIC)			1075.139	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 32 – Regression results of France 10-year YTM with equity tail risk

Linear regression

France5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.423	0.098	4.33	0.000	0.231	0.616	***
Constant	1.887	0.109	17.33	0.000	1.672	2.101	***

Mean dependent var	1.935	SD dependent var	1.843
R-squared	0.065	Number of obs	272.000
F-test	18.751	Prob > F	0.000
Akaike crit. (AIC)	1089.362	Bayesian crit. (BIC)	1096.574

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 33 – Regression results of France 5-year YTM with equity tail risk

Linear regression

France2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.392	0.098	4.00	0.000	0.199	0.584	***
Constant	1.380	0.109	12.64	0.000	1.165	1.594	***

Mean dependent var	1.424	SD dependent var	1.839
R-squared	0.056	Number of obs	272.000
F-test	15.978	Prob > F	0.000
Akaike crit. (AIC)	1090.687	Bayesian crit. (BIC)	1097.899

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 34 – Regression results of France 2-year YTM with equity tail risk

Linear regression

Italy10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.330	0.082	4.04	0.000	0.169	0.490	***
Constant	3.524	0.091	38.79	0.000	3.345	3.702	***

Mean dependent var	3.561	SD dependent var	1.532
R-squared	0.057	Number of obs	272.000
F-test	16.361	Prob > F	0.000
Akaike crit. (AIC)	990.909	Bayesian crit. (BIC)	998.120

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 35 – Regression results of Italy 10-year YTM with equity tail risk

Linear regression

Italy5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.369	0.089	4.15	0.000	0.194	0.543	***
Constant	2.716	0.099	27.46	0.000	2.521	2.911	***

Mean dependent var	2.758	SD dependent var	1.671
R-squared	0.060	Number of obs	272.000
F-test	17.228	Prob > F	0.000
Akaike crit. (AIC)	1037.245	Bayesian crit. (BIC)	1044.457

*** *p<0.01, ** p<0.05, * p<0.1*

Table 36 – Regression results of Italy 5-year YTM with equity tail risk

Linear regression

Italy2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.376	0.092	4.11	0.000	0.196	0.556	***
Constant	1.957	0.102	19.18	0.000	1.756	2.157	***

Mean dependent var	2.000	SD dependent var	1.721
R-squared	0.059	Number of obs	272.000
F-test	16.872	Prob > F	0.000
Akaike crit. (AIC)	1053.889	Bayesian crit. (BIC)	1061.100

*** *p<0.01, ** p<0.05, * p<0.1*

Table 37 – Regression results of Italy 10-year YTM with equity tail risk

Annex 11 – Impact of tail risk on government bonds – bivariate models

Linear regression

Germany10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.046	0.043	-1.07	0.283	-0.131	0.038	
monthEuribor	0.984	0.028	35.49	0.000	0.930	1.039	***
Inflation	-0.022	0.033	-0.67	0.502	-0.088	0.043	
Constant	0.840	0.079	10.61	0.000	0.684	0.996	***

Mean dependent var	2.302	SD dependent var	1.884
R-squared	0.843	Number of obs	272.000
F-test	481.214	Prob > F	0.000
Akaike crit. (AIC)	619.068	Bayesian crit. (BIC)	633.491

*** *p<0.01, ** p<0.05, * p<0.1*

Table 38 – Regression results of Germany 10-year YTM with equity tail risk, Euribor and inflation

Linear regression

Germany5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.069	0.034	-2.01	0.045	-0.137	-0.001	**
monthEuribor	1.034	0.022	46.67	0.000	0.991	1.078	***
Inflation	0.004	0.027	0.17	0.868	-0.048	0.057	
Constant	0.154	0.063	2.43	0.016	0.029	0.278	**

Mean dependent var	1.740	SD dependent var	1.917
R-squared	0.903	Number of obs	272.000
F-test	836.360	Prob > F	0.000
Akaike crit. (AIC)	497.065	Bayesian crit. (BIC)	511.488

**** p<0.01, ** p<0.05, * p<0.1*

Table 39 – Regression results of Germany 5-year YTM with equity tail risk, Euribor and inflation

Linear regression

Germany2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.103	0.024	-4.24	0.000	-0.150	-0.055	***
monthEuribor	1.037	0.016	66.25	0.000	1.006	1.068	***
Inflation	0.008	0.019	0.41	0.682	-0.029	0.045	
Constant	-0.268	0.045	-5.99	0.000	-0.356	-0.180	***

Mean dependent var	1.325	SD dependent var	1.868
R-squared	0.949	Number of obs	272.000
F-test	1671.430	Prob > F	0.000
Akaike crit. (AIC)	307.874	Bayesian crit. (BIC)	322.297

**** p<0.01, ** p<0.05, * p<0.1*

Table 40 – Regression results of Germany 2-year YTM with equity tail risk, Euribor and inflation

Linear regression

France10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.015	0.043	-0.36	0.718	-0.099	0.069	
monthEuribor	0.904	0.028	32.78	0.000	0.850	0.958	***
Inflation	0.015	0.033	0.46	0.645	-0.050	0.081	
Constant	1.191	0.079	15.12	0.000	1.036	1.346	***

Mean dependent var	2.604	SD dependent var	1.774
R-squared	0.825	Number of obs	272.000
F-test	422.159	Prob > F	0.000
Akaike crit. (AIC)	616.069	Bayesian crit. (BIC)	630.492

**** p<0.01, ** p<0.05, * p<0.1*

Table 41 – Regression results of France 10-year YTM with equity tail risk, Euribor and inflation

Linear regression

France5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.046	0.032	-1.44	0.150	-0.109	0.017	
monthEuribor	0.987	0.021	47.71	0.000	0.946	1.028	***
Inflation	0.034	0.025	1.36	0.175	-0.015	0.083	
Constant	0.363	0.059	6.15	0.000	0.247	0.480	***

Mean dependent var	1.935	SD dependent var	1.843
R-squared	0.909	Number of obs	272.000
F-test	892.416	Prob > F	0.000
Akaike crit. (AIC)	459.652	Bayesian crit. (BIC)	474.075

**** p<0.01, ** p<0.05, * p<0.1*

Table 42 – Regression results of France 5-year YTM with equity tail risk, Euribor and inflation

Linear regression

France2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.094	0.020	-4.61	0.000	-0.133	-0.054	***
monthEuribor	1.028	0.013	78.50	0.000	1.003	1.054	***
Inflation	0.003	0.016	0.22	0.827	-0.028	0.034	
Constant	-0.148	0.037	-3.96	0.000	-0.222	-0.075	***

Mean dependent var	1.424	SD dependent var	1.839
R-squared	0.963	Number of obs	272.000
F-test	2347.515	Prob > F	0.000
Akaike crit. (AIC)	211.070	Bayesian crit. (BIC)	225.493

**** p<0.01, ** p<0.05, * p<0.1*

Table 43 – Regression results of France 2-year YTM with equity tail risk, Euribor and inflation

Linear regression

Italy10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.029	0.058	0.51	0.613	-0.085	0.144	
monthEuribor	0.605	0.038	16.05	0.000	0.531	0.679	***
Inflation	0.125	0.045	2.75	0.006	0.035	0.214	***
Constant	2.397	0.108	22.29	0.000	2.186	2.609	***

Mean dependent var	3.561	SD dependent var	1.532
R-squared	0.563	Number of obs	272.000
F-test	115.017	Prob > F	0.000
Akaike crit. (AIC)	785.842	Bayesian crit. (BIC)	800.265

**** p<0.01, ** p<0.05, * p<0.1*

Table 44 – Regression results of Italy 10-year YTM with equity tail risk, Euribor and inflation

Linear regression

Italy5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.005	0.054	0.10	0.921	-0.101	0.112	
monthEuribor	0.730	0.035	20.83	0.000	0.661	0.799	***
Inflation	0.155	0.042	3.68	0.000	0.072	0.238	***
Constant	1.348	0.100	13.47	0.000	1.151	1.545	***

Mean dependent var	2.758	SD dependent var	1.671
R-squared	0.682	Number of obs	272.000
F-test	191.770	Prob > F	0.000
Akaike crit. (AIC)	746.263	Bayesian crit. (BIC)	760.687

**** p<0.01, ** p<0.05, * p<0.1*

Table 45 – Regression results of Italy 5-year YTM with equity tail risk, Euribor and inflation

Linear regression

Italy2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.043	0.040	-1.07	0.286	-0.123	0.036	
monthEuribor	0.859	0.026	32.84	0.000	0.807	0.910	***
Inflation	0.118	0.031	3.77	0.000	0.056	0.180	***
Constant	0.466	0.075	6.24	0.000	0.319	0.613	***

Mean dependent var	2.000	SD dependent var	1.721
R-squared	0.833	Number of obs	272.000
F-test	446.573	Prob > F	0.000
Akaike crit. (AIC)	587.065	Bayesian crit. (BIC)	601.488

**** p<0.01, ** p<0.05, * p<0.1*

Table 46 – Regression results of Italy 2-year YTM with equity tail risk, Euribor and inflation

Annex 12 – Impact of tail risk on government bonds – Italy credit rating control

Linear regression

Italy10y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.030	0.056	0.54	0.592	-0.081	0.142	
monthEuribor	0.380	0.063	5.98	0.000	0.255	0.505	***
Inflation	0.144	0.044	3.26	0.001	0.057	0.231	***
IT8	-0.943	0.218	-4.33	0.000	-1.371	-0.514	***
Constant	3.150	0.203	15.54	0.000	2.751	3.549	***

Mean dependent var	3.561	SD dependent var	1.532
R-squared	0.592	Number of obs	272.000
F-test	96.657	Prob > F	0.000
Akaike crit. (AIC)	769.392	Bayesian crit. (BIC)	787.421

**** p<0.01, ** p<0.05, * p<0.1*

Table 47 – Regression results of Italy 10-year YTM with equity tail risk, Euribor and inflation and credit risk dummy variable

Linear regression

Italy5y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	0.006	0.053	0.12	0.909	-0.098	0.110	
monthEuribor	0.549	0.060	9.21	0.000	0.432	0.666	***
Inflation	0.171	0.041	4.13	0.000	0.089	0.252	***
IT8	-0.759	0.204	-3.71	0.000	-1.161	-0.357	***
Constant	1.953	0.190	10.28	0.000	1.579	2.328	***

Mean dependent var	2.758	SD dependent var	1.671
R-squared	0.698	Number of obs	272.000
F-test	154.145	Prob > F	0.000
Akaike crit. (AIC)	734.558	Bayesian crit. (BIC)	752.587

**** p<0.01, ** p<0.05, * p<0.1*

Table 48 – Regression results of Italy 5-year YTM with equity tail risk, Euribor and inflation and credit risk dummy variable

Linear regression

Italy2y	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Tail_Risk	-0.043	0.040	-1.07	0.284	-0.122	0.036	
monthEuribor	0.755	0.045	16.81	0.000	0.667	0.844	***
Inflation	0.127	0.031	4.08	0.000	0.066	0.189	***
IT8	-0.434	0.154	-2.82	0.005	-0.738	-0.131	***
Constant	0.813	0.143	5.67	0.000	0.531	1.095	***

Mean dependent var	2.000	SD dependent var	1.721
R-squared	0.838	Number of obs	272.000
F-test	345.605	Prob > F	0.000
Akaike crit. (AIC)	581.083	Bayesian crit. (BIC)	599.112

**** p<0.01, ** p<0.05, * p<0.1*

Table 49 – Regression results of Italy 2-year YTM with equity tail risk, Euribor and inflation and credit risk dummy variable