Complementing Expected Shortfall with Directly Observable Risk Variables

Supervisor: Dag Rydorff[*]
MSc thesis at the Department of Economics at LUSEM

Pontus Johansson

August 5, 2021

[*]I would like to deeply thank Dag for being willing to put in a lot of time in helping me formulate this thesis. Without him, both the intention and the implementation of the thesis would be lacking in comparison to the produced thesis.

Abstract

This paper uses daily MSCI Sweden Index data to create one day out ES estimates on the 97.5% percentile level for a SEK 100 portfolio. Thereafter the variables (i) the Riksbank's policy rate, (ii) the Riksbank's balance sheet, (iii) the cyclicality of GDP, and (iv) animal spirits are introduced and compared with ES. As the variables are thought to affect financial markets, they are evaluated in regards to ES to see if the addition of them in an analysis improves estimation of the 2.5% worst losses. If ES does not incorporate signals of risk shown by the variables, increased predictive ability for losses is achieved by including the variables in an analysis. The results indicate that (i), (ii), and (iv) are worth including in addition to ES when estimating the cost of the 2.5% largest losses of a stock index.

Keywords — Expected shortfall, Risk management, Monetary Policy, Animal Spirits, Business Cycles

Contents

1 Introduction

Modern portfolio theory, and the efficient market hypothesis that it builds on, have had success within academia and have been awarded several Nobel prizes. Following this, focus on diversification has been central within investing, and broad index funds with low fees have blown up in popularity. As an increasing amount of investors have put their money into mutual funds and exchange-traded funds (ETFs), fund managers who are supplying these funds, such as Blackrock and Vanguard, have grown immensely. Based on the growing popularity of index investing, understanding the risk of a portfolio consisting of an index fund is of great interest both for fund managers as well as many investors. Furthermore, few people in the developed rich world are disconnected from a wide stock index as even individuals who are not directly investing in them often have some type of connection to the index. An example of this is that many large employers in a country likely are a part of the index, meaning that many employees have direct ties to the companies which form the index. Changes in equity prices could cause layoffs or increased hiring. Furthermore, another connection that people may have to a wide equity index is that pension funds often invest either directly in them or in many of the equities which make up a broad equity index. Because of this, price movements of a large stock index are relevant for most people.

Investors, workers in publicly traded companies, and pension savers who have exposure to a Swedish index should be interested in future potential price movements in the index as they are affected by it. Both increases and decreases in the index are things that could affect these people, and it is analyzed to a great extent as investors and financial institutions try to maximize their gains with the goal of minimal losses. The swings in prices, both upwards and downward, are often measured by volatility which within finance is synonym with "risk". Using historical data, one can calculate the standard deviation of a portfolio, and this estimate is called the risk for the said portfolio.

It would require an unprecedented breakthrough, or massive hubris, for a single paper to try to analyze everything related to the price movements of a stock index. Instead, increasing the understanding of a part of the distribution of price movements is more realistic for a paper. Hopefully, many papers will do this to better comprehend the many different parts of the distribution. This could lead to the aggregate of the papers establishing a complete understanding of the whole distribution of price movements. In this spirit, the purpose of this paper is to better *predict how costly the worst* 2.5% *losses* are of a distribution of returns. To clarify, delimitations are applied along the following lines. Firstly, this paper will ignore the upside of index investing and will instead solely focus on losses. Secondly, the size and frequency of a majority of losses will also be disregarded, and the focus will be put on *estimating how costly the very worst losses* are. Because of these delimitations, this paper will not help to answer the question if index investing is a good idea or what their expected result is. Rather, the ambition of this thesis is to improve predictions of future losses, given that the loss belongs to the very worst 2.5% of a distribution. Throughout this thesis, a portfolio consisting of SEK 100 invested in the MSCI Sweden Index will be used, and it is the statistical distribution of this portfolio that is being discussed.

To estimate the above-defined losses, Expected Shortfall (ES henceforth) will be used. This estimate, simply stated, answers the question of how costly a loss will be past a certain confidence level. ES, and Value at Risk (VaR henceforth) which ES builds on, are measurements that are widely used within finance, which means that it would be of great benefit to find possible improvements to these measurements. Rather than trying to optimize the measurements by using different estimation methods, something which is investigated to a great extent (Guermat and Harris, 2002; Kuester et al., 2005; Broda and Paolella, 2011; Gerlach and Chen, 2017; BIS, 2013; Polanski and Stoja, 2009), this thesis investigates how observable risk variables can complement ES to be used in addition to ES. The intuitive reasoning behind the thesis is as follows: ES exclusively uses historical price data of the MSCI Sweden Index to predict the cost of losses. If one accepts the premise that there are variables outside of historical price data which can affect losses, then the addition of those variables should improve estimations of losses. An extreme example, to hammer home the principle of observable risk, would be that for a Swedish stock index, Stockholm being nuked would definitely increase the estimation of the 2.5% worst losses for stocks and would therefore be a variable which improves the estimation of future losses in addition to historical prices. The principle of interest is; if an observable risk variable can be shown to capture something which ES does not, then including it in ones analysis of future losses will be better than using only ES. It will be investigated if there exists observable risk variables which, when included in an analysis, improves estimation of the 2.5% worst losses. If increases in the observable risk is already captured by ES, then the variable however does not need to be included in the analysis. But if it does not, then using both the risk estimate ES and observing the risks variable jointly would produce better estimations of the cost of the 2.5% worst risk than only using ES. This very connection is what this thesis is aspiring to evaluate by investigating the variables *Monetary policy*, *Business cycles* and *Animal spirits*. After empirically estimating the cost of tail risk using ES, an ordinary least squares regression will be used to examine if inclusion of the risk variables improves upon the results produced by ES. This connection between the risk variables and ES is the heart of this thesis and is what is the addition to the finance literature.

Between the lines, the above paragraph is implying that ES in itself might not be dependable and therefore needs additional variables to support it. The reason behind this skeptical tone is founded in the mathematical definition of ES, as it is only based on historical price data. Because of the mathematical limitations of the method, there is a group of people who are quite skeptical about how much the measurement actually helps in estimating the cost of the risk. As the London School of Economics professor Danielsson (2008, p.1) put it, "Having a number representing risk seems to be more important than having a number which is correct.". In a more recent blog post, he compares ES to a thermometer (Danielsson, 2021), playing on the fact that it only reads what has already happened. This very skeptical attitude is not generally held in finance, proven by the widespread usage of the model, but it highlights a weakness of the model. Proponents of ES would likely state that they need a number estimate, and although not perfect, it helps to some degree. However, its adversaries advocate variables known to affect risk to be directly observed as they deem measurements such as ES to be too unreliable (Danielsson, 2021). While most papers zoom in on either end of this spectrum, either how to optimize a time series approach like ES by changing details of the model specification, or by disregarding it and analyzing the predictive ability of some observable risk variable. The holistic approach this thesis is going for is to examine if it is possible to get the *best of both worlds*, having an ES estimate as a type of base rate which one then adjusts based on other risk variables. Due to the wide scope in ambition, it does run the risk of not being able to go into enough depth in the different topics.

The risk variables which will be analyzed all have theoretically found reasons to affect the stock index of interest, which is a daily MSCI Sweden Index ranging from 1980-01-01 to 2021-04-12, downloaded via Bloomberg. Furthermore, the variables also have *empirical* connections to the wide stock indexes, which will be presented in more detail in Section 2. The risk variables included are the two legs of monetary policy, that is the (i) the Riksbank's policy rate and (ii) the Riksbank's balance sheet. When a central bank engages in expansionary monetary policy, it boosts the economy and the financial markets by lowering the policy rate and increasing the size of their balance sheet (think quantitative easing). Furthermore, (iii) the business cycle will be analyzed as it at times moves with the equity markets. Lastly, (iv) animal spirits, which could also be thought of as speculation or changing risk appetite, are analyzed as a disconnect from fundamental variables that play an important role in bubbles forming and bursting. The results indicate that (i), (ii), and (iv) are worth including in addition to ES.

The outline of the thesis is as follows: Section 2 covers why these risk variables are selected and introduces empirical studies which have shown the variables' connection to a stock index. Section 3 introduces the econometric methods which will be used, which is followed by Section 4 describing exactly how the data is transformed such that it is usable for the model used. Thereafter Section 5 produces the ES results, which finally are compared in Section 6 with the observable risk variables. Finally, the conclusion is presented in Section 7 and further research is covered in Section 8.

2 Deciding Risk Variables

2.1 Delimitation

Preferably, all elements that affect a stock index would be included and properly tested in this thesis. However, due to limitations in either data availability or econometric models, many variables had to be excluded[1]. The point being this thesis neither tries nor claims to test all relevant risk variables which could affect a stock index. Rather, in Subsection 2.2 the variables that empirically seem to have the largest effect on the equity markets, and are deemed testable, are included in this thesis.

Due to econometric limitations of the method used, some variables which otherwise would

[1]Some examples of elements which would have been very interesting to incorporate would be: (i) Natural language processing applied to public statements, Twitter feeds of heads of states, CEOs' and central bank presidents. (ii) Surveying the remaining population on earth regarding their future behaviour such as consumption, due to the wisdom of crowds. (iii) Application and approval rates of loans, as well as the total amount of credit outstanding. (iv) Diplomatic relationships to predict things such as trade flows and technology adoptions from other areas. Further, even unfortunate happenings such as war would be very valuable to predict. Some of these are disregarded simply due to data not being available, such as (ii). But limitations are also needed due to the complexity in econometric methods which would be needed to interpret the effect of the risk variables on the stock index. It would not be feasible to explore all the connections between the variables in the detail that it would require to be able to interpret the results.

have been included, such as the total amount of credit in Sweden and the yield curve, were also excluded. Going into some detail, due to the business cycle, the policy rate and animal spirits all playing a *crucial* role in determining credit expansion and retraction. Including total credit in the economy would basically capture the same phenomenon twice. Macro variables often have problems similar to this, and even the variables which will be analyzed do have problems[2] to some extent. The reason they are accepted and kept in this thesis, while the credit amount was deemed too problematic and was excluded, is due to an assumption that the problem is vaster in regards to the credit amount. If deemed possible, the total amount of credit and the yield curve would have also been included in this thesis.

2.2 Literary Review

Papers that have empirically shown a connection between macro variables and equity prices will be presented concisely to support the variables' status as observable risk variables.

Supporting the inclusion monetary policy, Alam and Uddin (2009) finds a significant connection between interest rates and stock prices. By using monthly data from 1988-2003 for 15 countries, they run ordinary least squares regressions showing a significant relationship indicating that the interest rate cuts has a positive effect stock prices. This thesis includes the Riksbank's policy rate as it very directly affects the market interest rates. Furthermore, another way that the Riksbank can reduce interest rates is by open market operations, or Quantitative Easing as it is often called. Therefore both the size of the Riksbank's balance sheet as well as the policy rate will be included as directly observable risk variables.

Business cycles are included as a risk variable as Claessens et al. (2012) shows that there is a connection between financial cycles and business cycles, and they find that the linkage is especially strong during recessions. However, it also finds that financial cycles are longer than business cycles, showing that they do not overlap every cycle, which makes this connection hard to analyze. The paper analyzes how the business cycle moves over the longer financial cycle, but does not use methods that can imply causality. Rather, by using an extensive data set it points out commonalities found in the connection between the business and financial cycle to build upon a body of literature that is still evolving. Business cycles are included

[2]Monetary policy arguably affects all other variables, especially the business cycle. However, as the extent to which the affected variables are determined by monetary policy is assumed to be lower, it is still included.

in this thesis as the connection, although not perfectly understood, seems to exist.

Animal spirits, a term popularized by John Maynard Keynes, is a play on the observation that humans are not always completely rational, but at times act based on feeling instead. An article written by De Long et al. (1990) shows that investments based on noise, statistical data which does not contain valuable information, makes it such that equity prices can significantly differ from the value which is implied by fundamental variables. The disconnect from fundamental values can be thought of as speculation. Using an AR (1) process as their method, they show that traders whose sentiment is based on noise, which should be thought of as useless information, affect equity markets. Based on this result, the inclusion of a variable that portrays the degree of speculation will be included in this thesis. The $\frac{\text{Price}}{\text{Earnings}}$ ratio as well as the Buffett indicator, $\frac{\text{OMX30 Market cap}}{\text{Swedish GDP}}$, will be used to capture this.

3 Methodology

In a perfect world, all things which can possibly *cause losses* in a stock index should be included in a model which tries to estimate the downside risk, more specifically the probability and the size of losses, for said index. In other terms, no relevant variables are allowed to be excluded from the model used, as that would cause the estimates produced to be flawed by an omitted variable bias. This will be thought of as a gold standard, which unfortunately is unobtainable, but which will help in understanding flaws with actually implementable methods. The method that will be explained and implemented in this paper will later be compared with this utopian standard to understand how improvements can be achieved in regards to estimating risk.

3.1 Value at Risk

This paper's measurement to estimate the downside risk of an index is the commonly used Estimated Shortfall. As ES is conditional on VaR, to begin with, the VaR will be introduced and estimated. The data which is used in calculating VaR and ES is called loss scenarios, ℓ, and is defined as the percentage change of the index times a negative nominal amount[3].

[3]See Section 4 for further details

The following is the relevant mathematical definition of the VaR:

$$VaR_\alpha = min\{\ell : Pr(L > \ell) \leq 1 - \alpha\} \tag{1}$$

The way to interpret this equation is as follows: The VaR will present a value equal to the smallest simulated loss, ℓ, which still keeps the probability of a loss the following day [4] (L) smaller than $1-\alpha$. α stands for the confidence level, which might be more easily understood as the quantile of a distribution. If α, the confidence level, were to be 0.975. Then 97.5% of all loss scenarios would be less than the VaR output and the remaining 2.5% of the loss scenarios would be excluded from the VaR. The largest losses, which are all larger than the VaR output, are what make up the ES which will be explained further later. Lastly, a clarification about the input to the model, loss scenarios, will likely help the readers intuition in understanding the method as well as Figure 1. Loss scenarios are the percentage changes *flipped*, meaning that *increases* are flipped to *decreases* and vice versa, as they are multiplied by a negative number. Therefore, the left tail of Figure 1 are increases in the data set and the right tail represents decreases. In a case where the mean of the loss scenarios equals zero, everything left of μ is actual increases in the data set which means that the term "Loss scenarios" can be misleading for these positive returns. However, the VaR and ES disregard the loss scenarios which are to the left of the VaR output, meaning that in practice it is only the right tail that is of interest as we are analyzing losses.

[4] VaR assumes the portfolio to be unchanged during this time period, e.g. no trades. Furthermore, the time period in itself (1 day in this thesis) can differ for VaR models and usually is either 1 or 10 days (Jorion, 2007))

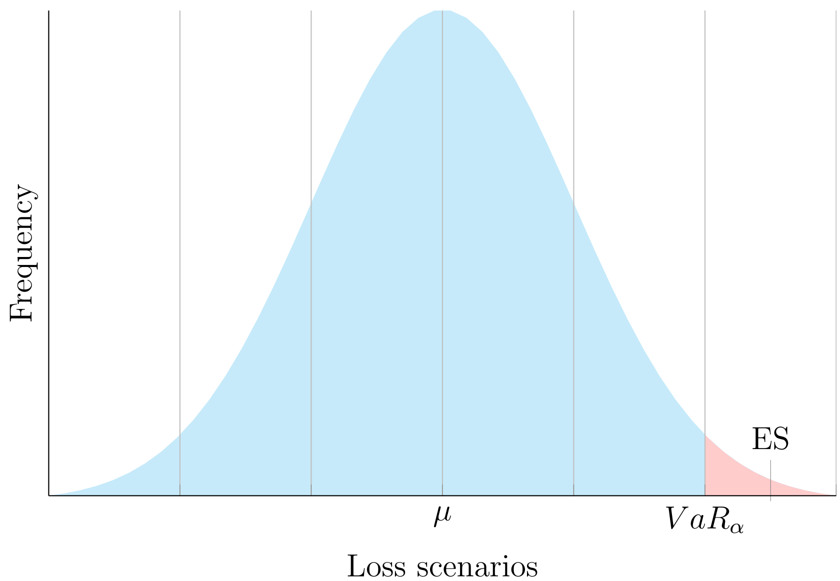

Figure 1: VaR_α denotes the size of the loss scenario which happens with the frequency $1-\alpha$. Rather than just denoting a single probability along the probability density function, the pink area represents all losses larger than VaR_α, which are the 2.5% largest losses. When thinking of the integral in Equation (2) as a Riemann sum, one can graphically understand that ES is the sum of all VaR_x with all x values $0.975 < x < 1$. ES can be thought of as the VaR at every single α larger than the selected one used for VaR_α, times the probability of that VaR, times the fraction which scales the integral up. The last part, scaling ES up, is needed such that the ES value becomes the expected loss *given* that it is larger than VaR_α, as seen in Equation (3).

In Figure 1, μ is the mean, mode, and median. If the skewness of the sample data were to be exactly zero, the graph correctly depicts the third central moment (skewness) of the data. However, for a financial data set it is likely the case that this does not hold true (Guermat and Harris, 2002; Polanski and Stoja, 2009). Still, some of the very same papers use methods that assume a skewness of zero (Guermat and Harris, 2002), which is what is done in this paper as well. There are methods that allow for, and adjust to, skewness differing from zero, however, this is outside the scope of this thesis and the methods used in this thesis assume the third central momentum to be zero.

A strength of VaR, which has helped it become implemented widely within finance, is that it is quite simple to understand. It produces an output that makes it possible to communicate risk to even those who are not especially well-read in the area of risk management. This is of key importance as it improves the possibility for clear communication, and therefore the understanding of risk to e.g. directors, shareholders, and senior management (Jorion, 2007).

3.2 Expected Shortfall

Going back to Figure 1, we will now focus on ES which will be the estimate mainly used in this paper. As mentioned in the VaR definition, the loss scenarios which are larger than VaR, which is determined through α, make up ES. The mathematical definition of ES is as follows:

$$ES_\alpha = \frac{1}{1-\alpha} \int_{x=\alpha}^{x=1} VaR_x \, dx \tag{2}$$

Interpreting this equation is likely the easiest if one thinks of it as two parts, the fraction and the integral. Firstly, the fraction acts as a scalar for the integral. If α is 0.975, then the fraction will scale the integral up 40 times. Secondly, the integral capture the losses which are larger or equal to the quantile α. Once again, Figure 1 is meant to help with the intuitive understanding. The red area, which covers all losses between the percentiles α and 1 (with 1 being the absolutely maximal loss which is possible according to the distribution), are the losses that the integral captures. The scalar multiplied by the integral becomes ES. A more intuitive expression, showing that ES is the average loss conditional on it being larger than the VaR_α:

$$ES_\alpha = E[L|L > VaR_\alpha] \tag{3}$$

3.3 Why ES over VaR?

There are two reasons why ES will be focused on rather than VaR. Firstly, a desirable risk measure should fulfill all four properties described in Artzner et al. (1999)[5]. ES meets all four criteria meanwhile the VaR falls short on one of the categories, subadditivity (Yamai and Yoshiba, 2005). Not being subadditive is problematic as it means that in practice, the VaR measurement does not always reduce measured risk by diversification. ES on the other hand does not have this problem, making it superior to VaR in this context. Secondly, as

[5] For the purpose of this thesis, detailed definitions of coherency and the four criteria - Monotonicity, Translation Invariance, Homogeneity, and Subadditivity - are not of great importance. However, if one wants to better understand this topic, the cited articles of this paragraph are completely devoted to this topic and reading them is recommended.

VaR disregards the very end of the right tail, large losses do not affect VaR. To exemplify this, a VaR at the confidence level 97.5% is unaffected by the size of $\frac{1}{100}$ losses and therefore incentives huge, but rare, risks. The above reasons make it such that ES is preferred over VaR (Acerbi et al., 2018; Basel Committee on Banking Supervision, 2013). In scenarios in which data is limited, ES might not always be preferred. As stated by Yamai and Yoshiba (2005), ES comes with higher estimation errors than VaR which means that ES requires a larger sample than VaR but due to the extensive data set used, this is less of a problem in this thesis.

3.4 Parametric Distribution

There are many different approaches to estimating ES. There are two broad categories which the approaches fall within, parametric or non-parametric. This thesis will use a parametric approach, but a concise explanation of a non-parametric approach will be given to begin with to better understand the broader context of ES and possible methods which could have been used.

When using a non-parametric method, loss scenarios are sorted to begin with. For example, the sample data could be arranged such that the largest losses are furthest to the right (referring to Figure 1) and the largest gains are furthermost to the left[6]. Note that this non-parametric ordering requires no assumptions about the distribution of losses. Thereafter, this empirical distribution is used when estimating VaR and ES in such a way that e.g. $VaR_{0.975}$ simply selects the loss which is strictly smaller, but closest, to the 97.5% percentile of said distribution. The key characteristic of non-parametric methods is that they use the empirical distribution rather than assuming a statistical distribution from which the losses are drawn. When using this approach no losses can be larger than what has previously been observed, which is quite unrealistic.

In contrast, parametric methods assume that the losses are drawn from some distribution that is inherent to the data. Which distribution to use is widely debated and there are many papers simply devoted to testing which model specification is the best for estimating risk (Polanski and Stoja, 2009; Guermat and Harris, 2002). Parametric methods will be

[6] Alternatives to this could be applied by weighting the losses differently depending on e.g. how far back in time they were. Meaning a tremendous loss 10 years ago could be sorted more centrally than a loss of half the size the previous week.

used to estimate ES in this thesis due to non-parametric methods being too reliant on the largest losses of the sample. A parametric method better handles the tails of the distribution (Gerlach and Chen, 2017), which is the focus of this thesis. The normal distribution, as well as the t-distribution, will be used to estimate ES and this will be covered in detail in Section 5.

3.5 Ordinary Least Squares

In order to compare the ES results with the downside risk that *monetary policy*, *animal spirits* and the *business cycle* can create, an ordinary least squares regression will be run for each variable with ES being the dependent variable. The reason for running the regressions separately is due to the high risk of multicollinearity between the risk variables. To expand upon this, due to many macro variables affecting each other, there is a problem in that the variables often do not meet assumptions needed for econometric models such as the variables being exogenous. It would require models which are orders of magnitude more complex than a plain ordinary least squares to estimate the effect which would have been preferred, the *causal effect of the variables on equity markets*. The ambition for the ordinary least squares regression is to roughly test the existence of a connection between ES and the mentioned risk variables quantitatively. It will be implemented quite simplistically without testing if assumptions are met due to the need for some type of limitation in the scope of how wide the thesis becomes. If the aim was to find every variable's true effect on ES, this thesis would likely have had to be several times longer than it currently is. A limitation with this type of regression, in the form it will be implemented, is that it will not be possible to take the beta value at face value.

The following is the equation which the ordinary least squares estimator is based on:

$$Y_t = \overline{\beta_0} + \overline{\beta_1} X_t \tag{4}$$

In Equation (4), "Y" stands for the value of an abstract dependent variable and the subscript t stands for a specific time period. $\overline{\beta_0}$ is a constant, often called the intercept and stands for an unobservable and unobtainable value which is an abstract *correct* value that is being estimated by the ordinary least squares regression. Furthermore, $\overline{\beta_1}$ is similarly the abstract value which is being estimated and as it is the scalar for by "X_t", the independent variable, it is often the variable of most interest. Equation (4) most commonly tries to answers the question: How much does X_t linearly affect Y_t? Here, $\overline{\beta_1}$ is the *correct* value which a good estimate will be very close to. Moving on from the abstract model, Equation (5) can be thought of as an econometric version of Equation (4) as it enables statistical methods to be applied to it and estimate the β values:

$$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{5}$$

Here, y_t is the observable dependent variable and x_t is the observable independent variable. β_1 is the star player of the equation as it is the output which will be evaluated and focused on the most. β_1 estimates how much an increase of 1 in x_t will effect y_t, and in a perfect ordinary least squares model this estimate is the size of a causal effect. "$\beta_0 + \beta_1 x_t$" produces an estimated y_t value, and ε_t is the difference between the actual and the estimated value, $Y_t - y_t$. When calculating an ordinary least squares regression, ε_t is being minimized with regards to the β values. The following minimization problem is what a statistical program will perform to estimate the β values:

$$\min_{\beta_0, \beta_1} \sum_{t=1}^{T} (y_t - (\beta_0 + \beta_1 x_t))^2 \tag{6}$$

Equation (6) is a minimization problem where $\sum_{t=1}^{T} \varepsilon_t^2$ is being minimized with "T" being the total amount of time periods for the data in the regression. One could go into much detail regarding which assumptions ordinary least squares require to estimate the *best linear unbiased estimator*. But to keep things concise[7], only the ways in which assumptions likely are broken will be presented shortly. Firstly, financial data does not have constant variance (Cont, 2007), which is assumed. Secondly, normally distributed data is assumed but the data has a kurtosis that is larger than that of a normally distributed data set. Thirdly, some of the data seem to be trending, at least in some periods, which breaks the assumption of stationarity. Fourth, due to cyclicality, it is likely to be autocorrelation present which breaks the assumption of independent error terms. Based on these assumptions likely being broken, one might question the usability of the estimates which will be produced. If the estimates can be useful or not will depend on the extent to which the assumptions are broken, something which will be discussed further in Section 6.

[7]For more details regarding specifications, many other papers and books can be used such as (Hutcheson, 2011).

4 Data

The data set ranges all the way from 1980/01/01 until 2021/04/12. It is a daily data set of a Swedish stock index, specifically the "MSCI Sweden Index" (MXSE for short) in SEK, which is downloaded from Bloomberg. The index is a weighted equity index that is calculated according to the free-float methodology. Its base, the value 100, is the 31st December of 1969. There are other Swedish indexes that could have been used, but this data set was the one that had daily data with the least duplicates of the comparable data sets from Bloomberg and Thomson Reuters Datastream as of April 13, 2021. By using such a long data set, ES meets its requirement of a large data set. Furthermore, economic and financial bubbles are included in the data set which allows analysis of the worst financial periods, which are of obvious interest when trying to estimate the downside risk for investments.

Dates with identical closing prices to the previous day, with zero in trading volume, have been removed from the data set as they are not meant to be included in the econometric method which is used. The data set started with 10670 observations and after 448 duplicates were removed, roughly 4% of the total data, there were 10222 observations left. Based on some spot checks in the data file, duplicates seemed to occur around holidays such as Christmas and New Year. Furthermore, the duplicates seemed to be more common during the beginning of the data set and were fewer and further in between towards the end. After having removed the duplicates, Figure 2 shows the data set:

Figure 2: Daily MSCI Sweden index from Bloomberg with its base value, 100, on the 31st December of 1969.

Using the data seen in Figure 2 the return is calculated according to $(\frac{P_t - P_{t-1}}{P_{t-1}})$. This transformation creates the data seen in both Figure 3 and Figure 4. The line graph makes it possible to see the distribution of the observations over time meanwhile the histogram makes it easier to see the distribution of the data:

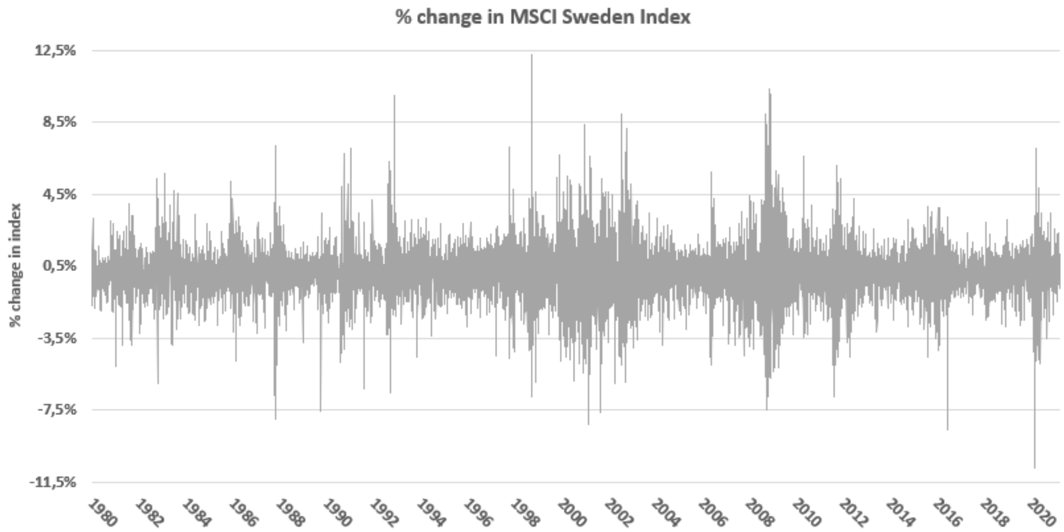

Figure 3: Using Daily MSCI Sweden index data from Bloomberg, percentage change is calculated.

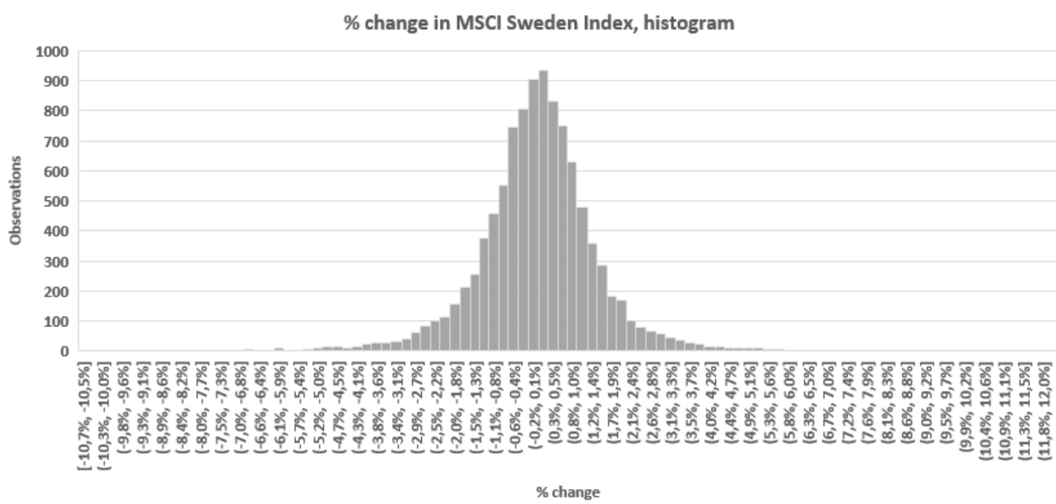

Figure 4: 100 bins are used for 10231 observations. Using Daily MSCI Sweden index data from Bloomberg, percentage change data is displayed.
Clarification, the x-axis is only showing the span for every second bin as the text would be too small otherwise. The squared brackets indicate that it includes the number and the round brackets indicate that it does not, e.g. (5%, 6%] (6%, 7%] means that a 6% change would be included in the first bar.

From Figure 4, the tail which is of interest is the left one containing the losses. Specifically, the 2.5% worst losses, which is shown in Figure 5.

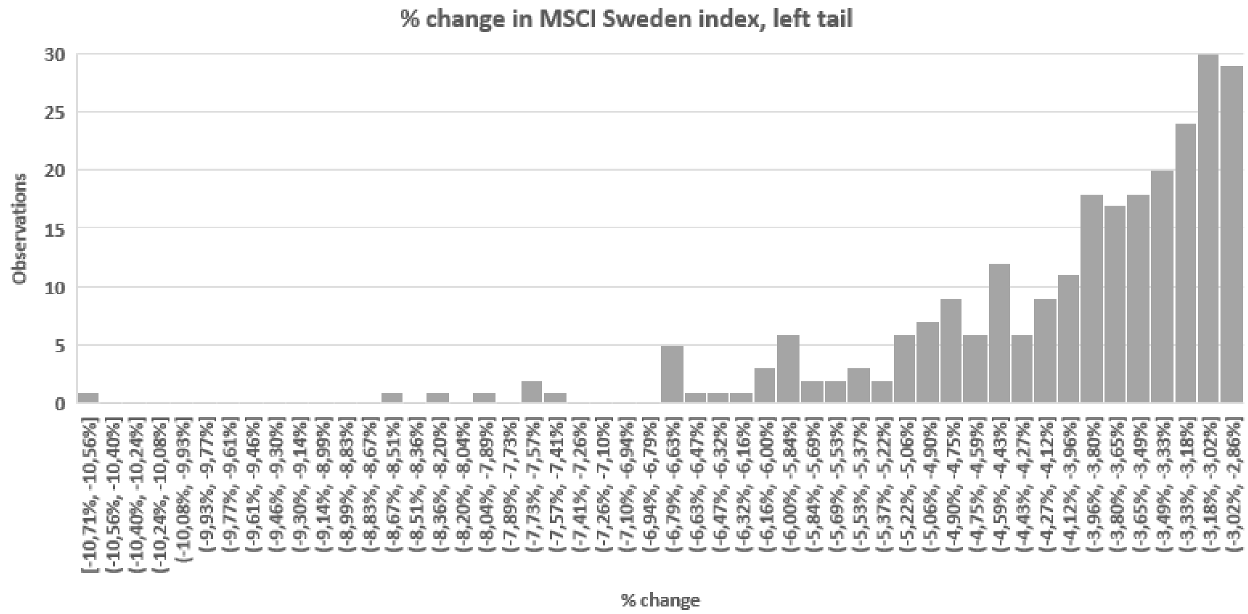

Figure 5: 100 bins are used for 256 data points. Using Daily MSCI Sweden index data from Bloomberg, percentage change data is displayed.

The histogram in Figure 5 is simply the very left tail of Figure 4. By zooming in on this left tail, which this whole thesis is centered around, one can better understand the data used for the later estimations in this thesis.

4.1 Loss Scenarios

Loss scenarios are created by taking the percentage change between index numbers, multiplied by -100, like the following expression:

$$L_t = -K \frac{P_t - P_{t-1}}{P_{t-1}} \tag{7}$$

The K stands for SEK 100 and is included to make the output an actual loss scenario, rather than just a percentage change. The minus sign is included to change losses to positive numbers, making interpretations and comparisons with VaR and ES easier. The fraction is a standard way to change a time series to the percentage changes of said time series. Compared to Figure 3, the only graphical difference for loss scenarios is that it is multiplied by -100, making Figure 6 flipped along the horizontal axis. The y axis is no longer the % change, but rather the SEK amount which would have been lost given a SEK 100 investment in the index the day prior.

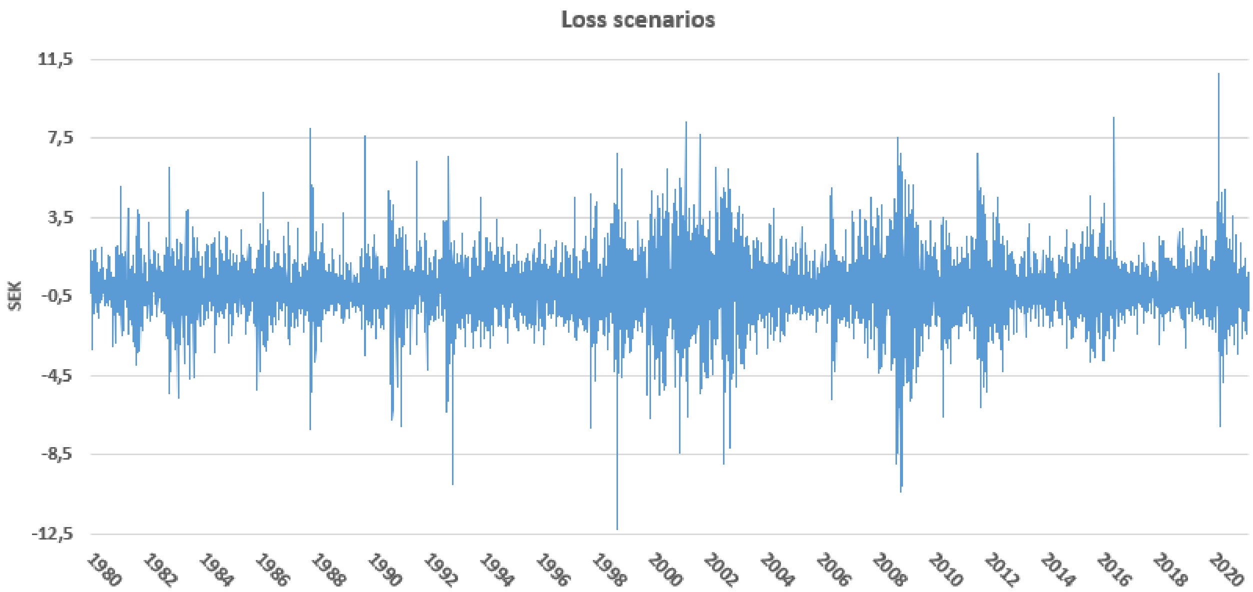

Figure 6: Using a daily MSCI Sweden index from Bloomberg, the graph shows how much SEK one would lose from an investment of SEK 100 the day prior. For clarification, a positive value of 5 means that 5 SEK was *lost* on that day per SEK 100 invested at T-1.

4.2 Descriptive Data

Table 1: Descriptive data

	Index values	% change (in MSCI Sweden index)	Loss scenarios
Mean	5421.2	0.00061	-0.06115
Median	4991.34	0.00084	-0.08396
Standard deviation	46371	0.14168	1.416751
Sample variance	19111217	0.0002	2.007
Kurtosis	-0.992	5.0356	5.0356
Skewness	0.4519	0.0659	-0.0659
Range	18121	0.2294	22.94
Minimum	91.65	0.1071	-12.228
Maximum	18211.68	0.12228	10.7124
Sum	55416008	6.25	625
Count	10222	10221	10221

Some of these numbers are not useful, e.g. the sum of the index values. However, as all of the rows give insight for at least one of the three variables, they are included such that the reader can get an unfiltered view of the data to better understand the three categories of data. For clarification, "% change" is the name of the data variable. It does not indicate e.g. that the mean increased by 0.00061%, but rather if that was written in % it would have been "0.061%". This descriptive data regards the dataset for ES calculations, the MSCI Sweden Index from Bloomberg which has daily observations from 1980/01/01 until 2021/04/12.

As anticipated, "% change" and "Loss scenarios", are extremely similar due to the Loss scenarios simply being the aforementioned multiplied by K, or -100. Figure 3 and Figure 6 perfectly illustrate this as well. As loss scenarios run the risk of being confusing, the inclusion of % changes hopefully helps the readers which are new to this expression to better grasp it. The reader is encouraged to focus on the rightmost column, Loss scenarios, as that is the data that will be used further on. The following comments are all regarding the Loss scenarios. The mean being slightly negative is reasonable as the index has gained over the sample period. However, due to the standard deviation being larger than the mean, the mean will not be significantly different from zero no matter the confidence level. The kurtosis being ≈ 5, compared to a normal distribution with a kurtosis of 3, supports the use of a t-distribution. The range is the maximum minus the minimum and shows how big of a difference there is between the largest and smallest data point.

5 Estimation Results of VaR and ES

5.1 Normal Distribution with simple volatility

To begin with, the widely known normal distribution will be the parametric approach to estimate VaR and ES. According to Ardia and Hoogerheide (2014), a daily, weekly, monthly, and quarterly forecast ahead all yield similar results. Therefore, 1 day ahead forecasts will be used to maximize the amounts of observations and minimize the risk of breaking the assumption regarding no trading in the portfolio. The confidence level affects the estimate greatly. To avoid arbitrariness, the standard values of 1 day out estimations and 97.5% will be used. Using a significance level of 97.5% is based on the decision Basel Committee on Banking Supervision (2013)[8] in which $VaR_{0.99}$ was replaced by $ES_{0.975}$.

$$VaR_\alpha = \mu + \sigma^{500}_{T+1} z_\alpha \tag{8}$$

Although stock indexes generally trend upwards over long periods of time. In a single day the mean, μ, is set to zero as the volatility of the index far outweighs the trend, meaning μ is not significantly different from zero as seen in descriptive data. In this simple specification, the estimated volatility, σ^{500}_{T+1}, is the standard deviation of the last 500 loss scenarios. z stands for the inverse of a standard normal cumulative distribution, and z_α is the aforementioned at the specific percentile 97.5%.

$$ES_\alpha = \mu + \sigma^{500}_{T+1} \frac{f^*_{std}(z_\alpha)}{1-\alpha} \tag{9}$$

The new notation introduced in Equation (9) for calculating ES, f^*_{std}, is the probability density function for a stochastic variable that follows a standard normal distribution. Furthermore, $f^*_{std}(z_\alpha)$ is the probability density function evaluated at the point z_α. The graph in Figure 7 illustrates estimates produced when assuming a normal distribution, which means it is a parametric method:

[8]"Based on the more complete capture of tail risks using an ES model, the Committee believes that moving to a confidence level of 97.5% (relative to the 99th percentile confidence level for the current VaR measure) is appropriate. This confidence level will provide a broadly similar level of risk capture as the existing 99th percentile VaR threshold, while providing a number of benefits, including generally more stable model output and often less sensitivity to extreme outlier observations" (Basel Committee on Banking Supervision, 2013, p.18)

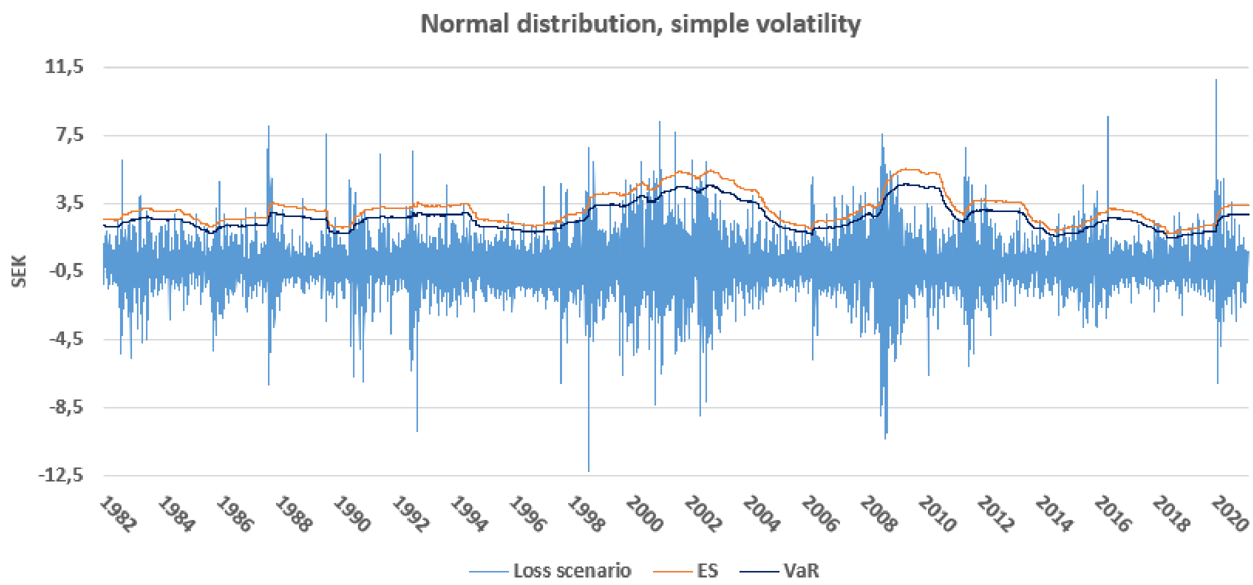

Figure 7: Loss scenarios show the daily losses of a portfolio in said index of SEK 100. VaR estimates the 97.5% percentile losses for the index and ES estimates the expected loss given that the loss is larger than VaR. For the estimation, normal distribution is assumed and the volatility used is the standard deviation of the last 500 loss scenarios. Daily MSCI Sweden index data is used from Bloomberg.

From a simple ocular inspection of Figure 7, the risk measurements clearly *underestimates* many of the larger losses drastically. Furthermore, there are periods in which returns have very similar volatility, e.g. large movements during March 2020 or the period of minimal movements during 2016. If volatility was constant over the whole period, the blue line (loss scenarios) would have the same height during all periods. Instead, there are bottlenecks during which movements are a lot smaller and other periods where price movements are a lot more drastic. This type of heteroscedasticity is called volatility clustering and makes it such that in Figure 7, in the periods with low volatility ES often *overestimates* losses meanwhile in high volatility periods ES produces many *underestimations*. This visual interpretation likely helps the reader in the best way to intuitively understand the problem of this model specification. These findings are also found in a lot of previous literature, but keep this graph and the visual interpretation in mind when reading the more technical part below to better understand what is happening.

5.2 EWMA volatility and a T-Distribution

Firstly, financial data is known to have *fat tails*, or more technically, the distribution of financial data is in general thought to have a kurtosis larger than 3 (Polanski and Stoja, 2009; Broda and Paolella, 2011; Mandelbrot, 1963). Models allowing for higher kurtosis makes it such that estimates of tail events occur with a higher frequency, which causes the estimates to better fit the data. Because of the aforementioned, a *t-distribution* will be used, rather than a normal distribution, to allow for a higher kurtosis. Secondly, financial data is also known to have *volatility clusters* (Cont, 2007; Kuester et al., 2005). This phenomenon causes different periods in time to have various amounts of volatility, and a model which does not reflect this will overestimate risk during low volatility periods, e.g. 2010, and underestimate risk during the volatility clusters, e.g. 2008. This problem in a model is caused due to the risk measurement being slow to adjust to changes in volatility. In Figure 7, equal weights are used for the last 500 observations which lead to the model not adjusting to volatility clusters. Using an Exponentially Weighted Moving Average (EWMA henceforth) volatility, a higher weight is put on the most recent observations and the older an observation is, the lesser weight it receives in an exponential fashion. By using EWMA volatility, the risk measures adapt a lot quicker to changes in volatility. The notation used for EWMA volatility is σ, rather than σ^{500}. The 1-day out EWMA forecast is defined as follows (Riskmetrics, 1996):

$$\sigma_{t+1} = \sqrt{\lambda\sigma_t^2 + (1-\lambda)L_t^2} \tag{10}$$

In Equation (10) , λ is a decay factor which is between 0 and 1, a constant which is chosen to best fit the data. In line with the authors of Riskmetrics (1996), 0.94 is used in this thesis as it was empirically observed to be the best fit for daily data. Different λ values will determine the rate at which EWMA exponentially reduces the weight of old volatility, with higher lambda values making the exponential decrease slower. As lambda approaches 1, the volatility estimation approaches a fixed value with no adjustments to changes in volatility. On the opposite side of that spectrum, as λ approaches 0 the volatility estimation approaches an MA(1) process. Here, the estimate simply is the expression $\sigma_{t+1} = \sqrt{L_t^2} = L_t$, meaning that the previous volatility has no weight but rather the estimate is exactly the previous days' loss.

The kurtosis of the dataset is assumed to be constant over the period, according to the model specification used, and is calculated during the first 500 trading days of the dataset. The empirically observed kurtosis is 5.27 which is comparable with the kurtosis found in Polanski and Stoja (2009). Their approach allows kurtosis to differ over time and as they are also looking at a stock index (SP 500), the fact that 5.27 is within the estimated kurtosis range is promising. In the model used, the kurtosis differing from 3 is expressed through degrees of freedom, v. By the following calculation, $v = \frac{4k-6}{k-3}$, v during the first 500 trading days is 6.64:

$$VaR_\alpha = \mu + \sqrt{\frac{v-2}{v}}\sigma_{T+1}t_{\alpha,v} \tag{11}$$

$$ES_\alpha = \mu + \sqrt{\frac{v-2}{v}}\sigma_{T+1}\frac{f^*_{std}(t_{\alpha,v})}{1-\alpha}\Big(\frac{v+t^2_{\alpha,v}}{v-1}\Big) \tag{12}$$

These equations are similar to Equation (8) and Equation (9) and should be interpreted similarly. These equations will simply be defined by what is changed from Equation (8) and Equation (9). Using EWMA and a t-distribution, z_α is replaced by $t_{\alpha,v}$ as the normal distribution is replaced by the t distribution. Further, σ^{500} is replaced by σ as EWMA volatility replaces the simpler volatility estimate which is just the standard deviation of the previous 500 loss scenarios. $\sqrt{\frac{v-2}{v}}$ and $(\frac{v+t^2_{\alpha,v}}{v-1})$ are adjustments made to properly include degrees of freedom into the estimates such that the kurtosis can differ from 3. Figure 8 shows the result of this specification.

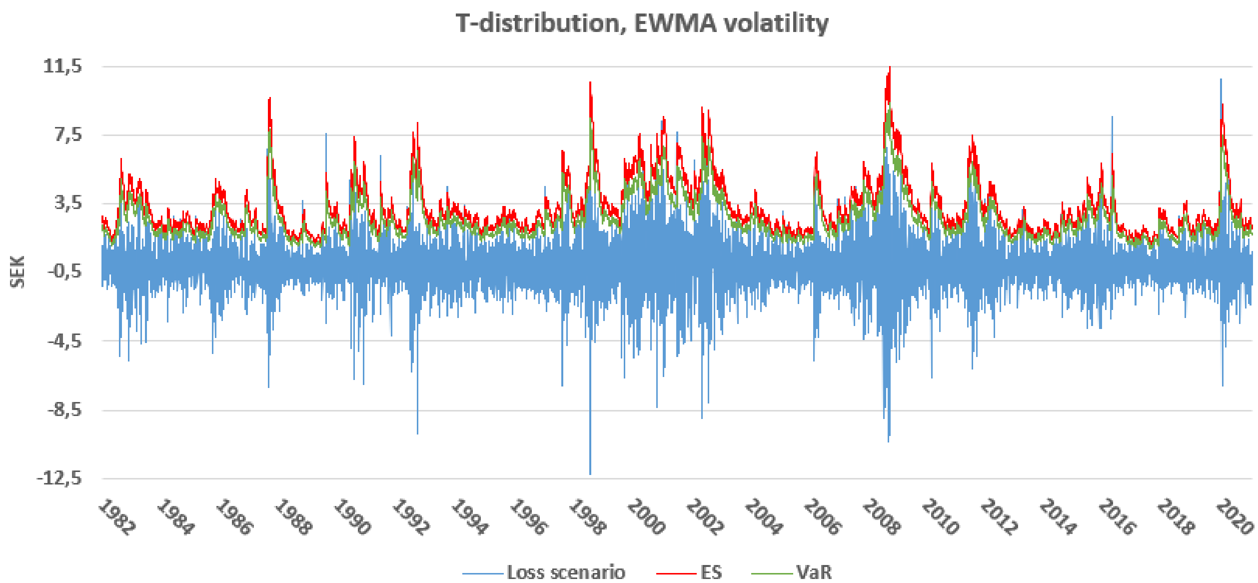

Figure 8: Loss scenarios show the daily losses of a portfolio in the MSCI Sweden Index of SEK 100. VaR estimates the 97.5% percentile losses for the index and ES estimates the expected loss given that the loss is larger than VaR. EWMA volatility and a t-distribution is used for the estimation. The data used is from Bloomberg.

Comparing Figure 8 with Figure 7, the estimate of ES is a better fit with the actual data. This is due to the t-distribution allowing for a higher kurtosis which causes many of the larger losses in Figure 8 not to be underestimated anymore, and those which are still underestimated are so to a lower extent. Further, as EWMA allows the volatility to quickly adjust when the market behavior changes, the estimates better adjust to changing amounts of volatility. Note that it is not only the largest losses that are estimated more realistically, moreover the low volatility periods are not drastically overestimated anymore. Out of the 9721 ES estimates, in 122 days the ES estimate is lower than the loss scenario, which equals 1.26% of the days. Having about half of the 2.5% tail above the estimate is a very reasonable number as both overestimation and underestimation are problematic and need to be taken into consideration. In summary, the model specification used for Figure 8 quickly adjusts to changes in volatility thanks to EWMA volatility and further estimates the size of outliers in a consistent manner with the indexes empirically observed kurtosis. The ES data from this model specification fits the loss scenarios very well, ratifying the results, and will be used from now on in the thesis when referring to ES.

6 Observed Risk Variables Compared to ES

This section is the soul of this thesis. In contrast to most papers that zoom in on details regarding optimization of ES model specifications, this thesis instead takes a holistic perspective on the tail of downside risk and compares the measurement of ES to observable downside risk variables. To reiterate, ES estimates the cost of a risk past a specific threshold defined by α, 97.5% in this thesis. This means that ES does not represent the risk of the MSCI Sweden Index in its entirety, but rather a portion of the whole distribution of risk. Based on this, a comparison between ES and variables known to affect downside risk does not necessarily have to correlate. Theoretically, it is completely possible that the increase in downside risk is not affecting the worst 2.5% cases, but exclusively the losses which are less extreme. For clarification, in Figure 9 it is the light gray area that is being discussed here, meaning that it will not be analyzed. If the light gray area of the probability density function were to change shape to any other pattern while the red area is unaffected, then downside risk would be affected but not ES.

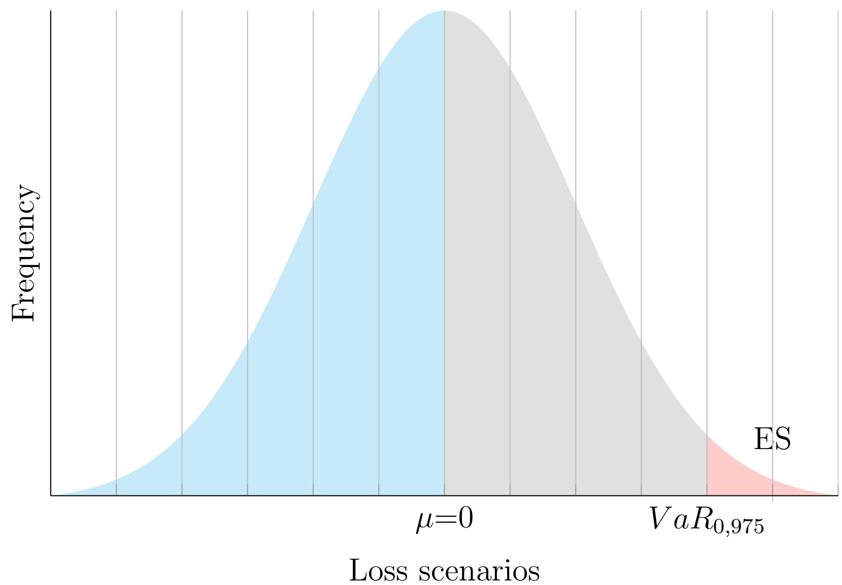

Figure 9: The blue area are all gains, or negative losses as it should be read in this context. The grey area are the losses which occur at a frequency of between the 50th and 97.5th percentile. VaR_α denotes the size of the loss scenario which happens with the frequency $1-\alpha$. Rather than just denoting a single probability along the probability density function, the pink area represents all losses larger than VaR_α, which are the 2.5% largest losses. When thinking of the integral in Equation (2) as a Riemann sum, one can graphically understand that ES is the sum of all VaR_x with all x values $0.975 < x < 1$. ES can be thought of as the VaR at every single α larger than the selected one used for VaR_α, times the probability of that VaR, times the fraction which scales the integral up. The last part, scaling ES up, is needed such that the ES value becomes the expected loss *given* that it is larger than VaR_α, as seen in Equation (3).

It seems very plausible that the whole right side of the bell curve, the downside risk, will be affected to some extent by the variables in this thesis which cause the downside risk to increase. The generalization that risks likely affect the whole distribution of losses might not be true for something like a nuclear war where the impact would completely play out at the very end of the tail. However, the variables discussed in this thesis are more general macro variables which are a lot less likely to have an outcome as binary as nuclear war. Nonetheless, no assumption will be made stating that the risk variables do affect the whole downside risk equally. To summarize, although it seems reasonable that the light gray area would correlate with the red area due to the nature of broad macro variables, no conclusions will be drawn regarding the light gray area in this thesis.

”Observed risk variables” should be thought of as factors that move the financial markets.

Due to the focus of this paper being the cost of the 2.5% worst outcomes, the variables introduced in Subsection 2.2 will specifically be evaluated in comparison to the tail of losses, which can be seen in Figure 5. The cost of these tail events is estimated by ES, which is exclusively calculated by using historical price data. An issue with this measurement, and likely other risk modeling methods which rely solely on historical price data, is its blindness towards observable risk. E.g., in a scenario in which ES have been calculated for January 2nd on the January 1st, no new data will be taken into consideration after the Swedish stock market closes on the 1st. So if something extreme were to happen after 17:30 on the 1st which obviously should affect downside risk, the estimate will not adjust. Imagine that Stockholm were to be devastated by a nuke at 11 am on January 2nd, then ES would not change until the closing of that date. It would be hard to find someone that argues that this kind of information is irrelevant for the expected price movements of the Swedish stock index. As a result of ES's blindness towards observable risk, complementing ES with direct observations of risk should improve the estimations of risk, and this connection is exactly what is being discussed and tested in Subsection 6.1, Subsection 6.2 and Subsection 6.3.

6.1 Monetary Policy

Through monetary policy, a central bank can indirectly boost a stock index by reducing the policy rate or by acquiring assets such as government bonds. Both of the aforementioned actions will affect the market for interest rates which in turn will affect the stock index. In response to the economic downturn following the covid-19 outbreak in early spring 2020, Igan et al. (2020) argues that monetary policy boosted equity valuations through significant reductions in discount rates, specifically the risk-free rate and risk premiums[9]. For equity valuations, both of these variables play a very significant role in discounting future cash flows as reducing the discount rate *increases equity valuations* (Damodaran, 2016). When approaching monetary policy from the perspective of this thesis, estimating the cost of the worst 2.5% downside risk for the MSCI Sweden Index, the following question emerges quite naturally. What happens to said index if the assets on the Riksbank's balance sheet needs to be *sold off* or the policy rate *increase*?

[9]Clarification for those who are not familiar with the terms used. The discount rate is the rate at which the value of future expected earnings is reduced to a present value. The risk-free rate is the alternative cost for investments, the returns which an investor could have achieved by investing in a secure asset, often government bonds. Risk premiums are the excess returns, compared to the risk-free rate, which is awarded to investors for shouldering the uncertainty of an investment

6.1.1 The Riksbank's Balance Sheet

As of April 30th, 2021, the Riksbank has SEK 1.32 trillion of assets on their balance sheet, a truly unprecedented amount. Compared to the beginning of 2020, 16 months before the latest data point available as of writing, the balance sheet has been expanded by 47% due to the vast expansive monetary policy during the covid-19 restrictions (Riksbanken, 2021a). Purchasing financial assets through open market operations, often called quantitative easing (QE), has stimulated the bond markets, lowering the interest rate. As the bond market acts as the natural alternative to equity markets, when bonds become less favorable money flows to equity markets instead, raising valuations of companies and therefore increasing the equity index.

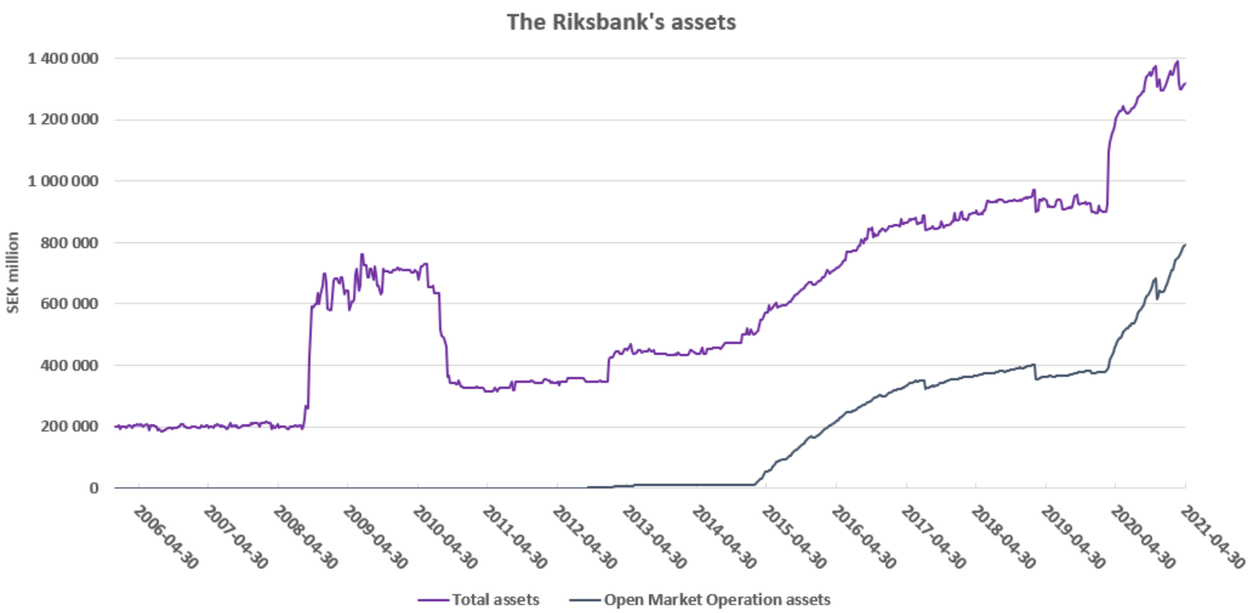

Figure 10: Weekly data, from 2006-01-06 until 2021-04-30, is gathered from the Riksbank's assets and liabilities weekly report. The purple line is all of their assets combined meanwhile the dark-grey line is the data they labeled "Securities to residents inside Sweden denominated in Swedish kronor", which roughly is the assets which are purchased through open market operations.

Compared to the beginning of 2006, roughly 15 years ago, the Riksbank has expanded its assets by 554% which can be seen in Figure 10. Either these assets can stay at high levels[10], or even increase, or the balance sheet will be unloaded as the Riksbank sells assets. Firstly, if

[10]Meaning that assets are never sold and that securities such as bonds which has a maturity date are replaced by very similar assets when those securities mature.

the Riksbank would not reduce the size of assets that they own, either by keeping the current level or by increasing it even further. Then there is an increased risk of default for the country of Sweden as well as a reduced possibility of future monetary expansionary policy. Secondly, the alternative would be that assets will be sold off at some future period in time. Similar to how the Riksbank increased its size of assets in the second half of 2008 as a countercyclical measure (Riksbanken, 2008b), the purchases of assets in 2020 have been communicated alike (Riksbanken, 2020). What followed the 2008 purchases was a reduction of their balance sheet two years later when economic recovery was happening according to Riksbanken (2010). If the actions of the Riksbank during the Great Recession (2007-2009) is any type of indication, the purchased assets during 2020 can be seen as something which increased the probability of selling assets in the future. Due to the Riksbank only quite recently started purchasing assets through open market operations, since 2015 (Riksbanken, 2021a), it is not well known how it will affect the market if the assets are sold. The assets in question during 2008-2010 were not acquired through open market operations, rather they were loans to Swedish credit institutions to keep them from having liquidity problems (Riksbanken, 2008a). If the assets during 2008-2010 would have been similar to those acquired during 2020, an analysis of the 2010 reduction of the balance sheet would have been performed as the unloading of the balance sheet is where the risk is argued to be present. However, the assets bought during 2020, mainly through open market operations, are fundamentally different than the loans during 2008-2010. An analysis of 2010 would not do justice to the current market situation.

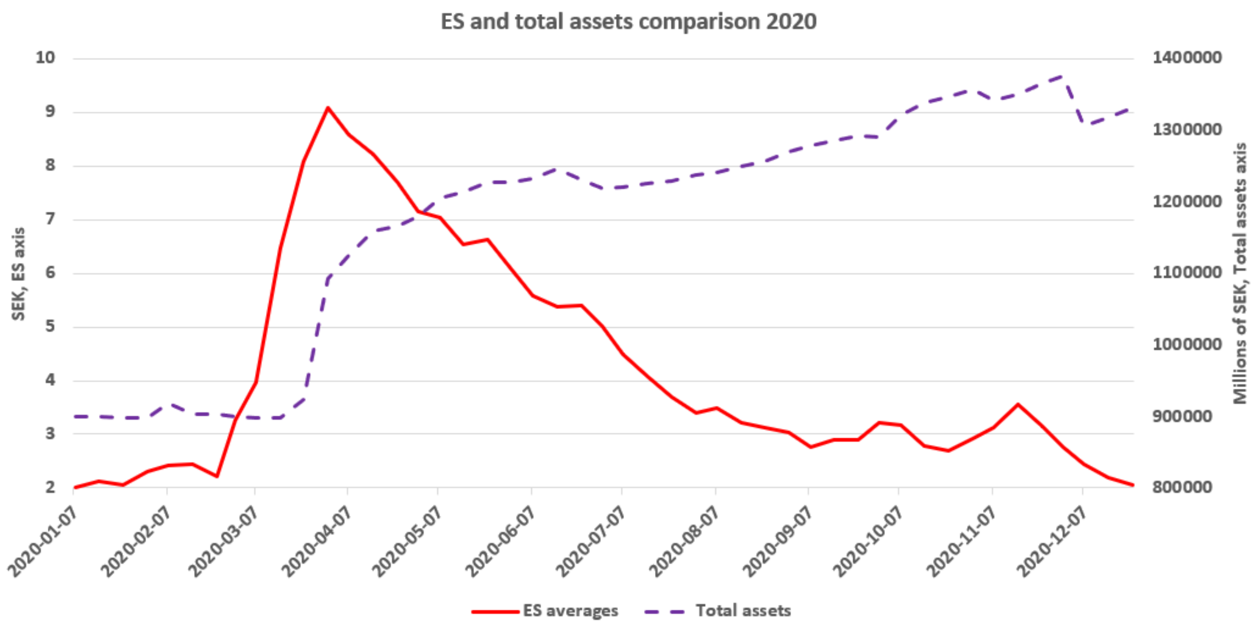

Figure 11: The left axis is connected to the red full line, showing ES averages, and the right axis is connected to the broken purple line showing total assets. The Riksbank's total assets is a data set updated every 8th day, downloaded from the Riksbank. As this roughly is weekly data, to make the ES data comparable it is transformed to the average of the 5 last observations, meaning it is like a moving average for a trading week. ES is calculated on the 97.5th percentile using data from Bloomberg. The ES averages are matched with the dates in which the Riksbank released their data. On non-trading days, the ES average on the closest trading day is used.

There are two key interpretations from Figure 11. Firstly, a subtle finding in Figure 11 is seen when comparing the first and last ES data points. 2.02 on January 7th in comparison to 2.20 on December 31st is a negligible difference as ES over the whole year has a standard deviation of 2.04. This ES result indicates that the estimated cost of the worst 2.5% downside risk is approximately the same before covid-19 and during covid-19. More so than covid-19 being present, the central bank has also increased the size of their balance sheet by 44%. As buying assets boosts the financial markets, selling assets causes the opposite. This increased risk during possible future sell-offs is not in any way included in the ES measure. Although the Riksbank, if selling their assets, will try to do it in a way that will not affect the financial markets or the economy harshly, the downside risk is likely higher compared to a situation in which they did not have the assets in the first place. Furthermore, if assuming there is some limit to how large the Riksbank can grow its balance sheet without it losing its *respect*, maybe the most important thing a central bank has during a fiat currency system. Then the higher amount of assets suggests that their possibility for future action is lowered.

If they are less able to dampen the blow of a future crisis, that should mean that an estimate which estimates the cost of the 2.5% worst losses should be larger, but that is not the case.

Secondly, following ES's steep incline in March, which was caused due to the covid-19 outbreak reaching Europe, the Riksbank started purchasing financial assets. From March 23 until March 31st, their balance sheet increased by 18%. Following this drastic increase in assets, ES decreases. During the rest of the year 2020, the assets keep on increasing[11] with few exceptions. From March 23rd until December 31st, total assets increase by 40%, and during this period ES steadily decreases. An ordinary least squares (OLS) regression on the data in Figure 11, starting from March 23rd with ES being the dependent variable and the Riksbank's total assets being the independent variable. Although the data is not stationary, an assumption of the model, if the downward effect on ES is caused by the increase in Total assets then the results can still hold. However, this is brought to light to emphasize that the results need to be interpreted with caution. The start date of March 23rd is selected as this is the very last data point before the asset purchases began.

Table 2: OLS regression, effect of the Riksbank's assets on ES

	Coefficient	Standard error	t-Stat	P-value
Intercept	29.13	2.84	10.25	3.1836E-12
β_1	-0.0000197	0.0000023	-8.7	2.234E-10

ES is the dependant variable and the Riksbank's total assets is the independent variable. Due to ES being a number between 2 and 9 meanwhile the Riksbank's total assets being around one million million SEK (the data is in million SEK), the very low coefficient needs to be scaled up to be more comprehensible. During the whole period, total assets increases by SEK 370 367 million, implying the total effect on ES to be $370367 * (-0.0000197) = -7.3$. Furthermore, $R^2 = 0.67$

The Riksbank's total assets is a data set updated every 8th day, downloaded from the Riksbank. As this is roughly a week, the ES data is the average of the 5 last observations, meaning it is like a moving average for a trading week. ES is calculated using data from Bloomberg and the data set used for the regression ranges from March 23rd, when the purchases began to ramp up, until December 31st of 2020.

The significant result, supporting the argument that the Riksbank's balance sheet should be a variable one includes in analysis, can be interpreted in different ways. The skeptical interpretation of this, which suggests that the result should be disregarded, is the following. As ordinary least squared has an assumption regarding stationarity, if it is not the case that the relationship between ES and total assets actually exists and that the changes in the variables are due to some random reason. Then the regression can be disregarded as it is simply

[11] As in further purchases by the Riksbank, not that their current assets increased in value.

a spurious regression. The high R squared of 0.67 and the suspiciously high t-statistic supports this as they tend to become large from spurious regressions. This explanation builds on ES not being affected by the vast amounts of assets bought by the Riksbank and that few seem to believe this. This interpretation would require a strong alternative hypothesis that explains the changes in the MSCI Sweden Index to completely disregard the regression.

Contrary to this, the other way of interpreting the regression is as if the decline in ES is entirely due to the increase in total assets. Then the data is not trending randomly but rather the increase in total assets is pushing ES down. During the period of the regression, from March 23rd when the purchases began to ramp up until December 31st, total assets increase by SEK 370 367 million, implying the total effect on ES to be $370367 * (-0.0000197) = -7.3$. The results of Table 2 indicates that the asset purchases by the Riksbank drastically lowered ES, further supporting the narrative that the Riksbank's balance sheet should be included when estimating the cost of the worst 2.5% downside risk. What the reader should bring from this is that the connection between asset purchases and ES becomes negative, according to the regression. The mechanism through which this causality happens could be through asset purchases pushing down interest rates, which acts as an alternative cost for equity investments, which when lowered in turn pushes the MSCI Sweden Index up.*However*, this is a result due to how ES is calculated, by exclusively using previous price data as input. As the measurement of ES does not correctly incorporate the increased downside risk due to the increased balance sheet of the Riksbank, a directly observable risk, the regression supports that the balance sheet should be included when analyzing the cost of the 2.5% worst losses.

From an ocular analysis of Figure 8, an observation is that the peaks of ES have never lasted for a long period of time as most of the volatility clusters have not lasted for such a long time. One could interpret this as even in the absence of the asset purchases during 2020, ES would have been reduced. This line of thought does not take into consideration that during many of the previous spikes, politicians or central banks have also acted to boost the economy that often coincides with a financial crisis. Relating this to the regression, it seems quite unlikely that ES would have stayed at 9 for the remaining year without any asset purchases. Although unlikely, this is what is being implied by the OLS result as everything not included in the model is assumed to be kept equal. It seems quite likely that ES would have reduced even if the Riksbank would not have purchased assets, but likely not as much or not as fast. To relate this observation to the above two paragraphs, one could interpret the connection between total assets and ES as it being somewhere in between the above-explained extremes. If one believes that the change in ES is not *entirely* due to the increased asset holdings but still believes that the changes in ES *to some degree* depend on total assets, then the results likely point towards the right direction, a significant and negative relationship. But the results are biased and the problem becomes to interpret to which extent the regression is spurious and to which extent it actually explains the true connection between the two. This seems like the most realistic interpretation.

6.1.2 The Riksbank's Policy Rate

There is a phenomenon in macroeconomics called *zero lower bound*, which states that lowering the policy rate below zero will not be effective, practically acting as a limit for how low the policy rate will be set. Although not completely uncontroversial, there are results indicating that the zero lower bound exists to some extent (Gust et al., 2017). This suggests that the policy rate is more likely to increase from the current level, zero, than to decrease below zero. Further backing the case for possible interest rate increases at the time of writing, Janet Yellen - the current US secretary of the treasury, also previous Chair of the Federal reserve - stated on May 4th "It may be that interest rates will have to rise somewhat to make sure that our economy doesn't overheat..." Yellen (2021). Due to Sweden being a small open economy, changes by the Fed in their policy interest rates are likely to affect Sweden. If the fed were to increase their policy rate while Sweden does not, then the US has, relatively to Sweden, become a more attractive investment. As long as the Riksbank does not defend the relation between the interest rates by changing it in a similar manner, the Fed affects Sweden through market forces. Because of this, the Riksbank might adjust the interest rate before the markets act. In either of these two scenarios, Sweden's equity market and the Riksbank has been affected by the Fed. As actions taken by the fed could affect the Riksbank's actions in the same direction, Yellen's indication that the American interest rate might rise is relevant for index investors in Sweden as it could negatively affect the stock index which is of interest. Further backing the case for mean reversion in the policy rate, the Riksbank is acting counter cyclically. An example of this is that the Riksbank reduced the policy rate drastically to "...dampen the fall in production and employment and to attain the inflation target of 2 per cent." (Riksbanken, 2008b, p.) in 2008 during the great recession.
To summarise, mainly due to the zero lower bound reductions in the policy rate towards, or past, zero increases the likelihood of future increases in the policy rate.

There is an empirically significant negative relationship between interest rates and stock markets (Alam and Uddin, 2009). This means that decreases in interest rates positively affects a stock index, and vice versa. Due to this effect, it is of interest to investigate interest rate *increases* as the topic of this thesis is the downside of investments. A difficulty in analyzing the connection between the two is that the Riksbank is not acting randomly, on the contrary, they are acting with a goal set by the Riksdagen (Riksbanken, 2021b) which in some cases is directly a reaction to the Swedish equity market such as in 2008 (Riksbanken, 2008a). Due to this simultaneity problem, which does not necessarily need to exist during all times due to the Riksbank having other variables than the financial market as their main focus. A simple graph of the two for a long time period likely consists of much noise which is hard to distinguish from actual effect between the two. Keeping the simultaneity and noise in mind, see Figure 12 for a visual interpretation:

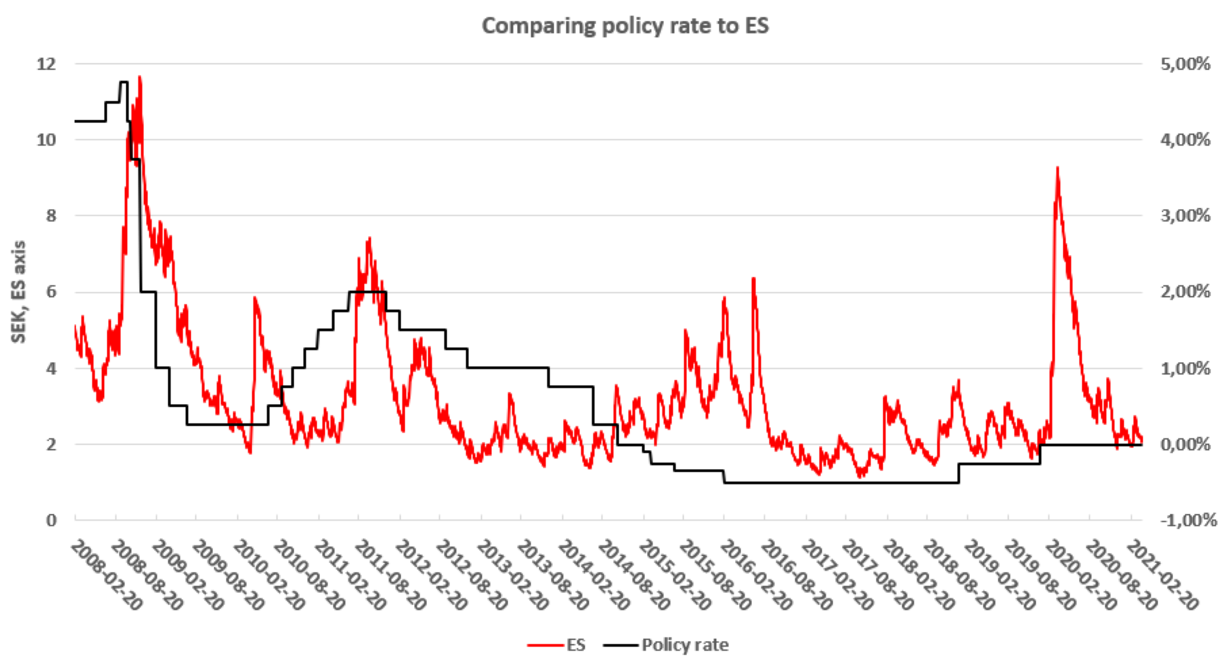

Figure 12: The policy rate, which is downloaded from and set by the Riksbank, on a daily basis from 2008-02-20 until 2015-03-02 Q2 1994 as well as ES for the same period. ES estimates the expected loss given that the loss is larger than VaR, both calculated at the 97.5th percentile. EWMA volatility and a t-distribution is used for the estimation of ES and the data used is from Bloomberg.

What should be emphasized from Figure 12 is that there is not a very clear pattern that always holds, it is not the case that every time one variable move in a direction the other one reacts in a consistent manner. Given the empirical relation between the interest rates and the equity markets, (Alam and Uddin, 2009) this could be interpreted in two ways which both are problematic for an ordinary least squares method. It could be the case that there is a very consistent causal relation between the two, but that other omitted factors play a larger role which causes much noise, making it very difficult to interpret the graph. The second interpretation is that due to a simultaneity problem, the ES estimate and the policy rate are not randomly changed with disregard to the other variable. If this is the case, although a true causal relation exists it is hard to interpret as the changes in policy rate could be caused due to variables that change ES. For example, if the Riksbank wants to stimulate the economy with expansive monetary policy by reducing the policy rate *due to* harsh times. The very same harsh circumstances could affect the stock market and cause losses, increasing ES. In this case, the reduction in policy rates will directly cause ES to become lower than it would be if the policy rate would not have been changed. However, what will be seen in a graph is that both decrease during the period, which could make it seem as they naturally move in the same direction as the causing factor behind the two, the harsh times, is omitted. Due to the problems mentioned in this paragraph, a simple ordinary least squares regression will need to be interpreted with caution and some model error should be expected. A regression will be used to test whether the policy rate affects ES. If the result indicates that it affects ES in the same direction, then it is shown that the marginally increased downside risk due to the lower interest rate is not always captured in ES. Although not the strongest of implications, a positive significant β will support that including the policy rate improves estimations of downside risk as ES does not always move in the same direction as the observable risk.

Table 3: OLS regression, the effect of the Riksbank's policy rate on ES

	Coefficient	Standard error	t-Stat	P-value
Intercept	2.76	0.024	113.01	≈ 0
β_1	39.1	2.98	13.1	3.43E-38

ES is the dependant variable and the policy rate is the independent variable. Due to ES being a number between 1 and 12 meanwhile the policy being between -0.005 and 0.02, the large coefficient needs to be scaled down to be more comprehensible. If the policy rate is increased by 1%, 0.01, then the β value implies that ES would increase by $0.01 * 39.1 = 0.391$. Furthermore, the $R^2 = 0.055$

The regression's data starts on June 10th, 2008, just after the policy rate was set to 0.25%, and ends on May 12th, 2021. Daily data is used and the data used to calculate ES is the MSCI Sweden Index downloaded from Bloomberg. The policy rate from Riksbanken is gathered from Riksbanken.

As seen in Table 3, the β value is relatively small, but positive and abnormally significant. Trying to avoid a spurious regression, the regression starts right after the policy rate is lowered to 0.25% in early June 2009. If the regression would have started from the first data point, the obvious downward trend in both variables would have been very problematic. The low R Squared value of 0.055 is a good sign, which should make the reader less concerned for a spurious regression than if R squared would have been close to 1. Although the policy rate is daily data, as it is only updated seldomly and no laggs are included, it may be the case that this specification of an ordinary least squares regression is not especially suited to estimate the connection of interest. This might explain the low β_1 value.

Moving on from the high t-stat (alternatively the low p-value, same thing), the coefficient being positive supports the logic previously discussed which is that the policy rate is a good addition to ES for those wanting to improve their estimation of the cost of the 2.5% worst loss scenarios. Explaining the reasoning behind this, essentially what this regression is meant to test is if ES seems to already incorporate the policy rate changes somehow, making the addition of the variable redundant. Based on the way ES is calculated, it seems self-evident that this type of risk is not included in ES estimates as the variable is not included. However, it is not obvious that a model must mathematically include something for it to predict some behavior, which is why it is tested here. There is a famous metaphor regarding expert billiards players[12] made by Friedman (1953), stating that they act *as if* they perfectly

[12]"Consider the problem of predicting the shots made by an expert billiard player. It seems not at all unreasonable that excellent predictions would be yielded by the hypothesis that the billiard player made his shots as if he knew the complicated mathematical formulas that would give the optimum directions of travel, could estimate accurately by eye the angles, etc., describing the location of the balls, could make lightning calculations from the formulas, and could then make the balls travel in the direction indicated by

calculate complex physics problems before making their shots. The point of the argument is that mathematical predictions do not need to include the variables leading to decisions if the predictions *acts as if* they do. So if the ES estimates correctly adjust according to the risk that the decreased policy rate brings with it, it is simply not enough to critique the analytical interpretation of the mathematical formula leading to the prediction. Relating this to the regression in Table 3. Although ES does not have the policy rate as an input variable, it could have still acted in accordance with the risk which the policy rate entails. As the result indicates that ES does not incorporate the policy rate risk in its own measure, the addition of observing the policy rate directly is beneficial.

6.2 Business Cycles and GDP

Due to the cyclicality in GDP, using a trendline in comparison to GDP can give an indication of whether the current state of the economy is a boom or a bust period. If the trend is above (below) the GDP line, a strong (weak) economy is implied and future decreases (increases) should be more likely than the opposite. Expanding upon this, although the trend is far from a perfect predictor of future GDP changes, being below the trendline can be thought of as a bust currently taking place making it *more likely* that a boom starts within the following years. Similarly if above the trendline, there could be a reason to worry about a coming downturn. Evaluating Figure 13 around the Great Recession, GDP clearly overshoots the trendline for a few years which is then followed by a famous and drastic bust. Being above the trend could be thought of as the economy overheating in an unsustainable fashion.

The relationship between financial cycles and business cycles is not as clear as one might think. Claessens et al. (2012) states that there is a strong connection between the two, but it is not perfectly straightforward from there. It is not as simple as a strong business cycle equals a strong financial cycle, they are to some extent disconnected and can move in separately. Furthermore, Borio (2014) states that the credit cycle is of very high importance in determining the financial cycle. As credit often contracts during a recession (Clair and Tucker, 1993), the business cycle should affect the financial markets through the credit market indirectly. As seen in the great recession, the decline in the financial cycle and the

the formulas. Our confidence in this hypothesis is not based on the belief that billiard players, even expert ones, can or do go through the process described; it derives rather from the belief that, unless in some way or other they were capable of reaching essentially the same result, they would not in fact be expert billiard players."(Friedman, 1953, p.21) business cycle overlapped to a great extent. Further than the business cycle affecting the equity markets through credit, it likely affects it in many other complex ways such as through changes in aggregate demand and unemployment.

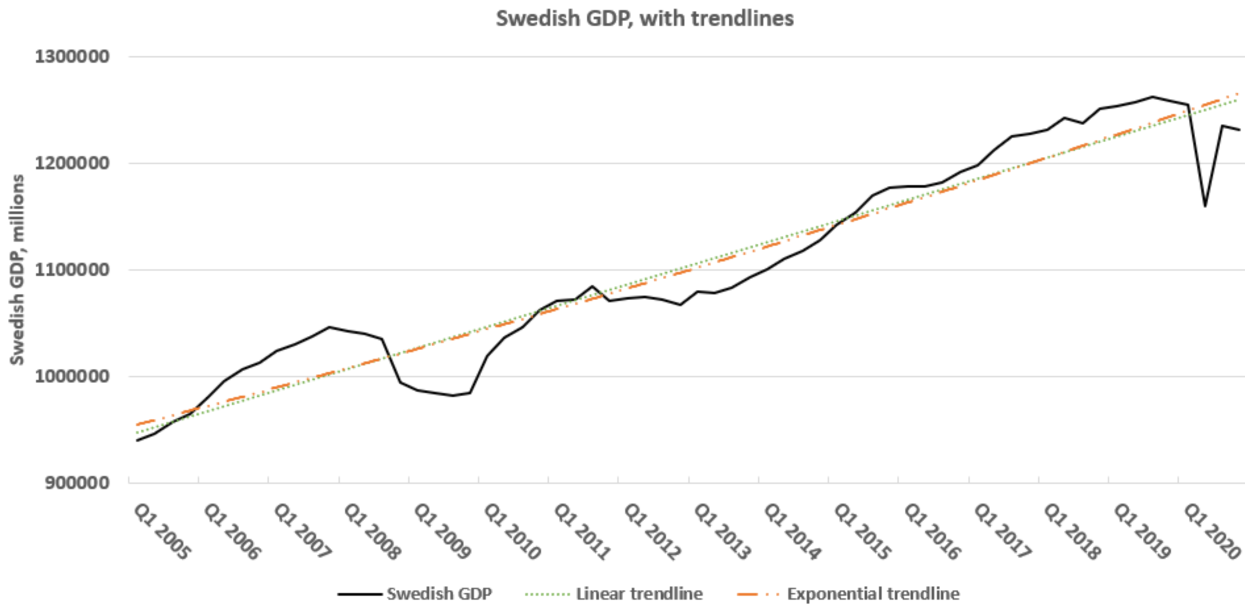

Figure 13: 16 years of Swedish Quarterly GDP data which is seasonally adjusted, ranging from 2005 Q1 until 2020 Q4, downloaded from Thomas Reuters Datastream. Both a linear and exponential line is created such that both a constant growth (exponential) and constant absolute increase (linear) are included. ES estimates the expected loss for a 100 SEK portfolio in the MSCI Sweden Index given that the loss is larger than VaR, both calculated at the 97.5th percentile. EWMA volatility and a t-distribution is used for the estimation of ES and the data used is from Bloomberg. The ES estimates are averaged per quarter to make the data comparable to the GDP data.

Both an exponential and linear trend line is included such that the reader can interpret both types of trends. As both of the trends are above the actual GDP, this indicates that there currently is a bust and that GDP has a higher probability to grow than to shrink in the coming years. So based on a connection between GDP and the MSCI Sweden index, ES would be expected to be higher during a boom than during a bust. To expand upon this, the business cycle suggests that a booming economy over the trendline increases the likelihood of a reduced GDP in the coming years. Furthermore, if this reduction in GDP to some extent is connected to a contraction in the equity market, then the booming economy could be seen as a downside risk indicator. This would be caused by the boom leading to things such as unsustainable credit expansion and speculative investments. Based on this connection holding, ES should be higher during a boom to incorporate the losses which are predicted to happen during a coming bust. Very similar to this, Danielsson et al. (2018) argues that good times with high-risk appetite and low volatility causes behavior to change such that risk increases. This directly contradicts the calculation of ES with EWMA volatility as calm periods create low predicted losses. If it is the case that good economic times cause the increased risk, meanwhile ES misses this risk completely, then the business cycle is a useful addition to use with ES. Graphically from Figure 13, both of the periods leading up to the Great Recession and the covid-19 bust indicated that the system was overheated, or fragile as one might think of it. Although covid-19 was an exogenous shock that caused the decline in GDP, if the economy would have been less overheated it might have been less harmed by the shock that covid-19 was. Moving along to the quantitative connection between ES and GDP, an ordinary least squares regression will be used. Due to the large extent to which GDP is trending, it will be log-diffed before the regression is run to make the data closer to stationary. Figure 14 shows the log-diffed data in comparison to ES and Table 4 shows the results of the regression.

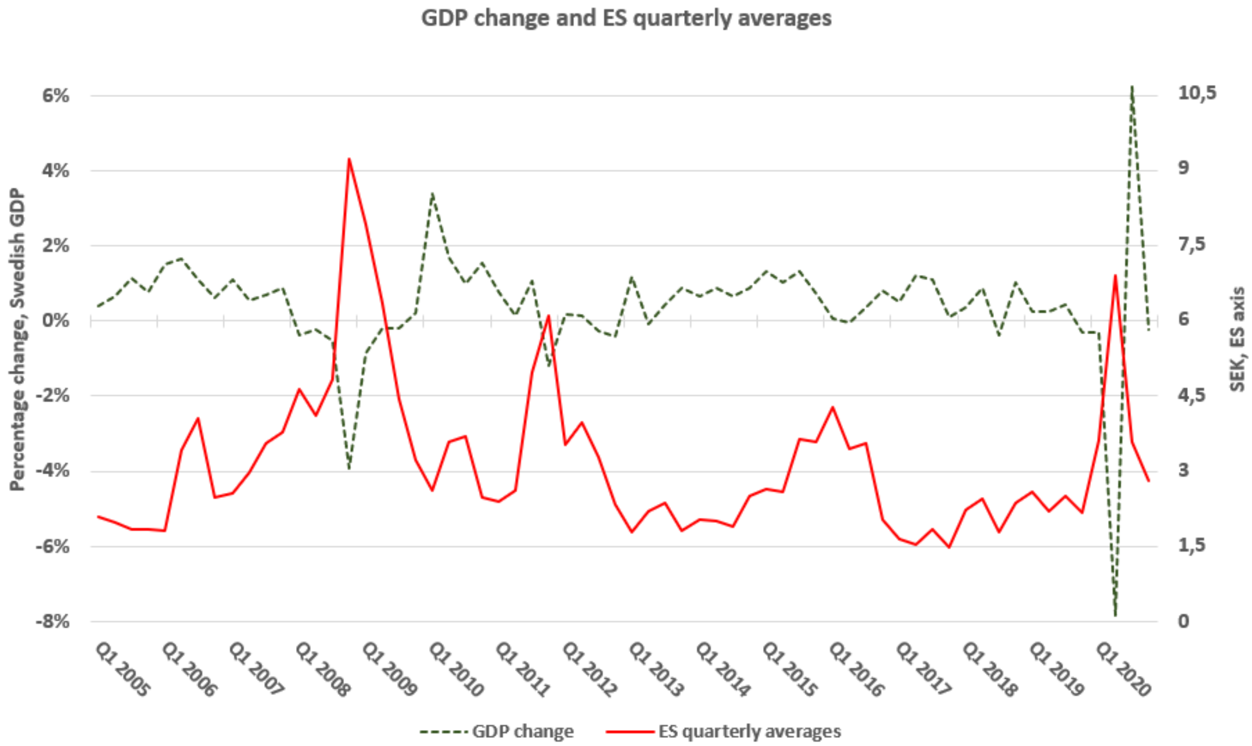

Figure 14: The change in Swedish Quarterly GDP data ranging from 2005 Q1 until 2020 Q4, downloaded from Thomas Reuters Datastream. ES estimates the expected loss for a 100 SEK portfolio in the MSCI Sweden Index given that the loss is larger than VaR, both calculated at the 97.5th percentile. EWMA volatility and a t-distribution is used for the estimation of ES and the data used is from Bloomberg. The ES estimates are averaged per quarter to make the data comparable to the GDP data.

Table 4: OLS regression, the effect of the business cycle on ES

	Coefficient	Standard error	t-Stat	P-value
Intercept	3.37	0.1697	19.869	1.41E-28
β_1	-50.786	10.524	-4.826	0.00000946

ES averages is the dependant and the log-diffed GDP is the independent variable. Due to ES being a number between 1.46 and 9.2 meanwhile the GDP change being between -0.008 and 0.062, the large coefficient needs to be scaled down to be more comprehensible. Lets say that GDP is increased by 1%, 0.01, then the β value implies that ES would decrease by $0.01 * (-50.786) = 0.50786$. Furthermore, the $R^2 = 0.273$

The regression's data starts at Q1 2005 and ends at Q4 2020. Quarterly data is used and the data used to calculate ES is the MSCI Sweden Index downloaded from Bloomberg. The Swedish seasonally adjusted GDP is gathered from Thomas Reuters Datastream.

The negative and significant result contradicts the arguments put forward as increases in

GDP actually lowers ES. This could be interpreted, referring to the Friedman (1953) reference, *as if* ES is integrating the risk which a higher GDP entails, assuming that GDP is mean reverting and that the business cycle gives valuable information regarding the financial cycle. Based on the regression, the GDP does not need to be incorporated as an extra variable when trying to estimate the cost of the worst 2.5% losses in the MSCI Sweden Index.

However, it could also be interpreted as the following. Unlike the ocular inspection of Figure 13, this regression does not take the long-run trend into consideration. A limitation with ordinary least squares is that it simply compares how the variables co-varies from quarter to quarter. This is unfortunate as the result can not take the trendline into consideration, therefore not testing the effect of the longer cycle. What Table 4 does illustrate is that increases in GDP will cause ES to reduce, and vice versa. This is also quite viable in Figure 14 as most of the larger GDP changes are simultaneous with increases in ES. Worth mentioning is that there are outliers at 2008 Q4, 2020 Q2, and 2020 Q3 which likely break OLS assumptions of normality as the movements seem larger than a normally distributed variable would. Furthermore, as the OLS regression does not incorporate different time periods, and the ES estimate has a decay rate which causes year-old observations to be weighted ≈ 0, the connection between ES and GDP is only tested in a single time period. The result does not cover business *cycles* as the cycle happens over many time periods. Due to ordinary least squares not incorporating effects that variables can have on each other in different time periods, and it relying on an assumption regarding normality which seems to be broken. Ordinary Least Squares does not seem like a tool especially well adjusted to handle what is meant to being tested between ES and business cycles.

6.3 Animal spirits

"Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as a result of animal spirits—of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities." (Keynes, 2018, p.141). This subsection will tackle the difference between future expectations which are speculative[13] and those which are rationally based on available fundamentals. A speculative investment is not based on facts, but rather an emotion, and due to herd behavior, these

[13] Speculative is used as the opposite of when an investment is based in fundamentals.

speculations do not always cancel each other out[14] (Lux, 1995). As beautifully put by Keynes (2018, p.141), if future expectations would have been the "weighted average of quantitative benefits multiplied by quantitative probabilities", then speculation would have been less[15] of a problem. One could give investors the benefit of the doubt and believe that this very calculated approach it what currently is happening. However, anecdotes will oppose this line of thought later on in this subsection, demonstrating at a bare minimum that not all investors follow this rational and calculated investment strategy.

A red flag in the world of investing, a sign which could indicate a bubble, is when speculative investments make it such that price differs far from the fundamental value of an asset. Already three decades ago, De Long et al. (1990) documented that trades based on sentiment, rather than fundamentals, can drive stock prices away from their fundamental value. Even before this empirical finding, there has been awareness about bubbles based on speculation such as the dutch 17th century Tulipmania and the Great Depression in the 1930s. When valuations are driven by fundamental changes, which change relatively slowly in most cases, risk is rather low. E.g., a large company will very seldom have a 50% change in their profits, revenues, or costs over a short period of time. In contrast to this, sentiment can change very quickly. As of spring 2021, the last year has been filled with situations where speculation seemed to have played a bigger role than fundamentals. The first example of an arguably unprecedented speculative investment case is the tale of GameStop. In 2021, seemingly independent retails investors performed a short squeeze on traditional financial institutions. Through cooperation on online forums such as Reddit, retail investors were able to get the stock of GameStop to surge from 17$ to 347$ during January of 2021, a 1941% increase. During the period, change in the fundamentals of GameStop was negligible as the price movement was dominantly based on speculation (Umar et al., 2021). Three weeks after the peak of $347, the stock was traded at $40 to then three weeks thereafter trade at $265. This very drastic and quick movement in price is an example of how speculation, rather than fundamentals, is a very volatile foundation for investing as sentiment can change *substantially* quicker than fundamentals.

[14] Imagine a bell-shaped curve in which the probability distribution represents how bullish or bearish people are towards an investment. If the distribution of irrational speculation were to be perfectly symmetrical around a rational mean, then the animal spirits would cancel each other out completely due to every opinion being represented by the same amount of the opposite.

[15] Less, rather than not at all, is used here as there likely would still be incorrect estimations of probabilities, which in a sense is also speculative. This is due to high transaction costs. Far from everyone would be able to educate themselves to the place where they would be able to estimate the utmost realistic probability.

The following examples and sources are based on newspapers rather than academic journals and are included to better have a *finger on the pulse*. Several recent anomalies, in addition to GameStop, that exemplify speculative investments are the hype in NFTs (Non-fungible tokens) (Kelly, 2021), explosive price changes in cryptocurrencies (Szalay, 2021; Westbrook and Carvalho, 2021) and companies such as Tesla getting valued with extreme expectations regarding future earnings (Lee, 2021). For context, a rough but helpful indication of the attention these topics are getting is that all of these terms are, in the moment of writing (May 12th), more popular google searches than "Joe Biden" (Google Trends, 2021). These analogies, although not quantifiable, are relevant as they are can be seen as a warning sign. There is a famous quote from one of the worlds most famous and successful practitioners of finance, Buffett (1987), "Our goal is more modest: we simply attempt to be fearful when others are greedy and to be greedy only when others are fearful.". This famous quote puts a spotlight on the danger of speculation, and is written in a context which often is lost. The very following sentence is "As this is written, little fear is visible in Wall Street."(Buffett, 1987). Speculation is at times a herd phenomenon which can cause bubbles (Hunter et al., 2005), which is why it is of utmost importance to understand how bullish or bearish others are at a point in time. When Buffett wrote the above shareholder letter in 1987, he deemed little fear was visible and implied that others were more greedy than fearful. The anecdotes brought to light could be interpreted as an indication that "little fear is visible" (Buffett, 1987) in 2021. Further backing this argument, the very reputable source the Fed deemed risk appetite to be high in their Financial Stability Report as of May 2021 (Board of Governors of the Federal Reserve System, 2021). Although the report of course focused on the US, rather than the MSCI Sweden Index which this thesis focuses on, the results are relevant for Sweden as the financial markets are quite global. The main point of this paragraph is that as of Spring 2021, risk appetite seems quite high which could be a warning sign for a bubble.

Moving along from anecdotes, the following question will attempt to be answered quantitatively: Are investors mostly *fearful* or *greedy* at a point in time? It will be answered by comparing the two fractions, $\frac{\text{OMX30 Market cap}}{\text{Swedish GDP}}$ and $\frac{\text{Price}}{\text{Earnings}}$, with ES over a period of time. An ordinary least squares regression will test the fractions' relevance in relation to ES. A flaw with this method is that *speculation* is not an isolated variable which is the sole cause for the fluctuations seen in the $\frac{\text{Price}}{\text{Earnings}}$ graph, Figure 15, and the $\frac{\text{OMX30 Market cap}}{\text{Swedish GDP}}$ graph, Figure 16. But as speculation is known to affect price (De Long et al., 1990), it is a question of *to what extent* speculation affects the price. In a perfect world, one could isolate the effect of speculation by keeping variables such as discount rates, profit margins, risk premiums, risk-free rate, and growth expectations out of the fraction. Unfortunately, this is not possible as a valuation of stocks is not a perfect science, but rather a mixture of an art form and science (Damodaran, 2016). Furthermore, the mentioned variables actually can not *objectively* be evaluated and isolated on an abstract level, rather, the subjective views of investors are depicted in these variables and the risk which one should be worried of is when too many views start to align in a certain direction without enough fundamental support for that perspective. Going back to the practical interpretations of the fractions used, the point is that one can not perfectly read the different levels as only different amounts of speculation. This is due to some differences being rational changes in the variables which determining price.

The P/E ratio, $\frac{\text{Price}}{\text{Earnings}}$, is common as it allows the reader to quickly understand how an asset is priced in relation to earnings. When assets are expected to grow, future cash flows are predicted to be large and therefore investors are willing to pay a higher price for a lower amount of current earnings, leading to a high PE ratio[16]. Differing PE ratios over time can be reasonable based on changes in fundamental variables, however, *sharp* changes in PE ratios can be caused by an overreaction to the news (De Bondt and Thaler, 1985) which is caused by speculation rather than fundamental changes. A benefit of using earnings as a denominator, rather than Swedish GDP as in the Buffett indicator, is that OMX30 companies are quite international. Therefore, having a denominator that is connected to their international operations is more representative than only using a number related to Sweden.

[16] The lower the earnings the higher the ratio, hence high ratios indicates expected growth. Some growth companies even have negative earnings and therefore have negative PE ratios. The ratio of high-growth companies does not help the investor in the same sense as it does with mature companies, and other ratios than the PE ratio would be preferred.

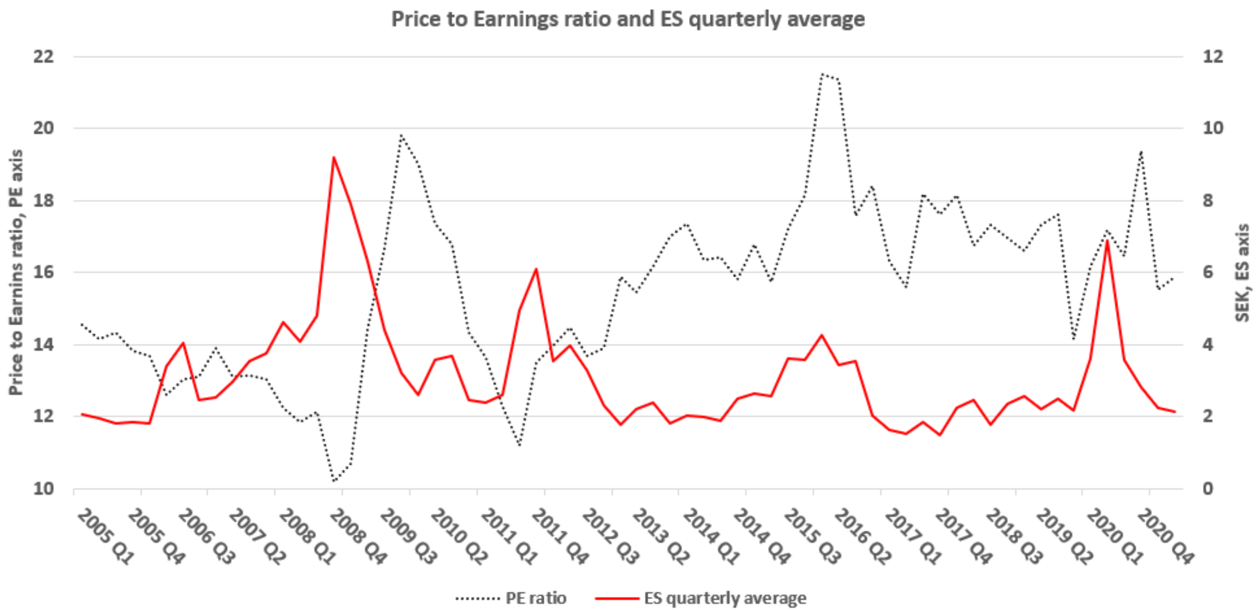

Figure 15: Quarterly data ranging from 2005 Q1 until present date. A PE value of 15.8674, the last observation in the data set, indicates that for OMX30 the average cost of one SEK of earnings is ≈ SEK 16. The last observation is Q2 2021, but only includes data until May 16th to calculate Q2. All data is gathered from Bloomberg, PE is based on OMX30 and the ES data is based on MSCI Sweden Index. As the PE data is quarterly, ES is transformed to quarterly averages for the data to be comparable, making this ES time series similar to a moving average of ES.

As seen in Figure 15, during the last decade the PE ratio has been at a higher level (16.4) than during 2005-2008 (13.1). This could indicate that the Swedish stock market currently is overvalued. But it could also be interpreted as a change in fundamental drivers causing a higher PE number to be justified. The main takeaway is that there currently is no drastic indicator of overvaluation as the most recent values are similar to those of the past several years.

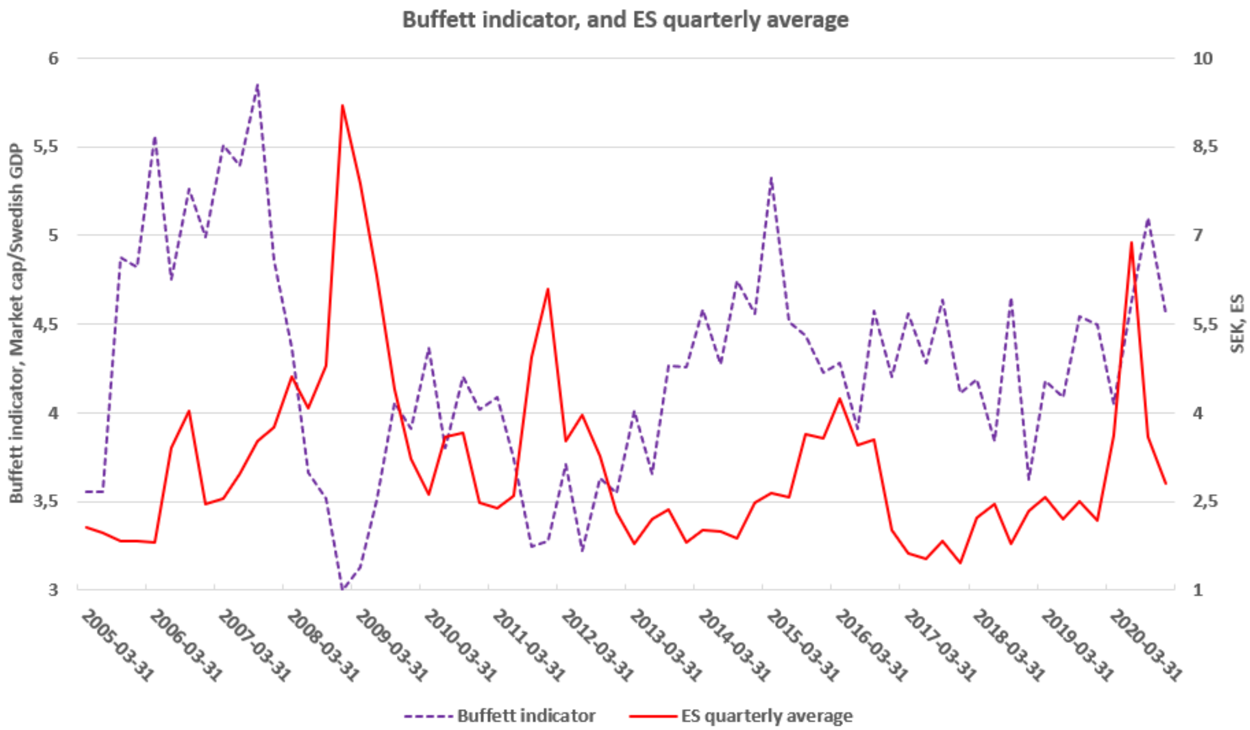

Figure 16: Quarterly data ranging from 2005 Q1 until 2020 Q4 by using OMX30 market cap, GDP and MSCI Sweden Index data from Bloomberg.As the Buffett indicator data is quarterly, ES is transformed to quarterly averages for the data to be comparable, making this ES time series similar to a moving average of ES.

Identically to the PE ratio, the Buffett indicator's "Market Cap" in the numerator should literately be the same thing as "Price" as both of the data sets are gathered from Bloomberg and are based on OMX30. The difference between the ratios is therefore the denominator. Whereas the PE ratio sets the price in relation to the fundamental variable earnings, the Buffett indicator instead uses Sweden's GDP. There is no right or wrong fundamental variable to use, but in contrast to the PE ratio the Buffett indicator uses a denominator that should be more stable as GDP can not turn negative and is likely not changing as much over a business cycle as earning does. Figure 16 shows that at the lowest point in the sample, the OMX30 market cap was 3 times the size of Sweden's GDP in Q4 2008. The highest point is 5.85 in 2007 Q3. What is interesting when comparing these points in time is that when the market was very highly valued in relation to Swedish GDP, 2007 Q3, ES was at a fairly low 3.5. Later in 2008 Q4, when the ratio hit the lowest point in the graph, ES hits the highest number of this whole sample of 9.2. ES is supposed to be used to estimate the cost of the worst losses, yet it produces low numbers at high valuations and high numbers during low valuations. This is contrary to what one would expect as a perfect risk measure should estimate a larger potential decline in valuations when they are very high and a lower estimate after a crash when the prices are not as inflated. Due to this relation, it will be interesting to see if this is just a one-off happening or if ordinary least squares will also find the relationship that the lowering of the ratio increases ES. Analytically, this is quite likely as the index price movements drive both the ratio and ES. For example, if the Swedish stock market were to decrease, ceteris paribus, then the Buffett indicator will reduce and ES will increase. Index price data is a co-founding variable both for ES and for the ratio, causing them to move in opposite directions. However, if Warren Buffett is correct in that other's greed, high acceptance for risk at high valuations, is an indicator of overvaluation. Then ES should move *with* the ratio, not in the opposite direction. Because of exactly this, separate regressions will be run on the relationship between both PE and the Buffet indicator to see their effect on ES.

Table 5: OLS regression, the effect of the Buffett indicator on ES averages

	Coefficient	Standard error	t-Stat	P-value
Intercept	7.16	1.22	5.85	0.000000201
β_1	-0.941	0.285	-3.305	0.001581

ES averages is the dependent variable and the Buffett Indicator is the independent variable. Furthermore, the $R^2 = 0.1498$

The regression's data starts at Q1 2005 and ends at Q4 2020. Quarterly data is used and the data used to calculate ES is the MSCI Sweden Index downloaded from Bloomberg. The Swedish OMX30 market cap data, as well as GDP, is gathered from Bloomberg too. As ES is calculated on a daily basis, but the Buffett indicator data is quarterly, ES is transformed to quarterly averages for the data to be comparable. The average of all ES estimates during each quarter is calculated to be that quarters average, making this ES time series similar to a moving average of ES.

The result of Table 5 supports the hypothesis driven that ES will not move with the Buffett indicator as the coefficient is significantly negative at -0.941. Both the p-value and the R squared seem very reasonable, and there are no obvious problems with clear trends in the data which would indicate that the regression is unreliable. With that said, no tests for stationary, normality, or other assumptions have been performed, and therefore the result should still be taken with some skepticism. Based on the result and the significance, using the Buffett indicator along sides ES should help improve estimation of risk in the context of animal spirits.

Next, the regression will be run with regards to PE instead of the Buffett indicator. The very same logic is applied here, meaning a positive coefficient will indicate that the speculative risk is incorporated in the ES measure and that the need for the extra variable is not needed.

Table 6: OLS regression, the effect of the PE ratio on ES averages

	Coefficient	Standard error	t-Stat	P-value
Intercept	6.668	1.137	5.86	0.000000172
β_1	-0.228	0.0723	-3.154	0.002456

ES averages is the dependent variable and the PE ratio is the independent variable. Furthermore, the $R^2 = 0.1345$

The regressions' data starts at Q1 2005 and ends at Q2 2021, with data up until May 16th being the data used for Q2. Quarterly data is used and the data used to calculate ES is the MSCI Sweden Index downloaded from Bloomberg. The Swedish OMX30 PE data is gathered from Bloomberg too. As ES is calculated on a daily basis, but the PE data is quarterly, ES is transformed to quarterly averages for the data to be comparable. The average of all ES estimates during each quarter is calculated to be that quarter's average, making this ES time series similar to a moving average of ES.

The result in Table 6 is quite similar to that of Table 5. Both the p-value and the R squared seem very reasonable, and there are no obvious problems with clear trends in the data which would indicate that the regression is unreliable. With that said, no tests for stationary, normality, or other assumptions have been performed, and therefore the result should still be taken with some skepticism. Based on the result and the significance, using the PE ratio, along with ES, should help improve estimation of risk in the context of animal spirits. The similarity of the results for the two ratios is promising as it shows robustness. Furthermore, it indicates that either of them would likely be fine to use without the other.

7 Conclusion

The essence of this thesis is to evaluate if ES estimates can be improved upon by complementing it with the inclusion of the directly observable risk variables; (i) the Riksbank's policy rate, (ii) the Riksbank's balance sheet, (iii) the business cycle and (iv) animal spirits. ES estimates the cost of the worst 2.5% of losses for a portfolio of SEK 100 in the MSCI Sweden Index and is calculated using daily data from Bloomberg. Due to ES solely using historical price data as input, it is hypothesized that there are relevant variables being omitted causing ES to fail in capturing some aspects of what it intends to predict. Therefore, variables that empirically have been shown to affect equity markets are compared to the estimates produced by ES. The aspiration behind this thesis is to use a more comprehensive approach in estimating the cost of the 2.5% worst loss scenarios. Some might interpret this as a critique of ES, however, that is not the point being argued as no comparisons to other methods, or backtests of ES, have been performed such that the performance of ES can be evaluated. Rather, the approach should be interpreted as a pragmatic endeavor in which ES is used as a baseline, which can then be improved upon by the inclusion risk variables.

The results indicates that the Riksbank's *policy rate*, the Riksbank's *balance sheet* and that either ratio which captures *animal spirits adds value* as complements to ES. These risk variables do not seem to be incorporated into ES correctly, indicating that ES is a biased measurement that could be improved upon. To which extent the expected cost of the worst losses should be adjusted have not been analyzed in-depth, rather the *presence* and *direction* of effects have been analyzed. The result should be interpreted such that ES should be used as a starting point for estimating the cost of the 2.5% worst losses. These estimates should then be adjusted upwards if: Policy rates have been lowered to such an extent that they are more likely to increase than decrease, which they are interpreted to be as of writing. The central banks' balance sheet has heavily been increased and therefore is more probable to decrease, which it is interpreted to be as of writing. And finally, ES should be adjusted upwards when the ratios of OMX30, $\frac{\text{Price}}{\text{Earnings}}$, or the Buffet indicator $\frac{\text{OMX30 market cap}}{\text{Swedish GDP}}$ have increased. The result does not show that the business cycle is worth including in the analysis. It is also acknowledged that the method used to evaluate the connection between ES and the risk variables, ordinary least squares, is flawed in the context in which it is used as the assumptions for it likely are not met. Therefore, the regression results need to be interpreted with some caution.

8 Further Research

The simple ordinary least squares regression used for the comparison between risk variables and ES is too simplistic and assumed everything else being held equal, which undoubtedly is violated in this type of macro data. Econometrically, there are likely more complex methods that could be used to better investigate the relationship between the variables. For example, using a structural VAR model and impulse response functions might better find the true relationship in the whole data set. Preferably, the inclusion of *credit* should be allowed according to another method as this is thought to be a very relevant risk variable which unfortunately was not possible to incorporate given the current method. Furthermore, using other methods would test the robustness of the results. Hopefully, other methods could also estimate the size of which ES should be adjusted.

The risk variables which have been chosen are arbitrary and affected by the author, although objectivity of course has been the goal. Other authors might find additional relevant variables which can be included in a similar analysis. Because of this, readers are encouraged to think of other variables, and methods, which could further improve the estimation of risk.

Lastly, the principle of comparing observable risk variables with time series *a risk measurement* is encouraged to be applied to other parts of the probability density function than only the worst 2.5% of losses. It is of the utmost importance to better estimate, or even better understand if that is possible, the whole distribution as properly estimating merely $\frac{1}{40}$ of the whole distribution barely gives any guidance in actually making decisions.

Feel free to contact me at PontusThorJohansson@Gmail.com for the data set used to be able to replicate, expand or change on any of the graphs or regressions in the thesis.

References

Acerbi, Carlo, Claudio Nordio, and Carlo Sirtori (Oct. 2018). *Expected Shortfall as a Tool for Financial Risk Management*. URL: https://arxiv.org/pdf/cond-mat/0102304.pdf.

Alam, MD and Gazi Uddin (2009). "Relationship between interest rate and stock price: empirical evidence from developed and developing countries". In: *International Journal of Business and Management (ISSN 1833-3850)* Vol.4.Nr.3, pp. 43–51. URL: https://ssrn.com/abstract=2941281.

Ardia, David and Lennart F Hoogerheide (2014). "GARCH models for daily stock returns: Impact of estimation frequency on Value-at-Risk and Expected Shortfall forecasts". In: *Economics Letters* Vol.123.Nr.2, pp. 187–190.

Artzner, Philippe, Freddy Delbaen, Jean-Marc Eber, and David Heath (1999). "Coherent measures of risk". In: *Mathematical Finance* Vol.9.Nr.3, pp. 203–228. URL: https://onlinelibrary.wiley.com/doi/epdf/10.1111/1467-9965.00068.

Basel Committee on Banking Supervision (Oct. 2013). *Consultative Document, Fundamental review of the trading book: A revised market risk framework*. Basel, Switzerland: BIS. Accessed on May 12th 2021. URL: https://www.bis.org/publ/bcbs265.pdf.

BIS (2013). "Fundamental review of the trading book: A revised market risk framework". In: *Bank of International Settlements Quarterly Review* Vol.29.Nr.6, pp. 523–535.

Board of Governors of the Federal Reserve System (May 2021). *Financial Stability Report*. Accessed May 22nd 2021. URL: https://www.federalreserve.gov/publications/files/financial-stability-report-20210506.pdf.

Borio, Claudio (2014). "The financial cycle and macroeconomics: What have we learnt?" In: *Journal of Banking Finance* Vol.45, pp. 182–198. URL: https://www.sciencedirect.com/science/article/pii/S0378426613003063.

Broda, Simon A. and Marc S. Paolella (2011). "Expected shortfall for distributions in finance". In: *Statistical Tools for Finance and Insurance*. Ed. by Pavel Cizek, Wolfgang Karl Härdle, and Rafal Weron and. Springer, Berlin, Heidelberg. Chap. 2, pp. 57–99. URL: https://doi.org/10.1007/978-3-642-18062-0_2.

Buffett, Warren (Feb. 1987). *To the Shareholders of Berkshire Hathaway Inc.* Direct letter to shareholders. Accessed May 20th 2021. URL: https://www.berkshirehathaway.com/letters/1986.html.

Claessens, Stijn, M. Ayhan Kose, and Marco E. Terrones (2012). "How do business and financial cycles interact?" In: *Journal of International Economics* 87.1. Symposium on the Global Dimensions of the Financial Crisis, pp. 178–190. URL: https://www.sciencedirect.com/science/article/pii/S0022199611001462.

Clair, Robert T and Paula Tucker (1993). "Six causes of the credit crunch". In: *Federal Reserve Bank of Dallas Economic Review* Vol.3, pp. 1–19.

Cont, Rama (2007). *Volatility Clusterin gin Financial Markets: Empirical Facts and Agent-Based Models*. 3rd ed. Springer, Berlin, Heidelberg. URL: https://doi.org/10.1007/978-3-540-34625-8_10.

Damodaran, Aswath (2016). *Damodaran on valuation: security analysis for investment and corporate finance*. Vol. 324. John Wiley & Sons.

Danielsson, Jon (2008). "Blame the models". In: *Journal of Financial Stability* Vol.4.Nr.4, pp. 321–328. URL: https://www.sciencedirect.com/science/article/pii/S1572308908000545.

— (May 2021). *Misleading measurements and garbage in - garbage out models of systemic risk*. Accessed May 23rd, 2021. URL: https://modelsandrisk.org/blog/measuring-systemic-risk/?fbclid=IwAR1hqpNm3rWJOYcGO2TGMUJ6cqE4INUnkQx4nK6jf4jX0iSy8Rlp_iu9kx4.

Danielsson, Jon, Marcela Valenzuela, and Ilknur Zer (Mar. 2018). *Low risk as a predictor of financial crises*. Vox EU Centre for Economic Policy Research. Accessed May 23rd, 2021. URL: https://voxeu.org/article/low-risk-predictor-financial-crises.

De Bondt, Werner FM and Richard Thaler (1985). "Does the stock market overreact?" In: *The Journal of finance* Vol.40.Nr.3, pp. 793–805.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann (1990). "Noise trader risk in financial markets". In: *Journal of political Economy* Vol.98.Nr.4, pp. 703–738. URL: https://doi.org/10.1086/261703.

Friedman, Milton (1953). *Essays in positive economics.* University of Chicago press.

Gerlach, Richard and Cathy WS Chen (2017). "Semi-parametric expected shortfall forecasting in financial markets". In: *Journal of Statistical Computation and Simulation* Vol.87.Nr.6, pp. 1084–1106.

Google Trends (May 2021). *NFT vs GameStop vs Bitcoin vs Joe Biden.* Accessed May 12th 2021. URL: https://trends.google.com/trends/explore?date=today%203-m&q=nft,joe%20biden,gamestop,bitcoin,tesla.

Guermat, Cherif and Richard D.F. Harris (2002). "Forecasting value at risk allowing for time variation in the variance and kurtosis of portfolio returns". In: *International Journal of Forecasting* Vol.18.Nr.3, pp. 409–419. URL: https://doi.org/10.1016/S0169-2070(01)00122-4.

Gust, Christopher, Edward Herbst, David López-Salido, and Matthew E Smith (2017). "The empirical implications of the interest-rate lower bound". In: *American Economic Review* Vol.107.7, pp. 1971–2006. URL: https://www.aeaweb.org/articles?id=10.1257/aer.20121437.

Hunter, William Curt, George G. Kaufman, and Michael Pomerleano, eds. (2005). *Asset Price Bubbles: The Implications for Monetary, Regulatory, and International Policies.* 1st ed. Vol. 1. Cambridge, Massachusetts: The MIT Press.

Hutcheson, Graeme D (2011). "Ordinary least-squares regression". In: *L. Moutinho and GD Hutcheson, The SAGE dictionary of quantitative management research*, pp. 224–228.

Igan, Deniz, Divya Kirti, and Soledad Martinez Peria (2020). *The Disconnect between Financial Markets and the Real Economy.* Special Notes Series on COVID-19, IMF Research. Accessed May 24th 2021.

Jorion, Philippe (2007). *Value at risk : The new benchmark for managing financial risk.* 3rd ed. McGraw-Hill.

Kelly, Jemima (Mar. 2021). *NFTs are the latest get-rich-quick scheme for the 'cryptosphere'.* Financial Times article, accessed May 16th 2021. URL: https://www.ft.com/content/2757d760-c29e-4834-8636-7601adbacf47.

Keynes, John Maynard (2018). *The general theory of employment, interest, and money.* Springer. URL: https://doi.org/10.1007/978-3-319-70344-2_1.

Kuester, Keith, Stefan Mittnik, and Marc S. Paolella (2005). "Value-at-Risk Prediction: A Comparison of Alternative Strategies". In: *Journal of Financial Econometrics* Vol.4.Nr.1, pp. 53–89. URL: https://doi.org/10.1093/jjfinec/nbj002.

Lee, Yen Nee (Apr. 2021). *A Roth Capital analyst says Tesla's stock is worth $150 — which would be a 78% discount*. CNBC article, accessed May 20th 2021. URL: https://www.cnbc.com/2021/04/06/tesla-tlsa-stock-is-overvalued-and-worth-150-says-analyst.html.

Lux, Thomas (July 1995). "Herd Behaviour, Bubbles and Crashes". In: *The Economic Journal* Vol.105.Nr.431, pp. 881–896. URL: https://doi.org/10.2307/2235156.

Mandelbrot, Benoit (1963). "New methods in statistical economics". In: *Journal of political economy* Vol.71.Nr.5, pp. 421–440. URL: https://www.journals.uchicago.edu/doi/pdf/10.1086/258792.

Polanski, Arnold and Everist Stoja (2009). "Incorporating higher moments into value-at-risk forecasting". In: *Journal of Forecasting* Vol.29.Nr.6, pp. 523–535. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/for.1155.

Riksbanken (Oct. 2008a). *New loans in SEK and USD*. Riksbanken web archive, accessed May 22nd 2021. URL: http://archive.riksbank.se/en/Web-archive/Published/Press-Releases/2008/New-loans-in-SEK-and-USD/index.html.

— (Dec. 2008b). *Repo rate cut to 2 per cent*. Riksbanken web archive, accessed May 10th 2021. URL: http://archive.riksbank.se/templates/Page.aspx@id=29849.html.

— (June 2010). *The Riksbank's company interviews: Recovery on a broad front but uncertainty in the period ahead*. Riksbanken web archive, accessed on May 19th 2021. URL: http://archive.riksbank.se/en/Web-archive/Published/Press-Releases/2010/The-Riksbanks-company-interviews-Recovery-on-a-broad-front-but-uncertainty-in-the-period-ahead/index.html.

— (Mar. 2020). *Riksbank initiates its extended government bond purchases*. Riksbanken press release, accessed on May 19th 2021. URL: https://www.riksbank.se/en-gb/press-and-pu blished/notices-and-press-releases/press-releases/2020/riksbank-initiates-its-extended-government-bond-purchases/.

Riksbanken (Feb. 2021a). *Annual Report for Sveriges Riksbank 2020.* https://www.riksbank.se/globalassets/media/rapporter/arsredovisning/engelska/annual-report-2020.pdf. The annual report of the Riksbank, accessed on May 14th 2021.

— (2021b). *The tasks of the Riksbank.* URL: https://www.riksbank.se/en-gb/about-the-riksbank/the-tasks-of-the-riksbank/.

Riskmetrics, TM (1996). *JP Morgan Technical Document.* URL: https://www.msci.com/documents/10199/5915b101-4206-4ba0-aee2-3449d5c7e95a.

Szalay, Eva (Apr. 2021). *Bitcoin: too good to miss or a bubble ready to burst?* Financial Times article, accessed May 16th 2021. URL: https://www.ft.com/content/be796d33-a5e7-4753-98a8-b586f1680d58.

Umar, Zaghum, Mariya Gubareva, Imran Yousaf, and Shoaib Ali (2021). "A tale of company fundamentals vs sentiment driven pricing: The case of GameStop". In: *Journal of Behavioral and Experimental Finance* Vol.30, n.p. URL: https://doi.org/10.1016/j.jbef.2021.100501.

Westbrook, Tom and Ritvik Carvalho (May 2021). *Ethereum breaks past $3,000 to quadruple in value in 2021.* Reuters article, accessed May 16th 2021. URL: https://www.reuters.com/technology/ethereum-breaks-past-3000-2021-05-03/.

Yamai, Yasuhiro and Toshinao Yoshiba (2005). "Value-at-risk versus expected shortfall: A practical perspective". In: *Journal of Banking Finance* Vol.29.Nr.4, pp. 997–1015. URL: https://doi.org/10.1016/j.jbankfin.2004.08.010.

Yellen, Janet (2021). *Future Economy Summit.* The Atlantic. Virtual event, interview. URL: https://econsummit.theatlantic.com/.