Is valuation uncertainty affected by ESG-ratings?

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Introduction:

This thesis will try to answer the question: Is valuation uncertainty affected by ESG-ratings?

The inspiration for this question comes from the fact that using ESG when managing assets is something that has grown significantly in a short time-period. This is evident by looking at the "Trends 2022 Executive Summary" report from the US Sustainable Investment Forum[1] where one can see, in their "Figure A", how "Sustainable Investing" in the US has increased from 1995 to 2022. They also report that in 2022 the total assets under management from sustainable investments in the United States were $8.4 trillion which represents 12.6% of the total United States assets under management. This indicates that sustainability is an important part when investing.

Golubov and Konstantinidi (2023)[2] use an accounting-based valuation model to estimate a distribution of a company's intrinsic equity value and then using the distribution to find the company's valuation uncertainty. Because of the importance of sustainability when managing assets, it should mean that sustainability is also an important factor in valuation of a company and the valuation uncertainty. From a paper by Derrien et al. (2022)[3] one can read about the effect that ESG-news had on the companies' earnings forecasts and in turn on the companies' stock value. Despite that the sustainability variable is slightly different compared to the usual ESG-rating, ESG-news is measured as the (Derrien et al. (2022) p. 4) "salient point in time shocks to analysts' beliefs about the ESG characteristics of the firm", this is again evidence for the effect that ESG can have on the companies' equity values. Therefore, I will in my thesis take their model and include a variable that will represent an estimate of the ESG-rating for each company. I will then compare the two models to see if there are any improvements by including the ESG-rating as a variable.

Because of the potential effect that ESG-performance can have on a company's market risk, financial stability, investor appeal and general market perception analyzing ESG-performance and valuation uncertainty together could prove to be important. Understanding the relationship between ESG-performance and valuation uncertainty would greatly improve the understandings of the "modern investor" and, potentially, the future of valuation. This will

[1] https://www.ussif.org//Files/Trends/2022/Trends%202022%20Executive%20Summary.pdf
[2] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3850807
[3] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3903274

make the purpose of the thesis to find if there is a connection between the ESG-performance of a company and its valuation uncertainty.

Previous literature:

Since my thesis is based on a cooperation between sustainability and valuation, these will be the two topics I will present now. Considering how relevant the topic of sustainability is, it is bound to be a highly researched topic. This sustainability is measured as ESG which makes literature that uses ESG both relevant and important for this thesis. Therefore, I will discuss literature connected to this part as well.

A paper regarding valuation uncertainty is Golubov & Konstantidini (2023) where they use an accounting-based valuation model to estimate a distribution of the intrinsic equity values. From this distribution they find the valuation uncertainty which they test in several ways e.g. if valuation uncertainty is conducive to valuation mistakes. This paper gives a demonstration of how an accounting-based approach can be used to summarize the uncertainty regarding intrinsic equity valuation, which I will expand on further down in the theory section.

An example of ESG-related literature is Derrien et al. (2022), which measures the effect that negative ESG incidents have on the firms' future profits. In their paper they find that negative ESG incidents are followed by a significant downward revision of earnings forecasts over both short (one quarter) and long (three years) horizons. They also found a negative effect on the stock price of the firm from a negative ESG incident but most of this decrease was explained by the change in earnings forecasts. With the result that firms should avoid negative ESG incidents since they found that it has a substantial impact on the firm's long-term earnings.

Another paper correlated with ESG ratings is Berg et al. (2022)[4], which discusses the relation between ESG and stock returns. Since ESG ratings aren't measured by one standardized formula but are measured differently for every ESG-measurer the ESG ratings can become

[4] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4249591

noisy which causes a regression done with them to suffer from attenuation bias. To overcome this problem, they use ESG-ratings as instruments on other ESG ratings from other rating agencies. They find that the noise-corrected model outperforms the old model and is therefore a superior way of measuring ESG performance, compared to other methods like averages and principal component analysis, on stock returns. I will also expand on this paper in the theory part further down.

In Collins et al (1997)[5], they discuss the value-relevance of earnings and book value over time and come to the conclusion that the value-relevance of the combined earnings and book value have slightly increased over the last 40 years. According to them, this result goes against claims in professional literature that say that it has declined. They also found that there was a shift in value-relevance from earnings more towards the book values. Lastly, they explain that much of this shift can be explained by the increased significance of one-time items, the increased frequency of negative earnings and changes in the average firm size and intangible intensity in time. The result from this article indicates that it is still very relevant, maybe even more relevant today, to use earnings and book value in a valuation. This article also validates my approach of using earnings and book values when performing my valuation.

In Friede et al. (2015)[6] they combine the findings from roughly 2200 different studies that studies the relationship between ESG and CFP (Corporate Financial Performance). They find that about 90% of all the studies found a non-negative relationship between ESG and CFP. The main finding of this study is that there is a positive relationship between ESG performance and CFP and as they say on page 227 *"our main conclusion is: the orientation toward longterm responsible investing should be important for all kinds of rational investors in order to fulfill their fiduciary duties and may better align investors' interests with the broader objectives of society."*. This further solidifies the approach I am taking in this thesis.

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[5] https://www.researchgate.net/publication/223825938_Changes_in_the_Value-Relevance_of_Earnings_and_Equity_Book_Values_Over_The_Past_Forty_Years
[6] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2699610

More in depth explanation of previous literature:

My thesis will be performed by using the accounting-based valuation method done by Golubov and Konstantidini (2023). In their paper they begin their valuation from the residual income valuation model, this model can be read about in Ohlson (1995)[7]. The following formula shows the residual income valuation model:

$$V = B_0 + \sum_{t=1}^{\infty} \frac{(ROE-r)B_{t-1}}{(1+r)^t} = B_0 + \sum_{t=1}^{\infty} \frac{RI_t}{(1+r)^t}. \qquad (1)$$

This formula, the residual income valuation model, shows that the equity value (V) is equal to the current book value (B_0) plus the future residual incomes (RI_t) discounted to their present value. The book values in the model are determined by the value of net assets-in-place and the residual incomes are determined by expected future earnings above the level required by the cost of equity capital. With two assumptions one can express the second term in the residual income valuation model as a multiple of net income. By assuming that, one, net income will in perpetuity grow at a constant rate (r > g) and, two, that residual income can be a constant fraction (d) of net income (NI_t) one can express the second term as follows:

$$\frac{NI_0(1+g)d}{(r-g)}. \qquad (2)$$

Rhodes-Korpf et al. (2005)[8] suggested that one could run a cross-sectional regression of market value of equity on book value and net income. The regression they ran was the following:

$$m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|ni_{it}| + a_{3jt}I_{(NI<0)} \times |ni_{it}| + a_{4jt}LEV_{it} + \epsilon_{it}. \qquad (3)$$

In this regression m_{it} is the log of the market value of equity, b_{it} is the log of the book value of equity, $|ni_{it}|$ is the log of the absolute net income, $I_{(NI<0)}$ is an indicator variable for loss making firms and LEV_{it} is the book leverage. This regression was developed even further by Golubov and Konstantidini (2023) where they add an additional valuation model predictor in the form of R&D capital. It should also be noted that the regression is performed for each industry sector determined by the Fama and French's 12 industry classifications. This created the new model shown below:

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7 https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1911-3846.1995.tb00461.x
8 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=412680

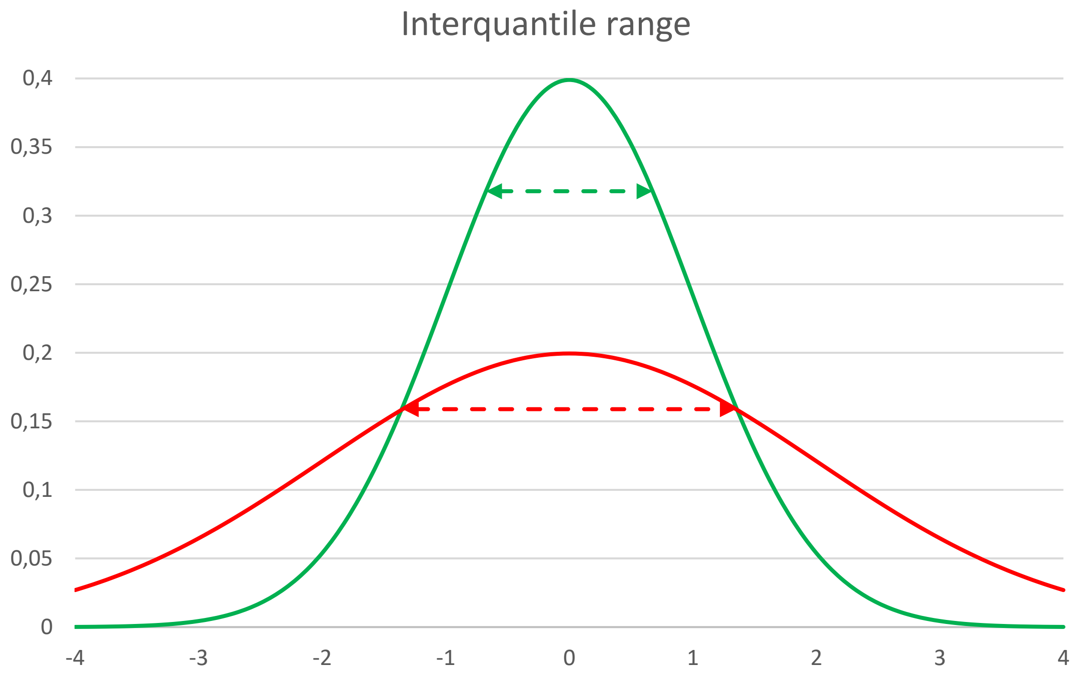
$m_{it} = a_{0jt} + a_{1jt} b_{it} + a_{2jt}|earn_{it}| + a_{3jt} I_{(EARN<0)} \times |earn_{it}| + a_{4jt} LEV_{it} + a_{5jt} rd_{it} + \epsilon_{it}$. (4)

In this new model one can also notice that net income is changed to earnings ($|earn_{it}|$) and was in this paper defined as the log of the absolute adjusted earnings. The new predictor R&D capital (rd_{it}) is defined as the log of the capitalized R&D. They also make small refinements on other measurements as well but nothing to major. The residuals from this model are called Price-To-Value and represent the deviations of the log of the market value of equity from the expected log of the fundamental equity value.

Golubov and Konstantidini (2023) differs from the two earlier papers (Ohlson (1995) and Rhodes-Korpf et al. (2005)) because they are interested in the expected fundamental equity value while Golubov and Konstantidini (2023) focus on the distribution of possible fundamental values and especially the spread of that distribution. Because of this Golubov and Konstantidini take this method a step further and calculate a variable for the Valuation Uncertainty (VU). This is done with the following formula after exponentiating the quantile-values:

$VU = \frac{Q_{75} - Q_{25}}{\frac{Q_{75} + Q_{25}}{2}}$. (5)

They define Valuation Uncertainty as the interquartile range of the distribution of fundamental values, the difference between the 75th and 25th percentile. To make this value comparable to firms of different sizes they scale it by the midpoint between the two quantiles.



Graph 1: This graph shows two different normal distributions with two different standard deviations (1 and 3). On both curves there is a dashed line that shows the interquartile range.

From graph 1 it becomes easier to understand how the calculation of the valuation uncertainty will be calculated and how the observations will differ from each other. In the graph there are two curves with different standard deviations, the green line has a mean of 0 and a standard deviation of 1 while the red line has a mean of 0 and a standard deviation of 3. Because of the fatter tails displayed by the red curve one can see that the interquartile range, the dashed line, is wider than the case of the green line. If one would imagine the two lines to be two different companies one would come to the conclusion that the company with the wider interquartile, the red line, range would have a larger valuation uncertainty than the one with the smaller interquartile range, the green line.

The method used in the paper Berg et al. (2022) was a regression, where they tried to explain stock returns with ESG-ratings and a stock-level controls variable. Their initial regression looked like this:

$$r_{k,t+1} = \alpha + \beta * Y_{k,t} + M_{k,t} + \epsilon_{k,t}. \qquad (6)$$

In this regression $r_{k,t+1}$ is the stock-return for company k for the time *t* to *t+1*, $Y_{k,t}$ is the true ESG performance of company k at time t, $M_{k,t}$ is an omitted variable that affects stock returns and is correlated with ESG performance and $\epsilon_{k,t}$ are explained as innovations assumed to be orthogonal to all regressors. They then determine a formula that says that ESG rating agencies' ratings for determining the true ESG performance is noisy which looks like this:

$$s_{k,t,i} = Y_{k,t} + \eta_{k,t,i}. \qquad (7)$$

In this regression $s_{k,t,i}$ is the ESG-rating for company k at time t from rating agency i and $\eta_{k,t,i}$ is the measurement error as in the errors-in-variables problem, orthogonal to Y, M and ϵ. From equation 7 they then take $s_{k,t,i}$ to be used in the first regression instead of $Y_{k,t}$ which looks like this:

$$r_{k,t+1} = \alpha + \beta * s_{k,t,i} + \upsilon_{k,t}. \qquad (8)$$

In this regression one can also notice that the error term from equation 6, $\epsilon_{k,t}$, is replaced by a new error term which is determined in the following way, $\upsilon_{k,t} = M_{k,t} + \epsilon_{k,t} - \eta_{k,t,i} * \beta$.

From equation 8 the authors created a new base-regression which looked like this:

$$r_{k,t+h} = \alpha + \beta * s_{k,t,i} + c_x * X_{k,t} + \upsilon_{h,k,t}. \qquad (9)$$

In the regression the variable $r_{k,t+h}$ is the monthly stock return, $s_{k,t,i}$ is the ESG-rating of firm i in month t, h is used to describe the horizon in months. The variable $X_{k,t}$ is a stock-level control which consists of the stocks *Beta, Dividends, Market Value, Book-to-market, Asset Growth, ROA, Momentum and Volatility*. This stock level control variable is taken from Lewellen (2015)[9]. The standard errors from the regression are clustered by month and the GICS sub-industry. Since their β is suffering from attenuation bias they determined the variable $s_{k,t,i}$ as in equation 7 but with the added control variable, shown below:

$$s_{k,t,i} = c_0 + \pi * Z_{k,t,i} + c_1 * X_{k,t} + \eta_{k,t}. \qquad (10)$$

In this regression $Z_{k,t,i}$ are the ESG-ratings from other agencies that are used as instruments. Since they assume that the control variable is orthogonal to all variables on the RHS they remove it from the empirical implementation and therefore remove the control variable in both the regression shown in equation 9 and equation 10. Their model determining if a rating agency's ratings is a valid instrument is done by either Pruning or Lasso procedures. Comparing the base-regression with both the Pruned and Lasso 2SLS they found that there is a clear tendency for the coefficients in both the 2SLS to be larger than in the base-regression. They also find that even though there might be a low correlation between agencies they are

[9] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2511246

still strong instruments for a given ESG rating. This makes the point that it is worthwhile relying on several complementary ESG-ratings.

Theory:

One theory that is relevant to this thesis is the Efficient Market Hypothesis (EMH). This theory is used to explain how efficient the market is and what is reflected in the market price. From Finance (Byström) one can read about the three different types of market efficiencies. According to Byström one would define the three efficiencies as follows:

- Weak efficiency: The market price reflects all historical information.
- Semi-strong efficiency: The market price reflects all public information.
- Strong efficiency: The market price reflects all information, including insider information.

On page 197 he says that "*is the market efficient or not? A cautios answer that many finance professionals would agree with is the following:*

Markets are probably weakly efficient and possibly also semi-strongly efficient!" He continues by saying that opinion is divided and that generally academics are more inclined to support this statement while practitioners are more inclined towards the belief that market prices can be predicted. He also adds that most markets are becoming more efficient with time and that old and large international markets are more efficient than young and small domestic markets.

This theory is relevant to my thesis since I am trying to find the distribution of the equity value of each company and then from that find the valuation uncertainty. From the support of the EMH the market price would reflect public information.

Stakeholder theory is another very relevant theory in this thesis. Stakeholder theory says that the company should not just maximize the value of the shareholders in the company but all stakeholders of the company.

Since stakeholder theory changes the focus from shareholders to stakeholders one might be able to see that it is a similar step as the increasing importance of ESG.

Because of the use of valuation uncertainty in this thesis, there are other important aspects to consider like risk premiums. Risk premiums are directly related to valuation uncertainty since investors usually demand higher returns when faced with higher risks. This also ties into investment strategies where companies decide on different strategies to manage their valuation uncertainty.

I also discuss the ESG-ratings which connects to risk management, similarly to how valuation uncertainty connects to risk premiums. In this case it would mainly relate to how well a company acts in terms of ESG, where a worse ESG-performance would indicate a higher risk and vice versa.

By combining the two large individual areas of valuation uncertainty and ESG one can see that the main areas of interest are investment analysis, portfolio management and corporate strategy.

Methodology:

In my thesis I will begin by finding the Valuation Uncertainty for every company in my data. This will be done by performing the regression from Golubov and Konstantidini (2023), namely equation 4:

$$m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|earn_{it}| + a_{3jt}I_{(EARN<0)} \times |earn_{it}| + a_{4jt}LEV_{it} + a_{5jt}rd_{it} + \epsilon_{it}.$$

After performing this regression, I will exponentiate the results and then also use their equation for calculating valuation uncertainty which is displayed as equation 5:

$$VU = \frac{Q_{75}-Q_{25}}{\frac{Q_{75}+Q_{25}}{2}}.$$

After calculating the valuation uncertainty, I will perform a similar two-stage least squares regression as Berg et al. (2022). After finding the right instruments as instrument variables I will find my ESG rating variable as in equation 10 but as they also did assume that the control-variable is orthogonal and can therefore be removed from the regression:

$$s_{k,t,i} = c_0 + \pi * Z_{k,t,i} + \eta_{k,t}. \qquad (11)$$

I will do this with every agency's ESG-ratings as the dependent variable being explained by the two other ESG agencies' ESG-ratings. This will give me three different ESG-variables based upon the data gathered from all three different agencies' ESG-ratings. I will then incorporate this new variable into the equation by Golubov and Konstantidini (2023), equation 4. In this way I will create my own regression model which would look like this:

$$m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|earn_{it}| + a_{3jt}I_{(EARN<0)} \times |earn_{it}| + a_{4jt}LEV_{it} + a_{5jt}rd_{it} + a_{6jt}s_{k,t,i} + \epsilon_{it}. \qquad (12)$$

In this regression I will determine the market value of equity, ME, by multiplying the stock price at (date) with the number of outstanding shares at the same time. The book value of equity, BE, will be determined as the book value of common equity plus the deferred taxes, as of the end of the fiscal year. Companies with a negative book value of equity will be excluded. The earnings, EARN, will be calculated by taking the income before extraordinary items, as of the fiscal year end, minus special items plus R&D expenditure minus R&D amortization. The indicator variable, I, is an indicator that is 1 for companies with negative earnings and 0 for companies with positive earnings. The book leverage, LEV, is determined by taking the long-term debt plus debt in short-term liabilities and then dividing that with the total assets, as of the end of the fiscal year. The R&D is calculated by taking the capitalized values of R&D expenses, at the end of the fiscal year, assuming a five-year life and straight-line amortization of 20%, following Chan, Lakonishok and Sougiannis (2001)[10]. Lastly the ESG-rating is calculated as explained above in equation 11.

The results from this regression model will then be compared to the old regression model, equation 4. The residuals from the regression run by Golubov and Konstantidini (2023) are the Price-To-Value. The Price-To-Value can also be called valuation mistakes. I would therefore like to test if my model would perform better and have smaller valuation mistakes. Having smaller valuation mistakes would also cause the valuation uncertainty to become smaller indicating that one would have a model which can predict the distribution of the valuation uncertainty with smaller deviations from the true intrinsic equity value.

Data:

My data consists of two parts. The first part comes from the accounting world, this data will be gathered from Capital IQ. The data will be gathered from the Capital IQ excel plug-in. While Golubov and Konstantidini (2023) gathered their data from Compustat and CRSP, there might exist small deviations in the names and exact item descriptions of the data they used

[10] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=227564

compared to my data. Despite this I don't believe that it will affect my thesis since I'm not comparing my results with their results, I'm simply using their initial model with my own modifications and the comparisons I make are all compared against each other with the same data items.

The second part is the sustainability ratings, since I'm using several different ESG-agencies' ratings I will gather my ESG-data from several different sources. In my data I am using ESG-ratings from Sustainalytics, LSEG and ISS. Both Sustainalytics and LSEG were used in Berg et al (2022), Sustainalytics was under the same name, but LSEG have acquired Refinitiv which was the one they used. ISS or Institutional Shareholder Services is a company founded in 1985 and its majority is owned by Deutsche Börse Group along with the ISS management. Morningstar Sustainalytics are a global leader in the research and data of ESG. They have been active for more than 30 years in finding and managing ESG risks. LSEG is the London Stock Exchange Group and is one of the leading providers of financial data. Based on this I am very comfortable in my choices for the ESG data providers.

From Morningstar Sustainalytics the ESG-score is a risk rating between 0 and 100, this means that a higher value would indicate a worse performance in the ESG department. They divide the score into five different categories ranging from Negligible to Severe. In order and with the associated number score is Negligible from 0-10, Low from 10-20, Medium from 20-30, High from 30-40 and Severe is 40+. The relatively low value for severe is because of their calculations on managed risk and unmanaged risk.

The ESG-score from LSEG is measured from 0 to 100. This rating is reversed from the Morningstar Sustainalytics approach which means that a high ESG-score from LSEG means that the company is performing well regarding ESG. They also divide up their ratings to give a sense of understanding how well or how bad a certain number is. They divide up their ratings into quartiles and say that companies with an ESG-rating between 0 and 25 have a poor ESG performance, between 25 and 50 is satisfactory, between 50 and 75 is good and lastly between 75 and 100 is excellent. LSEG also incorporates transparency in reporting material ESG data publicly.

ISS uses a different approach when measuring ESG-scores since they use an alphabetical grading system with 12 different achievable ratings, the ratings available from worst to best are: -D, D, D+, -C, C, C+, -B, B, B+, -A, A and A+. Because the data is ordinal, I will modify it by giving each rating a value ranging from 1 to 12. In my ranking system the worst rating, -

D, will be given the smallest number, 1, and the best rating, A+, will be given the largest number, 12. This makes it possible to compare it with the other rating agencies, which is very important when creating the ESG-variable for my regression.

Cleaning the data will be done by removing companies that are not in the NASDAQ GS. This is done since I want to do this analysis on the companies on the NASDAQ GS. I will also remove companies that are missing data that will be used in the regression (book value of equity, earnings, R&D, leverage and ESG). After doing this I will divide my data into their respective industries based on the Fama and French 12 industry classes. After classifying each company based on its industry, I will remove every company that is operating in the money-industry. This is because the information in their financial statement is not comparable to industrial firms, which would cause my work to be useless and because they are subject to capital regulation.

Calculations:

After cleaning the data, I will now begin my calculations. First, I will display a summary of statistics showcasing the basic results of the data.

Raw values	Mean	Median	S.D.	Min	Max
ME	25577	2404	1.672e+005	107.2	3.051e+006
BE	3993	660.4	16831	-7703.	2.757e+005
EARN	973.8	51.60	6742	-5017.	1.074e+005
I	0.3400	0.0000	0.4740	0.0000	1.000
RD	1348	54.38	9687	0.0000	2.021e+005
LEV	0.4351	0.3936	0.3075	0.02433	3.424
Log values					
m	7.943	7.785	1.733	4.674	14.93

B	6.397	6.493	2.322	0.0000	12.53
earn	4.945	4.772	1.780	-2.273	11.58
earnI	1.495	0.0000	2.232	-0.6574	8.521
rd	3.275	3.996	3.175	-0.9986	12.22

Table 1: This table shows a summary of statistics of both the raw values and the Log values of the variables used in the regression.

The table shows basic information and from the look of it everything appears to be normal. The ME shows the market value of equity in millions of USD as of 28th of June 2023. Next, we see BE which is the book value of equity for the fiscal year 2023. EARN shows the absolute earnings in millions of USD. The value I is the indicator variable which is one if the company has negative earnings and 0 if the company has positive earnings. RD shows the research and development expenditures, and LEV shows the book leverage. Below the raw values are the Log values where *m* is the natural log of ME , *b* is the natural log of BE, *earn* is the natural log of EARN, *earnI* is the natural log of EARN times the indicator variable and *rd* is the natural log of RD.

The log values (*m, b, earn, earnI, rd*) from table 1 and the LEV-value, from the raw data, are the ones that will be used in the regression, shown in equation 4:

$$m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|earn_{it}| + a_{3jt}I_{(EARN<0)} \times |earn_{it}| + a_{4jt}LEV_{it} + a_{5jt}rd_{it} + \epsilon_{it}.$$

In the table one might notice that the minimum value for both *earn* and *earnI* are negative, which might seem weird considering we used the absolute value of earnings. The result is negative since the natural logarithm of a number above zero and below one will be negative.

Performing a quantile regression, on 0.25, 0.5 and 0.75, on the data without ESG-ratings gives me the following results:

```
          tau    coefficient   std. error      t-ratio
  ---------------------------------------------------------
  const     0.250       2.46158     0.168348       14.6220
            0.500       3.12885     0.185455       16.8712
            0.750       4.05341     0.193512       20.9466

  b         0.250      0.216204    0.0223683       9.66563
            0.500      0.241300    0.0246413       9.79248
            0.750      0.187859    0.0257118       7.30635
```

earn	0.250	0.656640	0.0243144	27.0062
	0.500	0.569960	0.0267851	21.2790
	0.750	0.588698	0.0279488	21.0635
earnI	0.250	-0.187420	0.0172244	-10.8811
	0.500	-0.191787	0.0189747	-10.1075
	0.750	-0.168403	0.0197990	-8.50561
LEV	0.250	0.687150	0.146088	4.70367
	0.500	0.856910	0.160933	5.32463
	0.750	0.647932	0.167924	3.85847
rd	0.250	0.0779429	0.0116149	6.71058
	0.500	0.0940805	0.0127952	7.35279
	0.750	0.0952869	0.0133511	7.13703

Table 2: This table shows the results from running the quantile regression on the data without any ESG-ratings.

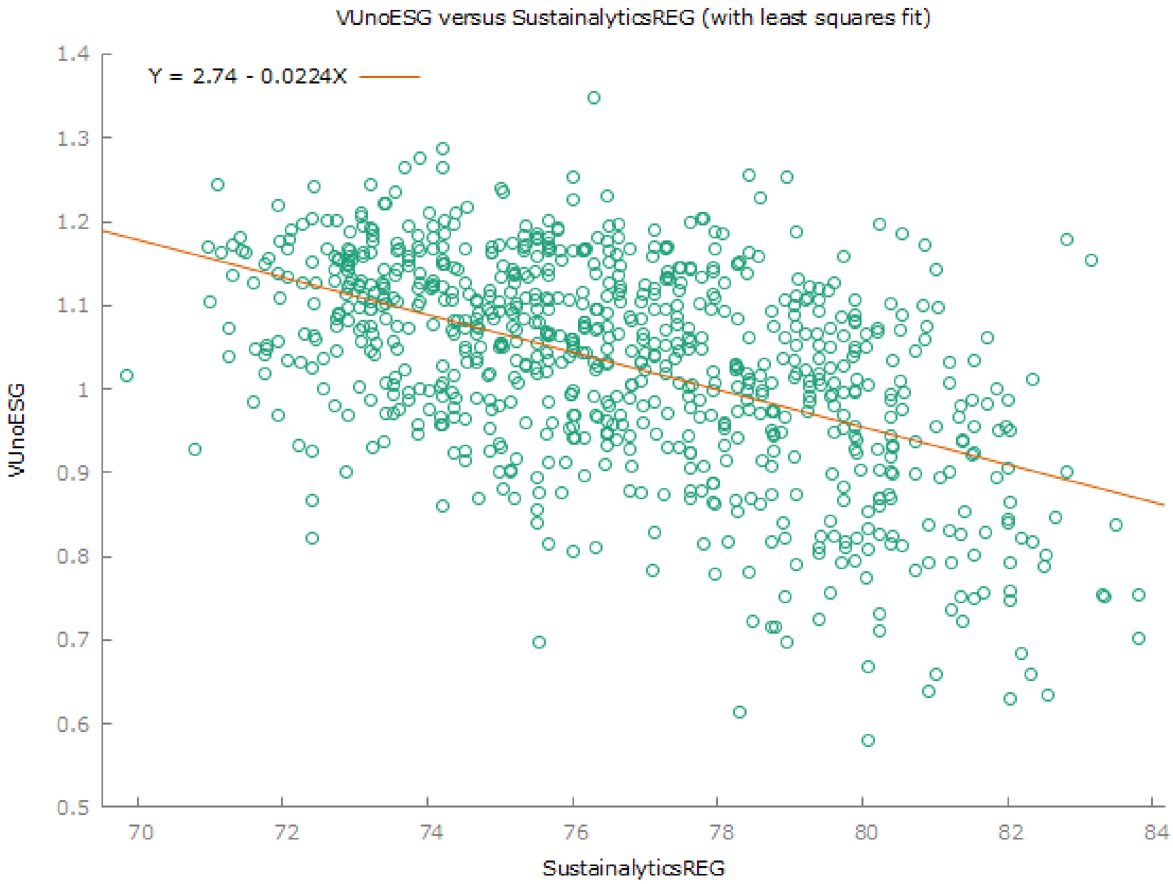
Looking at the table one might notice the negative coefficients related to *earnI*, this result is negative since that variable shows the log of the absolute earnings of those with negative earnings and one would assume that negative earnings would cause the market value of equity to decrease, which is what the table tells us.

After finding these values for each quantile and for each explanatory variable I use these to find the fitted values for each company. The fitted values for quantiles 0.25 and 0.75 are then used to calculate the valuation uncertainty for each company. By putting in each company's true value into the regression will give us an expected value for the log of the market value of equity. This value will then have to be exponentiated back to a standard value. The exponentiated value for quantile 0.25 and 0.75 will then be used to calculate the valuation uncertainty for each firm with the following equation, shown as equation 5:

$$VU = \frac{Q_{75} - Q_{25}}{\frac{Q_{75} + Q_{25}}{2}}.$$

After finding the Valuation uncertainty for the dataset without ESG-ratings I will now incorporate the ESG-ratings as a variable in the quantile regression. Before incorporating the ESG-ratings as variables in the regression of calculating the valuation uncertainty I will perform three regressions where the dependent variable is the valuation uncertainty, and the explanatory variable is the ESG-rating.

By first looking at the relation between the valuation uncertainty without ESG and the ESG-variable from Sustainalytics were I got the following results:



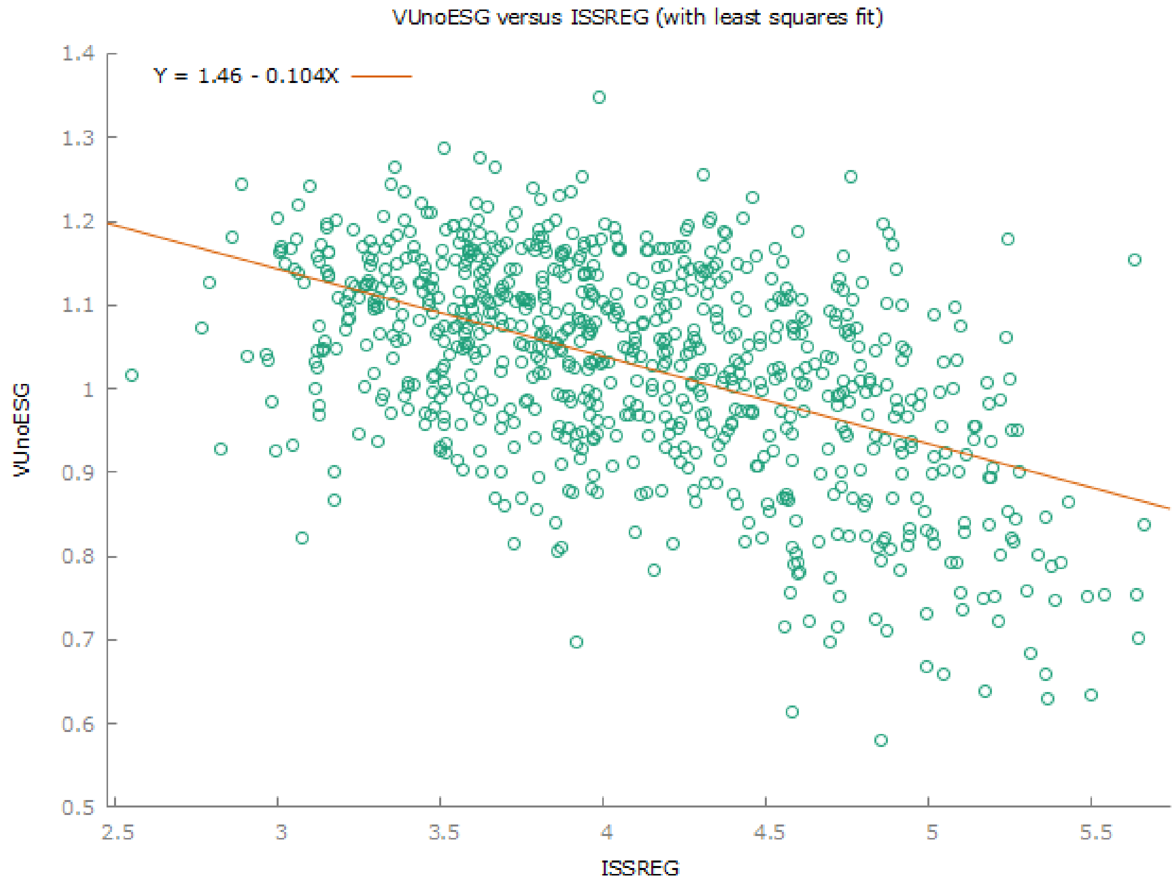
Graph 2: This graph shows the valuation uncertainty without any ESG-ratings on the y-axis and the ESG-variable from Sustainalytics on the x-axis.

The regression on the data shown in the scatter plot above is shown in the table below:

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
Const	2.74362	0.102244	26.83	<0.0001	***
SustainalyticsREG	−0.0223653	0.00133299	−16.78	<0.0001	***

Table 3: This table shows the results for the OLS-regression performed on the valuation uncertainty as the dependent variable and the ESG-variable from Sustainalytics as the explanatory variable.

I will now look at the relation between the valuation uncertainty without ESG and the ESG-variable from ISS where I got the following results:



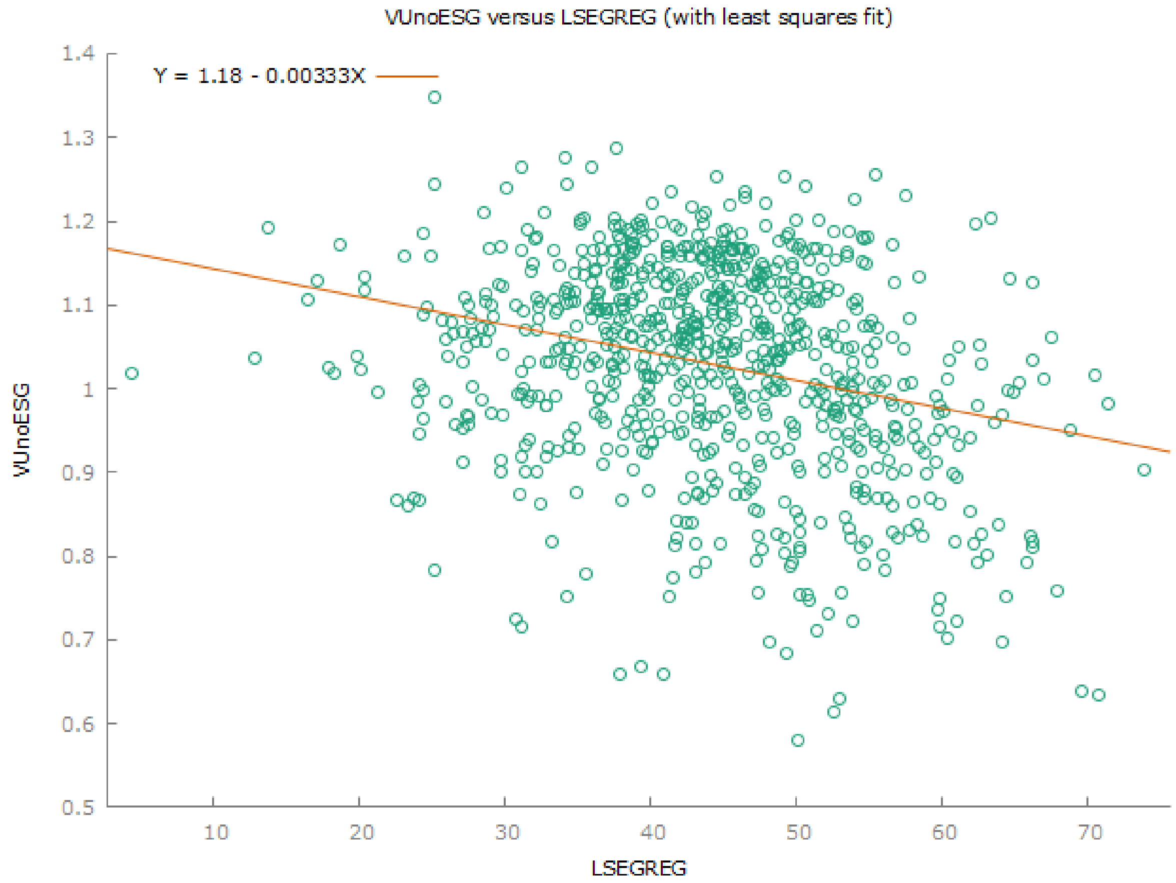
Graph 3: This graph shows the valuation uncertainty without any ESG-ratings on the y-axis and the ESG-variable from ISS on the x-axis.

The regression on the data shown in the scatter plot above is shown in the table below:

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1.45649	0.0257904	56.47	<0.0001	***
ISSREG	−0.104492	0.00623979	−16.75	<0.0001	***

Table 4: This table shows the results for the OLS-regression performed on the valuation uncertainty as the dependent variable and the ESG-variable from ISS as the explanatory variable.

Lastly looking at the relation between the valuation uncertainty without ESG and the ESG-variable from LSEG, I got the following results:



Graph 4: This graph shows the valuation uncertainty without any ESG-ratings on the y-axis and the ESG-variable from ISS on the x-axis.

The regression on the data shown in the scatter plot above is shown in the table below:

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1.17642	0.0190420	61.78	<0.0001	***
LSEGREG	−0.00332878	0.000420026	−7.925	<0.0001	***

Table 5: This table shows the results for the OLS-regression performed on the valuation uncertainty as the dependent variable and the ESG-variable from LSEG as the explanatory variable.

Just by looking at the three different scatter plots, graph 2, 3 and 4, one can see that the trend-line is negative indicating that there is a connection between the two variables that says that a higher ESG-rating, ceteris paribus, indicates a lower valuation uncertainty. To confirm this observation, I performed OLS-regressions to see if they have any statistical significance. When performing the regressions it turned out to be that all three had a three-star significance level. This can also be seen as the p-values all being smaller than 0,0001.

Because the ESG-ratings are noisy I will, as explained earlier, use the approach by Berg et al (2022) to perform a 2SLS where I created three different ESG-variables to incorporate in the regression from three different ESG-variables. Berg et al (2022) found the performance to increase when using this method so therefore I will begin to calculate the one ESG-variable.

Looking first at the correlation matrix of the ESG-ratings:

	ISS	LSEG	Sustainalytics
ISS	1		
LSEG	0,4242	1	
Sustainalytics	0,1156	0,3904	1

Table 6: Shows the correlation matrix of the three different ESG-agencies scores.

From table 6 one can see that there exist different levels of correlation between the scores. This is a good indicator since we want some correlation but not too high correlation when using them as IV-estimators.

Calculating the ESG-variable will be done by using equation 11:

$$s_{k,t,i} = c_0 + \pi * Z_{k,t,i} + \eta_{k,t}.$$

This formula takes one ESG-rating and regresses it on the other two ESG-ratings to determine a single ESG-rating, namely $s_{k,t,i}$. Because the ESG-ratings from Morningstar Sustainalytics have risk ratings from 0 to 100 Berg et al (2022) solves this problem by taking the risk rating and multiplies it with -1 and then adds 100. This inverts the risk rating and now the risk rating has become a normal ESG-rating comparable to the other ESG-ratings where a higher number is associated with a better performance regarding ESG.

ESG-rating	Mean	Median	S.D.	Min	Max
Sustainalytics	76.65	76.85	7.231	43.7	95.5
LSEG	44.19	42.00	18.55	6.000	92.00
ISS	4.088	4.000	1.425	1.000	9.000

Table 7: This table shows the descriptive statistics for the ESG-risk ratings from all three agencies after normalizing the risk rating from Sustainalytics.

From the three agencies I will create a new variable which is determined as the fitted values form a regression run with two agencies explaining the third. I will do this in every possible way giving me three different variables. I do this to see if there might be any differences in the way the variable is created.

The newly created variables, SUS(REG), ISS(REG) and LSEG(REG) will now be incorporated in the regression as the variable replacing $s_{k,t,i}$ in equation 12:

$$m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|earn_{it}| + a_{3jt}I_{(EARN<0)} \times |earn_{it}| + a_{4jt}LEV_{it} + a_{5jt}rd_{it} + a_{6jt}s_{k,t,i} + \epsilon_{it}.$$

Performing the same quantile regression, as before on the data without ESG-rating, will then give me new coefficients shown below:

	tau	coefficient	std. error	t-ratio
const	0.250	0.322304	1.20144	0.268264
	0.500	1.30894	1.26538	1.03442
	0.750	0.847534	1.15706	0.732487
b	0.250	0.217062	0.0247994	8.75273
	0.500	0.237327	0.0261192	9.08633
	0.750	0.173698	0.0238834	7.27275
earn	0.250	0.621557	0.0282570	21.9966
	0.500	0.562014	0.0297607	18.8844
	0.750	0.554992	0.0272133	20.3942
earnI	0.250	-0.177725	0.0194652	-9.13041
	0.500	-0.175778	0.0205011	-8.57409
	0.750	-0.154661	0.0187463	-8.25025
LEV	0.250	0.697723	0.162345	4.29778
	0.500	0.782743	0.170985	4.57785
	0.750	0.599782	0.156349	3.83618
rd	0.250	0.0828470	0.0127300	6.50802
	0.500	0.0895996	0.0134074	6.68283
	0.750	0.0943246	0.0122598	7.69382
SustainalyticsREG	0.250	0.0296820	0.0164849	1.80056
	0.500	0.0249718	0.0173622	1.43829

0.750	0.0454320	0.0158760	2.86168

Table 8: This table shows the results from the quantile regression on the data with the ESG-ratings included. In this quantile regression the ESG-rating is calculated where the ratings from Sustainalytics are the dependent variable and the other two agencies being the explanatory variables.

	tau	coefficient	std. error	t-ratio
const	0.250	2.12943	0.211569	10.0649
	0.500	2.81727	0.187941	14.9902
	0.750	3.57593	0.230884	15.4880
b	0.250	0.221881	0.0223070	9.94668
	0.500	0.246847	0.0198157	12.4571
	0.750	0.196350	0.0243435	8.06578
earn	0.250	0.633309	0.0252308	25.1007
	0.500	0.569190	0.0224130	25.3956
	0.750	0.551038	0.0275342	20.0129
earnI	0.250	-0.183777	0.0171880	-10.6922
	0.500	-0.180939	0.0152684	-11.8506
	0.750	-0.160699	0.0187571	-8.56735
LEV	0.250	0.759614	0.145704	5.21339
	0.500	0.843245	0.129432	6.51497
	0.750	0.737010	0.159006	4.63509
rd	0.250	0.0645115	0.0120663	5.34641
	0.500	0.0784692	0.0107187	7.32076
	0.750	0.0834403	0.0131679	6.33665
LSEGREG	0.250	0.00940294	0.00395736	2.37606
	0.500	0.00741115	0.00351540	2.10820
	0.750	0.0141145	0.00431865	3.26826

Table 9: This table shows the results from the quantile regression on the data with the ESG-ratings included. In this quantile regression the ESG-rating is calculated where the ratings from LSEG are the dependent variable and the other two agencies being the explanatory variables.

	tau	coefficient	std. error	t-ratio
const	0.250	2.07340	0.287163	7.22029
	0.500	2.75862	0.313038	8.81241
	0.750	3.49606	0.282462	12.3771
b	0.250	0.212693	0.0239899	8.86593
	0.500	0.241690	0.0261515	9.24190
	0.750	0.176170	0.0235972	7.46571
earn	0.250	0.628419	0.0275683	22.7950
	0.500	0.559567	0.0300523	18.6198
	0.750	0.553386	0.0271170	20.4074
earnI	0.250	-0.183516	0.0185459	-9.89526
	0.500	-0.176364	0.0202169	-8.72359
	0.750	-0.156740	0.0182423	-8.59212
LEV	0.250	0.683284	0.156531	4.36516
	0.500	0.804371	0.170635	4.71398
	0.750	0.646343	0.153969	4.19788
rd	0.250	0.0808815	0.0123182	6.56599
	0.500	0.0878188	0.0134282	6.53989
	0.750	0.0911449	0.0121166	7.52232
ISSREG	0.250	0.129093	0.0743721	1.73577
	0.500	0.108144	0.0810734	1.33391
	0.750	0.200544	0.0731546	2.74137

Table 10: This table shows the results from the quantile regression on the data with the ESG-ratings included. In this quantile regression the ESG-rating is calculated where the ratings from ISS are the dependent variable and the other two agencies being the explanatory variables.

These coefficients will then be used in the same way as before to calculate the quantile values for quantile 0.25 and 0.75. The quantile values will then be used to find the valuation uncertainty for the data with the ESG-ratings included.

I now have four different samples of data showing the Valuation Uncertainty calculated in two different ways, one with ESG-data and the other three without ESG-data. The summary statistics for these four samples will now be presented:

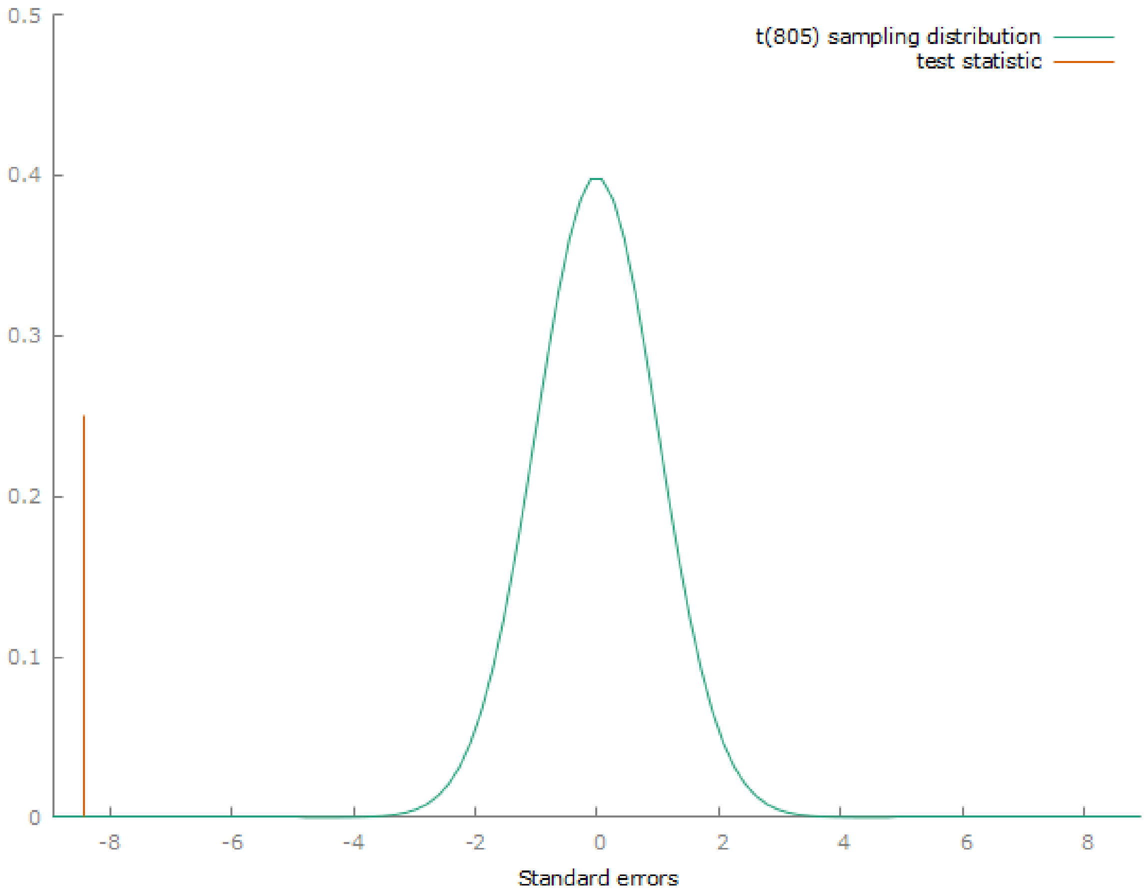
Variable	Mean	Median	S.D.	Min	Max
VU	1.029	1.048	0.1252	0.5794	1.348
VU (SUSESG)	1.039	1.062	0.1287	0.5874	1.380
VU (ISSREG)	1.047	1.072	0.1326	0.5831	1.404
VU (LSEGESG)	1.049	1.069	0.1339	0.5727	1.361

Table 11: This table shows the summary statistics for the valuation uncertainty samples without ESG-data, VU, and with ESG-data incorporated, VU(SUSESG), VU(ISSREG) and VU(LSEGESG).

From table 11 one can see that the mean of the valuation uncertainty without ESG-data incorporated is smaller than the mean of each of the three samples of valuation uncertainty with ESG-data. This difference in means will be tested by performing a paired t-test on the two samples of valuation uncertainties. To perform the paired t-test I first created a new variable, DIFF, which was calculated by taking the difference between the two samples, VU and VU(ESG). Then I performed a t-test on the new variable, DIFF, to see if there was a significant difference or not. The results from the t-tests were the following:

Test 1 (Sustainalytics):

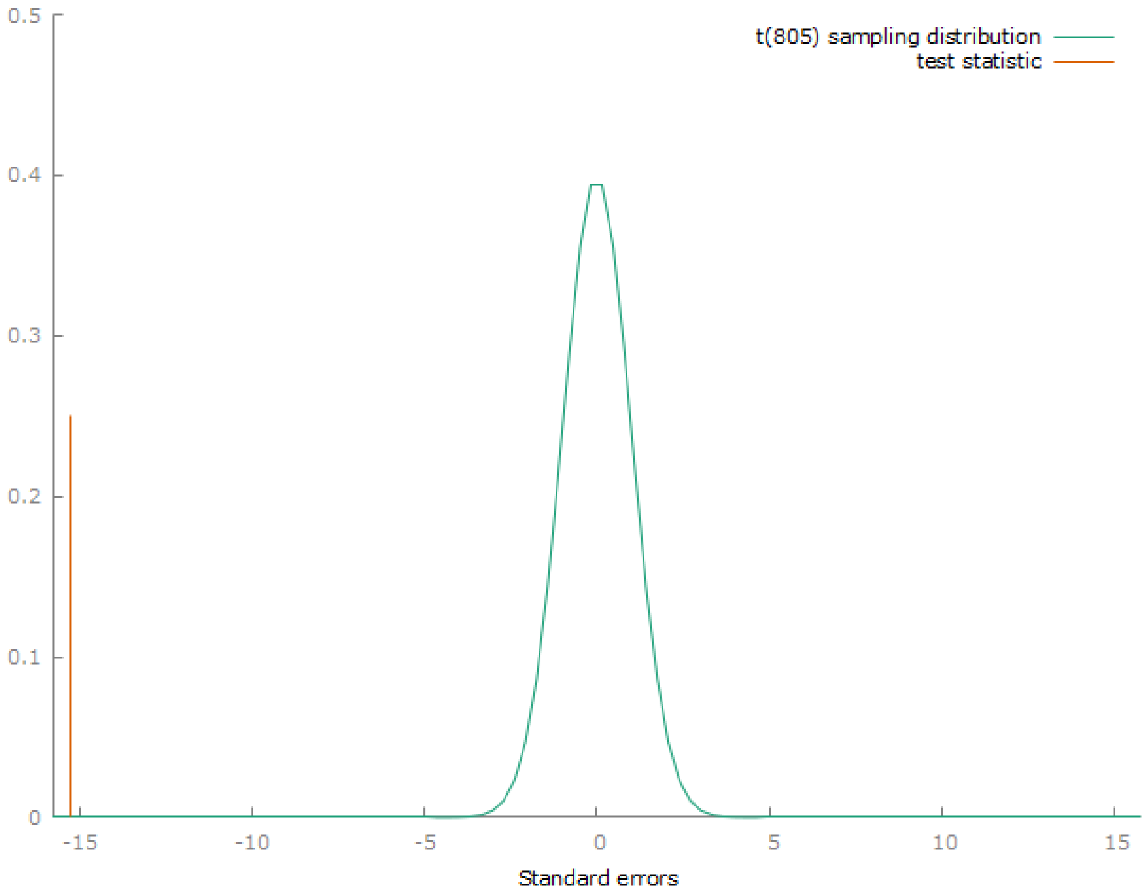
```
Null hypothesis: population mean = 0
Sample size: n = 806
Sample mean = -0.00982335, std. deviation = 0.033118
Test statistic: t(805) = (-0.00982335 - 0)/0.00116653 = -8.421
Two-tailed p-value = 1.703e-016
(one-tailed = 8.513e-017)
```



Graph 5: This graph shows the sampling distribution, green, and test statistic, yellow, for the first paired t-test between the VU without ESG and the VU with ESG from the variable SUS(REG).

Test 2 (ISS):

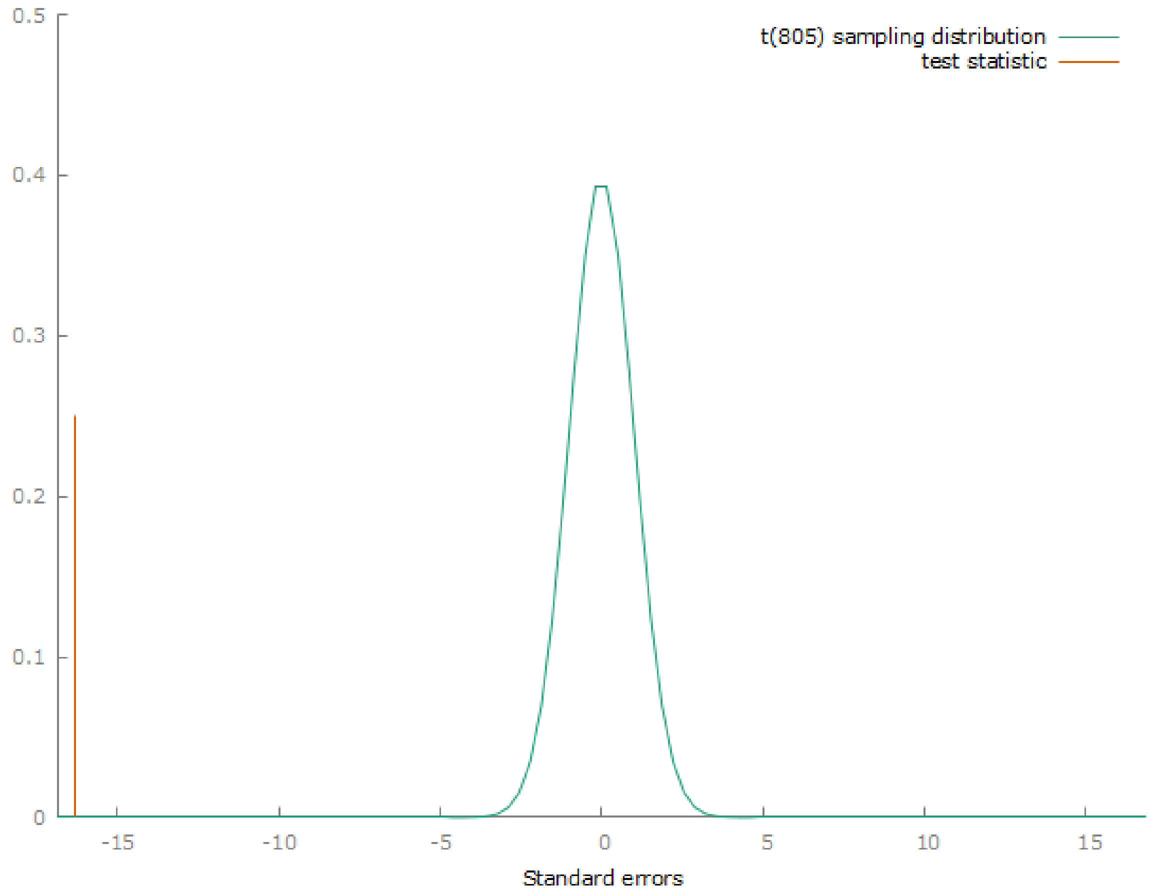
```
Null hypothesis: population mean = 0
Sample size: n = 806
Sample mean = -0.0178523, std. deviation = 0.0332239
Test statistic: t(805) = (-0.0178523 - 0)/0.00117026 = -15.255
Two-tailed p-value = 2.416e-046
(one-tailed = 1.208e-046)
```



Graph 6: This graph shows the sampling distribution, green, and test statistic, yellow, for the first paired t-test between the VU without ESG and the VU with ESG from the variable ISS(REG).

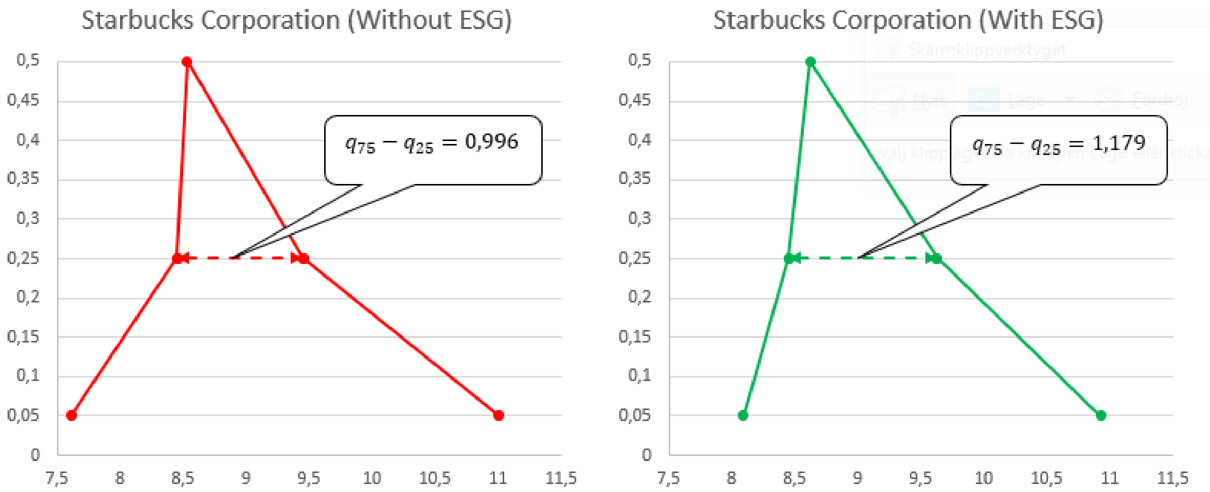
Test 3 (LSEG):

```
Null hypothesis: population mean = 0
Sample size: n = 806
Sample mean = -0.0195739, std. deviation = 0.0340068
Test statistic: t(805) = (-0.0195739 - 0)/0.00119784 = -16.341
Two-tailed p-value = 4.72e-052
(one-tailed = 2.36e-052)
```



Graph 7: This graph shows the sampling distribution, green, and test statistic, yellow, for the first paired t-test between the VU without ESG and the VU with ESG from the variable LSEG(REG).

From the three different tests the basic result was the same with some minor differences. In every test one can clearly see and read that there was a significant difference between the sample without ESG and each one of the samples with ESG. There was no difference in result depending on how the ESG-variable was determined. These tests conclude that the valuation uncertainty did on average increase when incorporating ESG. This means that the distribution of the valuation of the log of the market value of equity became on average wider. I will now show an example of how this can look like below:



Graph 8: This graph shows the distribution of the log of the market value of equity for Starbucks Corporation on the x-axis (q_{5}, q_{25}, q_{50}, q_{75} and q_{95}) and on the y-axis is the quantile of the distribution, with: x up to the 50^{th} percentile and (1 - x) above the 50^{th} percentile. In the left most graph, with the red line, is the calculated value for the log of the market value of equity without ESG-ratings in the model and the right most graph, with the green line, is the calculated value for the log of the market value of equity with ESG-ratings incorporated in the model.

From graph 8 one can see an example of how the distribution of the log of the market value of equity changes when incorporating ESG-ratings in the model. The two graphs both show the same company, Starbucks Corporation. In the middle of the graph is a dashed line that shows the interquartile range, which is defined as the difference between the 75^{th} and the 25^{th} quantiles. In the example without ESG-ratings included one can see that the interquartile range is only 0,996 while in the example with the ESG-ratings incorporated the interquartile range has increased to 1,179. Since the formula for calculating valuation incorporates the interquartile range, where a bigger difference leads to a higher valuation uncertainty, this becomes an example of the beforementioned effect that incorporating ESG-ratings in the model will cause an increase in the valuation uncertainty.

Results:

From the calculations one can conclude that there is a statistically significant connection between ESG-ratings and the valuation uncertainty without ESG-ratings included. In the beginning of the calculations, I found that there is a three-star significance level that says that

ESG-ratings have a negative effect on valuation uncertainty. This means that if the ESG-rating increases, ceteris paribus, then the valuation uncertainty would decrease. This was true for all different ESG-agencies included in this thesis. After finding the valuation uncertainties for the different variables of ESG I could also test the difference between the valuation uncertainty with and without ESG-ratings included in the regression. I performed three different paired t-tests to see if there were any significant changes by incorporating ESG-ratings in the valuation uncertainty model. The paired t-tests confirmed that there was a statistically significant difference when incorporating ESG-ratings in the model for valuation uncertainty. This statistically significant difference was that the valuation uncertainty increased when the ESG-ratings were incorporated into the model.

Conclusions:

Analyzing the results from the data shows me that ESG-ratings are important and shouldn't be neglected. When looking at the valuation uncertainty and comparing the valuation uncertainty with and without ESG-ratings incorporated it becomes clear that the incorporation of ESG-ratings had a statistically significant impact on the size of the valuation uncertainty. In this sample the valuation uncertainty became statistically significant larger when the ESG-ratings were incorporated. What this means is that the interquartile range was increased when the ESG-ratings were incorporated. When looking at the scatter plots and regressions for the valuation uncertainty, without ESG-ratings incorporated, and the ESG-ratings one could see that, with a three-star level of significance ($p<0.0001$), the valuation uncertainty was affected negatively by the ESG-ratings. This means that a higher ESG-rating would imply lower valuation uncertainty. A company with a low ESG-rating might be involved in some type of lawsuit which could cost them, this uncertainty is one reason why the valuation uncertainty would increase with a lower ESG-rating. The results from incorporating the ESG-ratings in the model for valuation uncertainty could possibly be explained by the results from the beforementioned regressions. If a higher ESG-rating would indicate a lower valuation uncertainty it might be the case that most of the companies in the sample are not performing well regarding ESG. If this is the case, then that would imply that the valuation uncertainty could possibly have become smaller if most of the companies had had better performances regarding ESG. Because of the results saying that the valuation uncertainty increased from incorporating the ESG-ratings on all the companies possible on the NASDAQ GS it could be an example showing that the general sustainability performance of the NASDAQ GS is not good enough to make the valuation uncertainty decrease. This is in my opinion an interesting topic to conduct further research on to see if the results are uniquely tied to NASDAQ GS or if other markets behave in a similar way.

The importance of the ESG-ratings cannot be understated and with several statistically significant results I personally believe that it should be further investigated.

Appendix:

Equation 1: $V = B_0 + \sum_{t=1}^{\infty} \frac{(ROE-r)B_{t-1}}{(1+r)^t} = B_0 + \sum_{t=1}^{\infty} \frac{RI_t}{(1+r)^t}$

Equation 2: $\frac{NI_0(1+g)d}{(r-g)}$

Equation 3: $m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|ni_{it}| + a_{3jt}I_{(NI<0)} \times |ni_{it}| + a_{4jt}LEV_{it} + \epsilon_{it}$

Equation 4: $m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|earn_{it}| + a_{3jt}I_{(EARN<0)} \times |earn_{it}| + a_{4jt}LEV_{it} + a_{5jt}rd_{it} + \epsilon_{it}$

Equation 5: $VU = \frac{Q_{75}-Q_{25}}{\frac{Q_{75}+Q_{25}}{2}}$

Equation 6: $r_{k,t+1} = \alpha + \beta * Y_{k,t} + M_{k,t} + \epsilon_{k,t}$

Equation 7: $s_{k,t,i} = Y_{k,t} + \eta_{k,t,i}$

Equation 8: $r_{k,t+1} = \alpha + \beta * s_{k,t,i} + v_{k,t}$

Equation 9: $r_{k,t+h} = \alpha + \beta * s_{k,t,i} + c_x * X_{k,t} + v_{h,k,t}$

Equation 10: $s_{k,t,i} = c_0 + \pi * Z_{k,t,i} + c_1 * X_{k,t} + \eta_{k,t}$

Equation 11: $s_{k,t,i} = c_0 + \pi * Z_{k,t,i} + \eta_{k,t}$.

Equation 12: $m_{it} = a_{0jt} + a_{1jt}b_{it} + a_{2jt}|earn_{it}| + a_{3jt}I_{(EARN<0)} \times |earn_{it}| + a_{4jt}LEV_{it} + a_{5jt}rd_{it} + a_{6jt}s_{k,t,i} + \epsilon_{it}$

Table 1:

Raw values	Mean	Median	S.D.	Min	Max

ME	25577	2404	1.672e+005	107.2	3.051e+006
BE	3993	660.4	16831	-7703.	2.757e+005
EARN	973.8	51.60	6742	-5017.	1.074e+005
I	0.3400	0.0000	0.4740	0.0000	1.000
RD	1348	54.38	9687	0.0000	2.021e+005
LEV	0.4351	0.3936	0.3075	0.02433	3.424
Log values					
m	7.943	7.785	1.733	4.674	14.93
b	6.397	6.493	2.322	0.0000	12.53
earn	4.945	4.772	1.780	-2.273	11.58
earnI	1.495	0.0000	2.232	-0.6574	8.521
rd	3.275	3.996	3.175	-0.9986	12.22

Table 1: This table shows a summary of statistics of both the raw values and the Log values of the variables used in the regression.

Table 2:

	tau	coefficient	std. error	t-ratio
const	0.250	2.46158	0.168348	14.6220
	0.500	3.12885	0.185455	16.8712
	0.750	4.05341	0.193512	20.9466
b	0.250	0.216204	0.0223683	9.66563
	0.500	0.241300	0.0246413	9.79248
	0.750	0.187859	0.0257118	7.30635
earn	0.250	0.656640	0.0243144	27.0062
	0.500	0.569960	0.0267851	21.2790
	0.750	0.588698	0.0279488	21.0635
earnI	0.250	-0.187420	0.0172244	-10.8811
	0.500	-0.191787	0.0189747	-10.1075

	0.750	-0.168403	0.0197990	-8.50561
LEV	0.250	0.687150	0.146088	4.70367
	0.500	0.856910	0.160933	5.32463
	0.750	0.647932	0.167924	3.85847
rd	0.250	0.0779429	0.0116149	6.71058
	0.500	0.0940805	0.0127952	7.35279
	0.750	0.0952869	0.0133511	7.13703

Table 2: This table shows the results from running the quantile regression on the data without any ESG-ratings.

Table 3:

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
Const	2.74362	0.102244	26.83	<0.0001	***
SustainalyticsREG	−0.0223653	0.00133299	−16.78	<0.0001	***

Table 3: This table shows the results for the OLS-regression performed on the valuation uncertainty as the dependent variable and the ESG-variable from Sustainalytics as the explanatory variable.

Table 4:

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1.45649	0.0257904	56.47	<0.0001	***
ISSREG	−0.104492	0.00623979	−16.75	<0.0001	***

Table 4: This table shows the results for the OLS-regression performed on the valuation uncertainty as the dependent variable and the ESG-variable from ISS as the explanatory variable.

Table 5:

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	1.17642	0.0190420	61.78	<0.0001	***
LSEGREG	−0.00332878	0.000420026	−7.925	<0.0001	***

Table 5: This table shows the results for the OLS-regression performed on the valuation uncertainty as the dependent variable and the ESG-variable from LSEG as the explanatory variable.

Table 6:

	ISS	LSEG	Sustainalytics
ISS	1		
LSEG	0,4242	1	
Sustainalytics	0,1156	0,3904	1

Table 6: Shows the correlation matrix of the three different ESG-agencies scores.

Table 7:

ESG-rating	Mean	Median	S.D.	Min	Max
Sustainalytics	76.65	76.85	7.231	43.7	95.5
LSEG	44.19	42.00	18.55	6.000	92.00
ISS	4.088	4.000	1.425	1.000	9.000

Table 7: This table shows the descriptive statistics for the ESG-risk ratings from all three agencies after normalizing the risk rating from Sustainalytics.

Table 8:

	tau	coefficient	std. error	t-ratio
const	0.250	0.322304	1.20144	0.268264
	0.500	1.30894	1.26538	1.03442

	0.750	0.847534	1.15706	0.732487
b	0.250	0.217062	0.0247994	8.75273
	0.500	0.237327	0.0261192	9.08633
	0.750	0.173698	0.0238834	7.27275
earn	0.250	0.621557	0.0282570	21.9966
	0.500	0.562014	0.0297607	18.8844
	0.750	0.554992	0.0272133	20.3942
earnI	0.250	-0.177725	0.0194652	-9.13041
	0.500	-0.175778	0.0205011	-8.57409
	0.750	-0.154661	0.0187463	-8.25025
LEV	0.250	0.697723	0.162345	4.29778
	0.500	0.782743	0.170985	4.57785
	0.750	0.599782	0.156349	3.83618
rd	0.250	0.0828470	0.0127300	6.50802
	0.500	0.0895996	0.0134074	6.68283
	0.750	0.0943246	0.0122598	7.69382
SustainalyticsREG	0.250	0.0296820	0.0164849	1.80056
	0.500	0.0249718	0.0173622	1.43829
	0.750	0.0454320	0.0158760	2.86168

Table 8: This table shows the results from the quantile regression on the data with the ESG-ratings included. In this quantile regression the ESG-rating is calculated where the ratings from Sustainalytics are the dependent variable and the other two agencies being the explanatory variables.

Table 9:

	tau	coefficient	std. error	t-ratio
const	0.250	2.12943	0.211569	10.0649
	0.500	2.81727	0.187941	14.9902
	0.750	3.57593	0.230884	15.4880
b	0.250	0.221881	0.0223070	9.94668
	0.500	0.246847	0.0198157	12.4571
	0.750	0.196350	0.0243435	8.06578

earn	0.250	0.633309	0.0252308	25.1007
	0.500	0.569190	0.0224130	25.3956
	0.750	0.551038	0.0275342	20.0129
earnI	0.250	-0.183777	0.0171880	-10.6922
	0.500	-0.180939	0.0152684	-11.8506
	0.750	-0.160699	0.0187571	-8.56735
LEV	0.250	0.759614	0.145704	5.21339
	0.500	0.843245	0.129432	6.51497
	0.750	0.737010	0.159006	4.63509
rd	0.250	0.0645115	0.0120663	5.34641
	0.500	0.0784692	0.0107187	7.32076
	0.750	0.0834403	0.0131679	6.33665
LSEGREG	0.250	0.00940294	0.00395736	2.37606
	0.500	0.00741115	0.00351540	2.10820
	0.750	0.0141145	0.00431865	3.26826

Table 9: This table shows the results from the quantile regression on the data with the ESG-ratings included. In this quantile regression the ESG-rating is calculated where the ratings from LSEG are the dependent variable and the other two agencies being the explanatory variables.

Table 10:

	tau	coefficient	std. error	t-ratio
const	0.250	2.07340	0.287163	7.22029
	0.500	2.75862	0.313038	8.81241
	0.750	3.49606	0.282462	12.3771
b	0.250	0.212693	0.0239899	8.86593
	0.500	0.241690	0.0261515	9.24190
	0.750	0.176170	0.0235972	7.46571
earn	0.250	0.628419	0.0275683	22.7950
	0.500	0.559567	0.0300523	18.6198
	0.750	0.553386	0.0271170	20.4074
earnI	0.250	-0.183516	0.0185459	-9.89526

	0.500	-0.176364	0.0202169	-8.72359
	0.750	-0.156740	0.0182423	-8.59212
LEV	0.250	0.683284	0.156531	4.36516
	0.500	0.804371	0.170635	4.71398
	0.750	0.646343	0.153969	4.19788
rd	0.250	0.0808815	0.0123182	6.56599
	0.500	0.0878188	0.0134282	6.53989
	0.750	0.0911449	0.0121166	7.52232
ISSREG	0.250	0.129093	0.0743721	1.73577
	0.500	0.108144	0.0810734	1.33391
	0.750	0.200544	0.0731546	2.74137

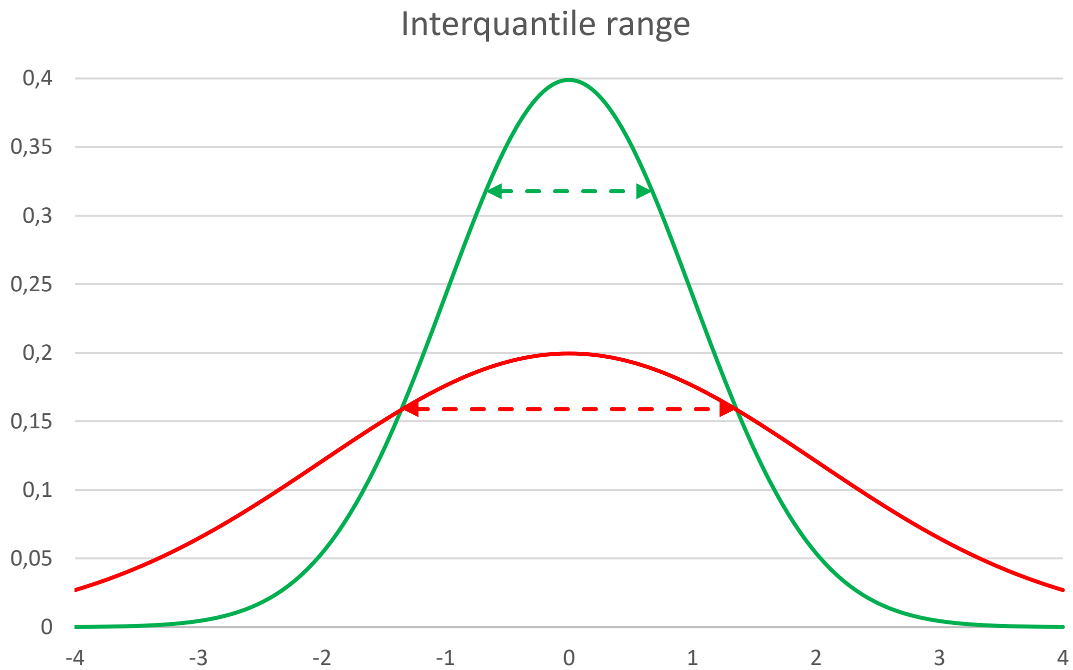
Table 10: This table shows the results from the quantile regression on the data with the ESG-ratings included. In this quantile regression the ESG-rating is calculated where the ratings from ISS are the dependent variable and the other two agencies being the explanatory variables.

Table 11:

Variable	Mean	Median	S.D.	Min	Max
VU	1.029	1.048	0.1252	0.5794	1.348
VU (SUSESG)	1.039	1.062	0.1287	0.5874	1.380
VU (ISSREG)	1.047	1.072	0.1326	0.5831	1.404
VU (LSEGESG)	1.049	1.069	0.1339	0.5727	1.361

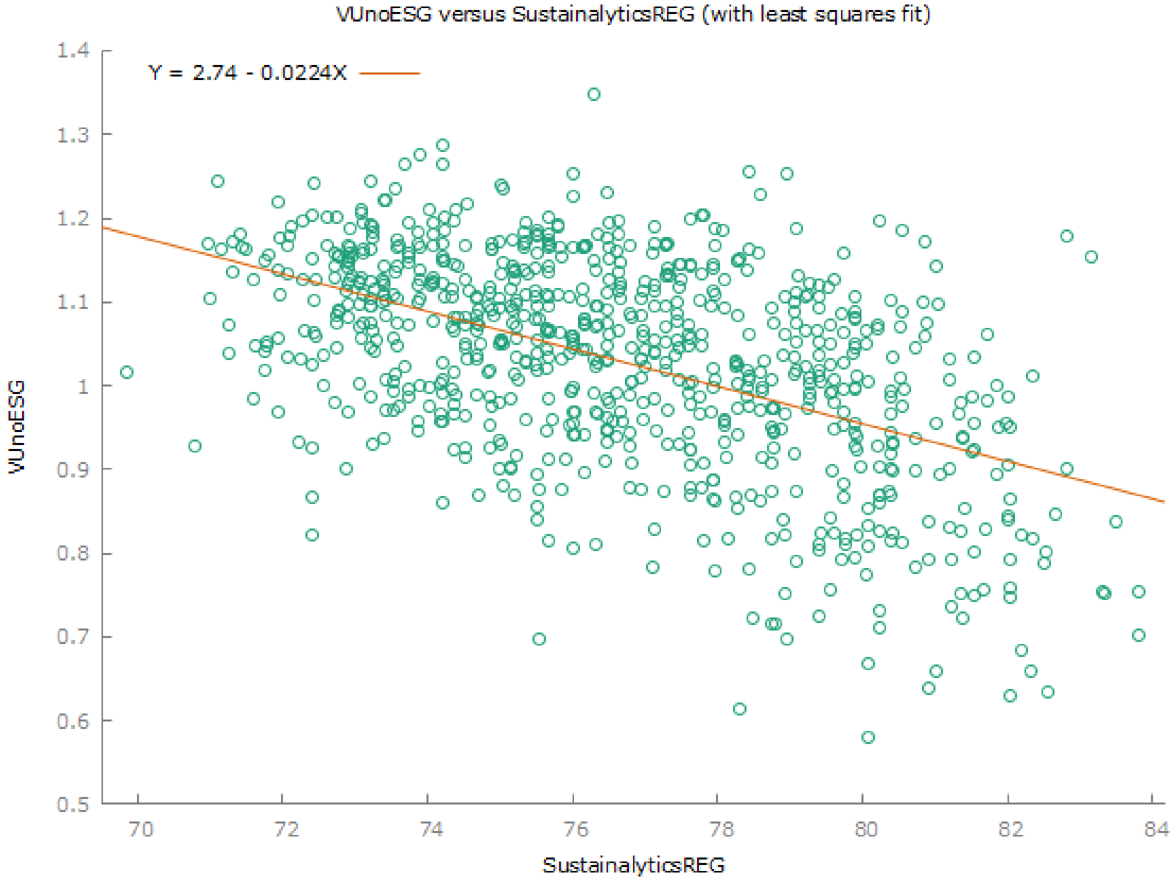
Table 11: This table shows the summary statistics for the valuation uncertainty samples without ESG-data, VU, and with ESG-data incorporated, VU(SUSESG), VU(ISSREG) and VU(LSEGESG).

Graph 1:



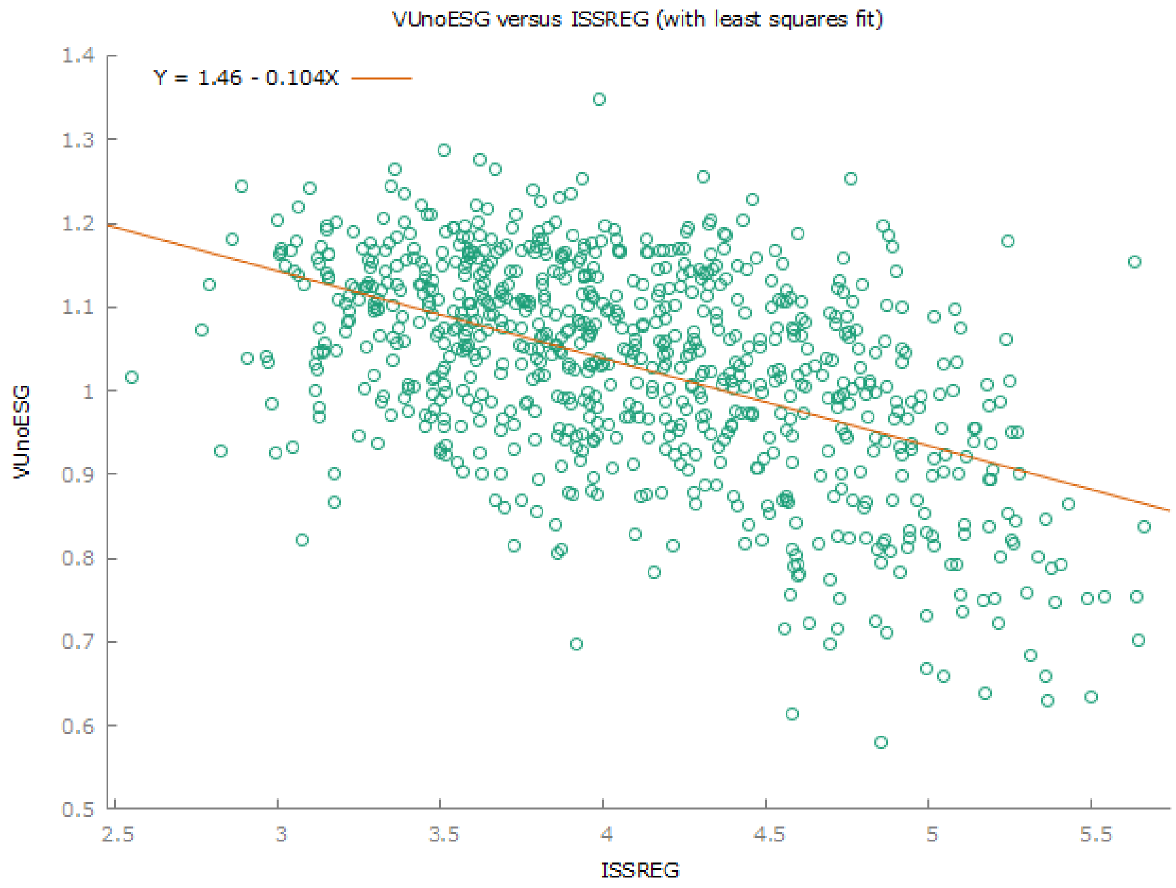
Graph 1: This graph shows two different normal distributions with two different standard deviations (1 and 3). On both curves there is a dashed line that shows the interquartile range.

Graph 2:



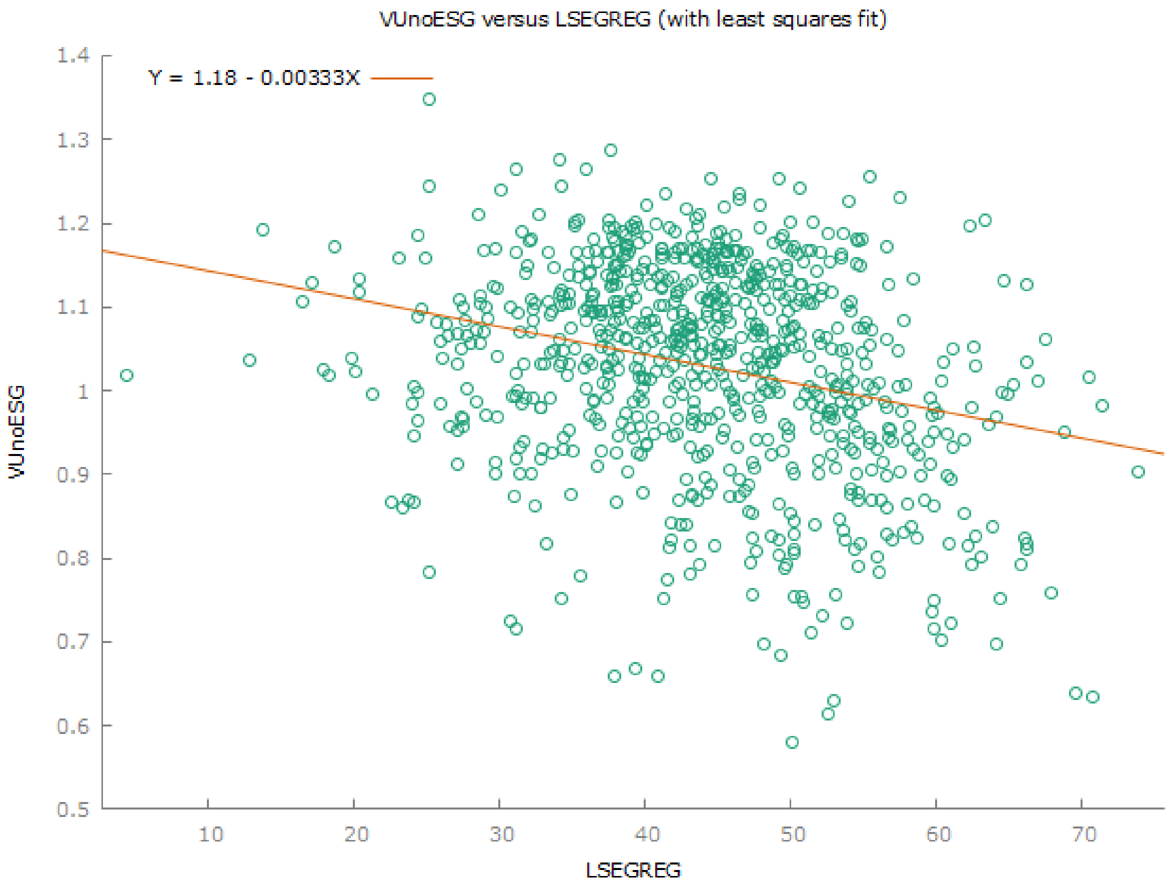
Graph 2: This graph shows the valuation uncertainty without any ESG-ratings on the y-axis and the ESG-variable from Sustainalytics on the x-axis.

Graph 3:



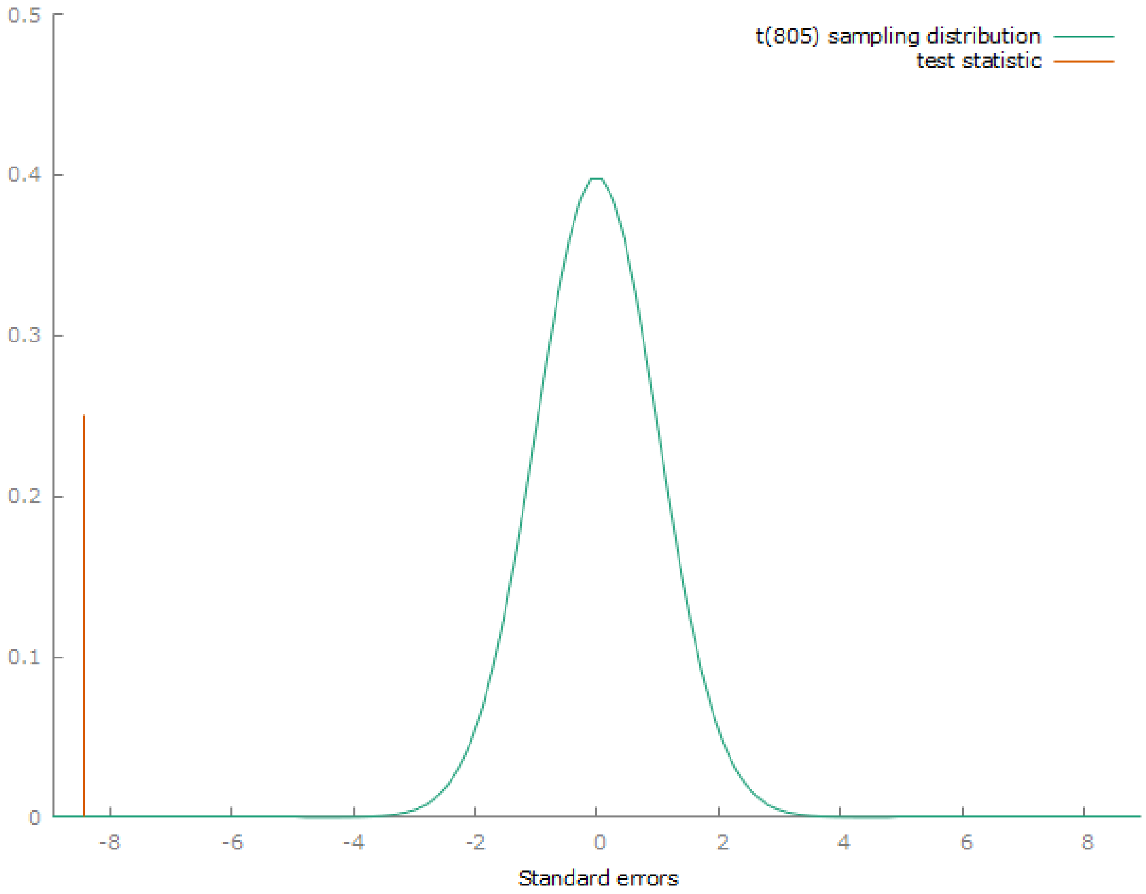
Graph 3: This graph shows the valuation uncertainty without any ESG-ratings on the y-axis and the ESG-variable from ISS on the x-axis.

Graph 4:



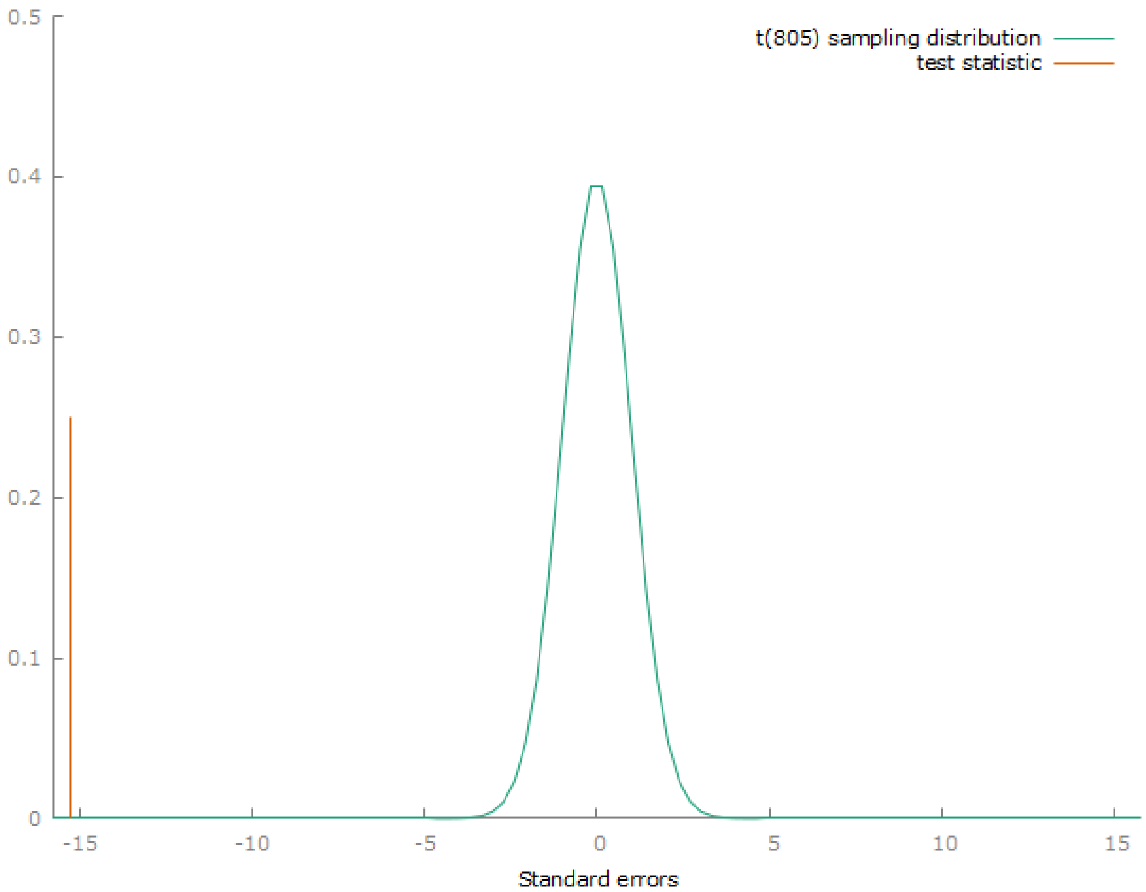
Graph 4: This graph shows the valuation uncertainty without any ESG-ratings on the y-axis and the ESG-variable from ISS on the x-axis.

Graph 5:



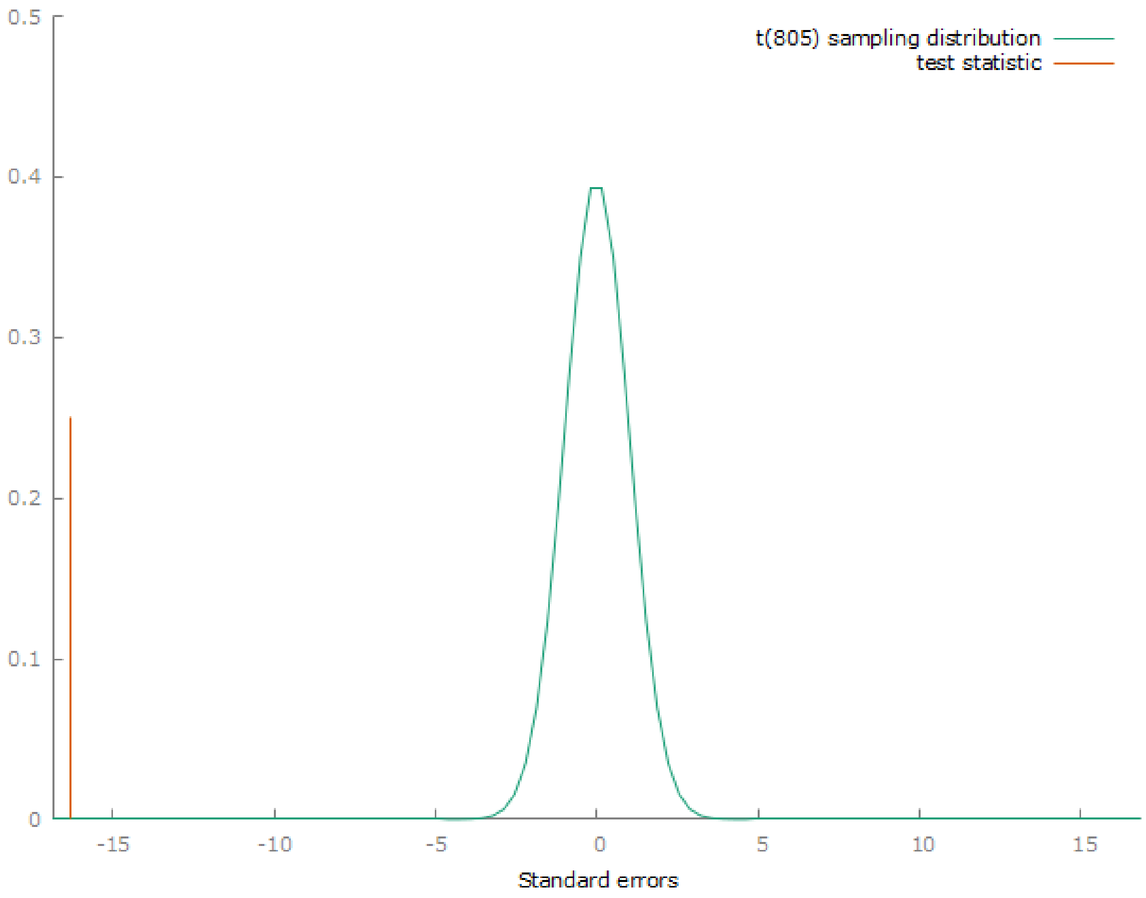
Graph 5: This graph shows the sampling distribution, green, and test statistic, yellow, for the first paired t-test between the VU without ESG and the VU with ESG from the variable SUS(REG).

Graph 6:



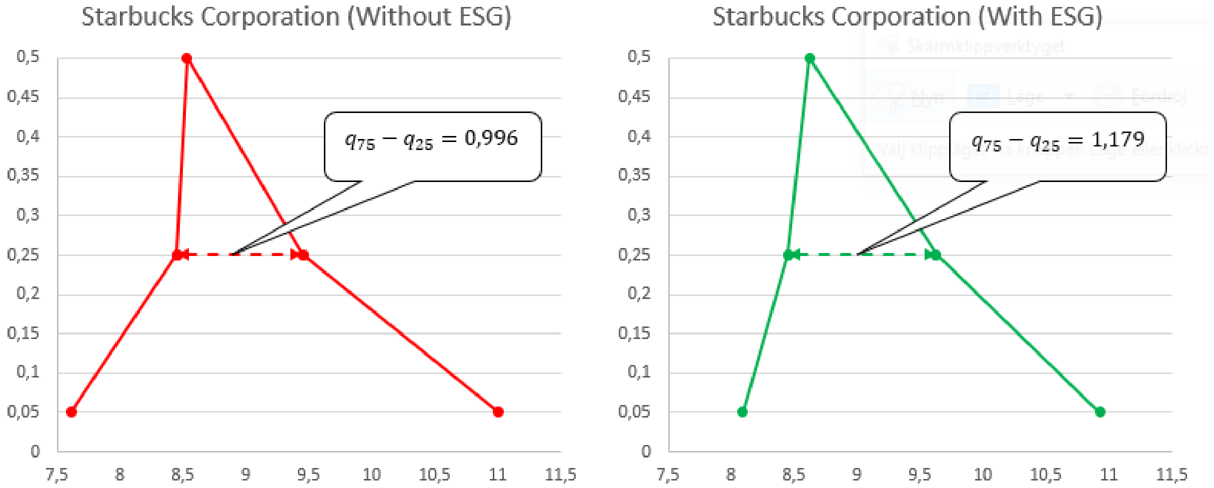
Graph 6: This graph shows the sampling distribution, green, and test statistic, yellow, for the first paired t-test between the VU without ESG and the VU with ESG from the variable ISS(REG).

Graph 7:



Graph 7: This graph shows the sampling distribution, green, and test statistic, yellow, for the first paired t-test between the VU without ESG and the VU with ESG from the variable LSEG(REG).

Graph 8:



Graph 8: This graph shows the distribution of the log of the market value of equity for Starbucks Corporation on the x-axis (q_5, q_{25}, q_{50}, q_{75} and q_{95}) and on the y-axis is the quantile of the distribution, with: x up to the 50th percentile and (1 - x) above the 50th percentile. In the left most graph, with the red line, is the calculated value for the log of the market value of equity without ESG-ratings in the model and the right most graph, with the green line, is the calculated value for the log of the market value of equity with ESG-ratings incorporated in the model.

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