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Do macroeconomic factors affect U.S. stock market returns?

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# **BI Norwegian Business School**

## **Master Thesis - GRA 19502**

“Do macroeconomic factors affect U.S. stock  
market returns?”

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Program:

MSc in Business, Major in Finance

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## **0 Abstract**

Macroeconomic factors and their influence on stock returns is a widely discussed topic in both previous and recent academic literature. In this paper, we examine whether macroeconomic factors affect U.S. stock market returns or their conditional volatilities. We approach this by estimating an EGARCH model of monthly stock returns, where returns and their conditional volatilities depend on different macroeconomic factors' changes. This analysis successfully finds three candidates (CPI, IP, and M1) affecting the level of returns and two candidates (GDP and M1) affecting the conditional volatility of those returns. The well-known measure for unemployment (UNEMP) is not represented as a potential candidate.

## 1 Introduction

The linkage between macroeconomic variables and stock returns is a central topic in financial economics, and there is a common belief that stock prices are affected by macroeconomic developments. Variables that can affect the future opportunity set or consumption level can be possible priced factors in equilibrium (Merton, 1973). Changes in macroeconomic factors then have the possibility to affect firms' investment opportunities and, therefore, their market returns. In a risk averse economy, stocks influenced by this systematic (undiversifiable) risk should then earn a risk premium (Ross, 1976). Macroeconomic shifts and changes may impact firms' cash flow and the risk-adjusted discount rate, which make macroeconomic variables suited as risk factor candidates.

An extensive prior literature, which we discuss below, have tried to identify valid relationships between stock returns and macroeconomic variables. Evidence consistent with the hypothesis that some macroeconomic variables do affect aggregate stock returns, either through to the level of returns or its implied volatility, have been presented. Macroeconomic variables should thus be taken into consideration when investigating stock returns.

The aim of this paper is to examine whether macroeconomic factors affect U.S stock market returns or their conditional volatilities. We estimate an EGARCH model of monthly stock returns, in order to identify variations in both the level of returns and their conditional volatilities, with five macroeconomic factor series. The estimated model takes into account that variations in volatility could arise in crises. Implying that, if the influence of a macroeconomic variable varies through different conditions in the economy, these time-varying effects would be adjusted for in our estimates.

The macroeconomic variables chosen for our study are well-known estimates, considered as important measurement rates and indicators for an economy and its stock market. The reason for picking these variables (CPI, IP, GDP, M1, and UNEMP) as potential factor candidates is because of their possible influence on the stock market returns, either directly or indirectly. Meaning, directly affecting the level of returns or indirectly through its conditional volatilities.

From our five macroeconomic factor series, we successfully identify three variables (CPI, IP, and M1) affecting the level of stock returns and two variables (GDP and M1) affecting the conditional volatilities of those returns. Only the measure for money supply (M1) affect both the level and conditional volatilities of stock returns. The macroeconomic factors found significant in affecting the level of returns have an inverse relationship with stock returns, indicating that an increase (decrease) in the factor candidates negatively (positively) affect stock returns. With regard to the conditional volatilities of those returns, our results show that stock returns are more volatile when the volatility of GDP increases and less volatile when the volatility of M1 increases. The measurement rate for unemployment (UNEMP) do not significantly affect returns nor its conditional volatility, which contradicts some earlier research and results.

We believe the factors we find significant in affecting the level of returns follow a similar pattern to the stock market, making their impact recognizable over several time periods. For the factors we find significant in affecting the conditional volatilities of those returns, are likely to have an influence on uncertainty for the economy as a whole and therefore impact the volatilities of returns. Factors lacking either one or both of the criteria above, are therefore not proven significant in affecting stock returns in the following manner.

Consistent with our findings, several researchers and previous studies have documented that inflation and monetary policy are negatively related stock prices [Bodie (1976), Fama (1981), Geske and Roll (1983), Pearce and Roley (1983, 1985)]. Further, Chen, Roll and Ross (1986) (CRR) additionally find industrial production significant in explaining expected stock returns, but present evidence that the market reacts differently to similar macroeconomic variables depending on the economic state we face.

Shanken and Weinstein (1990) later criticized the results of CRR's estimations. Instead of estimating the betas using backward-looking returns, they used the returns from the following year. This relatively "small" change reduced the statistical importance concerning the returns and showed that only the industrial production factor was significant in the sample period. Lamont (2001) shows that constructing a tracking portfolio of the growth rates of production, consumption

or labour income leads to abnormal returns. He also finds that inflation fails to achieve this.

Cutler, Poterba and Summers (1989) (CPS) find, in their definition, that macroeconomic news only explains about 20% of the movements in stock prices. Over the period 1926-1986, CPS find that industrial production growth is significantly correlated with stock returns. However, this is not the case in the period 1946-1965, which contradicts the findings of CRR and their sample period. Similar, our findings suggest that GDP do not affect the level of returns, only their conditional volatilities, which we believe is dependent on the estimated time periods. As in comparison to Roll (1988), CPS also conclude that macroeconomic factors have a quite modest explanatory power in the market variability.

Later, McQueen and Roley (1993) provide evidence that the effect of macroeconomic factors on stock prices depend on the state of the economy. They conclude that positive shocks to the real activity lead to lower stock prices in a strong economy, while it leads to higher stock prices in a weak economy. This result can contribute to explain the insignificance of macroeconomic factors in earlier studies. In the same direction, Hu and Li (1998) examine whether the effect of macroeconomic factors on stock prices varies in the different states of the economy. They provide strong evidence for different market responses to different states of the economy, using the same macroeconomic factors. Moreover, allowing the response coefficients to change over different states of the economy may therefore result in more significant macroeconomic variables.

The methodology utilized in this paper comprises volatility changes. Therefore, we review some articles concerning market return volatility and volatility modelling. Errunza and Hogan (1998) find that, for many European equity markets, macroeconomic factors can be used to make return volatility predictions. They conclude, by estimating VAR models, that monetary instability is a significant factor for France and Germany, while industrial production is a significant factor for Italy and the Netherlands. For countries as UK, Switzerland, Belgium, or the US, macroeconomic factors fail to improve any forecast ability.

Utilizing a model that estimates the conditional standard deviation for different monthly mean returns, Schwert (1989) finds evidence that future macroeconomic volatility can be predicted by looking at financial asset volatility. This goes hand in hand with theoretical aspects, since the price of an asset should react quickly to new information. This argument to some extent used by Fama (1990), who finds that a change in stock prices can be used to predict future macroeconomic conditions.

Using a GARCH model of monthly U.S. equity returns, Hamilton and Susmel (1994) conclude that equity returns are significantly affected by macroeconomic conditions. Consequently, implying that the volatility of equity returns is likely to remain high during recessions. This supports our findings in Figure 3, where we compare the conditional standard deviation of our model to the NBER recession indicator. In addition, our findings show that periods of high volatility may act as an indicator for periods of recession.

Flannery and Protopapadakis (2002) expand earlier research by employing a much more extensive data set, consisting of 17 macroeconomic announcement series. They find that six of these are strongly significant: three nominal (CPI, PPI, and a monetary aggregate) and three real (balance of trade, employment report, and housing starts). The new evidence resulted from this paper is that balance of trade, employment and housing starts are identified as significant risk factors on the returns' conditional volatility. More surprisingly, they do not find real GNP and industrial production to be significant as risk factors, which contradicts our results.

Taking the above a step further, the Exponential GARCH model (EGARCH) captures asymmetric behaviour in the conditional variance (Nelson, 1991). The EGARCH has no restrictions on its parameters, making it an applicable model for stock returns as changes in returns can be negative. In several studies, the EGARCH model has been determined to outperform other competing asymmetric conditional variance models (Alexander, 2009). This is some of the reasoning behind why we choose to implement an EGARCH model, after evaluating the different types of volatility models.



The rest of this paper will be structured as follows: First, we present a theoretical framework and a description of our methodology, where we further explain the data we implement in our calculations and where we extract it. Next, we visualize and explain our regression output. Lastly, we follow up with a conclusion and contribution to future research. An appendix and a bibliography are attached to the end of this paper, respectively.

## 2 Theory and Methodology

### 2.1 Stock prices and macroeconomic factors

The well-known model for pricing stocks is dependent on the sum of discounted expected future dividends, given the information known at the present time:

$$P_t = E\left(\sum_{\tau=1}^{\infty} \frac{d_{t+\tau}}{1 + r_{t+\tau}} \mid \Omega_t\right)$$

where  $P_t$  is the stock price at time  $t$ ,  $d_{t+\tau}$  is the paid dividend at time  $t+\tau$ ,  $r_{t+\tau}$  is the stochastic discount factor for cash flows that occurs at time  $t+\tau$ , and  $\Omega_t$  represents the information set known at time  $t$ .

The new information is explained by the difference between  $\Omega_t$  and  $\Omega_{t-1}$ . On the announcement day, the expected component of the news and all previous announcements have been included in  $\Omega_t$ . Under the assumption of efficient markets and rational investors, stock prices should only be affected by the unexpected part of the news.

A multi-factor model uses two or more factors in its calculations when trying to explain asset prices in the market. It can be used to either construct or explain an individual security or a portfolio of securities. According to Merton (1973), investors would want to hedge against two types of risk: volatility and uncertainty in the returns of the securities (current period) and possible future shifts in the investment opportunity set. For example, an unexpected and disadvantageous shift in the opportunity set will affect future consumption negatively for a given level of future wealth. Thus, if the opportunity set turned out to be “worse” than expected, the investor would, through his investments in positive correlated returns, expect a higher level of wealth as a compensation. In the same way, the investor would expect “better” investment opportunities if future returns are lower.

Macroeconomic factors that are correlated with a change in the opportunity set can therefore be said to be a possible price factor in an equilibrium state. This

could potentially occur through an unexpected change in the CPI that may cause a change in the gap between the expected return of different asset types, or an unexpected shift in the unemployment rate that may change the future returns to employees and human capital.

## 2.2 Regression models

This thesis' methodology will follow a similar path of previous articles from Flannery and Protopapadakis (2002) and Andritzky, Bannister and Tamirisa (2005). However, we will use an extension to their final statistical model.

In the single-factor case, previous research has tried to regress the market's monthly return ( $r_t$ ) on a potential macroeconomic factor's ( $Z$ ) unexpected changes,  $z_t = Z_t - E_{t-1}(Z_t)$ :

$$r_t = E_{t-1}(r_t) + \beta z_t + u_t \quad (1)$$

The coefficient  $\beta$  implies, if proven to be statistically significant, a relationship between the tested factor and the return of the market portfolio. However, it requires further analysis to determine whether the unexpected change to  $Z$  is actually priced in equilibrium or not.

Due to its simplicity, regression models like equation (1) could be unsuccessful to perceive important macroeconomic effects on the market portfolio's return. First, the simple linear regression may lead to an underestimate of the coefficient  $\beta$ , also known as the attenuation bias, which is caused by errors in the tested independent variables. This could further bias the estimated  $\beta$  toward zero. Second, all the noise in the expected value ( $E_{t-1}(Z_t)$ ) may also bias the estimated  $\beta$  toward zero, due to inaccurate evaluation or estimate of the announcement expectation component. Finally, statistical inference problems may arise when we apply a fixed-coefficient model to estimate a coefficient that actually is time varying. This can be shown in rewriting equation (1) as

$$r_t = \beta_t z_t + u_t \quad (2)$$

where  $\beta_t$ ,  $z_t$ , and  $u_t$  are jointly independent,  $u_t = h_t \varepsilon_t$ , and  $h_t^2 = h_0^2$ . When  $\beta_t$  is time-varying, its estimate, in Equation (2), will roughly be the mean of  $\beta$ ,  $\hat{\beta} = E(\beta_t)$ . Therefore, if we have a coefficient that switches sign and averages close to zero over time or is occasionally important, the estimated coefficient may fail to identify a potential macroeconomic factor. Furthermore, by implementing a fixed-coefficient model to estimate time-varying coefficients on the unexpected macro announcements may cause the estimated residuals to be heteroscedastic. To comprehend this heteroscedasticity, we assume that the true model is Equation (2) and that we cannot replicate the intertemporal variation in  $\beta_t$ . The estimated residuals will then be given by  $\hat{u}_t = u_t + [\beta_t - \hat{\beta}]z_t$ , and their variance will be

$$\hat{\sigma}_{u,t}^2 = \sigma_u^2 + E_{t-1}[(\beta_t - \hat{\beta})^2 z_t^2] + E_{t-1}[u_t(\beta_t - \hat{\beta})z_t]. \quad (3)$$

When  $\beta_t$ ,  $z_t$ , and  $u_t$  are jointly independent,  $E_{t-1}[u_t(\beta_t - \hat{\beta})] = 0$ . On days without macroeconomic news, we will get  $z_t = 0$  and the residuals' variance therefore reduces to  $\sigma_u^2$ . On days with macroeconomic news, the residuals' variance will exceed  $\sigma_u^2$ , because in general we have that  $\beta_t \neq \hat{\beta}$  and  $z_t \neq 0$ . Therefore, by modifying the rudimentary conditional variance specification, it seems plausible to extract information about the effect of an announcement data series.

### 2.3 Volatility modelling

One of the most important topics within the financial world is volatility. Measured by either the variance or standard deviation of returns, volatility is repeatedly used as a measure of the total risk of financial assets. For example, many VaR (value-at-risk) models for measuring market risk need the estimation or forecast of a volatility parameter. In a similar manner, the volatility of stock prices also enters the Black-Scholes formula for deriving the prices of traded options. Therefore, forecasting and modelling stock market volatility has been, and still is, an important concept of extensive theoretical and empirical investigation by academics and practitioners.

Engle (1982) developed the autoregressive conditional heteroscedasticity (ARCH) model. This model takes into account that the variance of the errors could be

heteroscedastic (i.e., not constant), as it is unlikely to assume that they will be constant over time in the context of financial times series. Another important aspect of the model is that it can capture both volatility clustering and unconditional return distributions with heavy tails, which are typical features of financial returns.

As an extension to the ARCH model, Bollerslev (1986) and Taylor (1986) introduced the generalized autoregressive conditional heteroscedastic (GARCH) model, which allows the conditional variance to be dependent upon own lags. In addition, the GARCH model overcomes some of the limitations of ARCH models, such as choosing the optimal number of lags and the possibility that non-negativity constraints might be violated.

When we examine the possible effect of macroeconomic factors on stock returns, it will therefore be through their conditional volatility. In other words, we will look at how the conditional volatility of both stock returns and macroeconomic factors from the previous period affect current conditional volatility of stock returns. The GARCH specification argues that the best predictor of the one-period ahead conditional variance of returns,  $h_t^2$ , is a weighted average of the long-run average variance,  $\alpha_0$  (unconditional variance), the last period's shock to the return generating process, the innovation term  $\varepsilon_{t-1}^2$  (ARCH term), and the conditional variance from the previous lag,  $h_{t-1}^2$  (GARCH term) (Engle, 2001). To generate the GARCH conditional variance series, we can estimate the following GARCH model with monthly market returns and monthly variations in the macroeconomic factors:

$$r_t = E_{t-1}(r_t) + \sum_{i=1}^5 \beta_{n,t} (F_{i,t-1}) + \varepsilon_t \quad (4)$$

$$E_{t-1}[r_t] = \mu + \varepsilon_t \quad (5)$$

$$\varepsilon_t \sim N(0, h_t^2)$$

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 + \gamma_1 TB3M_{t-1}^2 + \sum_{i=1}^5 \lambda_i (F_{i,t-1}^2) \quad (6)$$

where  $\alpha_0, \alpha_1, \beta_1 > 0$ . In order to ensure stationarity in the residual variance,  $\alpha_1, \beta_1 < 1$  should hold, and when this is the case the unconditional variance is given by  $\frac{\alpha_0}{1-\alpha_1-\beta_1}$ . The macroeconomic factors,  $F_{i,t-1}$ , enter both the mean and the

variance equation, while the risk-free rate,  $TB3M_{t-1}$ , only enter the variance equation.

However, we aim to use a further extension of the model above. The Exponential GARCH (EGARCH) model presented by Nelson (1991) allow for correlation between stock returns and volatility changes. The EGARCH model does so by introducing logarithmic transformation of volatility and can be presented as follows:

$$\ln(h_t^2) = \alpha_0 + \beta_1 \ln(h_{t-1}^2) + \theta \psi_{t-1} + \gamma_1 \left( |\psi_{t-1}| - \left(\frac{2}{\pi}\right)^{0.5} \right) + \gamma_2 TB3M_{t-1}^2 + \sum_{i=1}^5 \lambda_i (F_{i,t-1}^2) \quad (7)$$

where  $\psi_{t-1} = \frac{\varepsilon_{t-1}}{h_{t-1}}$ . In contrast to the GARCH model, EGARCH parameter values are unrestricted. EGARCH identify the conditional variance equation as a function of the conditional variance of returns from previous lag,  $h_{t-1}^2$ , the previous period's innovation term,  $\varepsilon_{t-1}$ , that has been standardized to have a unit variance,  $\psi_{t-1}$  (which is the ratio of the former two parameters), and the deviation of the absolute value of  $\psi_{t-1}$  from the mean absolute value,  $\left(\frac{2}{\pi}\right)^{0.5}$ . The GARCH model enforce a symmetric responsive for both positive and negative shocks, whereas the EGARCH model include the parameter *psi* ( $\psi$ ) to better capture this effect. If negative shocks to the stock market causes volatility to rise by more than positive shocks of the same magnitude, i.e. asymmetries, then the variance should increase and vice versa.

We work with eViews 7 to estimate the EGARCH model, where maximum likelihood estimation with the Marquardt optimization is used.

### 3 Data

In order to estimate the model, we require financial market returns, date and value of each macroeconomic factor, and a measure of the risk-free rate. We look to disclose how macroeconomic factors affect stock returns and their impact on the market. Macroeconomic data are reported in monthly intervals, which is why we use monthly stock returns. We are not interested in the day-to-day effects we might come across with daily data.

#### 3.1 Financial returns

As a proxy for the market return, we use the monthly return to the value-weighted NYSE-AMEX-NASDAQ-ARCA stock market index from the CRSP (Center for Research in Security Prices), reaching from the beginning of January 1980 to the end of December 2016. The fluctuations in the index's total market value and value-weighted return are displayed in Figure 1 and 2, respectively. Looking at Appendix 1, we can see that the data series is slightly negatively skewed with a positive excess kurtosis, indicating that large outliers are somewhat rare but do occur from time to time. However, when transforming the data into log differences, we can argue that it is better fitted within “normal” ranges and the classification of a symmetric distribution. These results are displayed in Appendix 2 and make a good basis for our research.

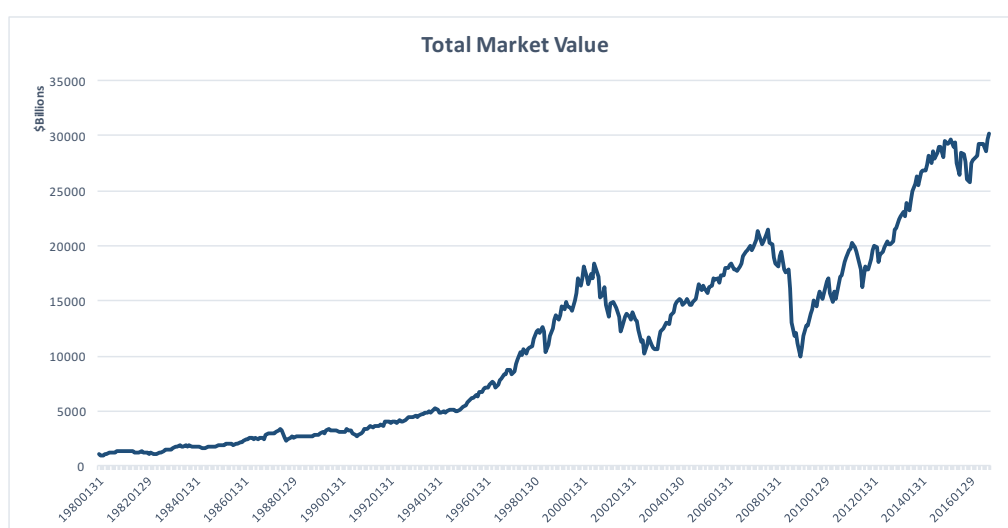


Figure 1: Showing the total market value, for all non-ADR securities with valid prices, on the CRSP value-weighted U.S. market portfolio, reaching from the beginning of January 1980 to the end of December 2016.

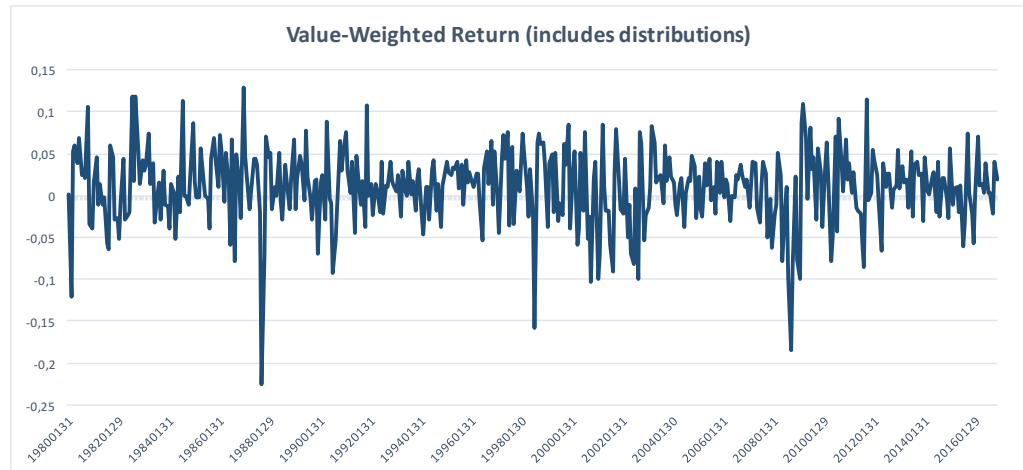


Figure 2: Showing the monthly returns, including all distributions, on the CRSP value-weighted U.S. market portfolio, reaching from the beginning of January 1980 to the end of December 2016.

The monthly yield to maturity for the three-month Treasury Bill (TB3M), computed from data in the Federal Reserve's H.15 release of interest rates, is our measure for the risk-free rate of return. We do not need to account for any weekend nor holiday adjustments, as the data occur monthly. In addition, other calendar effects and anomalies are also excluded in this research paper.

### 3.2 Macroeconomic factors

The macroeconomic factors we use in this study are extracted from the Federal Reserve Economic Data (FRED). They have an extensive database containing different economic indicators for United States, as well as other countries. Except for Real GDP (quarterly series), the data occur in monthly series, reaching from the beginning of January 1980 to the end of December 2016. We choose to use not seasonally adjusted data, because we want to see the raw and true changes each month. We transform the macroeconomic data into log differences, making it smoother to work with. The descriptive statistics before and after the transformation are displayed in Appendix 3 and 4, respectively.

Taking theory and prior research in consideration, we choose to examine five different factors: The Consumer Price Index (CPI), Industrial Production (IP), Money Stock (M1), Real Gross Domestic Product (GDP), and the Unemployment Rate (UNEMP).



The Consumer Price Index (CPI) is a measure of the average monthly change in the price of goods and services between any two-time periods (U.S. Bureau of Labour Statistics). Roughly 88 percent of the total population in the United States are included in this particular index, and it is based on prices for food, clothing, shelter, fuels, transportation fares, service fees, and sales taxes. Moreover, it can be used to recognize periods of inflation or deflation.

The Industrial Production Index (IP) is an economic indicator that measures real output for all facilities located in the United States, such as manufacturing, mining, electric, and gas utilities (Board of Governors of the Federal Reserve System). To bring attention to short-term changes in industrial production, the index is composed on a monthly basis. It measures movements in production output and highlights structural developments in the economy, making the month-to-month growth in the production index an indicator of growth in the industry.

M1 Money Stock (M1) is a metric for the money supply of a country, and consists of funds that are easily available for spending, such as demand deposits, currency outside the U.S. Treasury, traveller's checks, and other checkable deposits (FED). Therefore, the M1 can be used to reference how much money is in circulation in a country. It does not include financial assets like savings accounts.

Real Gross Domestic Product (GDP) is the value of services and goods that is produced within the United States, adjusted for inflation (FED). In the U.S., GDP is released as an annualized estimate each quarter, and it is a wide measurement of the country's overall economic activity. Therefore, it is fitted to be used as an indicator of a country's economic health and standard of living. Since GDP is adjusted for inflation, it allows us to use it as a comparison by comparing the present GDP measurements to measurements from previous periods.

The Unemployment Rate (UNEMP) shows the number, as a percentage of the labour force, which is unemployed and is actively searching for employment. The labour force includes people over the age of 16, that is fit to work (who do not live in institutions, such as penal or mental facilities) and who are not active in the army (BLS). The UNEMP is the most common measure of unemployment.

### **3.3 Specification bias**

Specification error or an endogeneity problem may occur as an undesirable feature with our data. This occurs if an independent variable, i.e. macroeconomic factor, to some extent is correlated with the error term. There are different reasons to what may cause this bias. Firstly, the use of an incorrect functional form could lead to specification errors. Secondly, excluding an important variable that should be in the statistical model could cause omitted-variable bias. Thirdly, the model may include an irrelevant variable, which should have been excluded. Lastly, an independent variable could be jointly affected by the dependent variable, leading to simultaneity bias.

## 4 Results and analysis

### 4.1 Estimation results

Estimation results for the whole sample period, from the beginning of 1980 to the end of 2016, are reported in Table 1. The results for each macroeconomic factor are represented in both the mean and conditional variance equation, while the risk-free rate is included as a variable in the conditional variance equation. In the mean equation, i.e. the return equation, the independent variables are lagged and log-differenced. In the conditional variance equation, the independent variables are squared differences, replicating a “rolling variance”.

Variable	Mean equation (4)	Variance equation (7)
CPI	-1.1705 *** (0.6171)	-0.0727 (0.0888)
GDP	0.2132 (0.5872)	0.0030 *** (0.0017)
IP	-0.1655 *** (0.0914)	0.0221 (0.0411)
M1	-0.2097 *** (0.1204)	-0.0053 ** (0.0027)
UNEMP	-0.0050 (0.0876)	0.0004 (0.0003)
TB3M		-0.0010 (0.2450)

Joint significance test	
Null hypothesis	Wald test p-value
All coefficients are jointly zero in the mean equation (4)	0.0003
All coefficients are jointly zero in the conditional variance equation (7)	0.0049
All coefficients are jointly zero	0.0000

*Table 1: Displaying estimation results for the five tested macroeconomic factors, including our measure for the risk-free rate. Coefficient estimates for all exogenous explanatory variables in both the mean and variance equation, resulting from running an EGARCH model with stock returns as a dependent variable. The results for the joint significance tests are p-values estimated using a Wald test, a parametric statistical test. \*\*, \*\*\* coefficients are statistically significant at the 5% and 10% level, respectively.*

Three of the macroeconomic factors affect returns in equation (4): CPI, IP, and M1 statistically significant at 10% level. The coefficients for CPI (-1.1705), IP (-0.1655), and M1 (-0.2097) are negative, indicating that an increase (decrease) in CPI, IP, or M1 negatively (positively) affect stock returns. GDP and UNEMP were not found to be statistically significant in affecting returns.

Two of the macroeconomic factors affect returns' conditional volatilities in equation (7): M1 statistically significant at 5% level and GDP statistically significant at 10% level. The coefficient for M1 (-0.0053) is negative, indicating that market returns are less volatile when the volatility of M1 increases. The coefficient for GDP (0.0030) is positive, indicating that market returns are more volatile when the volatility of GDP increases. The remaining factors were not found to be statistically significant in affecting returns' conditional volatilities.

The last section of Table 1 presents three joint hypothesis tests. Using a Wald test, we can test if the explanatory variables in our model are significant, i.e. that they “add something” to the model. Their following p-values indicates that the coefficients are significant in both the mean and the conditional variance equation, as well as jointly. Moreover, these tests successfully reject the null hypothesis that each pair of coefficients jointly equals zero.

Our results provided in Table 1 propose that four of the tested macroeconomic factors are influencing stock returns. Inflation (CPI), production output (IP), and money supply (M1) significantly affect the level of returns, while the conditional volatility for the overall economic activity (GDP) and money supply (M1) significantly affect the conditional volatilities of returns. M1 is the only candidate that tests significant in both the mean equation and the variance equation.

The evidence about the four significant factors candidates have been previously identified as influential for bonds, foreign exchange rates, and stock returns. However, in contradiction to some former studies, we do not find the popular measure for unemployment (UNEMP) to be an influential factor candidate, neither for the returns nor for its conditional volatilities.

The results of our estimations in Table 1 are designed to reveal any statistically significant impact the macroeconomic variables may have on stock returns. CPI, our chosen indicator for inflation, is proven to be statistically significant in having a negative relationship with stock returns. With a negative coefficient of 1.1705, it is the explanatory variable that contributes the most to our model when trying to explain the level of returns. This implies that for a given positive and unanticipated change in the inflation level, we can expect the aggregate stock return in the market to be lower. Moreover, when the cost of living goes up we experience lower returns from our investments in the stock market.

Industrial production (IP) is an indicator that measures the real output for all facilities in the United States. Given its statistically significant negative coefficient, our results imply that higher productivity leads to lower returns in the stock market. This is not a very intuitive result, as one would expect the opposite to be true. Since the valuation of future cash flows is a major factor in pricing stocks, monthly changes in stock returns may therefore not be highly related to changes in rates of industrial production in the same month. A change in industrial production may therefore already be reflected in the stock prices.

Our measure for money supply (M1) is the only factor candidate estimated to be statistically significant in affecting both the level of stock returns and its conditional volatilities. Its negative coefficients indicate that an increase in money supply and its volatility leads to lower returns and lower volatilities associated with those returns, respectively. A possible stimulus in money supply, as an instrument of monetary policy, may therefore affect risk and return associated with investors' portfolios, which results in reallocations of those portfolios. Money supply's negative relationship to stock returns is recognized by several researches. However, with regard to the volatilities of those returns, the estimation results have been more differentiated.

As a wide measurement of the country's overall economic activity, it is not surprising to find GDP as a potential factor candidate. However, we find it to be statistically significant in affecting the conditional volatilities of returns and not the level of returns. The coefficient is estimated to be positive, indicating that higher uncertainty concerning the country's overall economic activity will

increase uncertainty with regard to stock returns. Although our dataset is considered to be relatively long-term, the results are dependent on the dates, from start to end, as both the economy and stocks may follow a cyclical pattern. In addition, similar to our indicator for industrial production, GDP growth may not be entirely reflected in stock prices for a given month.

Our results do not present the unemployment rate (UNEMP) as a potential factor candidate. Given the long horizon of our analysis, including several periods defined as recessions, could possibly explain why we do not capture any effects, if any. Moreover, as the unemployment rate evolves over time, its effects on the economy may be captured in other variables, like GDP or CPI.

#### **4.2 Model diagnostics**

To assess the specifications of the EGARCH model, we want to examine the residuals. We create a standardized residuals series, displayed as a histogram with descriptive statistics in Appendix 5. The standardized residuals have a mean just above zero and a standard deviation very close to one, which makes it appear normal. The skewness is slightly negative, while the excess kurtosis is almost zero. However, we can reject the hypothesis of normal distribution at the 10% level but not at the 5% level. Therefore, in the wake of this, and by looking at the standardized residual graph in Appendix 6, we reject normality of the residuals.

We further examine the estimated variance of the returns by creating a variance series. We then plot the conditional variance, shown in Appendix 7, and the following conditional standard deviation:

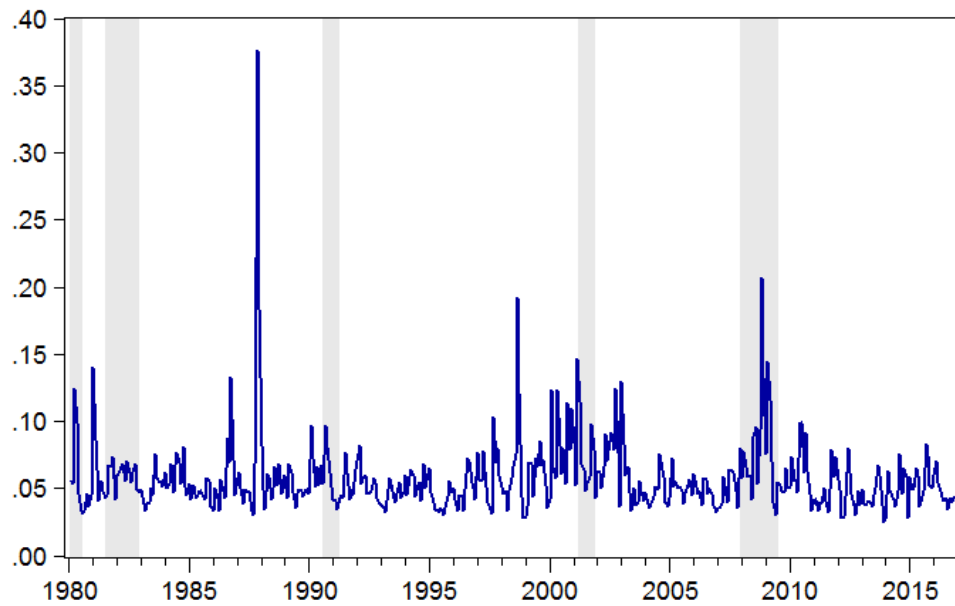


Figure 3: The variance series, visualized through a conditional standard deviation graph, of the estimated variance of the returns. In grey, the columns represents periods of recession provided by The National Bureau of Economic Research (NBER).

The conditional standard deviation graph shows that the standard deviation has been fluctuating around 0.05 over the years, including some heavy spikes. The heavy spikes are representing financial market “crisis”, which some of these include known periods like “Black Monday” (1987), the “dot-com bubble” (2001), and the global financial crisis (2007-08). The grey columns in the graph represent periods of recession, identified by NBER, to visualize and support the fact that heavy spikes in the conditional volatility are followed by a recession.

Next, we check for any remaining ARCH effects. The neglected heteroscedasticity can be examined by running an ARCH LM test on the standardized residuals. The results of the test, shown in Appendix 8, shows that we accept the hypothesis that the series have no remaining ARCH effects, meaning that no further evidence of heteroscedasticity is found. To complement this, we present a correlogram of standardized residuals squared in Appendix 9. This correlogram shows no evidence of remaining serial correlation, concluding the same as above.

### 4.3 EGARCH specifications

To appropriately evaluate the estimation results for the macroeconomic factors and put their estimated impact in a relative perspective, we interpret the estimation results for the EGARCH specification terms.

---

EGARCH specification term	Variance equation (7)
$\alpha$	-3.2275 * (0.6797)
$\beta$	0.6435 * (0.1403)
$\theta$	-0.0076 (0.1155)
$\gamma$	-0.5236 * (0.0027)

*Table 2: Displaying estimation results for coefficient estimates for the EGARCH specification terms, which are estimation output from the variance equation (7). \* coefficients are statistically significant at the 1% level.*

The GARCH specification argues, as mentioned earlier, that the best predictor of the one-period ahead conditional variance of returns is a combination of four volatility terms. From the table above, we can see that the coefficient estimates for the weighted average of the long-variance ( $\alpha$ ), the conditional variance of returns from previous lag ( $\beta$ ), and the deviation of the absolute value of the unit variance from the mean absolute value ( $\gamma$ ) are highly statistical significant. This, and their relatively high coefficient values compared to table 1, indicate the importance of the returns' own conditional variance. However, as the results in table 1 shows, the potential factor candidates do have some explanatory power, which implies that we cannot fully explain the conditional variance in the returns by its own conditional variance alone.



## 5 Conclusion

In this thesis, we find evidence that macroeconomic factors do affect aggregate stock returns in the U.S. market. We use an appropriately specified EGARCH model, which simultaneously identify any macroeconomic series that affect either returns or the returns' conditional volatilities. Three macroeconomic factors, Consumer Price Index, the Industrial Production, and Money Supply M1, are proven potential factor candidates in affecting the level of returns, with statistically significant results. Our results also reveal that the conditional volatilities regarding the GDP and the Money Supply M1 are statistical significantly affecting the returns' conditional volatilities.

We provide evidence that measures for inflation, industry output, and money supply have a negative relationship with stock returns. Their negative impact and potential association with stock returns are recognizable to previous research, which gives consent to our findings. Our coefficient estimate for CPI is relatively high, indicating the importance inflation has on the stock market.

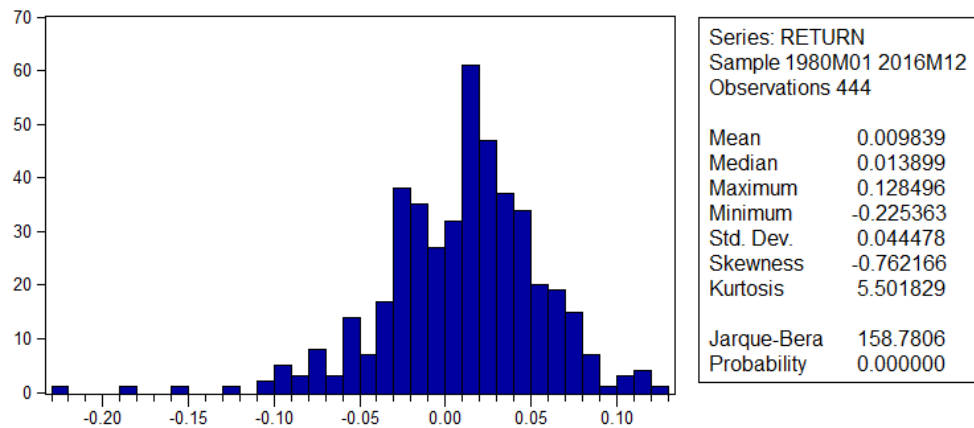
Further, through the conditional volatilities, we find evidence that GDP has a positive relationship with returns, which implies that the market is more volatile when the volatility of GDP increases. Likewise, we find evidence that M1 has a negative relationship, indicating that the market is less volatile when the volatility of M1 increases.

Previous researchers have found our remaining factor, UNEMP, to be statistically significant in affecting the stock returns. Our findings do not support this, and do not see UNEMP as a potential factor candidate.

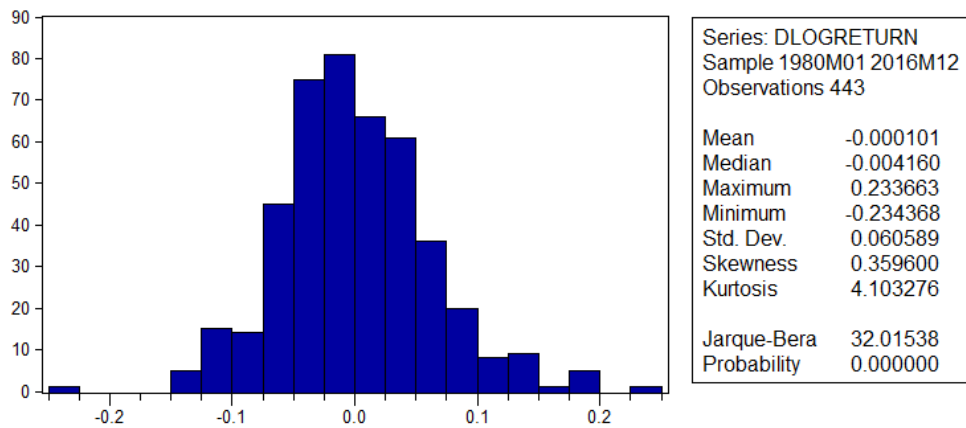
There are benefits in identifying macroeconomic factors that has an impact on aggregate stock returns and/or its conditional volatilities. The result of this thesis suggests that the effects of economic performance, economic stability and interest rates should be considered when attempting to explain stock returns in the U.S. market. Therefore, these macroeconomic factors should be taken into consideration when investigating or investing in this market.

Contribution to future research can be to further investigate on this topic by examining how the macroeconomic factors affect the different sectors in the market. The different factors may have bigger in some sectors than others, and vice versa. By doing so, one can possibly find a more detailed picture of their impact.

## 6 Appendix



*Appendix 1: Descriptive statistics of returns on the CRSP value-weighted market index. This histogram tells us that large outliers are rare. This because of the negatively skewness and positive excess kurtosis.*



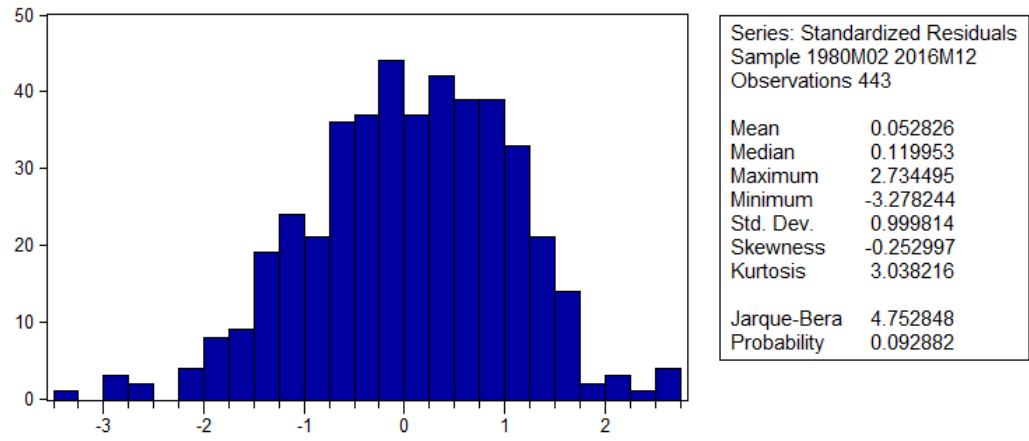
*Appendix 2: Descriptive statistics of log differenced returns on the CRSP value-weighted market index. By transforming the data into log difference, the symmetry of the distribution is closer to normal distribution.*

	<b>TB3M</b>	<b>CPI</b>	<b>GDP</b>	<b>IP</b>	<b>M1</b>	<b>UNEMP</b>
<b>Mean</b>	0.003055	0.002592	0.006507	0.001685	0.004981	0.001461
<b>Median</b>	0.004612	0.002501	0.007000	0.001000	0.005682	-0.016261
<b>Maximum</b>	0.041118	0.015209	0.023000	0.056000	0.078351	0.270270
<b>Minimum</b>	-0.081598	-0.019153	-0.021000	-0.049000	-0.035682	-0.180000
<b>Std. Dev.</b>	0.014936	0.003534	0.007316	0.019428	0.015659	0.064747
<b>Skewness</b>	-0.952320	-0.348062	-0.952422	0.023338	0.217102	1.249141
<b>Kurtosis</b>	6.281906	7.165630	5.412206	3.251328	3.740971	5.004413
<b>Jarque-Bera</b>	266.3735	329.9856	174.7726	1.208872	13.64508	189.7932
<b>Probability</b>	0.000000	0.000000	0.000000	0.546382	0.001089	0.000000

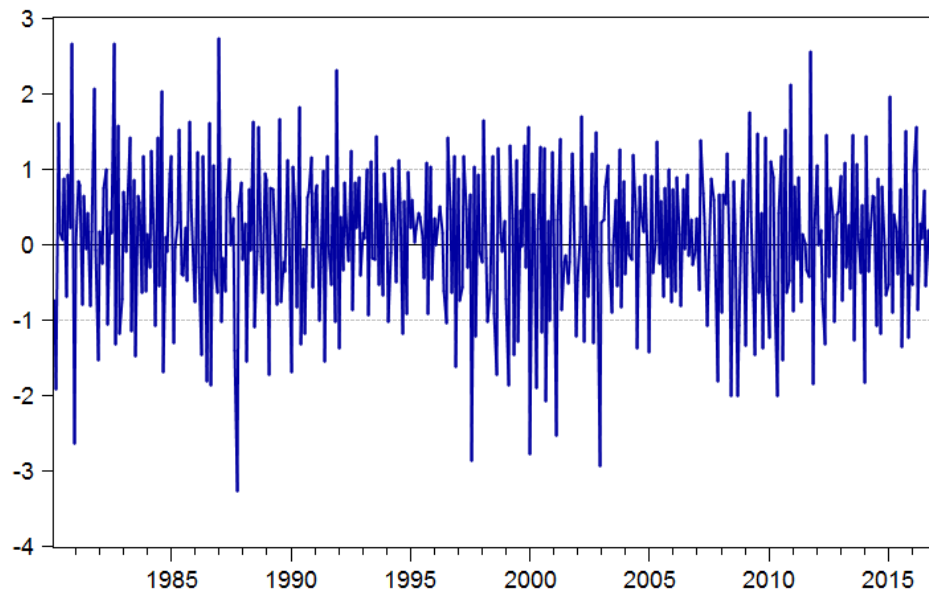
*Appendix 3: Descriptive statistics of macroeconomic factors. Different measures of the change in the different factors.*

	<b>DLOGTB3M</b>	<b>DLOGCPI</b>	<b>DLOGGDP</b>	<b>DLOGIP</b>	<b>DLOGM1</b>	<b>DLOGUNEMP</b>
<b>Mean</b>	-0.000081	-0.000031	0.000002	0.000018	0.000053	-0.000381
<b>Median</b>	0.000000	-0.000008	0.000000	0.001001	0.002123	-0.001008
<b>Maximum</b>	0.007566	0.014739	0.022134	0.095310	0.048119	0.239230
<b>Minimum</b>	-0.013890	-0.010942	-0.027807	-0.090423	-0.107555	-0.260736
<b>Std. Dev.</b>	0.001429	0.003278	0.004548	0.032790	0.023102	0.086128
<b>Skewness</b>	-2.171346	0.048028	-0.412407	0.0191123	-0.619671	-0.090949
<b>Kurtosis</b>	30.79051	4.766236	13.01023	3.875362	3.864718	3.609846
<b>Jarque-Bera</b>	14603.70	57.75274	1862.168	16.84084	42.15335	7.475613
<b>Probability</b>	0.000000	0.000000	0.000000	0.000220	0.000000	0.023806

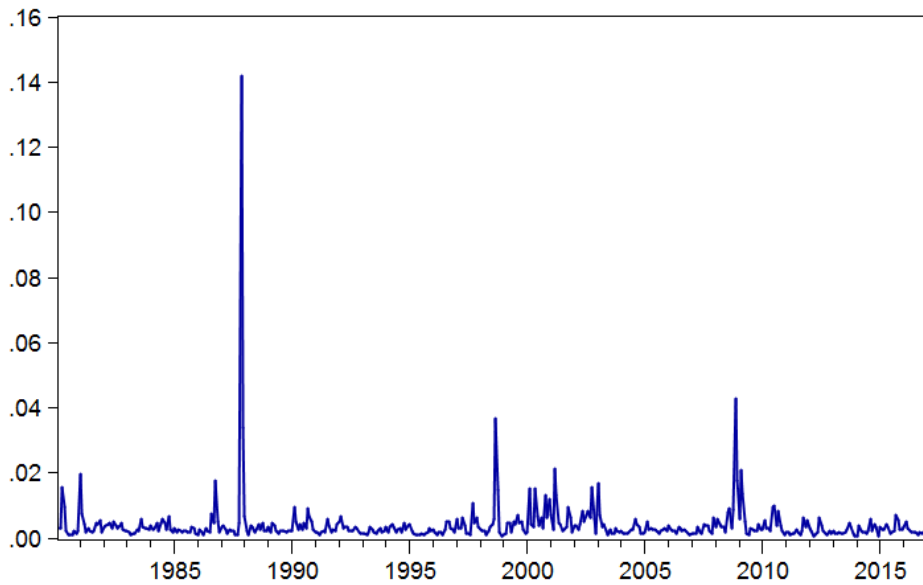
*Appendix 4: Descriptive statistics of log differenced macroeconomic factors. By transforming the macroeconomic factors into log differences make the data smoother to work with, eliminating possible specification errors without losing important features.*



Appendix 5: Histogram and descriptive statistics of standardized residuals. The excess kurtosis is close to 0, and the skewness is slightly negative.



Appendix 6: Standardized residuals graph, showing that we can reject normality of the residuals.



Appendix 7: Conditional variance graph. Shows how the variance fluctuates between 0.00 and 0.01. The heavy spikes shows the conditional variance “reactions” during crises.

Heteroskedasticity Test: ARCH

F-statistic	0.747490	Prob. F(5,432)	0.5883
Obs*R-squared	3.756854	Prob. Chi-Square(5)	0.5849

Test Equation:  
 Dependent Variable: WGT\_RESID^2  
 Method: Least Squares  
 Date: 04/13/18 Time: 09:57  
 Sample (adjusted): 1980M07 2016M12  
 Included observations: 438 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.079117	0.130319	8.280551	0.0000
WGT_RESID^2(-1)	0.022561	0.048113	0.468924	0.6394
WGT_RESID^2(-2)	-0.079922	0.048092	-1.661849	0.0973
WGT_RESID^2(-3)	-0.001789	0.048213	-0.037112	0.9704
WGT_RESID^2(-4)	-0.043902	0.047873	-0.917056	0.3596
WGT_RESID^2(-5)	0.019274	0.047915	0.402257	0.6877
R-squared	0.008577	Mean dependent var		0.995864
Adjusted R-squared	-0.002898	S.D. dependent var		1.408999
S.E. of regression	1.411039	Akaike info criterion		3.540133
Sum squared resid	860.1250	Schwarz criterion		3.596054
Log likelihood	-769.2892	Hannan-Quinn criter.		3.562198
F-statistic	0.747490	Durbin-Watson stat		1.999499
Prob(F-statistic)	0.588273			

Appendix 8: ARCH LM test on the standardized residuals. The results tells us that there are no remaining ARCH effects and no further evidence of heteroscedasticity.

Included observations: 443

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
		1	0.023	0.023	0.2419	0.623
		2	-0.081	-0.081	3.1490	0.207
		3	-0.011	-0.007	3.1987	0.362
		4	-0.037	-0.043	3.8045	0.433
		5	0.018	0.019	3.9549	0.556
		6	0.017	0.010	4.0905	0.664
		7	-0.046	-0.044	5.0278	0.657
		8	0.118	0.122	11.301	0.185
		9	0.079	0.068	14.137	0.118
		10	0.064	0.083	16.003	0.100
		11	0.026	0.035	16.316	0.130
		12	-0.038	-0.016	16.987	0.150
		13	0.096	0.111	21.183	0.069
		14	0.017	0.006	21.317	0.094
		15	-0.045	-0.021	22.253	0.101
		16	-0.011	-0.020	22.310	0.133
		17	-0.018	-0.030	22.465	0.168
		18	0.004	-0.021	22.472	0.212
		19	0.007	-0.029	22.492	0.260
		20	0.087	0.093	26.007	0.166
		21	0.062	0.035	27.827	0.145
		22	0.016	0.015	27.952	0.177
		23	0.071	0.082	30.346	0.140
		24	0.014	0.023	30.440	0.171
		25	0.007	0.045	30.461	0.207
		26	-0.039	-0.042	31.163	0.222
		27	0.008	0.030	31.197	0.263
		28	-0.004	-0.022	31.203	0.308
		29	0.114	0.096	37.369	0.137
		30	-0.032	-0.060	37.865	0.153
		31	-0.012	-0.026	37.929	0.183
		32	0.063	0.052	39.848	0.160
		33	-0.038	-0.084	40.535	0.172
		34	0.005	0.004	40.549	0.204
		35	-0.023	-0.040	40.814	0.230
		36	-0.031	-0.018	41.265	0.251

*Appendix 9: Correlogram of standardized residuals squared. Complement Appendix 8, showing that there are no remaining ARCH effects and no further evidence of heteroscedasticity.*

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**BI Norwegian Business School**

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**Preliminary Thesis GRA 19502**

Does macroeconomic news affect aggregate  
stock returns in the U.S. market?

Supervisor:

Paul Ehling

Program:

MSc in Business, Major in Finance

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## **0 Abstract**

Macroeconomic factors and their influence on stock returns is a widely discussed topic in both previous and recent academic literature. In our thesis, we are interested to examine whether unexpected news of different macroeconomic factors have a significant effect on stock returns in the U.S. market. Using extensive previous literature and frequent data on stock returns and macroeconomic announcements, we expect to find significant evidence that supports our hypothesis: there are certain macroeconomic news that do influence stock prices and returns.

## **1 Introduction**

There is a common belief that stock prices are affected by new information in the market. This has led to much research around how new information affect financial markets, where some researchers have focused on how the effect of macroeconomic announcements affect financial markets.

Variables that can affect the future opportunity set or consumption level can be possible priced factors in equilibrium (Merton, 1973). Changes in macroeconomic factors then have the possibility to affect firms' investment opportunities.

Researchers have documented that inflation and monetary policy have a negative effect on stock prices [Bodie (1976), Fama (1981), Geske and Roll (1983), Pearce and Roley (1983, 1985)]. However, in later years there have been evidence that the market reacts different to similar macroeconomic news depending on the economic state we face [Chen, Roll and Ross (1986)]. In a recession, news about a booming industrial future could be received, by the market, as an indication that the economy will recover and a better outlook for companies can increase the stock prices. On the contrary, the same news in a booming economic state, where companies have been expanding for a long time, can lead the market to believe that measures will be taken to slow the economy down and, thus, the stock market may fall. Hence, the timing of the macroeconomic news on the stock market is important, and the impact differs as whether the market sees the news as "good" or "bad". Assuming the market behaves in this way, earlier research may have

used a too “simple” estimates of the coefficient on the variable regarding the news. The coefficient estimate may therefore be biased toward zero.

In this paper, we will use more recent data to extend previous research. We will apply a GARCH model that helps us to identify variations in the conditional volatility of residuals. The model takes into account that variation in volatility could arise in crises, and is therefore a well-fitted model for our problem. We have followed the same approach to our methodology as Flannery and Protopapadakis (2002) and Andritzky, Bannister and Tamirisa (2005), who both implement a conditional variance GARCH model.

In this preliminary, there will be a literature review of previous research on the impact of macroeconomic news, how economic states affect the coefficient and which macroeconomic factors that previous have been found to be significant. Further, we explain what data we will implement in our calculations and where we will extract it.

Considering previous research and more recent theory, we have a hypothesis that consists of finding statistically significant results. Moreover, we expect to find macroeconomic factors that *do* influence aggregate stock returns in the U.S. market.

## **2 Literature review**

Bodie (1976) finds that there is a negative correlation between unanticipated inflation and the real return on equity. This result is supported by Fama (1981) and Geske and Roll (1983). Pearce and Roley (1983, 1985) extend the former and finds that new information related directly to monetary policy, especially money announcement surprises, have a significantly negative effect on stock prices. Chen, Roll, and Ross (1986) (CRR) then takes this a step further, and discover five potential macroeconomic factors: expected inflation, unexpected inflation, changes in the risk premium, spread in the yield curve, industrial production. These economic factors were found to be significant in explaining expected stock

returns. However, the inflation factors are somewhat less influential in highly volatile periods.

The results of CRR's estimations were later criticized by Shanken and Weinstein (1990), whom instead of estimating the betas using backward-looking returns used the returns from the following year. This relatively "small" change reduced the statistical importance with regards to the returns, and showed that only the industrial production factor was significant in the sample period.

Lamont (2001) shows that constructing a tracking portfolio of the growth rates of production, consumption or labour income lead to abnormal returns. He also finds that inflation fails to achieve this.

Cutler, Poterba and Summers (1989) (CPS) find, in their definition, that macroeconomic news only explains about 20% of the movements in stock prices. Over the period 1926-1986 CPS find that industrial production growth is significantly correlated with stock return. However, this is not the case in the period 1946-1965, which contradicts the findings of CRR and their sample period. As in comparison to Roll (1988), CPS also conclude that macroeconomic factors have a quite modest explanatory power in the market variability.

While earlier studies find that macroeconomic factors have little effect on stock prices, McQueen and Roley (1993) provide evidence that the effect depends on the state of the economy.

They conclude that positive shocks to the real activity leads to lower stock prices in a strong economy, while it leads to higher stock prices in a weak economy.

This result can contribute to explain the insignificance of macroeconomic factors in earlier studies.

In the same direction, Hu and Li (1998) examine whether the effect of macroeconomic factors on stock prices varies in the different states of the economy. They provide strong evidence for different market responses to different states of the economy, using the same macroeconomic factors. Hence, allowing the response coefficients to change over different states of the economy may therefore result in more significant macroeconomic variables.

Differences across markets and types of announcements tend to influence the effects of macroeconomic announcements (Andritzky, Bannister and Tamirisa, 2005).

For example, news about the trade balance seems to have an effect on the U.S. stock prices (Aggarwal and Schirm, 1998), while announcements about retail sales have greater impact on the U.S. Treasury bond market (Fleming and Ramola, 1997).

The methodology we use in this paper comprises volatility changes, and we therefore review some articles consisting of market return volatility and volatility models. Using a GARCH model of monthly US equity returns, Hamilton and Susmel (1994) conclude that equity returns are significantly affected by macro conditions. Consequently, implying that the equity volatility is likely to remain high during recessions.

Errunza and Hogan (1998) finds that, for many European equity markets, macroeconomic factors can be used to make return volatility predictions. They conclude, by estimating VAR models, that monetary instability is a significant factor for France and Germany, while industrial production is a significant factor for Italy and the Netherlands. For countries as UK, Switzerland, and Belgium, macroeconomic factors fail to improve any forecast ability.

Utilizing a model that estimate the conditional standard deviation for different monthly mean returns, Schwert (1989) finds evidence that future macroeconomic volatility can be predicted by looking at financial asset volatility. This go hand in hand with theoretical aspects, since the price of an asset should react quickly to new information. This argument is somewhat also used by Fama (1990), who finds that a change in stock prices can be used to predict future macroeconomic conditions.

Flannery and Protopapadakis (2002) expand earlier research by employing a much more extensive data set, consisting of 17 macroeconomic announcement series. They find that six of these are strongly significant: three nominal (CPI, PPI, and a monetary aggregate) and three real (balance of trade, employment report, and housing starts).



The new evidence resulted from this paper is that balance of trade, employment and housing starts are identified as significant risk factors on the returns' conditional volatility. More surprisingly, they find that real GNP and industrial production tend to be insignificant as risk factors.

### 3 Theory and Methodology

The well-known model for pricing stocks is dependent on the sum of discounted expected future dividends, given the information known at the present time:

$$P_t = E\left(\sum_{\tau=1}^{\infty} \frac{d_{t+\tau}}{1 + r_{t+\tau}} \mid \Omega_t\right)$$

where  $P_t$  is the stock price at time  $t$ ,  $d_{t+\tau}$  is the paid dividend at time  $t+\tau$ ,  $r_{t+\tau}$  is the stochastic discount factor for cash flows that occurs at time  $t+\tau$ , and  $\Omega_t$  represents the information set known at time  $t$ .

The new information is explained by the difference between  $\Omega_t$  and  $\Omega_{t-1}$ . On the announcement day, the expected component of the news and all previous announcements have been included in  $\Omega_t$ . Under the assumption of efficient markets and rational investors, stock prices should only be affected by the unexpected part of the news.

A multi-factor model uses two or more factors in its calculations when trying to explain asset prices in the market. It can be used to either construct or explain an individual security or a portfolio of securities. According to Merton (1973), investors would want to hedge against two types of risk: volatility and uncertainty in the returns of the securities (current period) and possible future shifts in the investment opportunity set. For example, an unexpected and disadvantageous shift in the opportunity set will affect future consumption negatively for a given level of future wealth. Thus, if the opportunity set turned out to be "worse" than expected, the investor would, through his investments in positive correlated returns, expect a higher level of wealth as a compensation. In the same way, the

investor would expect “better” investment opportunities if future returns are lower.

Macroeconomic factors that are correlated with a change in the opportunity set can therefore be said to be a possible price factor, in an equilibrium state. This could potentially occur through an unexpected change in the CPI that may cause a change in the gap between the expected return of different asset types, or an unexpected shift in the unemployment rate that may change the future returns to employees and human capital.

This thesis’ methodology will follow the path of previous articles concerning the time-constant effects of macroeconomic factors on equity prices. More precisely, we implement the same approach as Flannery and Protopapadakis (2002) and Andritzky, Bannister and Tamirisa (2005), and follow their definitions throughout this methodology. In the single-factor case, previous research have tried to regress the market’s monthly return ( $r_t$ ) on a potential macroeconomic factor’s ( $Z$ ) unexpected changes,  $z_t = Z_t - E_{t-1}(Z_t)$ :

$$r_t = E_{t-1}(r_t) + \beta z_t + u_t \quad (1)$$

The coefficient  $\beta$  implies, if proven to be statistically significant, a relationship between the tested factor and the return of the market portfolio. However, it requires further analysis to determine whether or not the unexpected change to  $Z$  is actually priced in equilibrium.

Due to its simplicity, regression models like equation (1) could be unsuccessful to perceive important macroeconomic effects on the market portfolio's return. First, by using monthly stock returns that incorporate huge amounts of information in each period, can make specific macroeconomic fluctuations difficult to capture. In this paper, we will use daily data instead of monthly, as it is more likely to show when the investors detect the announcements. Second, the simple linear regression may lead to an underestimate of the coefficient  $\beta$ , also known as the attenuation bias, which is caused by errors in the tested independent variables. This could then bias the estimated  $\beta$  toward zero.

Third, all the noise in the expected value ( $E_{t-1}(Z_t)$ ) may also bias the estimated  $\beta$  toward zero, due to inaccurate evaluation or estimate of the announcement expectation component. Finally, statistical inference problems may arise when we apply a fixed-coefficient model to estimate a coefficient that actually is time-varying. This can be shown in a rewriting equation (1) as

$$r_t = \beta_t z_t + u_t \quad (2)$$

where  $\beta_t$ ,  $z_t$ , and  $u_t$  are jointly independent,  $u_t = h_t \varepsilon_t$ , and  $h_t^2 = h_0^2$ . When  $\beta_t$  is time-varying, its estimate, in Equation (2), will roughly be the mean of  $\beta$ ,  $\hat{\beta} = E(\beta_t)$ . Therefore, if we have a coefficient that switches sign and averages close to zero over time or is occasionally important, the estimated coefficient may fail to identify a potential macroeconomic factor. Furthermore, by implementing a fixed-coefficient model to estimate time-varying coefficients on the unexpected macro announcements may cause the estimated residuals to be heteroscedastic. To comprehend this heteroscedasticity, we assume that the true model is Equation (2) and that we cannot replicate the intertemporal variation in  $\beta_t$ . The estimated residuals will then be given by  $\hat{u}_t = u_t + [\beta_t - \hat{\beta}]z_t$ , and their variance will be

$$\hat{\sigma}_{u,t}^2 = \sigma_u^2 + E_{t-1}[(\beta_t - \hat{\beta})^2 z_t^2] + E_{t-1}[u_t(\beta_t - \hat{\beta})z_t]. \quad (3)$$

When  $\beta_t$ ,  $z_t$ , and  $u_t$  are jointly independent,  $E_{t-1}[u_t(\beta_t - \hat{\beta})] = 0$ . On days without macroeconomic news, we will get  $z_t = 0$  and the residuals' variance therefore reduces to  $\sigma_u^2$ . On days with macroeconomic news, the residuals' variance will exceed  $\sigma_u^2$ , because in general we have that  $\beta_t \neq \hat{\beta}$  and  $z_t \neq 0$ . Hence, by modifying the rudimentary conditional variance specification, it seems plausible to extract information about the effect of an announcement data series.

We will further implement a GARCH model to this problem, as it is constructed to identify variations in the conditional volatility of residuals.

Expectantly, this method will improve the accuracy of continuous predictions, as the goal of a GARCH model is to minimize errors in future forecasting by adjusting for errors in previous forecasting. We will need to estimate an autoregressive model that is the best-fitting for our study, and calculate the

autocorrelations of the error term. Lastly, we need to test our model for any statistical significant results.

## **4 Data**

We need the value and the date of macroeconomic announcements, what the market expected about these announcement and financial stock returns to estimate the model.

### **4.1 Stock returns**

For stock returns, we will use daily (close-to-close) data from either a value-weighted market index or one of the largest indices in the US market, like the S&P 500. The dates and span of our dataset will depend on the macroeconomic announcement data we will be able to obtain. However, we are currently aiming for a 15-20-year span with data, that is as new as possible. This data will most likely be extracted from Thomson Reuters Eikon.

In addition, we will need to gather daily data on different interest rates, like treasury bills and bonds with different maturity. This data would possibly be available for us at The Fed's (Federal Reserve) home site online.

### **4.2 Macroeconomic announcements**

Either Bloomberg or Thomson Reuters Eikon will help us provide the dates and values of different macroeconomic announcements. This will be announcements (or indicators) like inflation, employment rate, GDP, industrial production, and so forth. The different indicators we will end up employing depends on availability and reliability on the data we are able to obtain, but hopefully we will be able to test around 15-20 indicators.

We also want expectations on these announcements, as we need to calculate the deviations in forecasts from actual outputs. Where to extract this kind of data is a

little bit more uncertain to us, but it seems plausible to either find it on a financial platform or receive/purchase it from a financial institution.

## 5 Thesis plans

January	<ul style="list-style-type: none"> <li>• Deadline for submission of Preliminary Thesis</li> <li>• Continue with the literature review</li> </ul>
February	<ul style="list-style-type: none"> <li>• Extracting data</li> <li>• Process and analyze data</li> </ul>
March	<ul style="list-style-type: none"> <li>• Further analysis and produce descriptive statistics</li> <li>• Testing and interpretation of results</li> </ul>
April	<ul style="list-style-type: none"> <li>• Writing on the thesis</li> </ul>
May	<ul style="list-style-type: none"> <li>• Finishing draft</li> </ul>
June	<ul style="list-style-type: none"> <li>• Hand in draft for feedback</li> </ul>
July	<ul style="list-style-type: none"> <li>• Work on corrections and improve layout</li> </ul>
August	<ul style="list-style-type: none"> <li>• Submit final thesis</li> </ul>
September	<ul style="list-style-type: none"> <li>• Deadline for submission of Master Thesis</li> </ul>

After the submission of this preliminary, we will continue to gather information and work around previous literature. Further, we need to extract the data needed to assemble our regression model. We will gather daily data from the U.S. stock market, either S&P 500 or a value-weighted market index. Furthermore, we also need to extract the data regarding macroeconomic announcements and the expectation the market had for these. This will be the basis for when we create our regression model and start testing. The results will show us which macroeconomic factors that do and which that do not affect the aggregate stock returns.

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