Master Thesis U.S.E.

Stocks, inflation, and market power.

Investigating stocks' inflation hedging ability in the European market.

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Abstract

This empirical research investigates the ability of stocks to hedge against inflation in European markets. In line with that, this work aims to identify whether companies' market power affects stock excess returns. Also, this research answers whether portfolios with different inflation hedging abilities perform differently and if investors would be willing to pay a premium on diversified portfolios with raised inflation exposure. These research questions are approached to be answered by conducting a time series regression analysis regarding stocks' exposure to macroeconomic and microeconomic factors. The empirical findings suggest that, while stocks, on average, do not have a hedging ability against changes in inflation, selected stocks do. Also, regarding inflation exposure, market power does not affect stock excess returns. Additionally, portfolios with low inflation hedging abilities perform better than good inflation hedged portfolios. Lastly, creating an additional inflation risk factor in the asset pricing environment suggests that investors would be willing to pay a higher price for portfolios with a raised inflation exposure.

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1. Introduction

This paper aims to answer whether stocks can be a hedging tool to protect against inflation. In light of that, it is inspected whether the individual market power of the company affects stock hedge ability. Furthermore, this paper investigates the performance of portfolios based on inflation exposure. Finally, it is inspected whether the difference in performance could be a way to quantify the inflation risk of a diversified portfolio. This research focuses on the European market.

Following the standard macroeconomic theory, inflation comes with benefits and shortcomings. While constant positive inflation is associated with high economic growth, possible macroeconomic costs are increasing unemployment and a decreasing value of the domestic currency. Furthermore, even though regulators aim for low but positive and stable inflation, policymakers cannot prevent inflation from reacting to macroeconomic factors such as economic shocks. With stable and positive inflation in place, prices increase over time, and, therefore, the purchasing power of money decreases. As a result, long-term institutional and private investors face the risk that inflation reduces the real returns of their investments. This issue is of increasing importance, especially in the current times, where the CPI growth rate is as high as 9.8% in the European OECD area (OECD, 2022). Following the Fisher hypothesis (Fisher, 1930), the real return of an investment is equal to the current return subtracted by the current inflation rate. Therefore, to write down positive real returns on your investment, the current return must be above 9.8%. The fact that the average return in the European market (Euro Stoxx 600) over the past 15 years is only 0.068% per month emphasizes the relevance of this topic.

An optimal hedge against inflation offsets the inflation risk so that with a change in inflation, the returns move equivalently in the same direction. Consequently, the inflation exposure of equities must be such that they move equivalently with inflation, taking into account other macroeconomic and microeconomic factors affecting this relationship. Therefore, I define the hedging ability as perfect if a stock's regression coefficient to inflation equals 1. Only in this case is the effect on the real return offset by inflation. The less the stock return covaries with inflation; the less the stock is protected against inflation. In light of that, the question arises whether stock's ability to hedge against inflation is affected by other factors. More specifically, the question is, what else could affect the covariation between stock returns and the change in the overall price level. With this in mind, a company's market power could answer part of this question. A company with significant market power can raise prices with less fear of being penalized with lost sales relative to their competitors with lower market power (Mankiw & Taylor, 2016). Therefore, assuming that higher market power results in higher profits, market power could affect stock prices. Moreover, there is a potential link between market power and the effect of inflation on stock returns. The higher the market power, the easier it is to react to price changes/inflation.

Besides private and institutional investors, regulatory institutions could be interested in the outcome of this research. Regulators aim to reduce the overall risk and provide stability in financial markets. For example, suppose an inflation risk factor for a diversified portfolio is identified. In that case, this could impact investment strategies and regulatory procedures protecting investors from macroeconomic variations. In turn, depending on the results of this study, a discussion about the role of inflation and its hedge ability in today's economic environment could be reopened.

The existing research concerning stocks' ability to hedge against inflation does not agree on one relationship between stock performance and inflation rates. While the early study, especially in the U.S. market, found a negative relationship between inflation and stock returns and, thus, no hedging ability (Bodie, 1976; Fama & Schwert, 1977; Wei & Wong, 1992), research on the U.K. and Latin America identifies a positive relationship (Alagidede & Panagiotidis, 2010; Choudhry, 2001; Firth, 1979; Li et al., 2010). Having determined a negative relationship, the literature also investigates hedging strategies that include short positions of stocks with negative inflation exposure (Ang et al., 2012; Bodie, 1976; Fama & Schwert, 1977). However, as Ang et al. (2012) indicated, these portfolios' performance is inferior to that of other portfolios, such as the market portfolio. Furthermore, Ang et al. (2012) conclude that creating portfolios reliably hedging against inflation is challenging. Bampinas and Panagiotidis (2016) find that high hedging ability portfolios perform superior to others. While there is a short supply of research on the effect of market power on stock returns' inflation hedging ability, a negative relationship between inflation and market power (Head et al., 2010; Richards et al., 2012) and a positive relationship between market power and stock returns (Sharma, 2011) has been identified.

This research aims to identify whether stocks can be used to protect investments against inflation in European markets. In light of that, one part of this research paper investigates whether the individual market power of a company affects a stock's profitability. On top of that, this paper approaches to answer whether portfolios with a high inflation hedging ability perform differently from portfolios with a low inflation hedging ability. Finally, questioning if investors would be willing to pay a different price for portfolios with different exposure to inflation, this research inspects a potential inflation risk factor in the asset pricing environment. While most of the existing literature covers the hedging ability of U.S. and U.K. stocks, equity in the European market has experienced less interest. This is where this research fills the gap in the literature. Additionally, this research adds to the scarce literature that investigates the linkage between inflation and stock excess returns in light of multiple other explanatory variables. Furthermore, this paper appends to the scarce literature investigating the linkage between market power and stocks' ability to hedge against inflation. Finally, examining the inflation risk factor adds to the scarce literature discussing inflationary risk in the asset pricing environment. Relative to the findings of this research, Investors active in the European market can use the information to optimize their portfolio structure, and regulators have a deeper insight into the inflation risk of diversified portfolios.

In the following section, I review the findings from previous literature to justify my hypotheses and situate this research piece within the existing literature. Section 3 presents and explains the empirical approach to answering the above research questions. In addition, the data used and its collection are presented. In section 4, I present and analyze the empirical results, followed by an interpretation of the results found. Finally, in section 5, I discuss the results, link them to the existing literature, point out possible limitations, and conclude the paper.

2. Literature review

The standard literature provides much research on the relationship between inflation and stock returns. Often, the main idea is to test the commonly known Fisher hypothesis (Fisher, 1930).

Investigating the relationship between portfolio returns (DJ Industrials, S&P 425 Industrials, S&P Utilities, S&P Rails, S&P 500 Stocks) and the inflation in the U.S. market, Reilly et al. (1970) inspect whether real rates of returns realized during high inflation periods outperform potential inflation-free periods. However, Reilly et al. (1970) do not find evidence for stock portfolios to be consistent or complete inflation hedges. Bodie (1976) identifies two measures that quantify the effectiveness of the hedging ability of a well-diversified minimum variance portfolio. First, the higher the ratio of the variance of the real returns of common stocks to the variance of unanticipated inflation, the less effective is equity as an inflation hedge. Second, the higher the absolute value of the difference between the nominal return on a nominal bond and the exposure of common equity to inflation, the less effective equity is as an inflation hedge. With that in mind, Bodie (1976) finds that a 1% increase in inflation causes stock returns to fall by 4%. Further, he points out that by shorting $0.03 of stocks for every $1.03 invested in the nominal bonds, 18 percent of the variation of real returns on nominal bonds can be hedged. Later research supports Bodie's (1976) finding (Fama & Schwert, 1977; Li et al., 2010; Wei & Wong, 1992). Fama and Schwert (1977) regress equity portfolio returns on expected and unexpected inflation on a monthly, quarterly, and semiannual basis in the U.S. market. Finding evidence for the ability to hedge against inflation for government debt and real estate, they miss out on evidence for human capital and common stocks. Nevertheless, they find negative coefficients of up to -6.5 for expected and unexpected inflation. Analyzing stock returns across 19 U.S. industry sectors during the pre-and post- World War II periods, Wei and Wong (1992) confirm the negative relationship, especially in the industries working with natural resources. Furthermore, Li et al. (2010) discover that the inflation hedging ability of stocks depends on the stock-holding periods and the inflationary regimes.

Moving from an analysis of the U.S. market to an investigation of stocks' ability to hedge against inflation in U.K. markets, Firth (1979) finds non-lagged inflation betas between 0.355 and 3.08 depending on the period considered. Hence, Firth (1979) provides proof of stocks' hedging ability. However, inspecting the lagged inflation, he mostly finds negative coefficients. More recent research on this relationship (Alagidede & Panagiotidis, 2010; Choudhry, 2001) complements the findings by Firth (1979). While conducting a time series regression analysis of stock returns on inflation and lagged inflation in four high-inflation Latin American countries, Choudhry (2001) finds a positive relationship between inflation and stock returns. Considering the current inflation rate, he finds coefficients between -0.45 and 1.3, with only the positive being significant. Moreover, the coefficients that solely consider the lagged inflation range from -0.8 to 0.9.

Research investigating the long-term relationship between stock returns and inflation agrees on a statistically significant relationship (Alagidede & Panagiotidis, 2010; Bampinas & Panagiotidis, 2016; Omay et al., 2015). While testing for cointegration between inflation and stock returns in African countries, Alagidede and Panagiotidis (2010) detect a statistically significant and positive relationship. Additionally, under consideration of global stock data, Omay et al. (2015) prove this long-term relationship to be linear.

Based on the previous findings (Bodie, 1976; Fama & Schwert, 1977; Reilly et al., 1970), another study points out a procedure for forming common stock portfolios with positive inflation exposure and thus hedge ability in the U.S. markets (Bernard & Frecka, 1983). After the strategy defined by Bernard and Frecka (1983), one should create portfolios based on the inflation exposure. Then, in line with the findings of Bodie (1976), by taking a long position in stocks with the best hedge ability and a short position in the stocks with the worst hedge ability, they create portfolios with a positive relationship with inflation. However, Bernard and Frecka's (1983) regression models are characterized by a relatively low explanatory power (0.19 and 0.52).

Following the idea of constructing portfolios with a good ability to hedge, Ang et al. (2012) first inspect the inflation hedge ability of individual stocks, followed by an examination of artificially created inflation hedge portfolios. By regressing returns from stocks that are constituents of the S&P 500 on the current inflation, Ang et al. (2012) compute stocks' exposure to inflation. Their sample period ranges from October 1989 to May 2010. If the regression coefficient is equal to 1, they define that stock as a perfect hedge against inflation. Next, by sorting equities by the size of their inflation beta, Ang et al. (2012) create multiple portfolios containing the quintiles of the previously sorted stocks. Subsequently, they run a regression on the portfolio returns following the Fama-French 3-Factor-model (Fama & French, 1993), including the momentum factor. Ang et al. (2012) find inflation betas equal to up to 15, but only a few of their findings are statistically significant. However, they identify a significant positive relationship between stock returns and inflation for individual sectors. Hence, they conclude that individual stocks can hedge against inflation. Furthermore, Ang et al. (2012) find that, on average, stocks with good protection against inflation earned higher nominal and real returns than others. Moreover, they find a considerable time variation of realized stock inflation betas, making it challenging to forecast inflation betas. According to Ang et al. (2012), this is why creating portfolios that are a reliable hedge against inflation is a challenging task. The portfolios constructed differ in their overall profitability, depending on the model. However, the portfolios with a high inflation beta tend to outperform those with a low inflation beta. Nevertheless, Ang et al. (2012) conclude that stocks cannot hedge against inflation, which points out the need for research on the hedging ability of other asset classes.

Finally, using a similar approach on S&P 500 stocks between January 1993 and August 2012, Bampinas and Panagiotidis (2016) find hedge ability for selected stocks. Especially from companies active in the Energy and Industrial sectors. Additionally, Bampinas and Panagiotidis (2016) create portfolios based on stock prices that are significantly (to the 10% level) cointegrated with the consumer price index and sort them based on their inflation coefficient. The weight of the stock in the portfolio is based on market capitalization. Bampinas and Panagiotidis (2016) find that portfolios with high inflation betas, on average, perform better than low inflation beta portfolios. Also, they conclude that the best inflation hedging stocks are growth stocks or stocks from large firms. Bampinas and Panagiotidis (2016) also construct dynamically rebalanced portfolios based on past cointegration and long-run inflation betas. Here Bampinas and Panagiotidis (2016) also find superior hedging abilities for the portfolio containing higher inflation beta stocks. In contrast to Ang et al. (2012), the results identified by Bampinas and Panagiotidis (2016) indicate the ability to forecast inflation betas if portfolios are rebalanced every first to the fourth year. Additionally, Bampinas and Panagiotidis (2016) identify a negative effect on the relationship between inflation and stock returns during crises.

While the literature covering the hedging ability of stocks is extensive, research concerning inflation risk factors in the asset pricing environment is scarce. However, previous research inspects the explanatory power of the inflation rate in the CAPM and Fama-French 3 Factor model (Sato et al., 2011). Sato et al. (2011) find that including inflation in the CAPM returns only significant negative inflation betas between-5.27 and -9.29 in the industries considered. Furthermore, Sato et al. (2011) suggest that incorporating inflation as an additional factor improves the performance of CAPM-based portfolios. Implementing the inflation rate as an additional factor in the 3 Factor model, Sato et al. (2011) find positive and negative significant inflation betas across the industries considered (between -5.78 and 10.12).

Addressing the role of market power in the relevant academic environment, Head et al. (2010) find that higher average inflation causes lower average markup (thus lower market power) and increases sensitivity of prices to fluctuations in either productivity or money growth. Analyzing the commodity market, Richards et al. (2012) find similar evidence for this relationship. They further argue that price volatility and market power have a positive relationship. In contrast, in a working Paper, Chirinko and Fazzari (2000) find evidence for a positive relationship between the overall price level and market power in industries with little market power. Furthermore, research on the effect of market power on stock returns identifies a positive relationship (Sullivan, 1974). While industries with low entry barriers have average returns of 13.67 %, industries with moderate entry barriers have average returns of 9.03 %.

Even though Ang et al. (2012) and Bampinas and Panagiotidis (2016) inspected the US market, due to close international connections to the European market, I expect the empirical results to be similar.

Hence, I expect a positive relationship between inflation and stock excess returns in European markets. Furthermore, I hypothesize that market power positively affects stock returns, as companies with higher market power perform better on average. Lastly, following the findings by Ang et al. (2012) and Bampinas and Panagiotidis (2016), I expect portfolios with high inflation betas to outperform portfolios with a low inflation beta.

3. Empirical Strategy and Data

3.1. Empirical strategy

With the ultimate goal to answer the above research questions, I structure my empirical strategy as follows. First, I divide my empirical approach into two steps. In the first step, I attempt to quantify the hedging ability of stocks under the potential influence of individual market power. In the second step, I form portfolios depending on their hedging ability from the first step. Subsequently, I compare their performance among themselves and relative to a potential market portfolio. Afterward, I test the significance of potential inflation risk factors in the asset pricing environment based on the previously formed portfolios.

3.1.1. Hedge ability and market power exposure

In the first step of the empirical procedure, I determine the exposure of stocks to the current inflation rate. For this purpose, I use a multivariate OLS time series regression model whose coefficients equal the individual exposure. Using this, I quantify the individual exposure to inflation of the stocks under consideration and draw generalized conclusions.

Consistent with Wooldridge (2014), I assume the underlying asymptotic time series assumptions. The basic assumptions can be summarized as follows: weak dependency and stationarity of all variables considered, contemporaneous exogeneity, non-perfect collinearity, contemporaneous heteroskedasticity of the explanatory variables, and no serial correlation of the explanatory variables. When these assumptions hold, the coefficients represent the individual exposure for each variable (ceteris paribus). The original regression model used to answer the research questions is given in Equation 1. In the analysis, I perform several robustness checks to verify the basic assumptions and test the significance of the regression coefficients. Subsequently, I derive the final regression model and the exposure to inflation.

Equation 1

$$R_{i,t} = \beta_0 + \beta_1 * \Delta\pi_{i,t} + \beta_2 * \Delta\pi_{i,t-1} + \beta_3 * \pi_{i,t-1}^2 + \beta_4 * \pi_{i,t-2} + \beta_5 * \pi_{i,t-2}^2 + \beta_6 * LI_{i,t} + \beta_7 * GDPG_{i,t} + \beta_8 * CAP_{i,t} + \beta_9 * BTM_{i,t} + \beta_{10} * R_{m_t} + \beta_{11} * t_{i,t} + \beta_{12} * s_i + u_t$$

$R_{i,t}$, as the dependent variable, represents the excess returns over the risk-free rate of a company i at a given time t. Therefore, t describes the current period in monthly terms. I choose excess returns over standard returns as the dependent variable because it provides additional information about a risk-free investment opportunity. In addition, investors are mainly interested in excess returns because they tell more about the risk-return ratio of financial assets. $\pi_{i,t}$ is the current inflation rate. As I aim to identify the current exposure of stocks to inflation, $\pi_{i,t}$ is the main variable of interest, which goes hand in hand with the empirical approaches of other researchers in this subject area (Choudhry, 2001; Alagidede &

Panagiotidis, 2010; Ang et al. 2012). π_t^2 controls for a possible nonlinear relationship between the contemporaneous inflation and excess returns. Implementing a variable that accounts for the nonlinear relationship is motivated by the assumption that economic shocks, such as the global financial crisis (2008/2009), where inflation has more severe extremes, could affect the (excess) return-inflation relationship. Also, as previous research has found a significant relationship between lagged inflation and stock returns (Choudhry, 2001; Firth, 1979), I implement $\pi_{i,t-1}$ as an independent variable to account for a possibly lagged relationship. $LI_{i,t}$ stands for "Lerner Index" and is a proxy for the individual market power of company i in period t. $GDPG_{i,t}$ represents the GDP growth in period t in the economy where company i is mainly based. It, therefore, accounts for the explanatory power of the macroeconomic environment on excess returns. Furthermore, previous research has identified that stock returns are affected by market capitalization (Bali et al., 2016; Fama & French, 1993). I, therefore, account for the explanatory relationship of the size by adding the market capitalization, $CAP_{i,t}$, to the model. Furthermore, the literature documents that stocks with low price-earnings ratios have greater long-run returns than stocks with high ratios (Bali et al., 2016; Fama & French, 1993). Accordingly, $BTM_{i,t}$ represents the Book-to-market value of a company I in period t. It accounts for variation in excess returns driven by the value of a company i. R_{m_t} represents the market excess returns over the risk-free rate and corrects for possible market-driven trends. I choose the market excess returns for the same reason that lead to choosing the stock excess returns. Additionally, I intend to treat the variable reflecting the performance of market returns in the same way as the variable reflecting the performance of stocks.

To avoid spurious regression results from ignoring a possible trending behavior, $t_{i,t}$ accounts for the explanatory power of a time trend of a series. In addition to the trending behavior, seasonal effects are also considered. Therefore, s_i is a vector containing seasonal dummy variables in monthly terms. The seasonality dummy trap is taken care of by including one seasonal dummy variable less than the total amount of seasons considered. Finally, u_t is the error term accounting for the variation in $R_{i,t}$ not explained by the endogenous variables.

As I make several assumptions in this model, these assumptions need to be justified to avoid spurious regression results. First, I test for stationarity and fix potential unit root problems. Then I test for autocorrelation and heteroskedasticity. Note that I test for autocorrelation and heterogeneity for each stock separately. Accordingly, I calculate the average significance of the two tests for all stocks to decide whether the model needs to be adjusted. Here it must be noted that I aim to keep the regression model and thus the treatment identical across all stocks. Next, I test for the joint significance of seasonal effects. I exclude seasonal effects from the model if these effects are statistically insignificant,. Subsequently, I elicit the final model by testing the coefficients of the variables in Equation 1 for statistical significance in different frameworks. In each framework, I analyze the coefficients after dropping explanatory variables. Hence I test for the hypothesis in Equations 2 and 3 in each framework. After formulating the final regression model, I test it for multicollinearity of the explanatory variables. I then proceed with the final model to the second step of the empirical analysis.

Equation 2

$$H_0: \beta_0, \dots, \beta_n = 0$$

Equation 3

$$H_1: \beta_0, \dots, \beta_n \neq 0$$

In Equations 2 and 3, subscript n represents each framework's total number of endogenous variables. Conducting the analysis, I work out whether inflation significantly affects stock returns. Simultaneously, by analyzing the significance of the market power coefficients, I investigate whether market power affects stocks' excess returns in light of inflation.

3.1.2. Portfolio creation

In the second step, I consider two different scenarios. In each scenario, I sort the equities based on the relationship between inflation and the stock returns. In scenario one, similar to the approach done by Bampinas and Panagiotidis (2016), I sort for the value of the inflation coefficient for each stock under the condition that the returns show significant cointegration with the inflation rate. This procedure is motivated by the fact that significant cointegration signals a long-term relationship between inflation and stock returns. In the second scenario, I sort for the ability of individual stocks to hedge against the current inflation. Thus, in this case, I assume the significance of the regression coefficient to be negligible. In contrast, in scenario two, I consider solely inflation betas that are statistically significant to the 10% level from running a regression on Equation 1. Hence, I aim to create portfolios with significant exposure to inflation.

In scenario one, I sort from highest inflation beta to lowest beta. In scenario two, I sort from the lowest difference of the stocks' inflation beta to 1 to the highest difference between the inflation beta and 1. The top quintile of each scenario represents the portfolio that is assumed to have a high ability to hedge against inflation. The bottom quintile is the portfolio assumed to have the lowest ability to hedge against inflation.

After creating the portfolios, I compare the portfolio variance, the average return, the arithmetic average return, and the Sharp ratio within each scenario. Also, in each scenario, I subtract the monthly returns of the low hedge ability portfolio from the returns of the high hedge ability portfolio.

Having calculated the difference in the returns, I investigate whether this difference has explanatory power in the asset pricing environment as an inflation risk factor. Therefore, similar to the Fama-French-

Model (Fama & French, 1993), I create a linear time series regression model for each scenario, including an additional Momentum factor. There, the difference in returns of the portfolios in each scenario is an additional independent variable reflecting a potential inflation risk factor. Consequently, the considered model is the following:

Equation 4

$$R_{M,t} = \beta_0 + \beta_1 * I_t + \beta_2 * R_t + \beta_3 * SMB_t + \beta_4 * HML_t + \beta_5 * MOM_t + \varepsilon_t$$

As in the previous model, stated in Equation 1, one period (t) equals one month. $R_{M,t}$ represents the excess returns of a diversified portfolio which is assumed to be affected by the inflation risk factor I_t. In line with the Fama-French-Model (Fama & French, 1993), R_t, SMB_t, and HML_t represent the market excess returns, the size factor Small-minus-Big and the value factor High-minus-Low. Additionally, I implement MOM_t as the Momentum factor in line with recent literature (Ang et al., 2012; Bampinas & Panagiotidis, 2016). ε_t is the error term and accounts for the variation in $R_{M,t}$ that is not explained by the other right-hand side variables.

I modify my data using Microsoft Excel and Python. Also, I use Python as my statistical tool in the empirical analysis. Furthermore, it must be mentioned that, for simplicity reasons, I create portfolios in which each asset has the same weight.

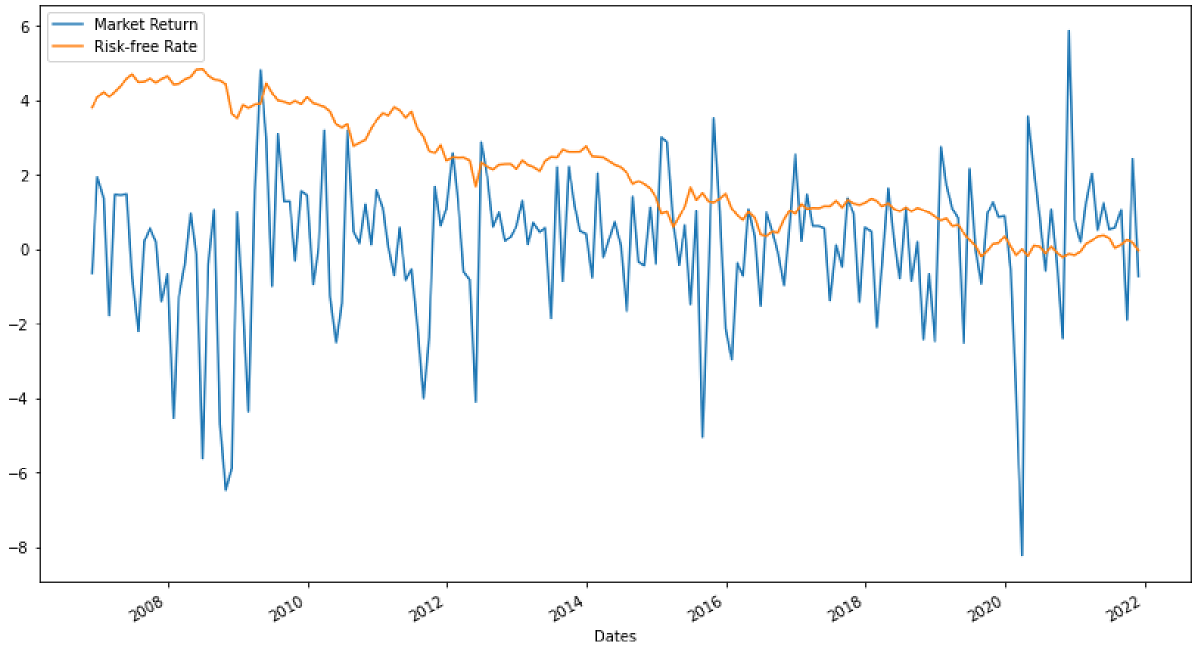
3.2. Data Collection and Description

Following the aforementioned empirical strategy, I gather company and market-related data from FactSet for the past 15 years, from December 1st, 2006, to December 1st, 2021. The decision to pick this period is motivated by two things. First, this period contains two crises, the global financial crisis, and the corona crisis. Both impacted the inflation rates. Investigating a dataset that includes multiple inflation shocks could identify an interesting relationship. Second, existing research lacks an analysis of the contemporaneous relationship between inflation and stock returns. In line with the existing literature, I gather monthly data, which is motivated by the fact that several variables used in the empirical analysis are only available monthly or quarterly. The total time considered in the analysis, therefore, covers 181 periods.

As this study focuses on the European area, the Stoxx Europe 600 is the proxy for the European market. Consequently, the sample consists of the 600 companies listed in the Stoxx Europe 600 (as of February 2022). Due to that, the analysis focuses on the 16 European countries in the Stoxx Europe 600 (Germany, United Kingdom, Italy, Denmark, France, Netherlands, Belgium, Poland, Sweden, Norway, Ireland, Austria, Switzerland, Spain, Portugal, and Finland). I gather monthly stock prices with dividends excluded at the beginning of each month. Also, in line with the standard academic finance research, I use asset prices to calculate continuously compounded returns, i.e., logarithmic returns, instead of simple returns. For that, I use the formula as stated in the Appendix. Subtracting the risk-free monthly rate (in percent) from the monthly logarithmic returns leaves the individual stock and market excess returns in percent. I use the yield on the German 30-year Treasury bond as the risk-free rate, which is considered one of the safes investment opportunities in Europe.

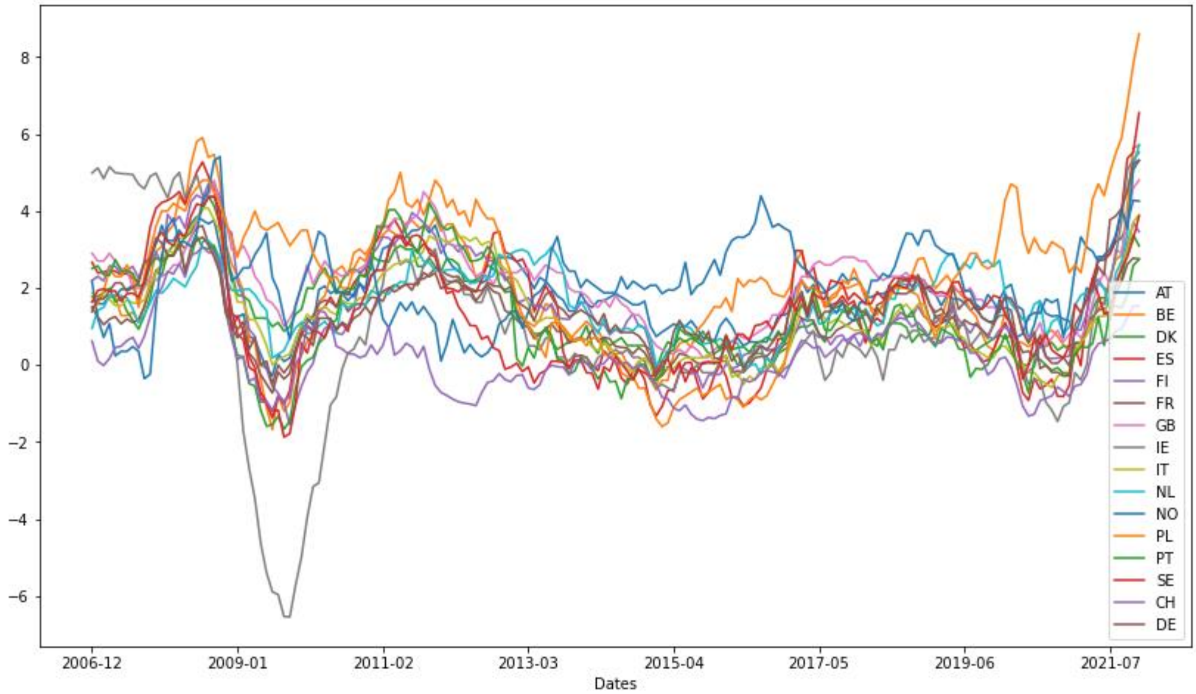
Figure 1 displays the logarithmic returns of the Stoxx Europe 600 and the risk-free rate in the period considered. The percentage returns are on the Y-axis, and time is on the X-axis. It is observable that the returns do not exceed -8% on their bottom end and 6% on their top end. Furthermore, one can observe the negative effects of the global Financial and Corona crises in 2009 and 2020, respectively.

Figure 1: Logarithmic market returns & risk-free rate



In line with previous research (Sharma, 2011), I imitate a company's market power by estimating the Lerner Index for each company in every period. As seen in the formula in the Appendix, the Lerner Index can never be higher than 1. While a value of 1 describes a monopolistic market environment, a value of 0 indicates a fully competitive market. A negative value indicates negative profitability and a possible exit from the market. The required data for Profit margin, Cost of Goods Sold (COGS), and Sales and General & Administrative expenses (SG&A) are the actual monthly data points in millions. Since these variables are not available monthly, their values are kept constant until the new data for the next quarter are available. However, since it can be assumed that market power will not change substantially in the short term, it can be assumed that the lack of data availability in the short term will not cause any problems in interpreting the final results. Market capitalization is calculated by multiplying the share price by the number of shares outstanding in each period and is stated in millions. The book-to-market ratio is calculated by dividing a given period's book value by the period's market value. Thus, the unit of the book to market ratio is in percent. I equate the book value with the value of the common equity as provided by FactSet. The data used to quantify inflation is the official data on the annual Consumer price growth index (CPI) in percent, provided through the official OECD online Databank. Consistent with the countries included in the sample, I collect inflation data for each country individually. The country-specific inflation data, considered in the empirical analysis, is visualized in Figure 2. The vertical axis measures the monthly inflation rate in percent, whereas the horizontal axis indicates the time dimension in months. In early 2009 a sharp decline in inflation associated with the global Financial crisis is observable. Furthermore, in 2020 one can observe the steady inflation rate increase during the Corona crisis.

Figure 2: Inflation rate per country considered



GDP growth of each country's economies is a factor that reflects the economic environment for each company of interest. Again, I use the official data found on the OECD website. Since GDP growth data are only available in quarterly periods, I assume, as with the Lerner Index, that GDP growth is constant for the three months of each quarter.

Finally, considering equation 4, I obtain monthly data for the Size factor, the Value factor, and the Momentum factor from the data library of the official Kenneth R. French Internet site (*Kenneth R. French - Data Library*, n.d.). The data for the European market extracted from French's database is based on monthly data points. The data provided for the three factors in Equation 4 considers all countries included in the rest of the Dataset. I use the Vanguard Ftse Europe ETFs' as my proxy portfolio. The choice of this portfolio is motivated by the fact that it has more holdings (a total of 1334) than the proxy market portfolio (Stoxx Europe 600). Therefore, the Ftse Europe ETF is broader and more diversified, thus, a good representation of an investor's portfolio. I gather monthly price data at the beginning of each month from the FactSet Databank and calculate the logarithmic returns given the formula in the Appendix. Subtracting the risk-free rate returns the excess returns. For the market excess returns in Equation 4, I use the excess returns from the Stoxx Europe 600 used earlier.

I use local currencies for all calculations and data points to avoid errors due to exchange rate fluctuations. More detailed information on the data extracted from the FactSet database for company-related information is provided in the Appendix. Furthermore, I address potential issues arising from a lack of data availability for a given company in the following ways. If less than four consecutive periods are missing, I assume a linear trend until the next available data point. If data is missing for more than three consecutive periods, I exclude the company from my analysis. Also, if more than 10 data points of a variable per company are missing, I exclude the company from my sample. After correcting the missing data, a sample of 287 out of 600 stocks remains.

4. Results & Interpretation

4.1. Hedge Ability

In this section, I conduct my empirical analysis as announced in the previous section. However, before running the regression based on Equation 1, one must execute multiple robustness checks and adapt the final model adequately. Furthermore, the assumption of stationarity and weak dependence must hold for the model to compute consistent estimators. Consequently, I test for a unit root in all variables considered in Equation 1. In order to do so, I execute an augmented Dickey-Fuller test on each of the explanatory variables in Equation 1. There, I allow for a maximum of 2 lags. The average p-values from testing for unit roots across the whole sample can be found in Table 1, respectively. I reject the H_0-hypothesis of a unit root if the average p-value is smaller or equal to 0.05.

Table 1: Unit root test results

	Min p-value	Max p-value	Average p-value	Median p-value
R_i	0***	0***	0***	0***
π_t	0.047*	0.991	0.549	0.647
π_t^2	0.002**	1	0.426	0.33
π_{t-1}	0.042*	0.984	0.556	0.701
LI	0***	0.99	0.255	0.112
$GDPG$	0***	0***	0***	0***
CAP	0.001**	1	0.554	0.570
BTM	0***	0.98	0.266	0.180
R_{m_t}	0***	0***	0***	0***

(Significant to 5% level; ** Significant to 1 % level; *** Significant to 0.1% level)*

For stocks' excess returns, GDP growth, and the market excess returns, I find an average p-value and a maximum p-value of 0. Consequently, I reject the H_0-hypothesis of a unit root and assume stationarity and weak dependency. However, the test results for the Lerner Index, the market capitalization, and the Book-to-Market ratio do not allow for a rejection of the H_0-hypothesis. Therefore, LI, CAP, and BTM have a unit root/are I(1) and do not fulfill the model's assumptions. This issue is taken care of by taking the first difference of the variables that contain are I(1).

Similarly, the variables accounting for inflation all have an average p-value more prominent than 0.05. Consequently, I accept the H_0-Hypothesis of a unit root in the three inflation variables. As the current inflation is the primary variable of interest, taking the first difference would affect the interpretation of the final results. Therefore, an error correction model would be more beneficial. However, to use an error correction model, both the dependent and independent variables must be I(1). According to Table 1, the excess returns as the dependent variable do not contain a unit root. Therefore, I cannot use an error correction model that leverages the possible cointegration for a possible long-run relationship between the excess returns and inflation. Thus, as in the case of the other variables that are I(1), I take the first difference of the inflation variables. Therefore, my primary variable of interest is now the change in the inflation rate. Figure 7 in the Appendix graphs the change of the current inflation rate across the period considered. In line with the changes stated, the updated model in Equation 5 now contains the changes in values for each variable that is proven to be I(1).

Equation 5: Model after correcting for unit roots

$$R_{i,t} = \beta_0 + \beta_1 * \Delta\pi_{i,t} + \beta_2 * \Delta\pi_{i,t-1} + \beta_3 * \Delta\pi_{i,t-1}^2 + \beta_4 * \Delta LI_{i,t} + \beta_5 * GDPG_{i,t} + \beta_6 * \Delta CAP_{i,t} + \beta_7 * \Delta BTM_{i,t} + \beta_8 * R_{m_t} + \beta_9 * t_{i,t} + \beta_{10} * s_i + u_t$$

Table 2: Unit root test results after taking the first difference

	Min p-value	Max p-value	Average p-value	Median p-value
R_i	0***	0***	0***	0***
π_t	0***	0.004**	0***	0***
π_t^2	0***	0.003**	0***	0***
π_{t-1}	0***	0.004**	0***	0***
LI	0***	0.061	0.001**	0***
$GDPG$	0***	0***	0***	0***
CAP	0***	0.001**	0***	0***
BTM	0***	0***	0***	0***
R_{m_t}	0***	0***	0***	0***

(Significant to 5% level; ** Significant to 1 % level; *** Significant to 0.1% level)*

Table 2 summarizes the p-values from testing for unit roots in the model stated in Equation 5. The maximum p-value for all variables does not exceed the significance level of 10%. Additionally, the average and median p-values do not exceed the significance level of 1%. Thus I conclude that the model no more contains variables that follow a unit root.

Besides stationarity, no serial correlation and homoscedastic standard errors are vital assumptions for reliably using confidence intervals and test statistics. Row one in Table 3 indicates the average and median p-values of a Breusch-Godfrey test for autocorrelation for Equation 5 across the entire sample. Row two displays the same results for a Breusch-Pagan test for heteroskedasticity.

Table 3: Heteroskedasticity and Autocorrelation test results

	Average p-value	Median p-value
Autocorrelation	0.25	0.12
Heteroskedasticity	0.04	0.02

I find insignificant average and median p-values when testing for autocorrelation. However, correcting for autocorrelation is necessary to get reliable test results, which is the case for about 36% of the sample. To keep the treatment identical across all instances, I correct for autocorrelation in all samples. Furthermore, correcting for autocorrelation where it is not the case still resolves reliable estimates, whereas not controlling for autocorrelation where autocorrelation is in place results in unreliable estimators. Next, I test for heteroskedasticity by conducting a Breusch-Pagan test for heteroskedasticity. I find an average p-value of 0,04 and a median p-value of 0,02 (significant to the 5% level). Therefore, I correct heteroskedasticity across all samples to ensure equal treatment. Correcting for heteroskedasticity without it in place still resolves reliable estimators, whereas this is not true in the opposite relationship. To correct for both autocorrelation and heteroskedasticity, I utilize Newey-West robust standard errors in the ongoing regression analysis, allowing for a maximum lag of 2 periods.

After correcting for autocorrelation, heteroskedasticity, and unit roots, the test statistics are now reliable. Thus, I test whether the seasonal factors have a significant effect on excess returns. To do so, I run an F-test in which I test for joint significance in the seasonal dummy variables. Testing for seasonality, I consider two possible scenarios. In the first scenario, I correct for possibly monthly seasonality. In the second scenario, I create quarterly dummy variables that account for possible quarterly seasonal effects, as I use data that is solely available on quarterly terms. The resulting average and median p-values of testing for joint significance across all samples are displayed in Table 4.

Table 4: Seasonality F-test results

	Average p-value	Median p-value
Monthly	0.25	0.16
Quarterly	0.3	0.2

Scenario one has an average p-value of 0.25 and a Median p-value of 0.16. I reject the H_0-Hypothesis of insignificance if the average p-value is smaller or equal to 0.05. Thus, a monthly seasonal effect is insignificant, and I drop monthly seasonal factors for the whole sample. Scenario two resolves test results with average and median p-values of 0.3 and 0.2, respectively. Hence, I drop the quarterly seasonal effects from the model used across all samples. After dropping the seasonality factors, the updated model equals Equation 6.

Equation 6: Model after dropping seasonal factors

$$R_{i,t} = \beta_0 + \beta_1 * \Delta\pi_{i,t} + +\beta_2 * \Delta\pi_{i,t}^2 + \beta_3 * \Delta\pi_{i,t-1} + \beta_4 * \Delta LI_{i,t} + \beta_5 * GDPG_{i,t} + \beta_6 * \Delta CAP_{i,t} + \beta_7 * \Delta BTM_{i,t} + \beta_8 * R_{m_t} + \beta_9 * t_{i,t} + u_t$$

Equation 6 leaves me with eight economic explanatory variables and one variable accounting for a possible trending behavior in the time series considered. To investigate the significance of each variable of interest, I study the mean coefficient results considering the regressions of 287 stocks. Again, I utilize mean results as I aim to run identical regressions across all equities and, thus, resolve comparable results. Finally, based on the mean regression coefficients analysis, I deduct the final model used in the ongoing research. The results can be found in Table 5. Each column shows the average regression coefficients and their average p-values across all stocks of interest in a specific regression framework (I-VI). In all frameworks, the dependent variables are stocks' excess returns, while the independent variables change.

Table 5: Framework coefficients (in averages)

Coefficients(Eq. 6)	I	II	III	IV	V	VI
Avg. Adj. R^2	0.89	0.89	0.89	0.89	0.89	0.89
$Intercept$	-3.34 (0.03)**	-3.33 (0.02)**	-3.33 (0.03)**	-3.32 (0.02)**	-3.33 (0.02)**	-3.33 (0.03)**
$\Delta\pi_{i,t}$	-0.22 (0.47)	-0.1 (0.49)	-0.21 (0.47)	-0.13 (0.48)	-0.15 (0.46)	-0.15 (0.46)
$\Delta\pi_{i,t}^2$	0.03 (0.42)	- -	0.02 (0.42)	- -	- -	- -
$\Delta\pi_{i,t-1}$	-0.19 (0.45)	-0.19 (0.43)	- -	- -	- -	- -
$\Delta LI_{i,t}$	2.92 (0.4)	2.85 (0.4)	2.78 (0.41)	2.7 (0.41)	2.64 (0.41)	- -
$GDPG_{i,t}$	-0.01 (0.48)	-0.02 (0.46)	-0.02 (0.45)	-0.02 (0.43)	- -	- -
$\Delta CAP_{i,t}$	0.004 (0.00)***	0.004 (0.00)***	0.004 (0.00)***	0.004 (0.00)***	0.004 (0.00)***	0.004 (0.00)***
$\Delta BTM_{i,t}$	-36.03 (0.03)**	-36.15 (0.03)**	-36.11 (0.03)**	-36.21 (0.03)**	-36.17 (0.03)**	-35.66 (0.03)**
R_{m_t}	0.24 (0.03)**	0.24 (0.03)**	0.24 (0.03)**	0.24 (0.03)**	0.24 (0.03)**	0.25 (0.02)**
$t_{i,t}$	0.02 (0.03)**	0.02 (0.03)**	0.02 (0.03)**	0.02 (0.03)**	0.02 (0.03)**	0.02 (0.03)**

(= Significant to the 5% level ; ** = Significant to the 1 % level ; *** = Significant to the 0.1% level)*

In Table 5, it is observable that across all frameworks considered, the coefficients of the intercept, $\Delta CAP_{i,t}$, $\Delta BTM_{i,t}$, R_{m_t}, and $t_{i,t}$ all resolve highly significant results. Furthermore, all variables mentioned above indicate constant average coefficients across all frameworks. Inspecting them individually, framework I contains the average results from running the regression model as stated in Equation 6. There, $\Delta\pi_{i,t}$ has no significant effect on the stock returns. I also fail to find significant evidence for $\Delta\pi_{i,t}^2$ and $\Delta\pi_{i,t-1}$. While $\Delta\pi_{i,t}^2$ indicates a positive average relationship across the sample, $\Delta\pi_{i,t}$ and $\Delta\pi_{i,t-1}$ suggest a negative mean relationship with excess returns. Also, testing for joint significance in the inflation variables and $\Delta LI_{i,t}$, an average p-value of 0.33 suggests accepting the H0-hypothesis of no significant combined effect. In framework II, I again, on average, find insignificant results for a negative relationship between $\Delta\pi_{i,t}$ and $\Delta\pi_{i,t-1}$, and a positive relationship. Furthermore, an increase in the $\Delta\pi_{i,t}$ variable is noticeable. Also, testing for joint significance of the inflation variables and $\Delta LI_{i,t}$ in framework II suggests no average significant combined effect of inflation and market power (p-value of 0.37). In framework III, I drop $\Delta\pi_{i,t-1}$ from Equation 6. Similar to the previous frameworks, the results for the remaining inflation variables and the test for joint significance (p-value of 0.35) indicate statistically insignificant results, on average. Again, dropping $\Delta\pi_{i,t-1}$ and $\pi_{i,t}^2$ in framework IV, increases the $\Delta\pi_{i,t}$ coefficient. No significant joint effect of inflation and market power can be found (p-value of 0.39). I drop $GDPG_{i,t}$ as an explanatory variable in framework V as its coefficient stays constant and insignificant, on average. Dropping $GDPG_{i,t}$ has a negligible average effect on the significance level and coefficients of the other variables in framework V with the joint effect of inflation and market power being statistically insignificant with a p-value of 0.39. Similarly, $\Delta LI_{i,t}$ does not suggest a statistically significant relationship with excess returns. After dropping $\Delta LI_{i,t}$ in framework VI, only $\Delta BTM_{i,t}$ appears to be positively affected, while the inflation variable remains constant. Therefore, on average, market power does not affect inflation and stock excess returns. Furthermore, the average adjusted R^2, and thus the explanatory power, does not seem to be affected across all frameworks as it stays at a constant and high level of 0.89. Therefore, I conclude that, on average, $\Delta\pi_{i,t}^2$, $\Delta\pi_{i,t-1}$, and $\Delta LI_{i,t}$ have a statistically insignificant effect on excess returns, individually and jointly. Also, $GDPG_{i,t}$ does not prove an average significant effect on excess returns. Therefore, I exclude $\Delta\pi_{i,t}^2$, $\Delta\pi_{i,t-1}$, $\Delta LI_{i,t}$, and $GDPG_{i,t}$ from my model. As a result, I formulate my final model used for the ongoing analysis as stated in Equation 7.

Equation 7: Final model

$$R_{i,t} = \beta_0 + \beta_1 * \Delta\pi_{i,t} + \beta_2 * \Delta CAP_{i,t} + \beta_3 * \Delta BTM_{i,t} + \beta_4 * R_{m_t} + \beta_5 * t_{i,t} + u_t$$

Finally, I test whether the assumption of no multicollinearity of the endogenous variables holds across all variables. Specifically, I calculate the Mean-Variance Inflation Factor (VIF) for each explanatory variable in the final model. The outcomings are displayed in Table 6. Given the common interpretation of the VIF, I assume multicollinearity to be in place if the average VIF factor is above 5.

Table 6: Mean-Variance Inflation Factor (Final Model)

	$\Delta\pi_t$	ΔCAP	ΔBTM	R_m	t
Mean VIF	1.87	1.82	2.42	1.91	12.34

According to Table 6, it is observable that, besides the trend variable, each variable used in the final model is below the threshold of 5. Moreover, as the trend variable is a categorical variable accounting for a possible trend in the other explanatory variables, the raised average VIF factor is negligible. Therefore, assuming the explanatory variables are contemporaneously exogenous, the estimators are consistent and asymptotically normally distributed. Thus OLS standard errors and test statistics are asymptotically valid.

Now that I have derived my final model, the following general relationship between inflation and excess returns can be concluded. Given the results from model VI in Table 5, I find an average negative relationship between the change in inflation and excess returns. The average inflation coefficient is -0.15, which is statistically insignificant with an average p-value of 0.46. Furthermore, the intercept and the trend identify significant (to 1%) average positive regression coefficients of -3.33 and 0.02. Moreover, a significant effect of R_m, ΔBTM, and ΔCAP on stocks' excess returns is observable. The corresponding regression coefficients and p-values are 0.25 and 0.02 for R_m, -35.66 and 0.03 for ΔBTM, and 0.004 and 0.000 for ΔCAP, respectively.

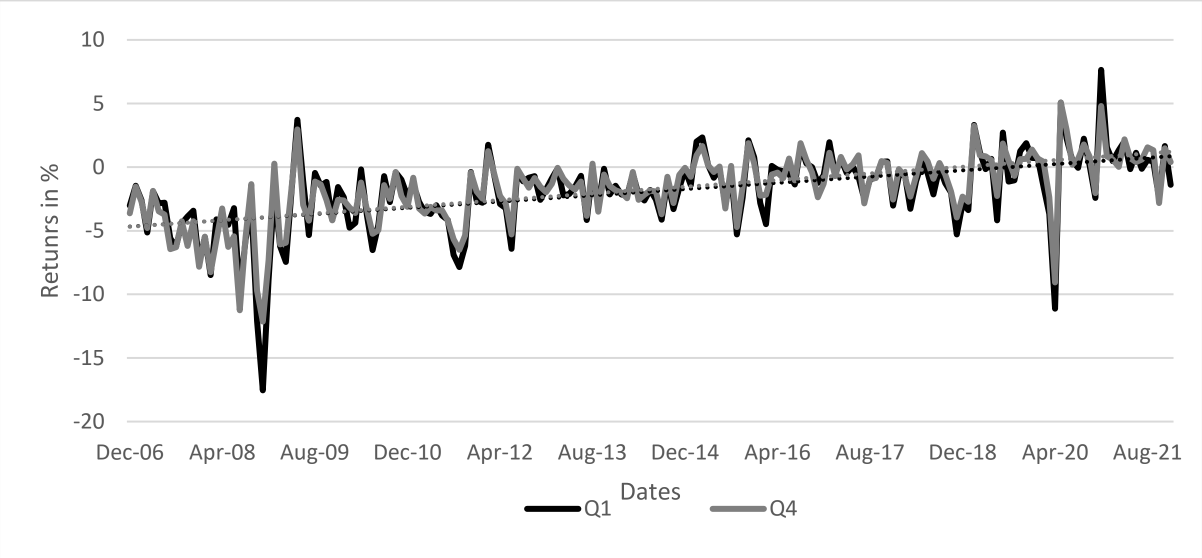
An investigation of the $\Delta\pi_t$-coefficient of the individual stocks provides more profound insights into stocks' individual ability to hedge against inflation. First, I find inflation coefficients between 1.5 and -1.95, of which more than one quarter (32%) indicate a positive relationship. Second, inspecting the statistically significant $\Delta\pi_t$-coefficients in Table 12 (see Appendix), one can observe that only 52 out of the 287 equities considered are significant. They range from 1.1 to -1.4, of which only 2 have a significant positive relationship. Third, Table 13 in the Appendix displays those stocks whose $\Delta\pi_t$-coefficients cannot be proven different from 1. In sum, 32 out of 287 stocks cannot be rejected as a perfect hedge.

4.2. Scenario 1: Portfolio based on long-term relationship

Consistent with the empirical approach announced in Section 3, I create a portfolio consisting of the stocks that exhibit cointegration with lagged inflation at a 5% significance level. Testing for cointegration, I find that the returns of all stocks in the sample are significantly cointegrated with the current inflation in their macroeconomic environment. Therefore, I sort all stocks by their inflation beta, calculated by running the regression based on Equation 7. The portfolios are formed accordingly. Q1 represents the portfolio created by combining the stocks from the top quintile and solely contains stocks with a positive inflation beta. Q4 represents the portfolio with stocks from the bottom quintile and solely consists of negative inflation beta stocks. The two portfolios consist of 71 stocks with equal weights. Furthermore, Q1 and Q4 have an average market beta of 0.3 and 0.25, respectively.

Figure 3 shows the returns of the two artificially created portfolios. The X-axis describes the temporal horizon, given in periods of the time series considered. The Y-axis defines the percentage return of the beta portfolios. While the black line represents the portfolio's data consisting of stocks with a positive inflation beta, the gray line represents the portfolio consisting of the equities with a negative inflation beta.

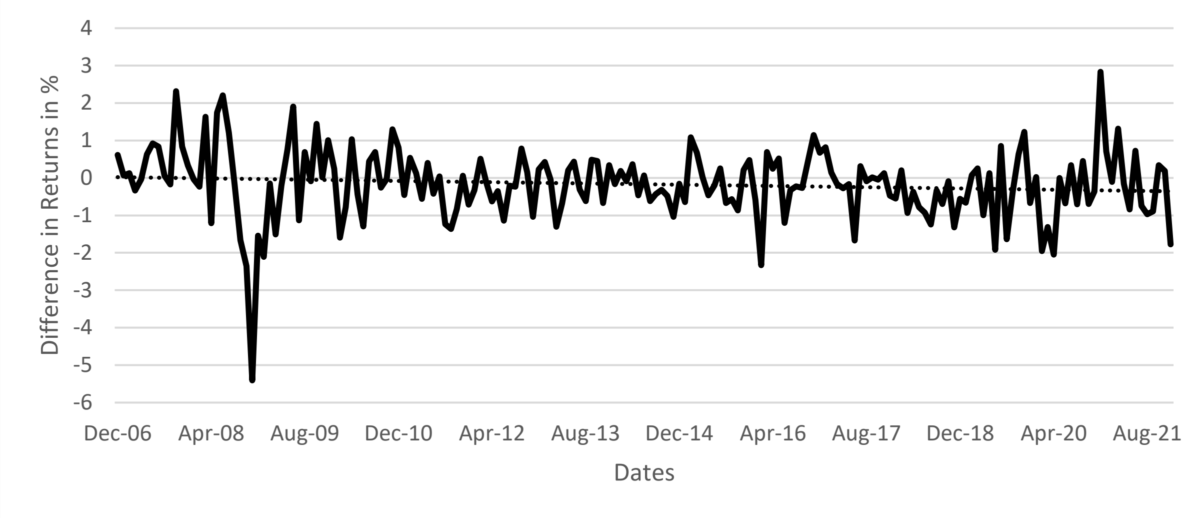
Figure 3: Portfolio performance Scenario 1



At first glance, one can see that both portfolios show an upward trend. In addition, Q1, especially between April 2008 and August 2009, and early 2020 and 2021, shows significantly larger extreme values, suggesting higher volatility of the returns of the high-beta portfolio. These periods are the times of the global Financial crisis and the Corona crisis. Also, it is notable that the returns of both portfolios are very similar, despite varying degrees of fluctuation. Compared to the market portfolio in Figure 1, both artificially created portfolios suggest more severe extremes.

Having studied the portfolio returns graphically, Figure 4 shows the difference in the performance of portfolio returns. The data shown in the graph are the returns of Q4 subtracted from the returns of Q1. On the one hand, the X-axis represents, as in Figure 3, the time frame periods under consideration. On the other hand, the Y-axis indicates the difference between the returns of the beta portfolios.

Figure 4: Comparing portfolio performance Scenario 1



While portfolio returns from Figure 3 indicate an upward trending behavior, the difference in returns in Figure 4 has a negative trending behavior. However, no clear pattern of outperformance achieved by one portfolio is visible, as the difference in returns varies around 0. Furthermore, while between April 2008 and August 2009, the difference has intense negative extremes, between early 2020 and 2021, the difference in returns indicates less intense and positive extremes. Therefore, Q1 performed worse in the global financial crisis, while no clear outperformance can be observed in the recent corona crisis.

Further investigating the performance of both portfolios, Table 7 summarizes the results from comparing the two portfolios in light of the market performance. The first column displays the results for Q1. The second and third columns show the findings for Q4 and an alternative market portfolio, respectively. The rows in Table 7 show the portfolio variance, the geometric average and average returns (both in %), and the Sharp Ratio for each portfolio. Moreover, the last row in Table 7 indicates the averaged difference in returns of the portfolios created, which is the average of the data displayed in Figure 4. The risk-free rate used for the calculation of the Sharp Ratio is equal to the average yield, of the time frame under analysis, on the German 30-year treasury bond (2.09%). Furthermore, I use the average portfolio return from row 3, and the portfolio's excess returns variance to calculate the Sharp Ratio (see Appendix).

Table 7: Portfolio comparison Scenario 1

	Q1	Q4	Euro Stoxx 600
σ^2	9.15	7.4	3.92
$\widetilde{r_p}$	-1.78	-1.96	0.05
$\bar{r}_p$	-1.91	-1.74	0.07
Sharp Ratio	-0.98	-0.98	-0.77
$\overline{r_{pH} - r_{pL}}$	-0.17		-

Both Q1 and Q4 have higher volatility than the market portfolio. While the former have a 9.15 and 7.4, respectively, the latter has a variance of 3.92. Therefore, the high beta portfolio has a higher variance than the low beta portfolio, confirming the observations made when comparing Figure 3 and Figure 4. Examining the geometric and average returns, I find that the artificially created portfolio returns are negative. The geometric average returns are -1.78 for the high beta portfolio and -1.96 for the low beta portfolio. In contrast, the market performs slightly above zero during the period under consideration (0.05). Also, Q4 has slightly lower average geometric returns compared to Q1. In contrast, when examining the average returns, it is noticeable that the low-beta portfolio has a slightly higher average return of -1.74 than the high-beta portfolio with an average return of -1.91. The market average returns 0.07, indicating higher returns than the artificially created portfolios. In addition, the Sharp Ratios of the portfolios are all negative. The beta portfolios identify identical sharp ratios of -0.98, which is lower than the Sharp Ratio of the market portfolio (-0.77). Looking at the difference in returns between the beta portfolios, it is observable that the returns of the low beta portfolio are, on average, 0.15% higher than those of the high beta portfolio.

Having compared the two portfolios, one can analyze the difference in inflation hedge portfolio returns as a potential inflation risk factor. Table 8 displays the regression output from running a regression on Equation 4 in Scenario 1. All variables included are I(0). Furthermore, I use Newey-West robust standard errors to account for existing autocorrelation and heteroscedasticity. Also, the variance inflation factors do not identify multicollinearity (Table 14). Therefore, assuming contemporaneous exogeneity of the explanatory variables, the estimators are consistent and asymptotically normally distributed.

Table 8: Fama-French & inflation factor; Scenario 1

OLS Regression Results

Dep. Variable:	FTSE Europe	R-squared:	0.836
Model:	OLS	Adj. R-squared:	0.831
Method:	Least Squares	F-statistic:	191.6
Date:	Sat, 25 Jun 2022	Prob (F-statistic):	5.06e-69
Time:	12:19:13	Log-Likelihood:	-298.84
No. Observations:	181	AIC:	609.7
Df Residuals:	175	BIC:	628.9
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0816	0.122	0.666	0.505	-0.158	0.321
inflation factor	0.4514	0.115	3.927	0.000	0.226	0.677
Market	1.0310	0.038	26.783	0.000	0.956	1.106
SMB	-0.0401	0.062	-0.649	0.517	-0.161	0.081
HML	0.0050	0.036	0.139	0.890	-0.065	0.075
MOM	-0.0067	0.040	-0.170	0.865	-0.085	0.071

Omnibus:	10.465	Durbin-Watson:	2.310
Prob(Omnibus):	0.005	Jarque-Bera (JB):	18.806
Skew:	-0.245	Prob(JB):	8.25e-05
Kurtosis:	4.501	Cond. No.	5.96

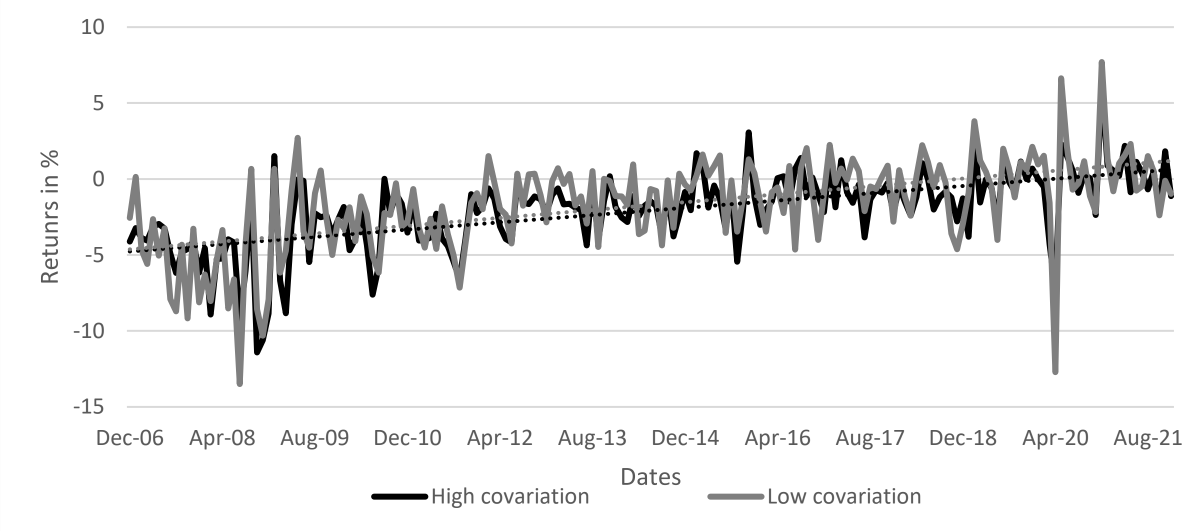
First and foremost, it is observable that the inflation factor has a positive regression coefficient of 0.45 and, therefore, positively affects the portfolios' excess returns. Moreover, the z-statistic (3.927) and the p-value (0.000) indicate a statistically significant effect. Additionally, according to the adjusted R-squared (0.831), the explanatory power of this model is notably high. Furthermore, the F-statistic indicates a highly significant joint effect with a p-value close to 0. The intercept shows statistically significant positive abnormal returns. Also, the portfolio excess returns variation with the market is positive and statistically significant. Finally, while SMB and MOM positively affect the portfolio, HML has a negative effect. However, SMB, HML, and MOM identify no statistically significant effect on the portfolio's excess returns.

4.3. Scenario 2: Covariation-based portfolio

As stated in Section 3, in Scenario 2, I create portfolios based on stocks' ability to hedge against changes in inflation. Moreover, I consider solely those stocks that identify an inflation coefficient significant to the 10% level when running a regression on Equation 7. In total, 52 stocks identify a statistically significant relationship. The high hedging ability portfolio consists of the quartile of stocks with inflation betas close to 1. Thus, it covaries close with the change in inflation. I, therefore, call this portfolio the high covariation portfolio. That makes the second portfolio the low covariation portfolio. The total holdings of each portfolio sum up to 13 stocks. The high and low covariation portfolios have an average market beta of 0.15 and 0.27, respectively.

Figure 5 displays the returns of the portfolios in the period of interest. While the horizontal axis represents the time dimension in months for the periods under consideration, the vertical axis measures the portfolio returns in percent. The black line represents the returns of the high covariation portfolio, while the line displays the returns of the low covariation portfolio.

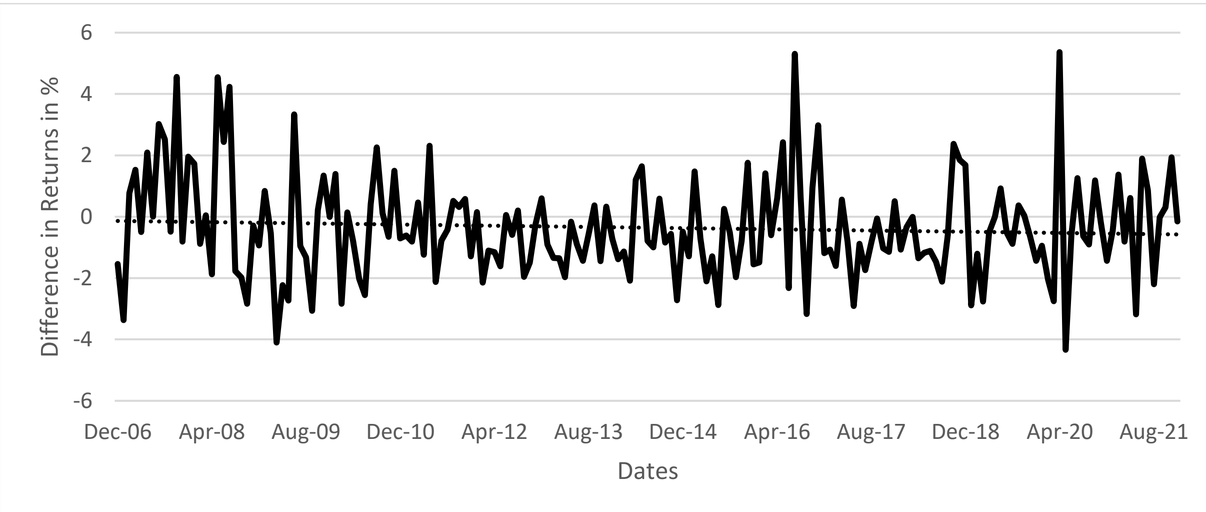
Figure 5: Portfolio performance Scenario 2



Similar to the portfolios considered in scenario 1, both portfolios in scenario 2 show increasing returns over time. In addition, one can observe that the high covariation portfolio has lower extreme values over the entire sample period, again indicating lower volatility. Also, the low covariation portfolio exhibits a steeper trend line than the high covariation portfolio. As in scenario 1, the portfolios in scenario 2 indicate extremes between April 2008 and August 2009, and 2020 and 2021 (global Financial crisis and Corona crisis, respectively). Comparing portfolio returns from Figure 5 with market returns in Figure 1, Figure 5 indicates more severe extremes during the abovementioned periods.

Another comparison of the portfolios is visible in Figure 6. There, the difference in portfolio returns is examined. The data used in Figure 6 is calculated by subtracting the returns of the low covariation portfolio from the returns of the high covariation portfolio. Therefore, as before, the X-axis describes the time dimension divided into the monthly periods of the considered period. Consequently, the y-axis also shows the difference in returns between the two portfolios.

Figure 6: Comparing portfolio performance Scenario 2



Here, the results also indicate a negative trending behavior in the difference in returns, suggesting that the returns of the high covariation portfolio increase slower than those of the low covariation portfolio. However, it is no clear outperformance done by one portfolio recognizable. Compared to Scenario 1, the difference in returns in Scenario 2 indicates no exceptional extremes in economic crises.

Having analyzed the portfolio returns graphically, Table 9 contains further results from analyzing both portfolios. Table 9 follows the logic of Table 7. The market betas are, again, calculated by running a regression on Equation 4. Again, I use Newey-West robust standard errors, and all variables are stationary.

Table 9: Portfolio comparison Scenario 2

	High covariation	Low covariation	Euro Stoxx 600
σ^2	6.6	9.46	3.92
$\widetilde{r_p}$	-2.1	-1.77	0.05
$\bar{r}_p$	-2.07	-1.72	0.07
Sharp Ratio	-1.11	-0.92	-0.77
$\overline{r_{pH} - r_{pL}}$	-0.36		-

Looking first at the portfolio variances, it is immediately apparent that the high hedge portfolio has much lower volatility of 6.6 compared to its counterpart of 9.46. However, with a value of 3.92, the market portfolio has distinctly lower variance. However, looking at the geometric average return, the high covariation portfolio has a lower value (-2.1) than its counterpart (-1.77). Both artificially created portfolios have a lower value for the geometric average returns than the market portfolio (0.05). The results for the average return show the same pattern. The Sharp ratio indicates the notably worse risk-return balance of the high hedge ability portfolio than its counterpart. While the portfolio with high covariance has a Sharp Ratio of -1.11, the low covariance portfolio has a significantly higher but still negative value of -0.92. However, the markets' Sharp Ratio of -0.77 is higher than that of both artificially created portfolios. The difference in the average return with a value of -0.35 shows that the low beta portfolio performs better on average.

Moving on to the analysis of the difference in portfolio returns in Scenario 2, the adapted Fama-French 3-Factor asset pricing model gives further insight into a possible inflation risk factor. The test results for a unit root in the explanatory variables let reject the H0-hypothesis. Thus, weak dependency and stationarity can be assumed. Also, using Newey-West standard errors, I account for existing autocorrelation and heteroscedasticity. Also, the variance inflation factors suggest no multicollinearity of the explanatory variables (Table 14). Therefore, if the explanatory variables are contemporaneously exogenous, the estimators are consistent and asymptotically normally distributed. The regression results according to Equation 4 are displayed in Table 10 below.

Table 10: Fama-French & inflation factor; Scenario 2

OLS Regression Results

Dep. Variable:	FTSE Europe	R-squared:	0.821
Model:	OLS	Adj. R-squared:	0.815
Method:	Least Squares	F-statistic:	106.5
Date:	Sat, 25 Jun 2022	Prob (F-statistic):	3.45e-51
Time:	12:31:33	Log-Likelihood:	-306.83
No. Observations:	181	AIC:	625.7
Df Residuals:	175	BIC:	644.8
Df Model:	5		
Covariance Type:	HAC		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.1199	0.146	0.819	0.413	-0.167	0.407
inflation factor	0.0517	0.063	0.825	0.409	-0.071	0.174
Market	1.0817	0.050	21.628	0.000	0.984	1.180
SMB	-0.0053	0.065	-0.082	0.934	-0.133	0.122
HML	0.0399	0.038	1.055	0.291	-0.034	0.114
MOM	0.0091	0.044	0.209	0.835	-0.077	0.095

Omnibus:	6.933	Durbin-Watson:	2.195
Prob(Omnibus):	0.031	Jarque-Bera (JB):	7.910
Skew:	-0.304	Prob(JB):	0.0192
Kurtosis:	3.824	Cond. No.	6.26

As in Scenario 1, the inflation factor positively affects the portfolios' excess returns. However, the effect is not statistically significant as the p-value is 0.409. In turn, the market excess returns significantly positively affect the dependent variable. The intercept, SMB, and MOM suggest a positive but statistically insignificant effect. The value factor (HML) indicates a negative but insignificant relationship. However, the model has a relatively high explanatory power of 0.815 and a substantially significant F-statistic with a p-value close to 0.

4.4. Interpretation

While the previous sections presented and analyzed the results, this section focuses on interpreting the results.

First, it is crucial to note that the inflation variable has changed to the first difference in inflation due to a unit root. Therefore, the interpretation of the outcome is remarkably affected. This, however, does not harm this research's relevance for investors and policymakers. Consequently, I find results that quantify the ability of stocks to hedge against inflation in a second degree. In line with that, the results indicate that stocks, on average, are negatively affected by the change in inflation. Thus, if the difference in the inflation rate is positive (inflation in two consecutive periods is increasing), holding everything else constant, stock excess returns in the European market tend to fall. The opposite ratio applies when inflation changes less. However, on average, the negative relationship is not statistically significant. This negative relationship, however, is against my expectations as I hypothesized a positive relationship between inflation and stock returns. I find a positive relationship is only the case for a minority of the stocks inspected (of which only two are statistically significant). I define the hedging ability of a stock to be perfect if the inflation beta equals 1. Therefore, for the ability to hedge against the change in inflation, the beta should be close to 1. As I cannot reject the beta to be significantly different from one for 32 stocks, one cannot argue that individual stocks cannot hedge against inflation. In summary, most stocks do not offer the possibility to hedge against inflation in a second degree by taking a long position. However, one cannot exclude that some selected stocks may allow this opportunity. Nevertheless, shorting stocks with a beta close to -1 could also provide the ability to hedge against inflation in a second degree.

The first difference in the variable accounting for market power affects the interpretation of market powers' effect on stock excess returns. After correcting for a unit root, the results reflect the relationship between the change in market power on stock excess returns. The findings suggest an average positive relationship between market power and stocks' excess returns while correcting for inflation. Therefore, if a company's market power increases/decreases, then stock excess returns increase/decrease, ceteris paribus. This positive relationship is in line with my expectations in section 2. However, on average, this relationship is not significant and, therefore, lacks statistical evidence. Furthermore, the results in Table 5 suggest that the change in market power does not affect the relationship between the change in inflation and stock excess returns. The tests for a significant joint effect of inflation and market power do not reject the H0-Hypothesis, which supports the finding that market power does not affect inflation's relationship to stock returns. However, one may explain the insignificant effect of market power differently. In the empirical analysis, the data is in monthly periods. Therefore, the monthly effect of market power on stock returns is estimated. However, one can assume that market power does not vary much within monthly periods. Thus, the insignificant effect on stock returns may be driven by choice of period size.

Under consideration of the other explanatory variables, in the regression model, it is observable that the considered stock excess returns, on average, vary positively with the market excess returns. For example, if the market excess returns increase by 1%, the stock excess returns increase by 0.25%, ceteris paribus. In addition, the excess returns vary, on average, positively with the change in market capitalization and negatively with the change in the book-to-market ratio. More specifically, if the change in market capitalization increases by 1 million, then, on average, excess returns increase by 0.004%, ceteris paribus, which is a negligibly low effect. In contrast, if everything else held constant, stock excess returns, on average, fall by about 0.36% when the book-to-market ratio increases by 1%.

Also, holding everything else constant, the significant intercept infers that the average excess returns of the stocks considered are -3.33%. Finally, the statistically significant trend variable suggests that, on average, stocks excess returns increase by 0.02% every month, ceteris paribus.

In Scenario 1, I sort for the size of a stock's inflation beta. While Q1 has mainly a positive inflation coefficient, Q4 has a negative inflation coefficient. Therefore, Q4 has an inverse inflation hedging ability. First, the findings from Figure 3 suggest portfolio returns are strongly affected by crises, more than a market portfolio, while still having a positive trend in the long term. Second, Figure 4 infers the difference in the portfolio performance to be affected by the market's well-being. Nevertheless, no portfolio outperforms the other graphically during the period considered. However, the negative trend of difference in performance and the negative average difference in returns suggest the low beta portfolios' outperformance in the future. Third, lower variance in returns and higher average returns make the low hedge ability more attractive than its counterpart. The lower variance indicates that a portfolio with a negative exposure to inflation reduces the overall volatility. Also, the negative Sharp Ratio indicates negative but equal risk-return ratios for both inflation beta portfolios. Thus, both portfolios are not attractive to investors. Therefore, investing in the market would be a dominant strategy, even though the market also has a negative risk-return relationship.

Furthermore, the significant effect of the inflation factor, in scenario 1, on portfolio excess returns can be interpreted as follows. If the inflation factor increases by 1 % (Q1 outperforms the Q4 by one percent), then the excess returns of a diversified portfolio increase by 0.45 %, ceteris paribus. Furthermore, the effect of the difference in returns cannot be caused by different market exposure in Q1 and Q4 as both identify a similar and low market exposure (0.3 and 0.25, respectively). Furthermore, one can infer that the diversified portfolio has a positive long-run inflation exposure of 45%, which is relevant additional information for quantifying a portfolio's inflation risk. Therefore investors would be willing to pay more for a portfolio with a higher inflation risk factor, as a higher factor results in higher excess returns.

Sorting the stocks for the statistically significant co-movements with the change in inflation, it is notable that the size of the portfolios is notably smaller than those of the portfolios in Scenario 1. Thus, there are fewer stocks that are significantly affected by the change in inflation than there are stocks that have a significant long-term relationship with the inflation rate. Second, Figure 5 suggests that the portfolios are more affected by crises than the market and less than the portfolios in scenario 1. Third, interpreting the findings in Figure 6, it can be inferred that the portfolios in scenario 1 do not comove closely together, even in a crisis. However, this could be since mainly negative significant inflation betas could be found, and thus both portfolios have a mainly a negative inflation exposure. Also, the negative trend suggests a possible outperformance of the low covariance portfolio in the future. Fourth, The portfolio that varies closely to the change in inflation has a notably lower variance in its returns than its counterpart. However, it must not necessarily be the case that the lower variance is due to the inflation exposure, as both portfolios mostly contain stocks with negative inflation exposure. Due to the lack of diversification in both portfolios, the lower variance could also be driven by individual stock performance. However, considering the average returns, Sharp Ratios, and average difference in returns, the low covariance portfolio is the more attractive option overall. Nevertheless, both artificially created portfolios in Scenario 2 are worse than the market portfolio. Also, this underperformance, however, could be due to a lack of diversification in the hedge ability portfolios.

While having identified a significant effect of the inflation factor in scenario 1, scenario 2 does not identify significant results. Therefore, the difference in returns of portfolios based on a statistically significant relationship with the change in inflation has no explanatory power for the excess returns of a diversified portfolio. Therefore, it does not explain part of the variation of a diversified portfolio.

5. Discussion and Conclusion

5.1. Discussion

In investigating stocks' exposure to inflation, the approach of running a time series regression model is common in the existing literature. About one-third of the sample identifies positive and two-thirds negative exposure, which is in line with Ang et al. (2012) and Bampinas and Panagiotidis (2016). However, the coefficients' size differs significantly from the existing literature. While I find coefficients between 1.5 and -1.95, Ang et al. (2012) and Bampinas and Panagiotidis (2016) find inflation betas above 10. This difference, however, could be because this research's betas represent the exposure to the change in inflation while Ang et al. (2012) and Bampinas and Panagiotidis (2016) investigate the exposure to the inflation rate. Comparing the cointegration-based portfolios resolves slightly different results to the existing literature (Bampinas & Panagiotidis, 2016), as I find similar risk-return ratios of both portfolios and a dominant market portfolio investing strategy. Bampinas and Panagiotidis (2016) find that the inflation beta portfolios outperform the market portfolio while the high inflation beta portfolio is superior to its counterpart. Comparing stocks based on their covariation agrees with previous research findings (Ang et al., 2012) that higher covariation portfolios have a lower variance. In contrast to the existing literature (Ang et al., 2012), I find lower average returns for the high covariance portfolio. However, in the portfolio creation, Ang et al. (2012) include stocks that do not identify a statistically significant relationship. Also, a difference in the comparison results could arise because they investigate the exposure to inflation, not to the inflation change. Furthermore, it has to be said that this research investigates stocks' inflation exposure relative to micro-and macroeconomic factors, which is usually not the case in the standard literature (Alagidede & Panagiotidis, 2010; Ang et al., 2012; Bampinas & Panagiotidis, 2016; Li et al., 2010), as they aim to test directly for the Fisher hypothesis. Lastly, inspecting a potential inflation risk factor in the asset pricing environment, a statistically significant positive exposure to inflation risk of a diversified portfolio is discovered. This finding is within the range of from Sato et al. (2011) findings as they find positive and negative inflation betas considering the Fama-French 3 Factor model.

Since this research work can only cover a tiny part of this subject area, further questions and logical follow-up issues cannot be addressed. However, I want to mention these now to present research suggestions to other academics. On the one hand, I create portfolios whose shares are equally weighted. An additional extension of this approach would be, creating two portfolios weighing their holdings so that the inflation beta equals one and minus one. Therefore, the performance of one perfectly hedging portfolio and one imperfect hedging portfolio can be compared. On the other hand, it would be possible to create portfolios of stocks whose inflation coefficient is not significantly different from 1 or -1. Thus, a portfolio with high hedging ability and a portfolio with low hedging ability is formed. Third, I investigate whether market power affects stock returns in combination with inflation. However, a more in-depth analysis of whether market power affects the ability of stocks to protect against inflation would be an academically relevant extension. For example, stocks could be sorted by their market power. After that, testing, if stocks with higher market power have higher inflation betas than those with lower market power could give interesting insights.

Some weaknesses and limitations of this research can be summarized as follows. Firstly, due to data limitations, the sample of 287 shares is relatively small and could be expanded by selecting a more extensive selection. Analyzing a more extensive sample could provide more precise estimators. Second, the choice of the period studied could distort the actual relationship between inflation and stock returns, as two crises are included in the period studied. These economic shocks could bias the regression outcomes. Third, I exclude a trend variable from the asset pricing regression models to maintain consistency in applying the Fama-French model. However, this may affect the validity and reliability of the estimators. Finally, in the empirical strategy, I assume the contemporaneous exogeneity of the regressors. Even though this assumption is reasonable, estimators are not valid if the assumption does not hold.

5.2. Conclusion

This study attempts to answer whether equities in the European market can serve as a hedge against inflation. While, for statistical reasons, this question cannot be answered concerning hedging against inflation, the results answer the question about hedging against the change in inflation. The results show that selected stocks can hedge against inflation due to a positive exposure. However, it should be noted that a large proportion of the stocks examined have negative exposure to the change in inflation. Furthermore, to answer the question of whether individual market power impacts stock excess returns when considering exposure to the change in inflation, the results indicate no relationship between market power and stock excess returns.

The empirical analysis results also answer whether portfolios with different hedging capabilities perform differently against the change in inflation. Defining hedging ability based on the size of the inflation coefficient of stocks with long-term exposure to inflation, the portfolio with an inverse hedging ability is preferred over the high hedge ability portfolio. However, the risk-return ratio between the two portfolios is the same. If the covariation with the change in inflation defines hedging ability, a low hedging ability portfolio is preferred over its counterpart. In both cases, however, an investment in a regular market portfolio is more profitable.

Finally, this paper also answers whether investors would pay a different price for portfolios based on an inflation risk factor in the Fama-French 3-factor model. The results suggest a positive and statistically significant coefficient if the inflation risk factor is the difference in portfolio returns based on the inflation exposure and the long-run relationship between inflation and stock returns. Thus, investors would be willing to pay more for a portfolio like this that is positively exposed to inflation risk.

With the identification of the hedging opportunity of equities and the discovery of an inflation risk factor in the asset pricing environment, investors can adjust their investment decisions to their inflation hedging desires. In addition, regulatory institutions can use the findings to revise their inflation stabilization targets.

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II. Appendix

II.I. Results

Table 11: Variance of portfolio excess returns

Scenario 1		Scenario 2		Market
Q1	Q4	High covariation	Low covariation	
16.72	15.3	13.96	17.31	6.88

Table 12: Statistically significant inflation betas

	index	Industry	betas	p-values
High hedge ability portfolio	MT-NL	METAL PRODUCERS	1.123276	0.004017
	RNO-FR	AUTOMOTIVE	0.546184	0.09839
	ORK-NO	FOOD	-0.15689	0.099006
	UCB-BE	DRUGS, COSMETICS & HEALTH CARE	-0.27895	0.039747
	FORTUM-F	UTILITIES	-0.28368	0.038146
	BP-GB	OIL, GAS, COAL & RELATED SERVICES	-0.30119	0.06501
	ABF-GB	BEVERAGES	-0.30617	0.091548
	ELE-ES	UTILITIES	-0.31093	0.042329
	UU-GB	UTILITIES	-0.31613	0.096373
	TATE-GB	CHEMICALS	-0.33101	0.090983
	SBRY-GB	RETAILERS	-0.33261	0.073993
	ASSA.B-SE	CONSTRUCTION	-0.35219	0.095078
	GSK-GB	DRUGS, COSMETICS & HEALTH CARE	-0.36321	0.035507
	KGF-GB	CONSTRUCTION	-0.38112	0.045974
	RCO-FR	BEVERAGES	-0.39021	0.073161
	PSPN-CH	FINANCIAL	-0.39774	0.049013
	SW-FR	FOOD	-0.4202	0.083115
	SECU.B-SE	MISCELLANEOUS	-0.43306	0.008414
	ELUX.B-SE	ELECTRICAL	-0.43606	0.030005
	JMAT-GB	CHEMICALS	-0.45189	0.096485
	WIHL-SE	FINANCIAL	-0.46926	0.015819
	CA-FR	RETAILERS	-0.4735	0.080045
	BARN-CH	FOOD	-0.47824	0.047922
	LR-FR	ELECTRICAL	-0.49027	0.022866
	CPR-IT	BEVERAGES	-0.49991	0.082363
	SU-FR	ELECTRICAL	-0.57321	0.085014
	SGE-GB	ELECTRONICS	-0.57823	0.022523
	DEMANT-D	DRUGS, COSMETICS & HEALTH CARE	-0.59293	0.04996
	SIKA-CH	CHEMICALS	-0.59551	0.089262
	FABG-SE	FINANCIAL	-0.59556	0.019319
	GIVN-CH	CHEMICALS	-0.59944	0.050103
	HUSQ.B-SE	MACHINERY & EQUIPMENT	-0.60556	0.00743
	WKL-NL	MISCELLANEOUS	-0.61611	0.094602
	HO-FR	AEROSPACE	-0.62017	0.014401
	AD-NL	RETAILERS	-0.62504	0.026291
	TEP-FR	MISCELLANEOUS	-0.66857	0.097071
	CAP-FR	MISCELLANEOUS	-0.67119	0.068599
	KNEBV-FI	MACHINERY & EQUIPMENT	-0.69764	0.085119
	HLMA-GB	MACHINERY & EQUIPMENT	-0.70658	0.04301
Low hedge ability portfolio	BWY-GB	CONSTRUCTION	-0.70907	0.008574
	BKG-GB	FINANCIAL	-0.76451	0.080376
	DLN-GB	FINANCIAL	-0.82994	0.022275
	BVIC-GB	BEVERAGES	-0.84218	0.043921
	VTY-GB	CONSTRUCTION	-0.8643	0.02108
	COLO.B-DK	DRUGS, COSMETICS & HEALTH CARE	-0.86846	0.030016
	IHG-GB	MISCELLANEOUS	-0.88732	0.093007
	SOBI-SE	DRUGS, COSMETICS & HEALTH CARE	-0.91654	0.034828
	GN-DK	ELECTRICAL	-0.92373	0.055053
	NIBE.B-SE	CONSTRUCTION	-1.16352	0.011427
	MBU.B-D	DRUGS, COSMETICS & HEALTH CARE	-1.1784	0.01914
	AIR-FR	AEROSPACE	-1.22722	0.010458
	UTG-GB	FINANCIAL	-1.47982	0.024635

Table 13: Inflation coefficients not different from 1

Index	Betas
FNTN-DE	0.457067
BLND-GB	0.386441
AVV-GB	1.184446
CNA-GB	0.234547
INCH-GB	1.443685
SDF-DE	0.580685
GL9-IE	0.516537
FPE3-DE	0.490318
EO-FR	1.282787
HUH1V-FI	0.040948
SOI-FR	-0.05214
RNO-FR	0.546184
ASM-NL	-0.20503
VOW3-DE	0.74282
TKA-DE	0.513592
STLA-IT	0.092576
SIM-DK	0.106931
STM-IT	0.202896
VWS-DK	1.202322
TECN-CH	0.174557
TEMN-CH	0.884133
LOGN-CH	0.300344
STMN-CH	0.241718
CDR-PL	-0.69205
LONN-CH	-0.1816
SCHP-CH	0.076679
MF-FR	0.467924
SFZN-CH	0.39964
MRO-GB	0.586727
MOCORP-F	0.669446
DUFN-CH	-0.03163
MT-NL	1.123276

Table 14: Variance inflation Factor: In inflation risk factor regressions

	I	R	SMB	HML	MOM
Scenario 1	1.2	1.2	1.1	1.6	1.6
Scenario 2	1	1.1	1.1	1.6	1.6

No perfect multicollinearity if VIF < 5

II.II. Formula

Logarithmic returns:

$$r_t = \log(\frac{Price_t}{Price_{t-1}})$$

Lerner Index (Sharma, 2011):

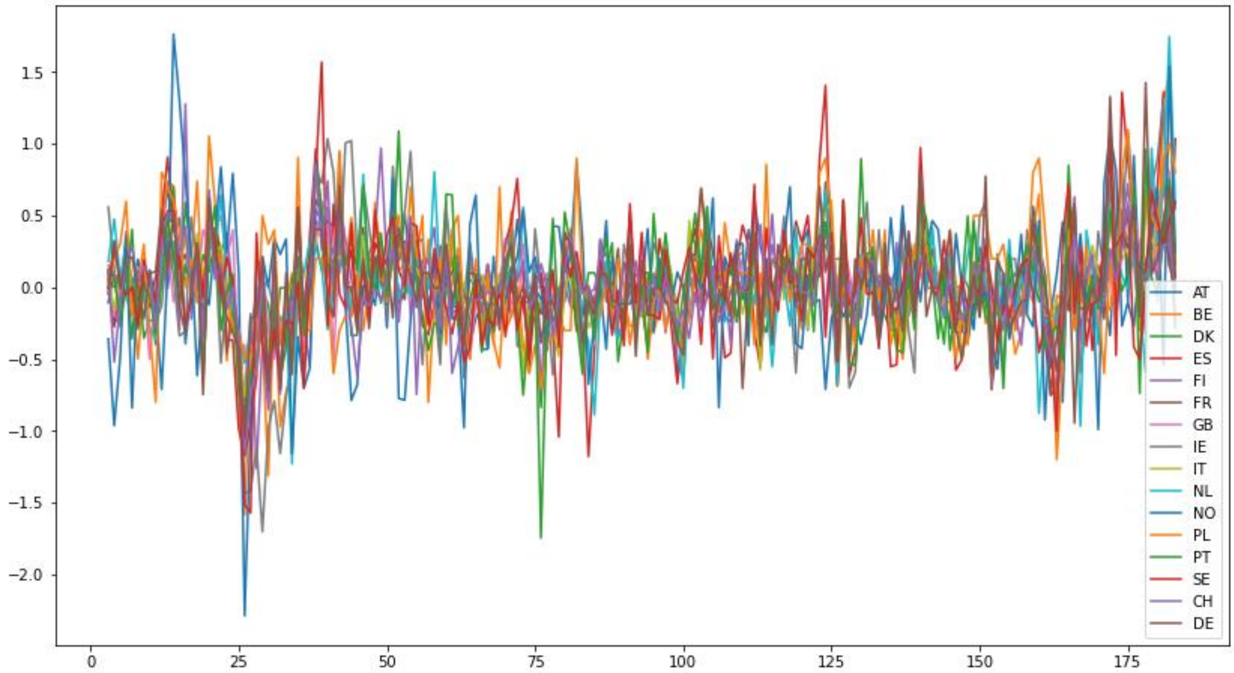
$$LI_{i,t} = \frac{Net\ Sales_{i,t} - COGS_{i,t} - SG\&A_{i,t}}{Net\ Sales_{i,t}}$$

Sharp Ratio: (σ_p= standard deviation of portfolio excess returns)

$$S = \frac{(\overline{r_p} - r_f)}{\sigma_p}$$

II.III. Graphs

Figure 7: Change in Inflation across all countries



II.IV. FactSet variable settings

Table 15: FactSet variable settings

Variable	**FactSet Definition**	**Non-Default Settings**
Book value	FF_COM_EQ Common Equity Units: Millions Annual, Interim and Preliminary Items - All Industries Represents the invested capital, accumulated retained earnings, surpluses, and reserves attributable to holders of the parent company's common stock, net of ownership interest reacquired by the company. It includes: - Common stock value - Retained earnings - Capital surplus - Capital stock premium - Cumulative gain or loss on foreign currency translation - Goodwill written off - For Non-U.S. Corporations preference stock which participates with the common/ordinary shares in the profits of the company	Report Basis: monthly

	- For Non-U.S. Corporations, if shareholders equity section is not delineated then the following additional accounts are included: - Appropriated and unappropriated retained earnings - Net income for the year, if disclosed separately from retained earnings (majority share of income is only included) - Compulsory statutory/legal reserves - Discretionary Reserves if other companies in that country include in their delineated shareholders' equity - Negative goodwill It excludes: - Common treasury stocks - ESOP Guarantees - Accumulated unpaid preferred dividends - Redeemable common stock (treated as preferred) - Compulsory convertible debt (South Africa) should be excluded from the equity section and include in long term debt	
Market value	FREF_MARKET_VALUE_COMPANY Returns the total public market value of the company's listed equity. This aggregates across all share classes, with options for currency and handling of nontraded shares. Units are in millions (MM). Prices are latest available, and by default adjusted to the trading currency of the security being evaluated. The NOW date argument is not supported by this code in Screening. By default, nontraded shares are excluded. When included, non-traded shares are added to the calculation basis by the proportion of their nominal or par value.	
Common Shares Outstanding	FF_COM_SHS_OUT Common Shares Outstanding Units:Millions Annual, Interim and Preliminary Items - All Industries Represents the number of common/ordinary shares issued and outstanding at the end of the year. Outstanding means the number of common/ordinary shares in issue after the deduction of treasury stock. It includes: - The number of shares of different classes which have been treated as ordinary shares - Shares subject to redemption If common shares outstanding is not reported in quarter/semi-annual time periods, then this item may be computed over par value. It may also use and compare share capital for current to prior time series, but in this case, prior	Report Basis: Monthly

	period common shares is not collected if there is a change in common shares reported in the current year while share capital is unchanged. It can also be drawn out from FDS file through Universal Screening in the product shares. If this item is reported in units, it is converted to actual shares. Per share items, such as common shares outstanding, are split-adjusted by default. ADR shares is calculated using the reported ADR ratio. For cases of multiple-issue companies such as CPO (Ordinary Participation Certificates) companies, the economic value of each share class relative to the primary issue is assessed using the Primary Share Equivalence Factor and the Earnings Participation Flag. For each share class, the formula is: ((Shares Outstanding x Primary Share Equivalence Factor) x Earnings Participation Flag)All share classes thus normalized to the primary share are then added together to calculate company-level shares. If a company has a different dividend payout ratio for securities, common shares outstanding will be estimated based on dividend ratio. This item is also available at the security level for 1987 and subsequent years. Note Pro-forma share counts are used for periods prior to the IPO date. Unit factor is only applied to company level shares for unit shares.	
SG&A	FF_SGA Selling, General and Administrative Expense Page: D10921Library: FactSet Fundamentals Category: Income Statement/Other Operating Cost Units:Millions Annual and Interim items - All Industries Represents all the operating costs not associated with the production or purchase of goods and / or services for sale but rather the costs of marketing and selling those goods or services and other indirect expenses of administrative and general nature, incurred in the ordinary course of business, including research and development. Note If the Research & Development expense (FF_RD_EXP) is found on the footnotes of the financial statement but is unallocated, then it is charged to Selling, General and Administrative Expenses. However if SG&A will become negative, the unallocated R&D expense will be ignored.	Report Basis: Monthly
COGS	FF_COGS Cost of Goods Sold Units: Millions	Report Basis: Monthly

	For Industrial, Other Financial Companies Returns the Cost of Goods Sold (COGS) for the period and date(s) requested in local currency by default. This represents the direct costs of production and/or costs of services rendered, including depreciation and amortization, incurred in the revenue generation process during the period. In the Functional Method presentation or Cost of Sales method, the cost of goods sold or services rendered is separated from selling, general and administrative expenses to the degree each relates to revenue. In the Cost Summary presentation or By Nature method, information is neither revealed on how the costs are related to the revenue generation process nor the degree of relationship between the two. It implies that all personnel costs are related to the revenue generation process and does not differentiate between the roles of employees. For development-stage or early-stage companies with no revenues or net sales, this item is collected with a 0. For US Tobacco Manufacturing companies, it includes Master Settlement Agreement (MSA) payments. This is calculated as the sum of COGS excluding Depreciation & Amortization (FF_COGS_XDEP) and Depreciation & Amortization (FF_DEP_AMORT_EXP).	
Net Sales	FF_SALES Net Sales or Revenue Page: D10907Library: FactSet Fundamentals Category: Financial Services/Income Statement Units:Millions Annual, Interim and Preliminary Items - All Industries For Commercial companies: Represents sales of goods and services, earned from the company’ score and recurring operations, reduced by cash and trade discounts, allowance for sales return and pass-through taxes, such as sales and excise taxes. It includes: - Franchise sales included in revenues - Consulting fees included in revenues - Royalty income included in revenues - Contracts-in-progress income - Commissions earned (not gross billings) for advertising companies It excludes: - Deductions from amortization of intangibles (for companies dealing with long-term service contracts)	

	- Gains and/or losses from hedging derivatives - Gains and/or losses from asset disposals - Gains from reversals of restructuring and other non-recurring items - Equity in earnings - Dividend and interest income - Non-operating income - Interest income - Interest capitalized - Equity in earnings of unconsolidated subsidiaries - Rental income - Dividend income - Foreign exchange adjustment - Gain on debt retired - Sale of land or natural resources - Sale of plant and equipment - Sale of investment - Security transactions - Income on reserve fund securities when shown separately - Operating differential subsidies for shipping companies - Net mutual aid assistance for airlines companies - General and Service Taxes - Value-Added taxes - Excise taxes - Windfall Profit Taxes - Government grants and subsidies For Banks, Insurance and Other Financial companies: This item represents the total operating revenue of the company. For Banks, it includes: - Interest and fees on loans - Interest on Federal Funds - Interest on Bank Deposits - Interest on State, County and Municipalities Funds - Interest on U.S. Government and Federal Agencies Securities - Federal Funds sold and securities purchased under resale agreements - Lease Financing - Net leasing revenue - Income from Trading Accounts - Foreign Exchange Income - Investment Securities gains/losses - Service Charges on Deposits	

	- Other Service Fees - Trust Income - Commissions and Fees For Insurance companies, it includes: - Premiums Earned - Investment income (if the company reports this item net of expenses then the net amount is shown after excluding interest expense) - Other operating income - Gains/Losses on sale of securities (pretax) For Other Financial companies, it includes: - Investment income - Interest income - Income from trading accounts - Trust income - Commission and fees - Rental Income - Securities purchased under resale agreements - Investment Banking income - Principal Transactions	
Germany 30Y Yield	FG_YIELD Returns the closing yield.	
Stock, Index, and ETF prices	FG_PRICE Returns the closing price. For Bonds, the Clean Price is returned.	