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TACTICAL ASSET ALLOCATION: STOCKS VERSUS BONDS

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ABSTRACT

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PURPOSE OF THE STUDY

The purpose of this study is to investigate the relative performance of stocks and bonds. Historically stocks have outperformed bonds over long time horizons, but for shorter, medium-term, time horizons bonds can provide superior returns if the allocation decision is timed correctly. This study uses a set of 5 indicators, namely the P/E ratio, dividend yield, equity share of new issues, consumer confidence index and the purchasing manager confidence index to predict future stock and bond returns. The study firstly assesses each indicator using a framework where the indicator values are arranged into quartiles based on the values for each period, and the subsequent values for the stock market are then investigated Secondly, he performance of each indicator is further assessed by an OLS regression and the results are documented. Thirdly, the regression coefficients obtained in the regressions are used in an investment strategy using out-of sample data by dividing the data into two different samples. This study adds to previous literature by providing analysis of the equity share of new issues in an asset allocation sense and also providing more updated data for the measure. Also, new information is provided on the confidence indices and how they act in an asset allocation framework.

DATA

The data for the study has been collected from the Datastream database, except for the equity share of new issues which has been collected from the Federal Reserve bulletins and the web pages of Jeffrey Wurgler. The S&P500 index is used for the stock market returns, and the Merrill Lynch bond total return index is used for bond market returns. The P/E ratio and dividend yield are for the S&P500 index. The consumer confidence index used is published by the Conference Board. The Purchasing manager confidence index is used is published by ISM (Institute of Supply Management).

RESULTS

Firstly, the quartile analysis of the indicators provides support for the predictive power of the P/E measure, also shown to have predictive power in previous studies, and for the ISM index. Limited predictive power is shown for the dividend yield and equity share of new issues measure. The regression analysis shows statistically significant predictive power for the P/E, dividend yield and ISM index. The most efficient time horizons for predicting future returns are the 6 and 12 month periods. The investment strategy fails to provide meaningful returns as the two periods under review proved to be rather different.

KEYWORDS

asset allocation, market timing, stock market, bond market,

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TUTKIMUKSEN TARKOITUS

Tutkimuksen tarkoituksena on selvittää miten osakkeet ja joukkovelkakirjat tuottavat eri ajanjaksoina. Historiallisesti osakkeet ovat tuottaneet joukkovelkakirjoja paremmin pitkällä aikajaksolla, mutta lyhyemmillä aikajaksoilla joukkovelkakirjat voivat tuottaa osakkeita paremmin jos sijoituspäätös ajoitetaan oikein. Tutkimus käyttää viittä eri indikaattoria ennustamaan osakkeiden ja joukkovelkakirjojen tulevia tuottoja: P/E –luku, osakkeiden osinkotuotto, osakkeiden osuus yritysten liikkeeseenlaskemista arvopapereista, kuluttajien luottamusindeksi ja ostajien luottamusindeksi. Jokainen indikaattori analysoidaan ensiksi kvartiilianalyysilla, jossa indeksien arvot järjestetään kvartiileihin ja julkaisemista seuraavan ajanjakson keksimääräinen tuotto osakkeille ilmoitetaan. Seuraavaksi jokaisen indikaattorin ennustusvoimaa analysoidaan regressiomallilla sekä osakkeiden tuoton ennustamiseen että osakkeiden ja joukkovelkakirjojen tuoton erotuksen ennustamiseen. Tutkielman lopuksi regressiomallista saatuja arvoja käytetään sijoitusstrategian tutkimiseen, jossa tutkimusaineisto on jaettu kahteen aikajaksoon. Ensimmäisen jakson regressiokertoimia käytetään toisen jakson tuottojen ennustamiseen ja päinvastoin. Tutkielma lisää aikaisempaan kirjallisuuteen tuoden tutkimustuloksia miten yritysten liikkeeseenlaskemien osakkeiden suhde velkaan hyödyttää allokointipäätöksia sekä lisää indikaattorin havaintoja. Luottamusindikaattoreiden toiminnasta allokointipäätösten tekemiseen saadaan myös lisää tietoa.

AINEISTO

Tutkimuksessa käytetty ainiesto on kerätty Datastream –tietokannasta, lukuunottamatta osakkeiden osuus yritysten liikkeeseenlaskemista arvopapereista –indikaattoria, jonka luvut ovat Federal Reserve Bulletinista sekä Jeffrey Wurglerin kotisvuilta. Osakkeiden tuoton laskemiseen käytetään S&P500 –indeksiä ja joukkovelkakirjojen tuoton laskemiseen Merrill Lynchin kokonaistuottoindeksia (TRI). P/E -luku ja osinkotuotto ovat S&P500 indeksin mukaan laskettuja. Kuluttajien luottamusindeksin on julkaissut Conference Board. Käytetty ostajien luottamusindeksi on Insitute of Suplly Management (ISM) julkaisema.

TULOKSET

Ensinnäkin, indikaattoreille suoritettu kvartiilianalyysi osoittaa, että P/E –luku ja ISM – indeksi ennustavat tulevia tuottoja parhaiten. Osinkotuotto ja osakkeiden osuus yritysten liikkeeseenlaskemista arvopapereista ennustavat myös rajoitetusti tulevia tuottoja. Regressionanalyysi tuottaa tilastollisesti merkittäviä tuloksia P/E luvulle, osinkotuotolle ja ISM – indeksille. Tehokkaimmat aikajaksot ennustamiselle ovat 6 ja 12 kuukautta. Sijoitusstrategia ei tuota mielekkäitä tuloksia johtuen luultavasti kahden aikajakson erilaisuudesta.

AVAINSANAT

varojen allokointi, markkinoiden ajoitus, osakemarkkinat, joukkovelkakirjamarkkinat

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1 Introduction

1.1 Academic and practical motivation

The past year the world stock markets saw a lot of turbulence. The dismantling of the US credit market stopped the steady rise in worldwide stock prices that had taken place since 2003. Beginning in August 2007, the general market trend has been downward with some markets coming down more than others.

Large turbulences in the stock market prompt investors to think about their investment decisions. Asset allocation is a fundamental choice all investors have to consider. One of the most basic decisions to make is whether to be in or out of the stock market. Historically it has shown larger profits, but larger one-time falls can cripple a portfolio for a long time.

Historically, stocks have given higher returns than bonds when the time period is extended far enough. Butler (1991) find using a simulation on actual historical returns that over a period of 10 years, common stock will underperform bonds by a chance of 11%, and when the period is extended to 20, the chance goes down to 5%. These percentages are even less if the normal bull-bear cycle is assumed (that is bull years are more likely to be followed by bear years and vice versa).

This might make one argue that stocks are the only right choice for long-term investors. Thaler (1994) argue in their study that investors with a seamlessly infinite time horizon should invest 100% in stocks due to the long-term dominance over bonds. They give an example: a dollar invested in 1926 in common stocks would have yielded $800 in 1993; a dollar invested in bonds would have yielded only $300.

Although the long-term dominance of stocks seems crushing, it does not refute the point that tactical asset allocation, also called market timing, still has its merits. Avoiding stock market crashes or other low-yielding periods in the stock market and hitting higher-yielding times in the bond market can further enhance long-term profits. For shorter-term investors or professional fund managers, it is one of the ways to "beat the market" and justify the management fees.

Two studies using British pension fund data Brinson (1991) and Brinson (1986) show that a portfolios asset allocation strategy dominates portfolio performance, and explains over 90% of portfolio returns. The rest of the returns are explained by active asset allocation and security selection. This study has spawned some commenting, first in Jahnke (1997) and later Singer (1997).

An interesting thought set out in Lofthouse (2001) is that since it his highly unlikely that there exist people who can systematically see the future, it also unlikely that someone would make systematic gains from market timing. This does not rule out the possibility that markets may be mispriced.

1.2 Research problem and purpose

The purpose of this study is firstly to explore the different methods for predicting stock and bond returns, and the relative performance of these two asset classes. The universe of studies covering this area is rather large, so the purpose is to provide a coherent selection of the most relevant findings.

In the empirical section different predictors found to have predicting power in previous studies will be analyzed and their performance evaluated on a data set that spans a larger share of the modern financial era, since a large share of previous studies have been made in the 1990's. These predictors will be assessed on a stand-alone basis and in a comparative way using OLS regressions. Also, a more recent addition to the lineup of predictors, the equity share of new issues will be given emphasis. In addition to the regular price-related indicators, some confidence indices will be used.

The chosen predictors are also put to the test through an investment strategy. Special emphasis is put on how the equity share of new issues adds power to the stocks versus bonds asset allocation conundrum. A trading strategy optimization exercise will also be performed.

1.3 Contribution

This study sets out the methods available for conducting the basic asset allocation decision of stocks versus bonds. The equity share of new issues has not been used to my best knowledge in studies comparing stock and bond returns. It also provides an additional test of robustness of the models found to have predictive power and that have shown results that can be implemented.

The study also explores confidence indices and if they serve as valid inputs for an asset allocation strategy.

The trading strategy optimization provides a view if the above mentioned indicators serve as inputs for an investment strategy between stocks and bonds.

1.4 Limitations of the study

- Study is set out in the US market, so it does not provide evidence how the selected measures would perform in other markets
- Study only considers a limited portfolio of assets available to investors; stocks and bonds. Commodities and real estate are excluded.
- Does not split markets into individual stocks, but rather gives results on an aggregated level
- The investment strategy provides results for an optimized strategy, but as it is based on previous data it is no guarantee for future returns

1.5 Structure of the study

The first section of the study will provide a general introduction to the area of research as well as a motivation for the study. It will also cover the limitations and contribution. The second part of the study focuses on the basics of asset allocation and the findings from previous research in the area. Section three sets out the research question and the initial hypothesis. Section four presents the data and the methodology used in the empirical section. Section five is the empirical part, the different predictors as well as the overall investment strategies are set out. Section six concludes and provides suggestions for further research based on the results of this study.

2 Theoretical background and previous research

2.1 Principles of asset allocation

Generally, when people invest, their objective is to increase purchasing power of capital Darst (2003). Asset allocation refers to how an investor distributes his assets (money) between different asset classes. A classic approach involves calculating average returns, standard deviations and correlations between assets and calculating the most suitable risk-reward profile to suit the needs and preferences of the investor.

Following are some conditions that need to be present for asset allocation to work:

- Rotating price leadership of assets
- Stable relationships of asset attributes (risk, return, inter-asset relationships)
- Low correlations between asset classes
- Appropriate rebalancing operations

Source: Darst (2003)

The first point touches the point made earlier in the introduction about stocks dominating bonds over the long run. In order for asset allocation to have any meaning, one asset class cannot dominate over the others. If stocks outperform bonds every single year (or any other period under review), it makes the asset allocation choice rather easy.

The second attribute implies that asset classes behave as they have done in the past, meaning that stocks don't suddenly start behaving like bonds in their risk/return profile and vice versa.

The third point is also rather straight forward. With correlations approaching 1, asset allocation loses most of its meaning. In a study by Li (2003) the average stock-bond monthly correlations during 1958-2001 from 7 industrial countries average 0.13-.31. The reported correlations between stocks and bonds vary greatly according to source, and in a 1950's investment book Benjamin Graham claimed the correlation to be negative, and suggested a 50/50 allocation policy as the best alternative (Li (2003).

The fourth point addresses more the successful implementation of asset allocation rather than the fundamental economical conditions that need to be present. For any asset allocation strategy to perform as wanted it must be followed by balancing the portfolio according to set guidelines.

In addition to conditions that need to be present for asset allocation to work, there are conditions that make asset allocation not work:

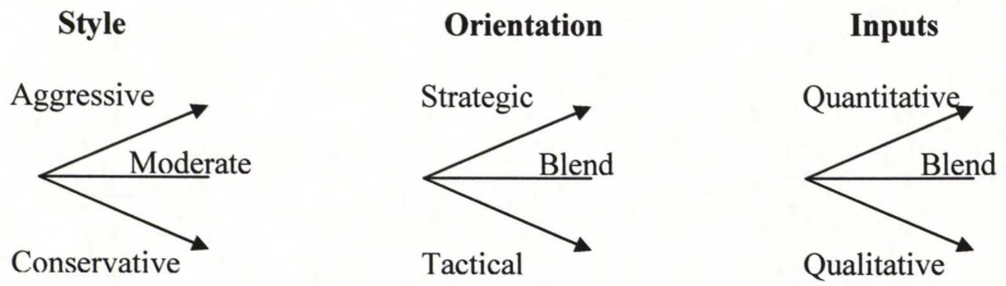
- Unusual financial environments
- Unstable relationships
- Rising correlations
- Unstable Ingredient/Result profile
- Inappropriate rebalancing activity
- Investor Error

Source: Darst (2003)

Most of these points are just the reversal of the ones mentioned for successful asset allocation, but some are new. The most important one is the last point. Humans are prone to errors, and sometimes they can't be avoided. More importantly, psychological factors can sometimes have an effect on the investment results. Overconfidence or being overly cautious can hamper results that otherwise would have been satisfactory.

Another variable in asset allocation is the scope. This defines the universe of investment activity. The scope basically sets out the boundaries for asset allocation, which can be geographical or certain asset classes. After defining the scope the next step is to choose the type of asset allocation. Types may be classified according to style, orientation and inputs, and different combinations of these may be made.

Figure 1. Types of asset allocation



Source: Darst (2003) p.24

Figure 1 sets out the different types of asset allocation. The first choice and investor has to make is between his preferred risk level. Traditionally, on a wider asset allocation level, investing heavily in stocks has been considered aggressive and investing in bonds more conservative. Inside each asset class there is a range of assets of which some can be considered more aggressive or risky.

The second choice has to do with activity. Strategic asset allocation aims to maximize the investors' long-term return on investments. Tactical asset allocation on the other hand tries to profit from short-term fluctuations in asset prices. A general guideline to distinguish these two can be the investment period; choices with investment horizons over a year are considered strategic and choices that involve a shorter time-frame are considered tactical.

To construct an investment strategy an informed investor must have data to back up the decisions. A separation can be made between quantitative and qualitative data. Quantitative inputs are realized and expected returns and standard deviations, and correlations of asset classes. These inputs are then taken and run through an optimization to get to the desired choice of assets. The qualitative approach uses fundamental, valuation, or psychological/technical/liquidity measures such as economic indicators, monetary figures, real interest rates or investment sentiment indicators.

In the book Lofthouse (2001) the different *tactical* asset allocation for asset groups (excluding intra-group methods e.g. stock-picking) methods are classified as follows:

- Business cycle anticipation
- Comparative valuation
- Liquidity measures
- Technical analysis

The first method tries to identify low cycles and upturns in the economy and allocate funds accordingly. During booms and recessions company profits vary, and profits are often a fundamental part of valuating stocks, so it is no wonder that economic cycles could play a role in tactical asset allocation. It is actually a common belief that the stock market anticipates the business cycle.

The comparative valuation method strategy compares, example given, the bond yield and equity earnings yield and tries to see which one is valued more favorably. The more favorable asset is then chosen. The comparative valuation method can also be performed by comparing asset yields between different countries.

The third method uses measures such as money supply or cash reserves as a base for predicting returns. One method is to follow funds flowing in and out of countries and believe the lack of liquidity has an effect on stock prices.

Technical analysis methods are numerous, from simple moving averages to more complicated methods. More on the different technical analysis methods and their usefulness is provided in section 2.4.3 of this study.

2.2 Efficient markets hypothesis – are stock and bond returns predictable?

One key question when performing studies that deal with forecasting asset returns or researching trading strategies that can this actually be done on a theoretical level. The Efficient Markets Hypothesis (EMH) states that since markets include all publicly known information, it is not possible to make excess profits by trading on such information. The vast number of studies that contradict or suggest that the EMH might not hold strictly speaking allow for a differing view.

In finance literature, the efficient markets hypothesis is traditionally interpreted as the impossibility of constructing a trading rule, based on publicly available information, that is capable of yielding positive excess profits (discounted at an appropriate risk-adjusted rate) (Pesaran (1995)). More recently, the more common view in financial literature is that predictability of time-varying assets can exist in efficient markets. A question of debate still exists between which are more predictable, long term or short-term horizons. This has importance on a practical level, as long-horizon predictability could be exploited in dynamic asset allocation strategies (Otoo (1999)) .

It is very difficult to prove or disprove the efficient market hypothesis. In addition, if evidence of an exploitable anomaly is found, it is possible that the effects disappear after it has been published to the general public.

2.3 Effect of inflation on expected stock and bond returns

Much has been written about the effects of inflation on stock prices and bond prices and how investors value the effects of inflation. The one basic difference between stocks and bonds in regards to inflation is that stocks can be considered as hedges against inflation and bonds not. The rationale stems from the fact that stocks are claims against real assets, and with inflation companies can adjust prices up. Bonds on the other hand are a nominal asset, and severe inflation can destroy the value of bonds as the fixed coupon loses its value with inflation.

The concept of real versus nominal returns is sometimes overlooked by investors, causing valuation errors, as shown in Modigliani (1979). In this study the effect of inflation does not play a pivotal role, as the comparison will be between two nominal returns. The rationale behind this is that the investor will be better off getting the larger nominal return from the two asset classes regardless of the effect of inflation. The inflation will affect the overall return, but not the order of the two asset classes. In some parts of the empirical section real returns will be used, but that will be specified case by case.

2.4 Stock market prediction

Predicting the future stock market returns is a constant struggle for many investors. In asset allocation sense, stock market returns play a fundamental part of the overall returns in most investment strategies. Many investment strategies in academic literature allocate 100% of assets in stocks when they are expected to yield more than bonds, and 100% in bonds when stock markets are predicted to crash. This makes stocks investment the "status quo", and bonds only are a safe haven when stocks are believed to underperform.

Some indication on the performance of 3 basic market indicators is given by Cole (1996). They study the dividend yield, market-to-book ratio and P/E ratio. For each indicator, the monthly figures are grouped into 4 buckets based on the value. The subsequent 1-year return of the stock market is then calculated and the returns averaged for each bucket. The P/E gives rising averages for the 4 different buckets, while for dividend yield and market-to-book ratios the return rates do not follow a linear pattern.

In Bleiberg (1989) the P/E figure is analyzed further, with P/E figures sorted into quintiles and results for the following 6, 12 and 24 month periods calculated. The study gives evidence that P/E has predictive power over stock returns. For the 6 and 24 month periods, the highest P/E quintile shows average negative returns. It also documents the highest P/E quintile to underperform bonds for all time frames. A problem arises when the absolute P/E numbers from the first 25 years are used in an investment strategy for the next 25 years, as this does not produce superior returns.

Studies suggest that managers might have more information than the markets and that they might time their equity and debt issuances accordingly. Evidence for this timing hypothesis is shown in Loughran (1995) and Spiess (1995). The aggregate effect of equity and debt issuance by companies on the stock market returns has been studied in Baker et. al (2000). The study shows strong evidence supporting the market timing hypothesis. Divided into 4 quartiles, the debt/equity issue ratio shows negative returns for the highest equity share quartile, and above average returns for the lower three quartiles. The period under review is one year after the issuance.

2.4.1 Macroeconomical variable models

A wide range of studies[1] have documented macroeconomical variables that have been statistically significant in predicting stock market returns. Variables suggested by early studies to be linked with stock prices include short and long interest rates, dividend yields, industrial production, company earnings, liquidity measures and the inflation rate (Pesaran, (1995)).

In the same study, Pesaran (1995) use macroeconomical variables to predict the stock market returns. They employ a framework where all information used would have been available to investors at the time, avoiding hindsight as much as possible. Variables used to predict stock market development are dividend yield, earnings/price ratio, 1 month T-bill rate, 12-month T-bond rate, year-on-year inflation rate of inflation, industrial output, and narrow money stock. After each period, each regressor is assessed using different efficiency criteria, and if deemed significant, then included in next period's estimates. This allows for the predictor to reflect "best knowledge" at point of time *t*. Then, a simple switching strategy is applied to see the economic performance of such a trading strategy. The results show a substantially higher mean return than the market average when using Akaike, R^2 and Sharpe criteria to choose the forecasters. They also report a lower standard deviation for the portfolio in question, allowing for a high Sharpe ratio. The authors also find predicting the stock market to be easier in times of high market volatility.

Some investment strategies also consider cash as an alternative to stocks and bonds. This is mainly to decide whether what to hold when not invested in stocks. A study by Boehm (1991) formulates an investment strategy using leading indicators of bear and bull markets to decide when to be in the stock market and leading indicators of inflation to decide whether to invest in cash or bonds when out of the stock market. The investment strategy is based on thresholds for bull and bear market that are compared with a rolling 12-month average. The study reports superior returns for the strategy following their method than for pure stocks or bonds, combined with a lower average standard deviation due to the periods when not in the stock market. This is consistent in 4 out of the 5 markets studied. The leading indicators for the stock market are new housing permits, real M1 or M2, a price-cost ratio (which remains unclear what it actually represents) and the inverted yield on long-term bonds.

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[1] See Pesaran (1995) for more studies

2.4.2 Confidence indices as predictors of stock markets

2.4.2.a Consumer confidence indices

Consumer confidence indices measure the sentiment of consumers with the help of a questionnaire. There are several different indices that measure consumer confidence in the US. One index is published by the Survey Research Center of the University of Michigan. It studies consumer confidence based on five questions related to household financial conditions and general business conditions. Another one is the Consumer Confidence Index published by the Conference Board. It measures the same thing with a slightly larger set of indicators relating to business conditions, household purchases and vacation plans.

It is easy to understand the rationale behind using a consumer confidence index for stock predicting purposes. As a large part of many economies is based on consumer spending, a slowdown in this could trigger a larger effect on the economy and eventually on the stock market. The major drawback of the measure is that consumers tend to base their thoughts largely on things they hear from the press as well as how the markets have been performing. This makes it somewhat difficult to reason which event is the cause and which is the effect.

For the European Union, a similar consumer confidence index is published by the European Commission. A study on the European market consumer confidence index (Jansen et al (2002)) investigate the short-run relationship between stock market developments and consumer confidence. Out of the eleven studied countries, 9 exhibit a positive correlation between the stock returns and changes in sentiment.

In a study (Fisher et al (2003)), the two consumer confidence indices (Michigan University and Conference Board) are studied with stock market returns. The study finds that rising stock prices are generally followed by rising consumer confidence. They also find that high consumer confidence is generally followed by lower returns. Otoo (1999) notes that this can be due to two reasons: The first one states that higher stock returns bring wealth, which in turn can boost consumer confidence, and the second one states that high stock returns are a leading indicator of high wealth. This negative correlation could be of use in tactical asset allocation. The study also finds that the two consumer confidence indices move in unison.

The consumer confidence indices have not been used in academic literature to the extent that many other measures have (for example the P/E ratio or P/B ratio). Thus it is interesting to see whether they play a role in the asset allocation world and how they behave in predicting future returns on stocks and bonds. .

2.4.2.b Purchasing manager confidence index

In addition to consumer confidence, business confidence is regularly measured through an index called the ISM manufacturing index (in the US). It is tracked by the Institute of Supply Management and it tracks different components including new orders, employment and production. As is the case with the consumer confidence index, it is more of a sanity check measure rather than a leading indicator (although more than consumer confidence). In previous literature the purchasing manager confidence index has mostly been used in studies relating to how macroeconomical variables predict stock market returns. During the research I did not come across a study that would assess the purchasing manager confidence from the perspective of direct stock return correlation.

2.4.3 Technical analysis

With the improvement of financial calculation capabilities and the availability of detailed financial data, a wide range of technical analysis methods have been put to use over the past few decades. The range in different technical measures is huge, going from simple moving averages to oscillators of different types. As the purpose of this study is no to concentrate on technical analysis, this section will be kept rather short and at an introductory level.

The most widely used technical analysis measure is most likely the moving average. The most common application has a 30-100 day moving average compared to the index or stock price, and at crossovers either sell or buy signals are generated. In Brock et al (1992) evidence is found for the usefulness of moving averages and trading range breaks. For a more detailed analysis of technical trading measures, see for example Brock et al (1992) and Thomas et al (2008)

2.5 Empirical claims of models for stock versus bond allocation

To predict the future returns of stocks is one thing, and to predict the future return on bonds is another thing. What is even more interesting to the individual investor is how these two returns compare. Predicting low stock returns doesn't help if bonds perform even worse during the same period. To provide answers to this question, there are some specific models that take both stock and bond returns into consideration simultaneously. This section covers some of the more well known versions.

2.5.1 Yield differential model

One of the more controversial asset allocation models for stocks and bonds is the stock earnings and bond yield differential. This is sometimes also called the Fed model. In its most basic form it compares the earnings yield on the stock market with a bond yield. When the bond yield is above the earnings yield, bonds are perceived the better investment option. An assumption behind this model is that stocks and bonds compete for space in investors' portfolios. The basic yield on bonds is sometimes augmented by a risk premium to compensate for the risks associated with stocks. The model considers that the "yield" on stocks are the earnings generated each year. Technically this can't be considered a yield, since the money is not paid out to the investors as is the case with the regular bond yield. A more technically correct way would be to use the dividends that are paid out as the "yield" on stocks. That in turn would not be theoretically correct, as the model would never catch the appreciation of the stock price in its predictions. The appreciation in bond price is not relevant on an investment horizon that is long enough, as the bond expires and the value drops to zero. This is not the case with stocks, as they are an infinite term asset.

Berge (2002) study the predictive ability of the bond stock earnings yield differential in 6 different markets worldwide. They use the E/P ratio and long-term government bond yield as the variables. Since the value of the differential at a given time cannot explain anything, the values are compared to historical averages. In essence, the bond stock earnings yield differential (BSEYD) is used as a leading indicator of stock market overvaluation (Berge (2002)). To test on the implementability of the results, Berge (2002) use a market timing strategy where 100% of the wealth is placed in stocks when the BSEYD is in normal range and 100% bonds when the BSEYD is in the "danger" zone. They find statistically significant results for all 6 countries, with a 10-year average to define the critical values giving the best results.

In another study, Koivu (2005) analyze the Fed model using cointegration analysis on US, UK and German data. They find the Fed model has predictive power, better for predicting crashes (or overvaluation) than for subsequent price rises.

Clifford Asness (Asness (2003)) has criticized the bond-stock earnings model for built-in flaws. One of the critique concerns the model being a good explainer of the current situation, but a bad predictor of future returns. Another piece of critique involves comparing a real number (P/E) to a nominal one (Y). It is also argued that investors suffer from inflation illusion, i.e. forecasting the same nominal growth rate for real assets in periods of varying inflation. Asness also shows an interesting chart with 10-year future and historical returns put into buckets according to the prevailing interest rate. The months ending in a low interest rate produce an average return of -2% for the next ten years, while the two last buckets have a return of over 10% each.

The effect of inflation illusion has been further investigated in Campbell (2004). They decompose the S&P500 dividend yield into three different components and find that over 80% of time-series variation in stock market mispricing can be explained by the level of inflation. They argue this is understandable due to the erroneous use of the "Fed model" on Wall Street.

In a recent working paper (Thomas and Zhang (2008)) the Fed model is deemed, once again, as a useful tool for investors. The paper is titled "Don't fight the Fed model", following Asness' study. The paper claims that the Fed model, albeit its shortcomings, does prove to be a valuable tool for investors to evaluate the overvaluation of the stock market for example.

2.5.2 Comparing different methods

In (Fuller (1990) two prediction models, namely an autoregressive model and a dividend yield model, are compared to two more simple prediction models, one a mere random walk (RW) and the other a naïve forecast, using the previous period's return as a forecast for the next period (MR). They use out-of-sample data and calculate root mean squared errors (RMSE) for each model. The four methods are then given a rank from 1-4 based on the RMSE for each respective return horizon. The dividend yield model comes out as the best predictor, with an average rank of 1.50. The autoregressive model come third after the MR approach, with and average rank of 3.38, well behind the dividend yield model. Fuller and Russell also test the practical implementation of trading strategies based on these measures, but find very limited use of the models in investing sense.

3 Research question and hypotheses

In this empirical section of this study, the following issues will be investigated:

- The equity share of new issues has documented results in predicting stock market returns for subsequent periods. This study aims to investigate whether using this measure, in addition to other documented measures, proves useful in stocks versus bonds asset allocation decisions. These measures are tested for their statistical significance in predicting stock returns. The hypothesis is that certain measures cannot forecast stock returns, although some studies have documented contrary evidence.
- Using the chosen measures (equity share of new issues, P/E, dividend yield and the consumer and purchasing manager confidence indices), can a trading strategy be created using optimized parameters that beats the risk-adjusted market returns over long time periods in a statistically significant way. According to the EMH this shouldn't be possible, but studies mentioned earlier have found statistically significant evidence against this with other trading strategies. Each trading strategy is a case by itself, so the one documented in this study is a unique case and it cannot be exactly compared to any previous study.

4 Description of the data and methodology

4.1 Data description

The studied market is the United States, mainly due to the availability of data. Normal market indices as well as yields, P/E figures and dividend yield figures would be readily available for other markets, but the equity share of new issues is not available for meaningful time periods for other markets.

The data is gathered from Datastream, and it consists of monthly numbers. Since some of the data was by default monthly in nature, and since it was for the middle days of the month (15^{th}), all other data has been picked from daily to monthly based on the same days. Thus, in this study, the end-of-the-month and end-of-year figures will be used when evaluating the overall investment strategy performance and when assessing the predictive ability of the equity share of new issues measure.

For the purpose of comparing stocks and bonds and their returns, a suitable index for both is needed. A well-known and probably most used index for stocks is the S&P 500 stock index, published by Standard and Poor's. It tracks the 500 leading US companies in the leading industries and represents roughly 75% of all US equities. The default S&P 500 index is a price index, not taking into consideration the effect of dividends. For this study, it is important to get the total returns for investors, as that is what matters in the end. To change the price index to a total return index taking dividends into consideration, the dividend yield of each month has been added to the price index return using equation (1):

S&P500 total monthly return = S&P500 monthly return + dividend yield^(1/12) (1)

The S&P 500 index also gives access to P/E ratio and dividend yield data. The same monthly data is used as for the total return index. No adjustments have been made as they are unnecessary in this context.

For bonds, there are different indices for corporate bonds, government bonds and combinations of these two. Since bonds are finite-terms securities, there exist different indices for different maturities. Merrill Lynch provides a set of indices for government bonds with different maturities. Since it can be argued that long-term bonds resemble stocks the most due to the infinite term structure of stocks, in this study the chosen bond index is the total return index for government bonds with a maturity of 7-10 years.

Financial literature often talks about a risk-free rate. For this purpose, the US T-bill 3-month secondary market middle rate will be used. It takes into account investors' perceived risk involved with these assets.

To transfer nominal returns into real returns, the US CPI index for all items will be used. Its base year is in 1967. There are various forms of consumer price indices covering different aspects of the goods available to consumers. Sometimes special categories are excluded (such as energy, which can fluctuate a lot due to market circumstances) but for this study the index including all items will be used..

The P/E ratio and dividend yield have been gathered from Datastream as well. They are linked to the S&P 500 index and are figures calculated by Datastream.

The equity ratio of new issues numbers have been taken from the web pages of Jeffrey Wurgler. The data from spans the years 1927-2004, and is on a yearly basis. The previous study only goes up to 1996, but the author of the study has added some more additional years to the data series on his web pages. To get a more up-to-date time series, the data for the remaining is gathered by hand from the Federal Reserve Bulletins. This data goes up until end of 2007. The specific categories in the Bulletin are Issues of equity by US corporations by public placement and bonds sold in the United States by US corporations.

The consumer confidence index is published by the Conference board and is also from the Datastream database. The purchasing manager confidence index (ISM) is published by the Institute of Supply Management and is also from Datastream.

The availability of e.g. relevant bond indexes somewhat limits the time scope. The first year with all data available is April 1973, so that will be used as the starting year. The last data points available are for February 2008. This gives a total of 419 data points for roughly 35 years. The data points for the equity share of new issues are less, totaling 34 yearly data points.

For this study, I will consider the following measures that have shown predictive power in previous studies: equity share in new issues (Baker et al (2000)), the dividend yield (Kothari (1997)) and Cole (1996) and the P/E ratio (Bleiberg (1989)). In addition, the two consumer confidence indices will be used, although they don't have so much documented proof of their success as predictors as the other measures have.

4.2 Methodology

4.2.1 General principles

There are two common documented sources of distortion that I will try to avoid in this study. The first common error as documented by Fuller (1990) is using in-sample data to verify the results obtained. This refers to using the same data point first to calculate the model parameters and then using the same data point to validate the model. Fuller (1990) claim this to be almost too common in studies in this field. To check for robustness of the investment strategy, any thresholds used will be based on out-of-sample data.

The second common problem mentioned in Pesaran (1995) is using too much hindsight and letting it affect the results. In practice, this surfaces when many alternatives are compared and then the best one chosen as an example. It can mean choosing, example given, the time frame that produces the best results and then using that as a default time period. If the investors never know beforehand should they use a 3 or 5 year average it takes away from the implementability of any study's results. This study will fall victim to this to a certain extent, but all care will be taken to avoid too much hindsight. One way to minimize the impact of this error is to show all scenarios; also the scenarios where the results have not went the desired way.

The four measures selected (P/E ratio, equity share in new issues, dividend yield and book-to-market) are all for predicting equity values. For them to make sense in asset allocation terms, the predicted yield on them has to be less than the bond yield. Thus, they will be compared to a relevant government bond yield (depending on the time frame of the period under review).

The debt and equity issued by US corporations is aggregated as yearly totals. The rest of the data is on a monthly basis (as described in section [4.1]). Thus, all analysis regarding the equity share of new issues will be done on a yearly basis (the results obtained in Baker et al (2000) were with the same yearly data set). It can be justified by the process of issuing new securities; it is not done overnight. When management takes decisions to issue new debt or equity, the whole process with regulatory clearance, investor actions takes a while. For this reason using monthly data might be misleading, as it could have significant variances due to timing of different issuances. For the trading strategy this means that the overall allocation decisions will be made firstly by the equity share of new issue criteria on a yearly basis, and after that, when the decision to stay in stocks has been made, the monthly allocation decisions will be made on a monthly basis. It is much easier to assume that indicators such as P/E react faster to market conditions than aggregate issuance of equity or debt.

4.2.2 Preliminary analysis and data descriptives

The selected indices are analyzed using basic descriptive statistics. The average monthly returns are calculated for both indices using the arithmetic mean. The standard deviation of the monthly returns is also calculated. The annual compounded return rate is also calculated using the Equation (1).

Annual compounded growth rate = [(Index value at t=n) / (Index value at t=0)] ^ [1/n] -1 (1)

Monthly standard deviations of returns are also calculated for both indices. To get a feel of how often stocks outperform bonds and vice-versa the share of months with higher returns on the stock market is calculated as is the share of months with higher returns on the bond market. In terms of an investment strategy, an optimal strategy would be able to pick out all the months when stocks outperform bonds and when bonds outperform stocks.

The variables chosen will are analyzed firstly by a simple quartiles analysis. Many studies classify the different months/years in order according to the value of the predictor. The different quartiles (or in some cases quintiles) are then averaged and the results shown. This shows, in general, how the different indicators perform with differing values.

4.2.3 Predictive power of variables

The predictive power of the different indicators will be investigated using an OLS regression. The OLS framework, as set out for example by Lehtonen (1998) and Dougherty (2002), assumes that the dependent variable Y depends on k explanatory variables according to Equation (2)

$$Y_i = \beta_0 + \beta_1 X_{i1} + ... + \beta_k X_{ik} + \varepsilon_i . \qquad (2)$$

where Y is the explained variable, X_1 to X_k are the explanatory variables, β_0 to β_k are the explanatory variables and ε is the error term. Given a set of n observations on $Y, X_1, X_2, ..., X_k$, the OLS method is used to fit the equation

$$\hat{Y}_i = b_0 + b_1 X_{1i} + ... + b_k X_{ki} . \qquad (2)$$

where b_0 to b_k are the estimates for the coefficients. To minimize the sum of the squares of the residuals, $b_0, b_1, ..., b_k$ are chosen that min $\sum_{i=1}^{n} e_i^2$ holds. The residual, e_i, is defined as $e_i = Y_i - \hat{Y}_i$. The regression coefficients, $b_0, b_1, ..., b_k$, provide an estimate of the impact of explanatory variables, $X_1, X_2, ..., X_k$, on the dependent variable, Y. For example, the regression coefficient β_1 (or its estimate b_1) shows the average change in Y for each one unit increase in X_1 and when the other variables remain the same.

In addition to the regression coefficients, the goodness of fit R^2 will be reported. This is an overall measure that explains how much of the total variance the model has explained. The R^2 is a number between 0 and 1, where low figures show that the model hasn't been able to explain the phenomenon well, and high figures tell the opposite. When analyzing the R^2 one must keep in mind that it is a technical measure, and that it doesn't really explain the empirical content or its relevance.

In this study, the dependent variable is the stock market index (or more correctly the return rated for different time periods of the index), and the independent variables are the selected indicators. The regressions are based on monthly data except for the equity share of new issues which uses yearly data and is done as a separate regression. The dependent variable is calculated for time t, the independent variable is delayed one month/year, resulting as time t+1. To test for the predictive power of the indicators regarding bond returns, they will be regressed also against the bond index.

To allow for a magnitude comparison of the variables, the regression coefficients will be standardized. The standardization is done by changing all variables to have a variance of 1. The standardized coefficients represent a change in the dependent variable that results from a change of one standard deviation in an independent variable. This measure can be used to see which variable has the largest change on the dependent variable regardless of the scale of the underlying units.

Despite its widespread use, the OLS has some limitations, and has received some critique for its econometrical qualities. Some of the undesired qualities relating to using regressive models to forecast return predictability are, for example, the high persistence of the forecasting variables (large autoregressive root in their univariate representation and a lagged endogenous variables) and serially correlated error terms (when using overlapping data (Lanne (2002)) . Nevertheless, it will be used in this study due to its widespread use and ease of implementation. It does provide the right results at least directionally.

4.2.4 Trading strategy optimization

The trading strategy will be based on the results received from analyzing the different predictors and indices. The predictors are likely to have different characteristics on timing for example. Some are leading indicators, others are lagging indicators. Also the time frames involved can vary between the various predictors.

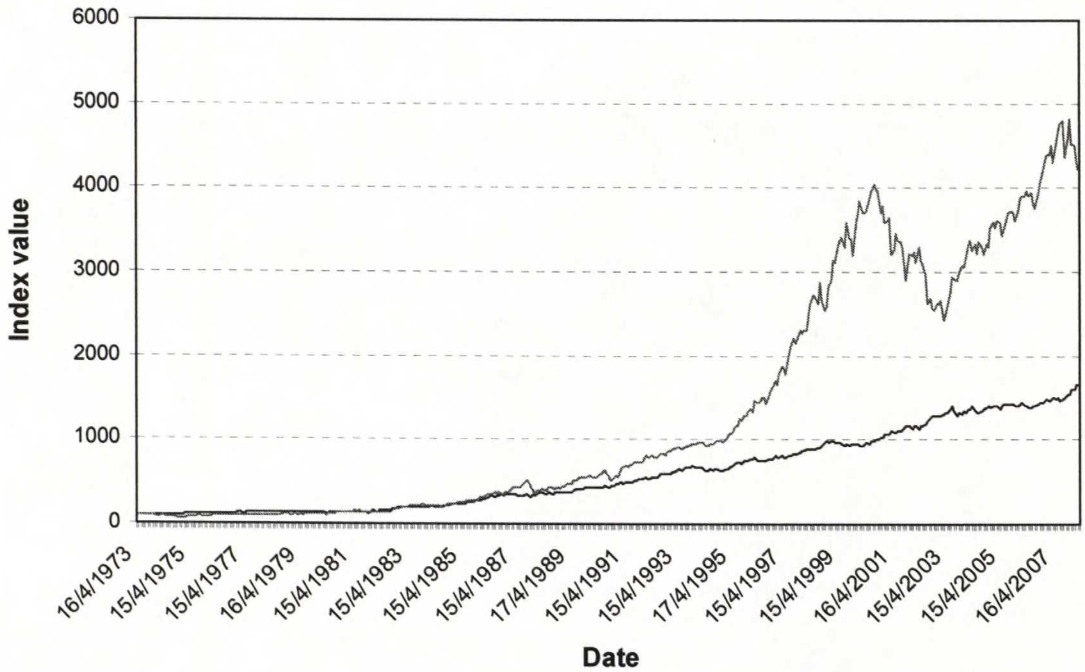
To measure the performance of the trading strategy and to assess whether the differences in performance are statistically significant we will use the t-test. For performance-related calculations, the most basic measure of performance is the absolute return of the strategies, measured as the simple cumulative or annualized (or monthly/daily) return over the period under review.

5 Analysis and results

5.1 Overall performance of stocks versus bonds

The historical performance of the S&P500 is set out in Figure 2.

Figure 2. S&P500 total return index and Merrill Lynch US government bonds 7-10 year maturity total return index April 1973-February 2008



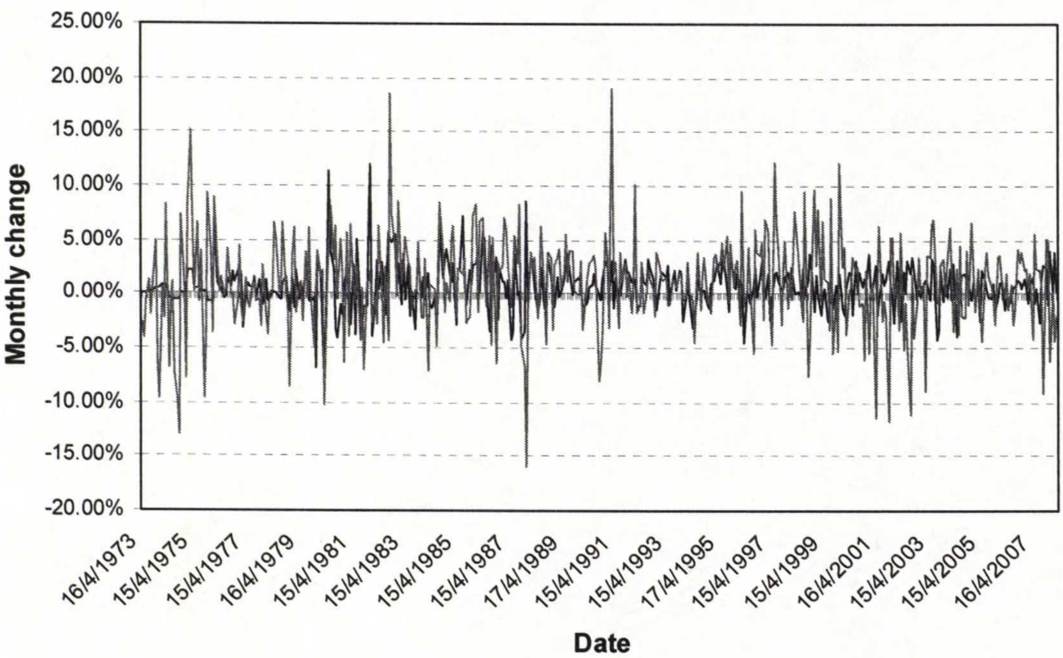
As can be seen, the stock market has outperformed bonds in terms of total return by roughly 3 times. A dollar invested in 1973 would have yielded \$42 if it was invested in stocks and \$14 if invested in bonds. For comparison, the S&P 500 index without dividends (only price appreciation) would have yielded roughly the same amount as the bond index. The largest dip in the stock market occurs around the tech crash of 2000-2003. Smaller dips can be seen around1974, 1988, 1991 and the 2007-2008 credit crisis.

Table 1. Summary statistics on S&P500 TRI and Merrill Lynch government bond TRI April 1973 - February 2008

Statistic	S&P500 TRI	Merrill Lynch 7-10 year bond TRI
Average monthly return %	0.99%	0.70%
Standard deviation of monthly returns	4.40%	2.19%
Annual compounded return 1973-2008	11.3%	8.4%
% of months with greater return	57%	43%

As we can see from Table 1, on a monthly basis, the average return has been 0,99% for the S&P and 0,70% for the bond index. The equity index has shown double standard deviation compared to the bond index. In terms of relative monthly performance, the stock market overperformed the bond market 57% of times. The correlation coefficient of the two monthly returns is 0,16. Based on this, it seems feasible that a strategy picking stocks and bonds in different periods would yield superior overall returns.

Figure 3. Monthly change in index value for S&P500 and Merrill Lynch 7-10 year government bond index.



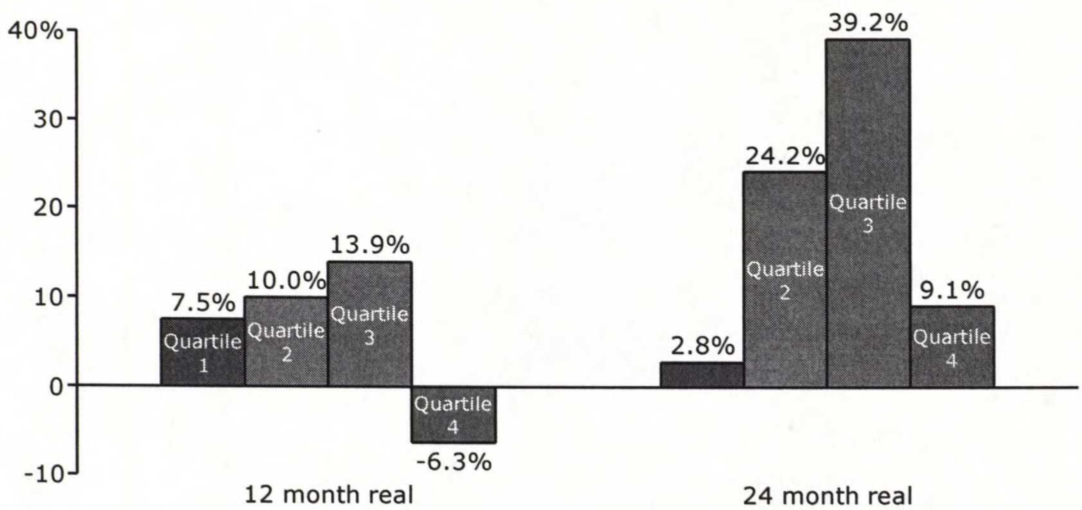
From Figure 3 it can be seen that bond returns exhibit much less variation than stock returns. The largest monthly returns for bonds are slightly over 10%, while stocks have had monthly returns closer to 20%.

5.2 Performance of selected indicators

5.2.1 Equity share of new issues

The equity share of new issues demonstrated strong evidence in Baker et al (2000) . When divided into quartiles, the bars showed a gradual decline in returns when the equity share got lower. Adding 12 years into the time series and taking out the pre-seventies period changes the picture slightly.

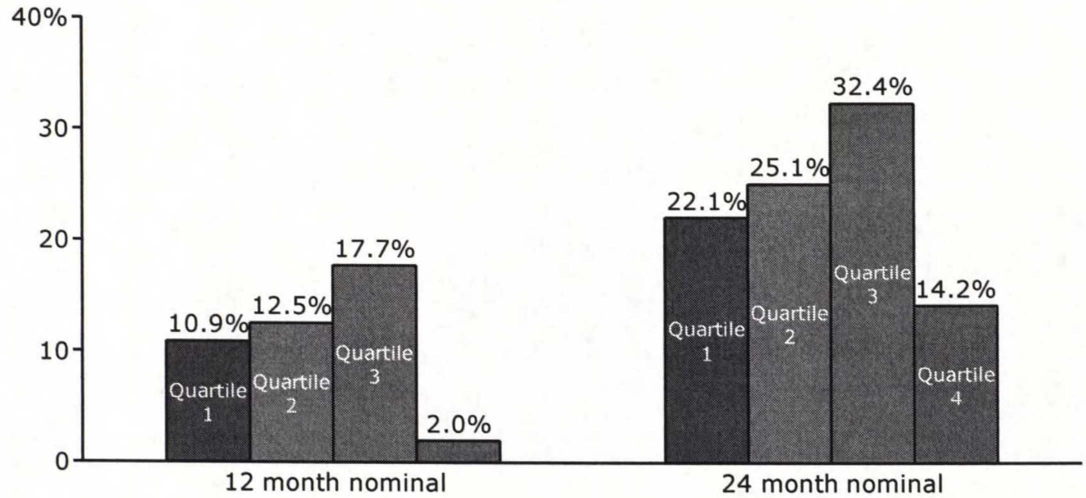
Figure 4. Average *real* return on the S&P500 index split into quartiles by the equity share of new issues.



Considering the 12 month period, the returns for the fourth quartile (largest share of equity in new issues) is still negative. This can be interpreted as rather strong evidence for the predictive ability of the predictor. The following quartiles do not replicate the behavior found in the previous study, but anyways demonstrate positive returns. For the sake of completeness, the analysis was also performed by arranging the data into quintiles, but this did not alter the picture significantly and thus are not worth reporting as a separate section. For the 24 month period the pattern is roughly the same, except for the first quartile showing positive returns. The other quartiles exhibit the same pattern as for the 12 month period.

Curiously, most of the years that fall into quartile one (the one when least equity was issued as a percentage of the total) begin with a 2. The threshold for quartile 1 is 0.10 (compared to 0.14 in the previous study) and 0.20 for the fourth quartile (compared with 0.27 for the previous study). Overall, this can be interpreted as a general increase in the issuance of debt over the issuance of equity during the past decades.

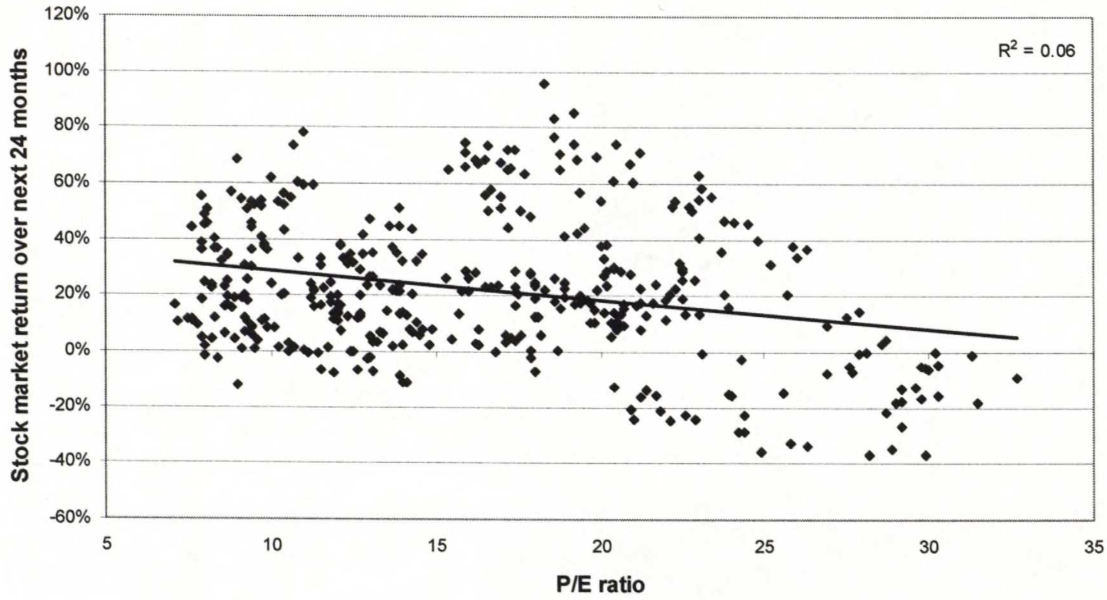
Figure 5. Average *nominal* return on the S&P500 index split into quartiles by the equity share of new issues.



5.2.2 Price to earnings ratio

The Price-to-earnings ratio (or its inverse, the earnings-to-price ratio) has been shown to have predictive power over stock returns (e.g. in Cole, Helwege and Laster (1996) and Bleiberg (1989)) In Bleiberg (1989) the highest differentiation in stock market performance for the quintiles was found for a subsequent period of 24 months. The performance was notably differentiated between quintiles also for periods of 6 and 12 months. Also, the frequency of a rising market (positive return over the subsequent periods for different quintiles) was greatest for the 24 month period, ranging for 95% for the lowest P/E quintiles and down to 54% for the highest P/E quintile.

Figure 6. The P/E ratio of the S&P500 plotted against the subsequent 24-month return for the S&P500 index.



Plotting the S&P500 subsequent return for 24 months based on the prevailing P/E figure can be seen in Figure 6. The overall trend leans towards a lower P/E number providing subsequently higher returns. The R^2 equals to 0.06 (compared with 0.03 and 0.05 for the 6 and 12 month periods respectively). The same figure for the 6 and 12 month periods can be seen in Appendix 8.2.

When split into quartiles, the P/E ratio yields the following results (Table 2).

Table 2. The P/E ratio split into quartiles and the subsequent returns for periods of 6, 12 and 24 months (1974-2007).

P/E ratio quartile	Subsequent 1 month return (%)	Subsequent 6 month return (%)	Subsequent 12 month return (%)	Subsequent 24 month return (%)
Quartile 1	1.2%	9.4%	18.5%	39.1%
Quartile 2	1.3%	7.1%	15.2%	29.0%
Quartile 3	1.1%	5.7%	13.9%	39.1%
Quartile 4	0.4%	3.3%	6.1%	14.0%

The P/E ratio has been considered as one of the most robust measures for market valuation, and the results shown in Table 2 do not disprove this thought. For the 6 month returns the returns follow a common trend: the higher the P/E ratio, the lower the subsequent returns.

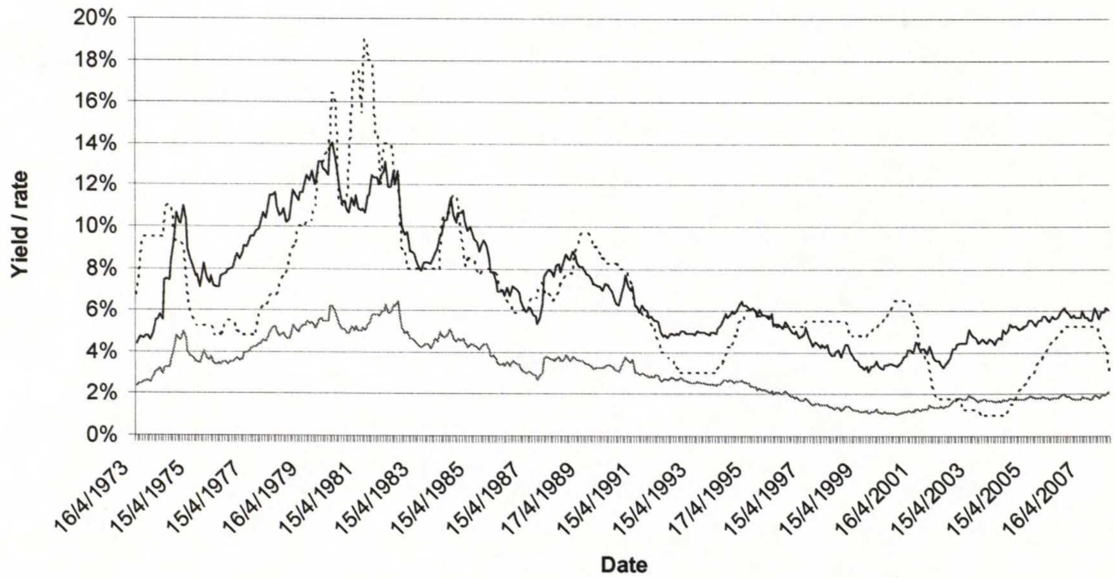
Quartile 4 (highest observations for the P/E ratio) exhibits average returns of 3.3%, while quartile 1 shows average returns of 9.4%. The same pattern can be seen for the 12 month returns. The 24 month inspection period has more scattered results, although quartile 4 is still considerably lower than the other quartiles. Real returns are shown in Appendix 8.1.1.

5.2.3 Dividend yield

As explained in the theory section, the dividend yield has shown some power in predicting future stock market returns.

In Figure 7 the dividend yield of the S&P500 index is set out together with the Fed funds target middle rate and E/P of the S&P500 for comparison purposes.

Figure 7. The dividend yield of the S&P500 index (bottom line), the E/P of the S&P500 index (top line) and the Fed Funds rate (dotted line) 1973-2008.



The dividend yield measure can be seen to have settled from the high values in the 70's and beginning of the 80's. One potential reason for this phenomenon might be the increased activity in share repurchases since 1985. This effect is to some extent offset by the issuance of new share at the same time. In Cole et al (1996) the effect of share repurchases is studied, and the conclusion is that even with the adjustments for share repurchases the dividend yield measure cannot be brought up to historical averages

Interestingly, the Fed funds rate and the E/P measure all seem to follow a rather similar trajectory. The dividend yield follows suit, albeit at lower absolute levels. This is constant with previous studies done on the Fed model, where the bond yields and E/P ratio (which can be seen as a proxy for stock "yield") follow a similar trajectory. The only difference is that here the Fed funds rate is used instead of an average yield on bonds. This is close to the findings of Thomas and Zhang (2008) , as they claim that stocks are priced the same way as bonds, meaning both priced according to expected yield (or earnings) and expected inflation.

Previous research suggests that setting the dividend yield into quartiles is a decent predictor of future above-average returns. In Cole, Helwege and Laster (1996), when broken into quartiles, the lowest quartile (with lowest dividend yield) demonstrated average returns of 6.4%, and above–average returns 30% of the time. The highest quartile (with highest dividend yield) showed average subsequent returns of 17.4% and above-average returns 70% of the time. The quartile analysis was performed on yearly numbers from 1927-1995.

The results for arranging the dividend yield into quartiles as was done for the P/E ratio is shown in Table 3.

Table 3. The dividend yield split into quartiles and the subsequent nominal returns on the S&P500 index for the period of 1973-2008 (for 6-month, 12 month and 24 month periods)

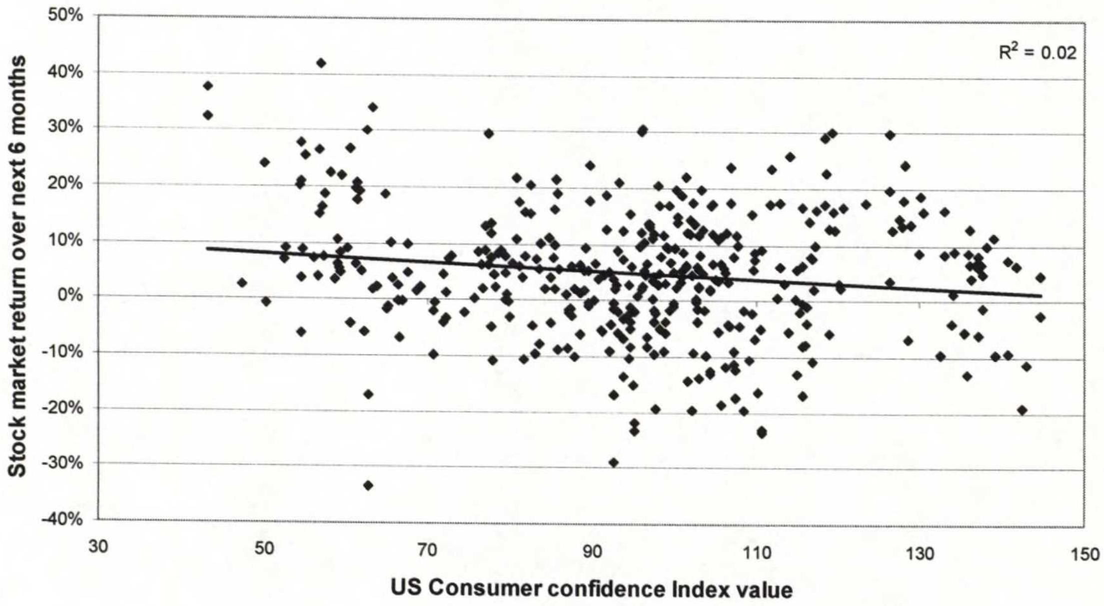
Dividend yield quartile	Subsequent 6 month return (%)	Subsequent 12 month return (%)	Subsequent 24 month return (%)
Quartile 1	2.9%	5.8%	12.2%
Quartile 2	5.8%	13.0%	34.3%
Quartile 3	3.8%	8.9%	16.4%
Quartile 4	6.6%	12.7%	27.3%

The results aren't as consistent as they were for the P/E ratio. When dividend yields are low (quartile 1), the subsequent returns are lowest for all time periods, The other quartiles don't exhibit the same kind of pattern. For clarity, the returns calculated in the table (as well as the previous tables) are based on the price index and not the total return index. This avoids that the high dividend yield would show up in the returns. If the total return index were used, the high dividend yield could show up in the returns. The reason for this can be seen in Figure 7, where the dividend yield doesn't show much fluctuation over short time periods, but rather over longer periods of time. Real returns are shown in Appendix 8.1.2.

5.2.4 Consumer confidence index

The consumer confidence data is firstly plotted out together with the subsequent return over a six month period for the S&P500 index. This is shown in Figure 8.

Figure 8. The consumer confidence index plotted against the subsequent 6n month return on the S&P500 stock index.



From Figure 8 we can see that the consumer confidence index doesn't show any clear pattern over the stock market returns. An R^2 of 0.02 shows rather low explanatory power overall.

Next, arranging the consumer confidence index values into quartiles, we can see the average returns that are attributable to each quartile. This is set out in Table 4.

Table 4. Consumer confidence index set out into quartiles and the subsequent return on the S&P500 index for the subsequent periods for the period 1974-2007.

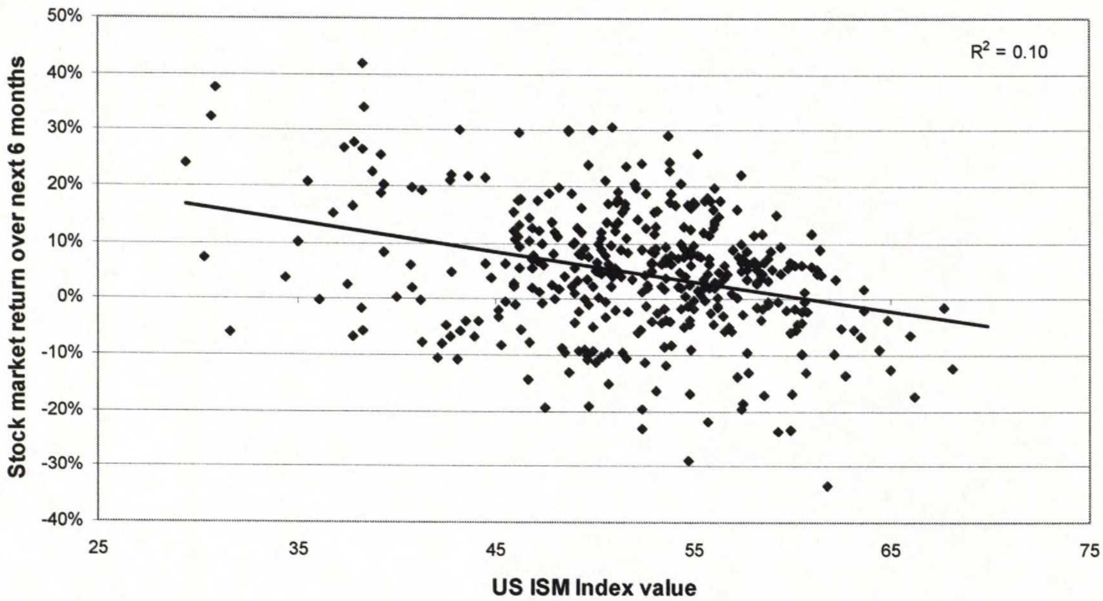
Consumer confidence quartile	Subsequent 6 month return (%)	Subsequent 12 month return (%)	Subsequent 24 month return (%)
Quartile 1	8.27	14.14	23.32
Quartile 2	2.51	6.22	18.90
Quartile 3	3.71	10.97	29.47
Quartile 4	4.69	9.07	17.25

As can be seen, there isn't any clear trend for the consumer confidence index and stock market returns. The fourth quartile (highest consumer confidence) provides lowest returns for the 24-month period, but only the third lowest for the 6 month period. For the 6 month period for example, the second quartile provides returns of 8.27%, and the fourth quartile provides returns of 4.69%. The two remaining quartiles are left in between these two returns. Real returns are shown in Appendix 8.1.3.

5.2.5 Purchasing manager confidence index

For the purchasing manager confidence index we will follow the same procedure as for the consumer confidence index. In Figure 9 we set out the consumer confidence index together with the stock market returns.

Figure 9. US ISM index value plotted against the subsequent 6 month return for the S&P500 index.



As can be seen in figure 9, the purchasing manager confidence index gathered by the ISM shows stronger predictory power than the consumer confidence index. The R^2 is up to 0,10. This suggests that consumers are more followers in the stock markets as well as in their perceptions of the state of the economy. The purchasing managers on the other hand seem to have a better sense of the overall economy, as their sentiment and investment decisions show larger predictive ability of stock returns.

When arranged into quartiles, the purchasing manager confidence index shows interesting results. This is set out in Table 5.

Table 5. The US ISM purchasing manager confidence index set out in quartiles and the subsequent stock market returns for the S&P500 index for the period 1974-2007 (nominal).

Purchasing manager confidence index quartile	Subsequent 1 month return (%)	Subsequent 6 month return (%)	Subsequent 12 month return (%)	Subsequent 24 month return (%)
Quartile 1	1.8%	10.3%	19.6%	35.5%
Quartile 2	0.9%	6.6%	14.6%	31.4%
Quartile 3	1.2%	7.1%	13.8%	28.5%
Quartile 4	0.1%	1.4%	5.9%	24.1%

As can be seen in Table 5, the purchasing manager index shows a rather consistent performance over the different time horizons. Quartile 4 shows the lowest subsequent returns (this is when the confidence index receives its highest values). This is somewhat counter-intuitive, as one would suppose that when purchasing managers feel confident, the economy would show positive trends over the following months and years. The evidence is rather strong, though. Based on the data in Table 5, it would seem most plausible to use the US ISM index and the 6 month period when constructing the specific investment strategy. Real returns are shown in Appendix 8.1.4.

It is interesting to notice that when the financial department of companies prefers to issue debt the stock market usually underperforms in subsequent periods. This is to say that they don't see the company's future very brightly. When the purchasing managers, on the other hand, see the future in a bright way, stocks also tend to undeperform. Maybe companies could benefit from internal communication (assuming these two take place simultaneously).

5.3 *Multivariate OLS regression*

To test for the predictive abilities of all the predictors, a multivariate regression will be constructed. The multivariate regression allows for the comparison of different predictors at the same time, and also shows if some predictors lose their predicting power when other measures are introduced with them. The predictors will themselves serve as the explanatory variables. The dependent variable will be the change in stock price for the chosen time frame. The setup of the regression is shown in equation (3)

$$SP_{nt} = a + b_1PE_{t-1} + b_2DY_{t-1} + \ldots + b_nXX_{t-1} \qquad (3)$$

Where n is the time frame for returns (1 month, 6 months, 12 months, 24 months) and t is the month. The list of variables and their explanations can be seen in Appendix 8.6

The equity share of new issues is included, even though the figures are annual. The regression is set up in the way that the same number is used for all the months in a given year, and otherwise the regression is carried out normally

The first set of regressions is run with the four mentioned variables. The regression summary statistics are shown in Table 6

Table 6. Regression summary statistics for the S&P500 (*nominal*) regressions.

Regression period	R	R^2	Adjusted R^2
Nominal 1-month returns	0.200	0.040	0.028
Nominal 6-month returns	0.380	0.144	0.134
Nominal 12-month returns	0.473	0.224	0.214
Nominal 24-month returns	0.483	0.234	0.224

The results suggest that the longer the time period, the better the model can explain the changes in the S&P500. The adjusted R^2 for the regression with 1-month subsequent returns is quite low.

In Table 7 the results of the regression are shown for the different coefficients. Analyzing the different coefficients and their performance, we can see some variations in the performance of he different indicators for the different time periods. The PE variable shows increasingly significant power in predicting the returns when the time period increases. For the 6-month returns the t-test shows significance on a 95% level and for the 12 and 24 month returns on a 99% level. The indicators that show statistically significant values in explaining the stock market returns are DY, PE and ISM. CC is the most limited in that it only show significance on a 95% level

Table 7. Regression coefficients for DY, PE, CC, EQ_SHARE and ISM regressed against the future 1, 6, 12 and 24 month *nominal* returns on the S&P500 price index.

	1-month returns		6-month returns		12-month returns		24-month returns	
Variable	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)
(Constant)		2.126		5.249		7.230		9.369
		(0.034)*		(0.000)***		(0.000)***		(0.000)***
DY	0.027	0.170	-0.138	-0.893	-0.296	-1.991	-0.928	-6.053
		(0.865)		(0.372)		(0.047)*		(0.000)***
PE	-0.090	-0.673	-0.343	-2.676	-0.595	-4.746	-1.151	-8.710
		(0.501)		(0.008)**		(0.000)***		(0.000)***
CC	-0.011	-0.185	0.012	0.214	0.080	1.511	0.028	0.531
		(0.853)		(0.83)		(0.132)		(0.596)
ISM	-0.145	-2.687	-0.299	-5.818	-0.356	-7.229	-0.208	-4.179
		(0.007)**		(0.000)***		(0.000)***		(0.000)***
EQ_SHARE	-0.094	-1.280	-0.065	-0.944	-0.067	-1.029	0.124	1.932
		(0.201)		(0.346)		(0.304)		(0.054)

The unstandardised B-coefficients for the nominal return regression are provided in Table 8. This data serves to assess the economic significance of the coefficients. While the standardized coefficients provide information on the relative performance of the measures, the unstandardized coefficients provide insights on the absolute performance. The values of the indicators range from roughly 1-7 for the dividend yield, 7-33 for the P/E ratio, 43-145 for the consumer confidence index, 29-70 for the ISM index and 0.05-0.43 for the equity share of new issues. From the regression we can calculate that a 1 unit change in the predictor value would correspond to a change in returns the value of the coefficient. Based on this, a 1 point change in P/E ratio would correspond to a change of 1.6% in 12 month returns. This degree of change can be considered economically significant in addition to being statistically significant.

Table 8. Unstandardized B coefficients for S&P500 nominal return regression

a)	Regression period			
Variable	1 month B	6 month B	12 month B	24 month B
(Constant)	0.079	0.481	0.951	1.958
DY	0.001	-0.011	-0.036	-0.173
ISM	-0.001	-0.005	-0.009	-0.008
CC	0.000	0.000	0.001	0.000
EQ_SHARE	-0.045	-0.080	-0.123	0.356
PE	-0.001	-0.006	-0.016	-0.048

Table 9 set out the summary statistics for the real return regressions. We can observe the same general pattern of increasing explanatory power as the forecasting period gets longer. The R^2 for the ome month period is 0.039, while it eraches 0.200 for the 12-month period.

Table 9. Regression summary statistics for the S&P500 (*real*) regressions.

Regression period	R	R^2	Adjusted R^2
Real 1-month returns	0.198	0.039	0.027
Real 6-month returns	0.362	0.131	0.121
Real 12-month returns	0.448	0.200	0.190
Real 24-month returns	0.434	0.189	0.178

Table 10 sets out the regression coefficients for the real return regression. We can observe a similar significance level as for the nominal returns. The PE ratio and ISM indicators prove to be the best predictors in this analysis as well.

Table 10. Regression coefficients for DY, PE, CC, EQ_SHARE and ISM regressed against the future 1, 6, 12 and 24 month *real* returns on the S&P500 price index.

	1-month returns		6-month returns		12-month returns		24-month returns	
Variable	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)
(Constant)		2.390 (0.017)*		5.527 (0.000)***		7.572 (0.000)***		9.461 (0.000)***
DY	-0.039	-0.244 (0.808)	-0.257	-1.658 (0.098)	-0.454	-3.002 (0.003)**	-1.077	-6.823 (0.000)***
PE	-0.110	-0.829 (0.408)	-0.362	-2.796 (0.005)**	-0.606	-4.767 (0.000)***	-1.107	-8.140 (0.000)***
CC	-0.025	-0.423 (0.672)	0.007	0.134 (0.893)	0.066	1.230 (-0.220)	0.008	0.147 (0.883)
ISM	-0.152	-2.816 (0.005)**	-0.321	-6.206 (0.000)***	-0.392	-7.826 (0.000)***	-0.271	-5.288 (0.000)***
EQ_SHARE	-0.085	-1.162 (0.246)	-0.047	-0.683 (0.495)	-0.037	-0.558 (0.577)	0.163	2.476 (0.014)*

The unstandardized coefficients for the real regression are laid out in Table 11. As can be seen, these coefficients are similar in magnitude as were the coefficients for the nominal returns.

Table 11. Unstandardised B coefficients for S&P500 real return regression.

	Regression period			
Variable	1 month	6 month	12 month	24 month
	B	B	B	B
(Constant)	0.091	0.533	1.076	2.196
DY	-0.001	-0.022	-0.058	-0.216
ISM	-0.001	-0.006	-0.011	-0.011
CC	0.000	0.000	0.001	0.000
EQ_SHARE	-0.041	-0.061	-0.072	0.506
PE	-0.001	-0.007	-0.018	-0.050

The next phase is regressing the predictors against the difference in bond and stock returns. The summary statistics are shown in Table 12. As was the case in the two previous regressions, the overall explanatory power of the model increases with the time period.

Table 12. Regression summary statistics for the equity and bond return difference.

Regression period	R	R^2	Adjusted R^2
1-month return difference	0.131	0.017	0.005
6-month erturn difference	0.282	0.080	0.068
12-month return difference	0.380	0.144	0.133
24-month return difference	0.432	0.187	0.176

To find out which indictors can predict the differences between stock and bond returns, and if there are such predictors, the same regression is run against the difference in returns for the two indices. The return of the bond index is subtracted from the stock index returns, and the remainder is regressed against the predictors. The results are shown in Table 13.

Table 13. Regression coefficients for DY, PE, CC, EQ_SHARE and ISM regressed against the future 1, 6, 12 and 24 month return difference between stocks (S&P500) and bonds (Merrill Lynch Total Return Index).

	1-month returns		6-month returns		12-month returns		24-month returns	
Variable	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)
(Constant)		1.128		3.918		5.458		6.623
		(0.26)		(0.000)***		(0.000)***		(0.000)***
DY	0.022	0.132	-0.212	-1.330	-0.377	-2.411	-0.848	-5.370
		(0.895)		(0.184)		(0.016)		(0.000)***
PE	-0.086	-0.634	-0.387	-2.909	-0.641	-4.869	-1.088	-7.988
		(0.526)		(0.004)		(0.000)***		(0.000)***
CC	-0.014	-0.245	-0.008	-0.142	0.053	0.956	0.027	0.497
		(0.807)		(0.887)		(0.34)		(0.62)
ISM	-0.055	-1.006	-0.165	-3.097	-0.192	-3.713	-0.019	-0.374
		(0.315)		(0.002)		(0.000)***		(0.709)
EQ_SHARE	-0.108	-1.460	-0.115	-1.611	-0.171	-2.496	-0.120	-1.816
		(0.145)		(0.108)		(0.013)		(0.07)

As can be seen in Table 13, the real explanatory variables do not exhibit significantly different results for the real returns. The one-month returns are still not very well predicted.

5.4 Investment strategy

5.4.1 Formulation

Now that we have the predictors analyzed, we can formulate an investment strategy using the stock market index and the bond index as the inputs for the performance analysis, and the relevant predictors as the inputs for making the investment choices. If we consider the findings from the previous section, we can se that the PE, ISM and DY measure proved efficient for all three sets of regressions (nominal, real and the return differential). The ISM measure showed statistically significant predictive ability for the nominal and real S&P500 regressions, but lost some of its power when the returns were compared. For the nominal and real return regressions on the S&P500 the ISM index showed statistically significant returns for all time frames, but for the return comparison only one time frame showed statistically significant returns. The CC and EQ_SHARE measures failed to show statistically significant predictive ability, so they are excluded from the regression-based investment strategy. In conclusion, the PE, DY and ISM measures make the first cut based on previous results

The second cut will be based on the robustness of the measures. For this investment strategy, we will divide the period into two subgroups, the first half spanning the time frame 1973-

1990 and the second one 1991-2008. To get an idea of how robust the indicators are, a set of regressions was run with the 2 different subperiods. The results of these regressions are shown in Table 14.

Table 14. Regression coefficients for DY, PE, CC, EQ_SHARE and ISM regressed against the future 6 and 12 month return difference between stocks (S&P500) and bonds (Merrill Lynch Total Return Index) divided into two subperiods: Period 1 = 1973-1990, and Period 2 = 1991-2008.

	6-months / period 1		6-months / period 2		12-months / period 1		12-months / period 2	
Variable	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)	Standardized Coefficients Beta	t (sig.)
(Constant)		1.246 (0.214)		0.083 (0.934)		0.868 (0.386)		0.715 (0.476)
DY	0.131	0.687 (0.493)	0.116	0.804 (0.422)	0.296	1.713 (0.088)	0.030	0.216 (0.829)
PE	-0.210	-1.221 (0.223)	-0.505	-4.603 (0.000)***	-0.178	-1.142 (0.255)	-0.687	-6.645 (0.000)***
CC	-0.123	-1.207 (0.229)	0.286	2.608 (0.01)	0.095	1.024 (0.307)	0.321	3.099 (0.002)
ISM	-0.085	-0.859 (0.391)	0.052	0.816 (0.415)	-0.253	-2.818 (0.005)	0.090	1.506 (0.134)
EQ_SHARE	-0.190	-2.176 (0.031)	0.189	2.578 (0.011)	-0.216	-2.717 (0.007)	0.172	2.536 (0.012)

The results from Table 14 suggest that the DY and PE measures are rather robust, since they exhibit the same sign in their beta-coefficients for both subperiods and both the 6 and 12 month time frames. The picture is slightly more worrying for the rest of the measures, as they have a different sign for their coefficients (albeit not statistically significant in most cases for the CC and ISM measure). Based on these results the logical choice would be to exclude the measures that fail to show consistent results over different time subperiods. If the EQ_SHARE measure had been included based on the first cut, it would have been excluded based on the above results.

The next step is to estimate the coefficients for the actual investment strategy using the predictors that met the criteria (PE and DY). A new regression is needed with only these measures included. For the calculation of the prediction by using the regression variables, the unstandardized coefficients will be used, since the standardized coefficients cannot be used in calculating the regression estimates.

5.4.2 Performance

The results obtained by using the regression coefficients to estimate the returns for the subsequent period proved to be useless. For subperiod 1, the returns were estimated to be all positive, while for subperiod 2 the estimated returns were all negative. For that reason, the reporting of those results is unnecessary. This might be due to the two subperiods being fundamentally different in some manner so that the predicted variables from the first are not consistent with the predicted variables from the second one.

The regressions were also run for the three-variable set (PE,DY and ISM). This had exactly the same results as the previous one, with subgroup one returns predicted as all positive and subgroup 2 returns as all negative

For further study, a simpler investment strategy using "lock-up" periods when certain thresholds are met could be investigated. The thresholds could be calculated for subperiod 1 and then used to estimate subperiod 2 returns. When the thresholds from one or two measures are met, then all investment would be switched to bonds, while otherwise always be in stocks. This strategy would be based on the results from the quartile analysis that proved to be rather promising.

6 Summary and conclusions

6.1 Summary and conclusions

This study first assessed the overall framework for asset allocation and went through previous literature relevant to the area. Five indicators were chosen for the empirical section based on previous literature and previously documented performance.

The empirical section started out with the quartile analysis for the chosen indicators. The values that the various predictors received for the time period were set out in quartiles based on the value. The returns for the subsequent 1, 6, 12 and 24 months were then calculated, both the real and nominal returns. The PE ratio and ISM index proved to be rather robust predictors, and these two measures documented increasing returns for each subsequent quartile. The equity share of new issues failed to provide similar robust performance, contrary to the previous study (Baker et al. (2000).

Although the results cannot be used as such to make investment decisions, the strong evidence for the PE measure for example does provide interesting insights to investors. As the problem for an investor is setting the thresholds right, previous data can be misleading. What these results do provide, though is evidence that these indicators serve as a tool for determining market overvaluation and possibility to gain superior profits from investing in bonds, for example.

Next, the different predictors were set in an OLS regression framework. Three different regressions were run, one against the nominal returns, one against the real returns and one against the return difference between stocks and bonds. The regression analysis performed for the various predictors confirms what was found out in the quartile analysis. The most statistically significant results were obtained for the PE, ISM and dividend yield. Out of the regression perhaps the most interesting is the one forecasting the return differential between stocks and bonds. For this regression none of the indicators show statistically significant predictive power for the 1 or 6 month returns, and only PE and ISM show statistically significant predictive power for the 12 month period. For the 24 month period it is the dividend yield and PE ratio that prove to be the most efficient.

The investment strategy studied is based on the estimated coefficients for dividing the period into two subperiods. This avoids using hindsight or double-counting the data. Unfortunately the periods forecast coefficients that proved to be rather distinct, thus forcing all the predicted returns for one period as positive and all predicted returns for the second period as negative. Basing investment decisions on these criteria would result in owning an all-stock portfolio or an all-bonds portfolio. Alternative strategies could be investigated, potentially basing the criteria more on the estimated thresholds that were used in the quartile analysis. Another strategy could use the same regression coefficients, but add an additional component to invoke both positive and negative returns.

6.2 Suggestions for further research

Further research could be carried out by adding more predictors to the analysis. Also, the investment strategy could be devised differently using alternative methods. As for most studies, adding different geographies could prove useful in obtaining global information on the predictive ability of different variables. Additionally, more indicators could be used to predict purely bond returns, as this study is largely focused on predicting the stock market returns.

7 References

References

Arnott, Robert D. and Peter L. Bernstein. 2002. What Risk Premium is 'Normal'? Financial Analysts Journal 58, 64.

Asness, Clifford. 2003. Fight the Fed Model. The Journal of Portfolio Management 11-24.

Asness, Clifford S. 2000. Stocks Versus Bonds: Explaining the Equity Risk Premium. Financial Analysts Journal 56, 96.

Berge, K. and W. T. Ziemba. 2002. The Predictive Ability of the Bond Stock Earnings Yield Differential in World-Wide Equity Markets. Sauder School of Business Working Paper .

Bierman, Harold,Jr. 1998. "Why Not 100% Equities?": Comment. Journal of Portfolio Management 24, 70.

Blake, David; Bruce N. Lehmann and Allan Timmermann. 1999. Asset Allocation Dynamics and Pension Fund Performance. Journal of Business 72, 429-461.

Bleiberg, Steven. 1989. How Little We Know...About P/Es, But Also Perhaps More Than We Think. Journal of Portfolio Management 15, 26.

Boehm, Ernst A. and Geoffrey H. Moore. 1991. Financial Market Forecasts and Rates of Return Based on Leading Index Signals. International Journal of Forecasting, 7, 357-374.

Boudoukh, Jacob and Matthew Richardson. 1993. Stock Returns and Inflation: A Long-Horizon Perspective. Am. Econ. Rev. 83, 1346.

Brennan, Michael J.; Eduardo S. Schwartz and Ronald Lagnado. 1997. Strategic Asset Allocation. Journal of Economic Dynamics and Control 21, 1377-1403.

Brennan, Michael J. and Yihong Xia. 2002. Dynamic Asset Allocation Under Inflation. J. Finance 57, 1201.

Brinson, Gary P.; L. Randolph Hood and Gilbert L. Beebower. 1986. Determinants of Portfolio Performance. Financial Analysts Journal 42, 39-44.

Brinson, Gary P.; Brian D. Singer and Gilbert L. Beebower. 1991. Determinants of Portfolio Performance II: An Update. Financial Analysts Journal 47, 40-48.

Brock, William; Josef Lakonishok and Blake LeBaron. 1992. Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. The Journal of Finance 47, 1731-1764.

Butler, Kirt C. and Dale L. Domian. 1991. Risk, Diversification, and the Investment Horizon. Journal of Portfolio Management 17, 41.

Campbell, John Y. and Robert J. Shiller. 1998. Valuation Ratios and the Long-Run Stock Market Outlook. Journal of Portfolio Management 24, 11.

Campbell, John Y. and Robert J. Shiller. 1988. Stock Prices, Earnings, and Expected Dividends. J. Finance 43, 661-676.

Campbell, John Y. and Tuomo Vuolteenaho. 2004. Inflation Illusion and Stock Prices. NBER Working Paper .

Canner, Niko; N. Gregory Mankiw and David N. Weil. 1994. An Asset Allocation Puzzle.

Cole, Kevin; Jean Helwege and David Laster. 1996. Stock Market Valuation Indicators: Is this Time Different? Financial Analysts Journal 52, 56-64.

Cullity, John P. 1987. Signals of Cyclical Movements in Inflation and Interest Rates. Financial Analysts Journal 43, 40.

Darst, David M. 2003. The Art of Asset Allocation. 396.

Dopfel, Frederick E. 2003. Asset Allocation in a Lower Stock-Bond Correlation Environment. Journal of Portfolio Management 30, 25.

Dougherty, C., 2002. Introduction to econometrics, 2nd edition. Oxford University Press, New York.]

Fama, Eugene F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. J. Finance 25, 383-417.

Fama, Eugene F. and Kenneth R. French. 1989. Business Conditions and Expected Returns on Stocks and Bonds. Journal of Financial Economics, 25, 23-49.

Fama, Eugene F. and G. William Schwert. 1977. Asset Returns and Inflation. Journal of Financial Economics, 5, 115-146.

Fisher, Kenneth L. and Meir Statman. 2003. Consumer Confidence and Stock Returns. Journal of Portfolio Management 30, 115.

Fleming, Michael J. and Eli M. Remolona. 1999. What Moves Bond Prices? Journal of Portfolio Management 25, 28.

Fuller, Russell J. and John L. Kling. 1990. Is the Stock Market Predictable? Journal of Portfolio Management 16, 28.

Jahnke, William W. 1997. The Asset Allocation Hoax. Journal of Financial Planning 10, 109.

Jansen, W. Jos and Nahuis, Niek J. 2002 The Stock Market and Consumer Confidence: European Evidence. De Nederlandsche Bank publication.

Keim, Donald B. and Robert F. Stambaugh. 1986. Predicting Returns in the Stock and Bond Markets. Journal of Financial Economics, 17, 357-390.

Koivu, Matti; Teemu Pennanen and William T. Ziemba. 2005. Cointegration Analysis of the Fed Model. Finance Research Letters, 2, 248-259.

Kothari, S. P. and Jay Shanken. 1997. Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis. Journal of Financial Economics, 44, 169-203.

Lamont, Owen. 1998. Earnings and Expected Returns. The Journal of Finance LIII, 1563-1587.

Lanne, Markku. 2002. Testing the Predictability of Stock Returns. The Review of Economics and Statistics 84, 407-415.

Lehtonen, Tilastollisen Analyysin Jatkokurssi, 1996

Li, Lingfeng. 2003. Macroeconomic Factors and the Correlation of Stock and Bond Returns.

Lofthouse, Stephen. 2001. Investment Management.

Loughran, Tim and Jay R. Ritter. 1995. The New Issues Puzzle. J. Finance 50, 23-51.

Modigliani, Franco and Richard A. Cohn. 1979. Inflation, Rational Valuation and the Market. Financial Analysts Journal 35, 24.

Otoo, Maria. 1999. Consumer Sentiment and the Stock Market. Federal Resrve System Working Paper .

Pesaran, M. Hashem and Allan Timmermann. 1995. Predictability of Stock Returns: Robustness and Economic Significance. J. Finance 50, 1201-1228.

Pontiff, Jeffrey and Lawrence D. Schall. 1998. Book-to-Market Ratios as Predictors of Market Returns. Journal of Financial Economics, 49, 141-160.

Ritter, Jay R. and Richard S. Warr. 2002. The Decline of Inflation and the Bull Market of 1982-1999. Journal of Financial & Quantitative Analysis 37, 29-61.

Siegel, Jeremy J. 1991. Does it Pay Stock Investors to Forecast the Business Cycle? Journal of Portfolio Management 18, 27.

Singer, Brian D. 1997. Asset Allocation, Hoaxes, and the Creation of Straw Men. Journal of Financial Planning 10, 14.

Spiess, D. Katherine and John Affleck-Graves. 1995. Underperformance in Long-Run Stock Returns Following Seasoned Equity Offerings. Journal of Financial Economics, 38, 243-267.

Thaler, Richard H. and J. Peter Williamson. 1994. College and University Endownment Funds: Why Not 100% Equities? Journal of Portfolio Management 21, 27.

Thomas, Jacob and Frank Zhang, 2008. Don't Fight the Fed Model! .

Wachter, Jessica A. and Missaka Warusawitharana. 2007. Predictable Returns and Asset Allocation: Should a Skeptical Investor Time the Market? .

8 Appendix

8.1 Real returns for S&P500 for different quartiles of the predictors

8.1.1 P/E ratio

P/E ratio quartiles real returns	**Subsequent 1 month return (%)**	**Subsequent 6 month return (%)**	**Subsequent 12 month return (%)**	**Subsequent 24 month return (%)**
Quartile 1	0.6%	5.7%	11.3%	24.5%
Quartile 2	0.9%	4.7%	10.5%	19.3%
Quartile 3	0.9%	4.3%	11.2%	33.2%
Quartile 4	0.2%	1.6%	2.7%	7.2%

8.1.2 ISM index

Purchasing manager confidence index quartiles real returns	**Subsequent 1 month return (%)**	**Subsequent 6 month return (%)**	**Subsequent 12 month return (%)**	**Subsequent 24 month return (%)**
Quartile 1	1.4%	8.1%	15.4%	27.4%
Quartile 2	0.6%	4.6%	10.5%	23.6%
Quartile 3	0.8%	5.0%	9.6%	19.5%
Quartile 4	-0.3%	-1.5%	-0.1%	11.7%

8.1.3 Dividend yield

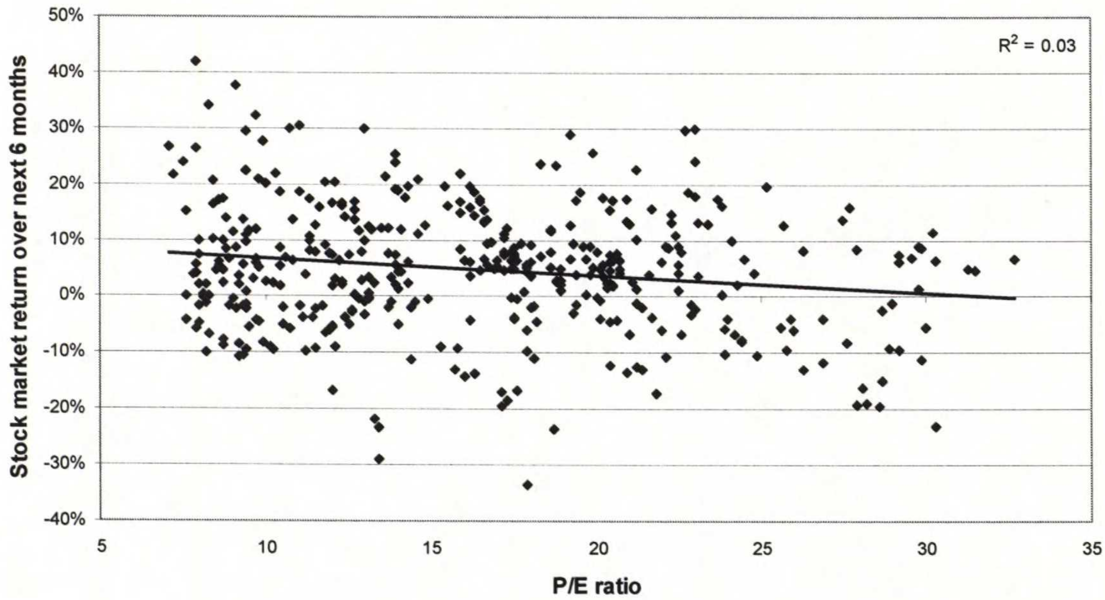
Dividend yield quartiles real returns	**Subsequent 1 month return (%)**	**Subsequent 6 month return (%)**	**Subsequent 12 month return (%)**	**Subsequent 24 month return (%)**
Quartile 1	0.1%	2.3%	4.8%	10.2%
Quartile 2	1.0%	5.4%	12.0%	33.3%
Quartile 3	0.5%	2.8%	7.4%	13.7%
Quartile 4	0.8%	5.9%	11.3%	26.3%

8.1.4 Consumer confidence index

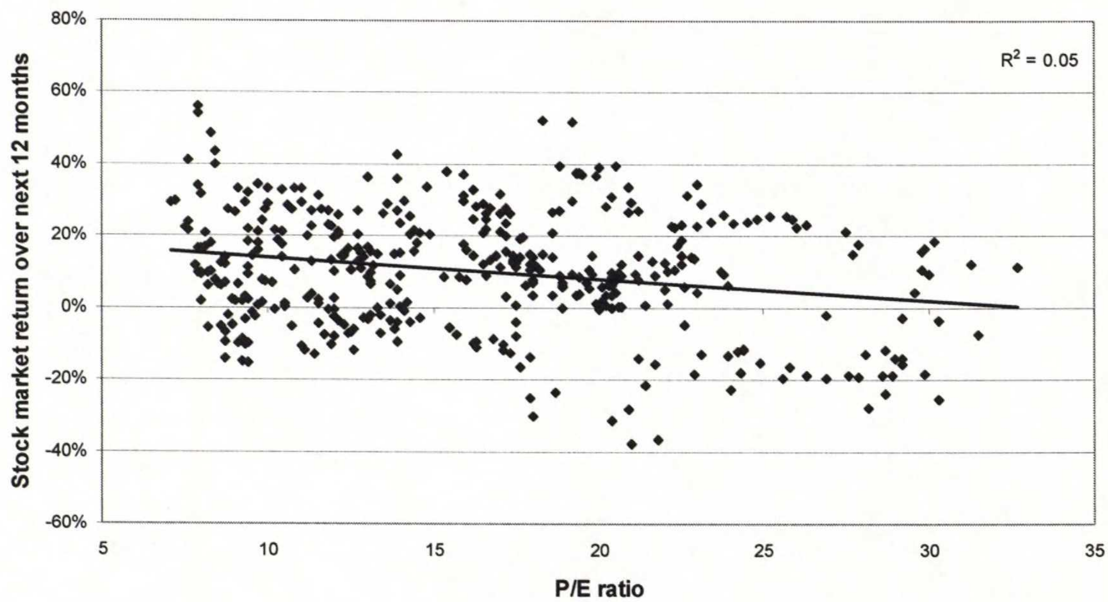
Consumer confidence quartiles real returns	**Subsequent 1 month return (%)**	**Subsequent 6 month return (%)**	**Subsequent 12 month return (%)**	**Subsequent 24 month return (%)**
Quartile 1	1.4%	7.7%	13.1%	22.8%
Quartile 2	0.4%	1.3%	4.1%	15.9%
Quartile 3	0.4%	3.2%	10.0%	28.3%
Quartile 4	0.3%	4.0%	8.0%	15.2%

8.2 P/E ratio and stock market return

P/E ratio and stock market return for the subsequent 6 month period.

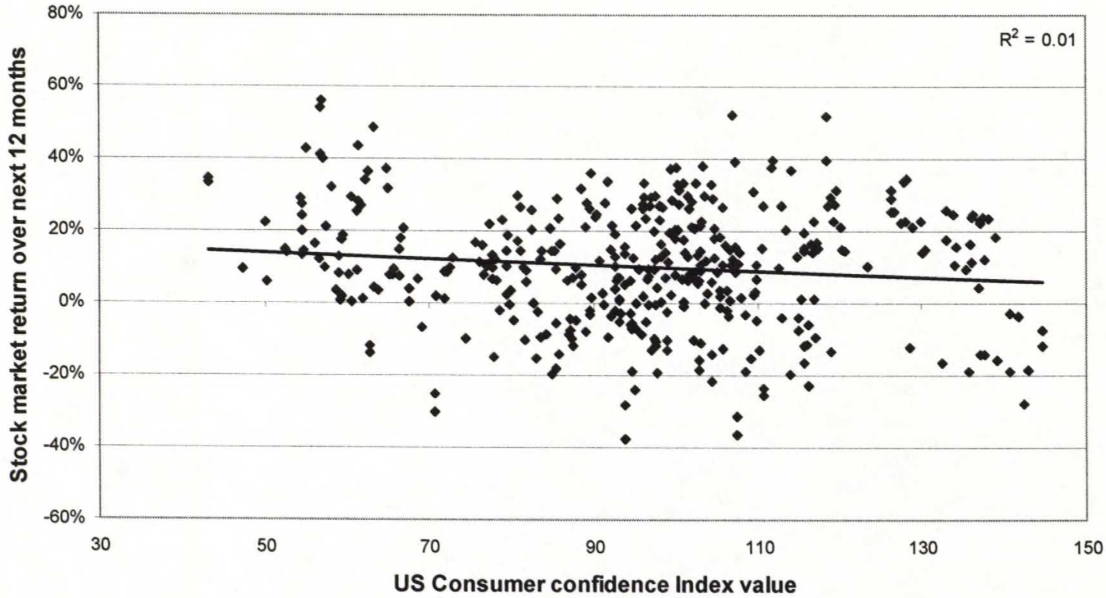


P/E ratio and stock market return for the subsequent 12 month period.

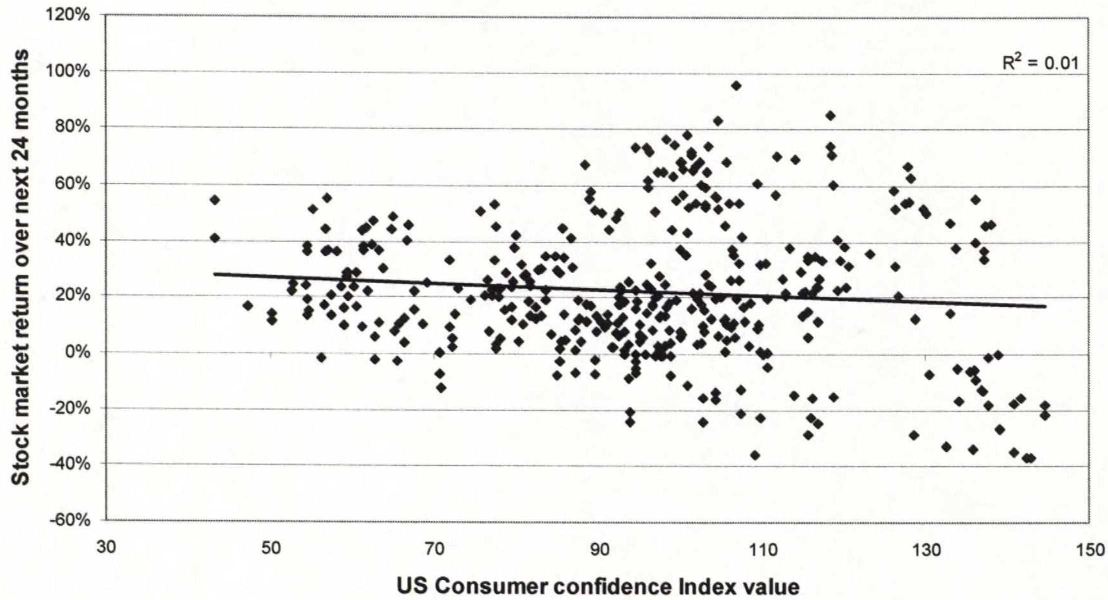


8.3 Consumer confidence index

Consumer confidence index plotted against the subsequent 12 month returns.

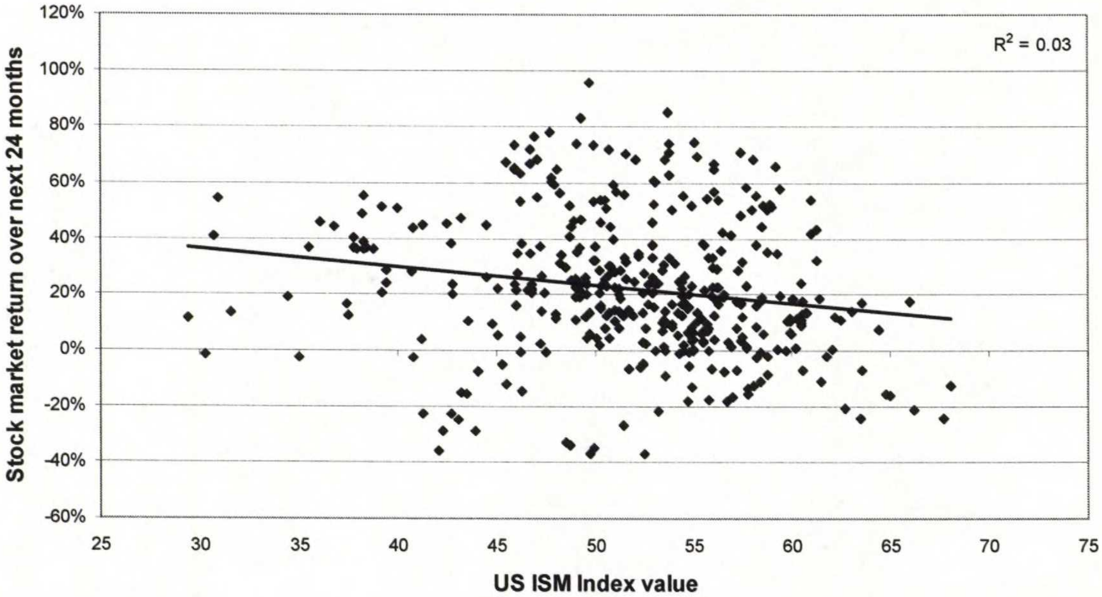


Consumer confidence index plotted against the subsequent 24 month returns.



8.4 Purchasing manager confidence index

ISM index plotted against the subsequent 24 month returns.



8.5 Regression variables

Dependent variables:

SP1_N	Nominal return of the S&P500 index for the following month
SP6_N	Nominal return of the S&P500 index for the following 6 months
SP12_N	Nominal return of the S&P500 index for the following 12 months
SP24_N	Nominal return of the S&P500 index for the following 24 months
SP1_R	Real return of the S&P500 index for the following month
SP6_R	Real return of the S&P500 index for the following 6 months
SP12_R	Real return of the S&P500 index for the following 12 months
SP24_R	Real return of the S&P500 index for the following 24 months
DIF_1	Return difference for S&P500 and ML bond index following 1 month
DIF_6	Return difference for S&P500 and ML bond index following 6 months
DIF_12	Return difference for S&P500 and ML bond index following 12 months
DIF_24	Return difference for S&P500 and ML bond index following 24 months

Explanatory variables:

DY	The dividend yield on the S&P500 index
PE	The P/E ration on the S&P500 index
CC	Consumer confidence index value
ISM	Purchasing manager survey index value
EQ_SHARE	Equity share of new issues

8.6 Variable correlations

Correlations

		SP24	DY	PE	CC	ISM
Pearson Correlation	SP24	1.000	.245	-.361	-.136	-.126
	DY	.245	1.000	-.934	-.468	-.187
	PE	-.361	-.934	1.000	.439	.142
	CC	-.136	-.468	.439	1.000	.371
	ISM	-.126	-.187	.142	.371	1.000

The P/E ratio and dividend yield show high correlation, this is most likely due to the fact that they have the same component in their calculation, that being the stock price. The P/E has the price divided by earnings and the dividend yield has the dividend divided by price. As the P/E number is an inverse of the E/P number, which in turn would be most representative of the "yield" on stocks, it is common sense that the correlation present is negative. The ISM index has rather low correlations with all the other measures.