Vaasan yliopisto
UNIVERSITY OF VAASA

Olli Airaksinen

Dividends tracing bears

Predicting bear markets using dividend yields

School of Accounting and Finance
Master’s Thesis in Finance
Master’s Programme in Finance

Vaasa 2021

UNIVERSITY OF VAASA
School of Accounting and Finance
Author: Olli Airaksinen
Title of the Thesis: Dividends tracing bears : Predicting bear markets using dividend yields
Degree: Master of Science in Economics and Business Administration
Programme: Master's Degree Programme in Finance
Supervisor: Janne Äijö
Year of completion: 2021 **Pages:** 65

ABSTRACT:

Discussion on the state of the stock market and the current market cycle is an ongoing debate in financial literature. Trying to time the market correctly has proven to be a difficult task even for professional investors. No perfect guide or rule has yet to emerge that would consistently predict shifts in market cycles has yet been discovered.

The purpose of this thesis is to study the ability to predict bear market cycles using dividend yields. Two different market indices are studied, the S&P 500 and the OMX Helsinki. The data sample consists of monthly observations covering the period 1989-2021. The empirical part of this paper is divided into two parts. First, we study if the dividend yields have any return predictability abilities. Secondly, we study if the dividend yields can be used to forecast future bear markets.

Previous literature has been inconclusive of the predictive power of dividend yields for stock returns. While stock return predictability using financial variables has gained a lot of attention in the literature, some recent studies have shifted the focus to bear market predictability. Forecasting shifts in market cycles can be a considerable benefit for investors. The hypothesis is that low dividend yields can forecast future low returns.

The results of this paper are divided. Dividend yields show no significant predictive power for the S&P 500. The results for the bear market predictability are similar. For the OMX Helsinki index, the results are more complicated. The results show a negative correlation between the dividend yield and market return, which is against the original hypothesis. There is also evidence for bear market predictability using dividend yields.

KEYWORDS: Dividend yield, Bear market, Return predictability

Table of contents

Figures

Tables

Abbreviations

CAPM	Capital Asset Pricing Model
DDM	Dividend Discount Model
DY	Dividend Yield
EMH	Efficient Market Hypothesis
NYSE	New York Stock Exchange
OMXH	Nasdaq OMX Helsinki stock Exchange
PI	Price index
S&P 500	Standard & Poor's 500 Composite Index

1 Introduction

Since the start of the current bull market in the US starting in 2009, investors have debated when the next bear market will eventually happen. Market cycles and trying to time them are an ongoing debate among academics, professional investors, and ordinary people trying to make a profit on the stock market. However, no perfect guide on how to time or predict the market has yet to emerge. Various research has been done on the subject, and different formulas for predicting market outcomes have been made—some more promising than others.

With the eventual bear market lurking in the future, this thesis will try once more to take on this task of finding a way to predict shifts in market trends. It will focus on the dividend yield and its ability to forecast a possible bear market cycle. The original view that periods of low dividend yields can be interpreted as an overvalued stock market (Fama & French, 1988) might have since become outdated (Grullon & Michaely, 2002). Dividend payout policies and ratios have been shown to fluctuate over time and between markets. This study will incorporate two very different stock markets, The US and the Finnish, under examination.

With investors' focus shifting towards value stocks that often also provide a steady dividend yield, it can be argued that this can be seen as an indicator for a macroeconomic downturn, resulting in a bear market. Dividend payouts are connected to earnings of the company, and a steadily rising dividend is a question of status for some companies (Strauss, 2020).

This thesis hypothesizes that changes in the dividend yield can predict a bear market. Evidence showing that dividend yields have been able to predict market returns has been made (Fama & French, 1988; Lewellen, 2004; Verdickt et al., 2019), but the connection of the dividend yield to the prediction of market returns have been studied less (N. K. Chen et al., 2017; S. S. Chen, 2009).

1.1 Previous literature

Several studies evaluating the ability to make reliable predictions for stock markets have been done. The predictive power of financial and macroeconomic variables has been a popular area of academic research since at least the 1980's when several studies, such as, Campbell and Shiller (1988) and Fama and French (1988), argued that the dividend yield could be used as a predictor for stock returns. The hypothesis of dividend yields predicting stock returns dates back to Charles Dow (1920) in the 1920s. Since then, studies have shown evidence for or against the hypotheses that dividend yields could be used for predictive purposes regarding the future movements of stock market returns (Goetzmann & Jorion, 1993; Lewellen, 2004).

Although the idea that publicly available information, such as the dividend yield, could be used to predict stock returns violates the principals of the semi-strong market efficiency theorem by Fama (1970). Dividend yield as a variable capable of predicting stock returns is supported by Rozeff (1984), who shows empirical evidence that the returns increase continuously as the prior year's dividend yield increases. Rozeff's (1984) theory is that dividend yields measure the ex-ante risk premiums and contradict the view of stock market returns being a random walk.

Fama and French (1988) use a regression framework to study the explanatory value of dividend yields within the NYSE index. Their results indicate that the explanatory value of the dividend yield increases as the time horizon increases. Fama and French (1988) state that their intuition on the hypothesis that dividend yields predict returns is that stock prices are low relative to dividends when discount rates and expected returns are high. Hence, yields capture variation in expected returns. The difficulty of using yields as estimators for future returns is that they contain noise, variation unrelated to expected returns, that may cause the estimates to understate the variation of expected returns (Fama & French, 1988).

Shiller (1984) provides evidence that stock prices tend to overreact to changes in dividends. The simple correlation coefficient between the annual real S&P composite index and the corresponding annual real dividend between 1926 and 1983 is 0.91. During the same time period the correlation between the price and the earnings is only 0.75. According to Shiller, since dividends are somewhat predictable, and in spite, we are unable to forecast well any change in return, it must be true that stock prices are somewhat determined in anticipation of dividends paid. (Shiller, 1984.)

Campbell and Shiller (1988) examine time variation in corporate stock prices relative to dividends. Their study proposes a log dividend-price ratio as the rational expectation of the present value of future dividend growth rates and discount rates. Their study provides some evidence that the dividend price ratio can predict future one-period real discount rates and dividend growth rates. However, as Campbell and Shiller (1988) state, their econometric methods are subject to some bias, and their measures of discount rates are only applicable under certain assumptions.

As Cochrane (2008) points out, the ink was hardly dry on the first studies (Campbell & Shiller, 1988; Fama & French, 1988; Rozeff, 1984; Shiller, 1984) running regressions on dividend yields and returns before literature ran to examine their econometric properties and statistical significance.

While the studies mentioned above have provided evidence that regressions of returns on dividend yields provide evidence for predictability of stock returns, Goetzmann and Jorion (1993) present a contrary view. They argue that the previous studies have failed to recognize serious biases that arise when regressing lagged dependent variables. In their study, Goetzmann and Jorion (1993) use bootstrapping techniques to model the null hypothesis that returns conform to a random walk while keeping the dividends at their actual patterns. They show that overall, no significant statistical evidence indicates that dividend yields can be used to predict stock returns. Goetzmann and Jorion (1993) argue that the implications of their results extend beyond the test of the predictive power of dividend yield. The reported biases can be extended on any time series studies of returns conditioned upon any ratio involving price levels. (Goetzmann & Jorion, 1993).

As stated by Cochrane (2008), the implications of return forecastability have a reach throughout finance. So far, the research has been mainly focused on portfolio theory, that a few investors could benefit by market-timing portfolios (Cochrane, 2008). Cochrane's (2008) theory is that if returns are not forecastable, then dividend growth must be. Cochrane (2008) sets up a null that returns are not forecastable and finds that the absence of dividend-growth forecastability provides a stronger evidence against the null than does the presence of one-year return forecastability. (Cochrane, 2008.)

The literature on stock price predictability has evolved in the last 40 years. The first studies presented evidence that dividend yields can be used to predict market returns. But as Lewellen (2004) points out, predictive regressions are exposed to small-sample biases. More recent studies are able to correct some of these biases and still find robust data that dividend yields are a valid method to predict aggregate stock returns. Lewellen (2004) shows that dividend yields predict market returns during the period 1946-2000 using monthly returns regressed on lagged dividend yields.

While the number of studies done on the predictive power of financial ratios is vast, the amount of studies done on specifically predicting market cycles is more limited. Maheu & McCurdy (2000) uses a Markov-switching model to sort returns into a high-return stable state and a low-return volatile state, which they label as bull and bear markets, respectively. They find nonlinear behavior in monthly stock returns and state that their empirical model estimates clearly identify high-return and low-return market states.

S. S. Chen (2009) specifically studies the ability to use macroeconomic variables to predict bear markets. His paper uses monthly data from the S&P500 index to perform an empirical study on the ability to predict market recessions from 1957 to 2007. The results indicate that yield curves and inflation rates are the most useful predictors of recessions in the US markets. While S. S. Chen (2009) does not specifically use dividend yields as an independent variable in his regression, the study provides an encouraging result that market cycles are predictable. S. S. Chen revisits the topic of bear market predictability, together with N. K. Chen and Chou in their 2017 paper (N. K. Chen et al., 2017). N. K. Chen et al. (2017) include the dividend yield of S&P 500 in their variables. S. S. Chen's (2009) methods of identifying the bear markets will provide a basis for this study. The macroeconomic framework will be presented and discussed in more detail later on in this paper.

1.2 Purpose of the study

This thesis studies the informational value of dividend yields in predicting stock market returns and future stock market cycles. Difficulties in different economies during the past years have increased the interest in different market cycle forecasts (Hanna, 2018). The literature presented in the previous chapter has found evidence of return predictability using the dividend yield. However, most of the studies have been made during the 20th century. A more comprehensive literature view will be presented in chapter 2.

For investors, the information of market trends and shifts in market cycles is valuable in order to allocate assets accordingly. The ability to make reliable predictions of the market cycles increases the potential to use timing strategies in investing. The relationship that a low dividend yield predicts low future returns is the basis of this study (Mcmillan, 2014). The hypotheses of this thesis are:

H1: Dividend yields are able to predict market returns.

And

H2: Dividend yields can predict recessions in the stock market.

The value of this study is that it will evaluate the capability to predict shifts in market cycles by using the dividend yields in two very different markets. This study will use the S&P 500 and the Nasdaq OMX Helsinki indices. *H1* expects a positive relation between the dividend yield and the market return. *H2* expects changes in the dividend yield to indicate changes in the market cycles.

The majority of the academic literature uses US data, while smaller markets are often overlooked. The time period used in this study provides an addition to the previous literature. It captures the effects of the changes in the US dividend yield payout policies studied by Skinner (2008). Incorporating a smaller stock market as the Finnish one gives an interesting comparison of a less studied market against the global benchmark as the S&P 500.

2 Literature review

This chapter focuses solely on presenting the existing literature that is used as the basis of this thesis. As mentioned in the previous chapter, stock return predictability has attracted attention in academic literature. Dividend yields are among the most studied financial variables used in return predicting (Golez & Koudijs, 2018). Instead of only predicting stock returns, some studies have shifted their focus on predicting bear markets (N. K. Chen et al., 2017; S. S. Chen, 2009). We will first focus on literature discussing the return predictability of the dividend yield and then look at the literature focusing on bear market predictability.

2.1 The relation between stock returns and dividend yield

As mentioned in chapter 1.1, the origins of the return predictability discussion can be traced to the studies of Campbell and Shiller (1988) and Fama and French (1988). They use US data to provide evidence that the dividend yield can be used as a predictive variable for estimating out of sample market returns. However, the data used by Campbell and Shiller (1988) and Fama and French (1988) naturally only reach until 1986. Since then, there is growing evidence that changes in corporate financial policies in the US have created persistent changes in dividend growth rates (Fama & French, 2001).

Lewellen (2004) uses a logarithmic dividend yield variable to predict market returns during the period 1946-2000. This period captures the 1990s, which saw severe changes within the dividend yield during the 1995-2000 period. During this period, the dividend yield dropped from 2.9% to 1.5%, while the NYSE value-weighted index almost doubled. Despite this unusual price run-up Lewellen (2004) states that the return predictability remains strong, confirming the findings of Campbell & Shiller (1988) and Fama & French (1988).

A comprehensive review on stock market predictability is done by Welch and Goyal (2008). They state that previous literature is difficult to absorb, as different articles use different techniques, variables, and time periods. Results from previous studies may change when more recent data is used. Welch and Goyal (2008) use data from the S&P 500 index to study the return predictability attributes of the dividend yield, among several other variables. They estimate the predictive performance of the dividend yield during different time periods starting from 1925 using an OLS regression model. Their findings state that the DY predicted equity premia (total return of the S&P 500 minus the prevailing short-term interest rate) well during the great depression, the period from 1940-1958, the oil shock of 1973-1975, and the market decline of 2000-2002. Correspondingly to Lewellen (2004), Welch and Goyal (2008) state that the dividend yield had large prediction errors during 1995-2000. (Welch & Goyal, 2008.)

Ang & Bekaert (2007) study the predictive power of the dividend yield of S&P 500 for forecasting excess returns, cash flows, and interest rates. They use quarterly data, and the sample period covers 1935-2001. Omitting the 1990s, they confirm the results of Campbell and Shiller (1988) that dividend yield is a significant predictor of returns at all horizons (Ang & Bekaert, 2007). However, when using the full data sample, the significance level drops to 5% for the one-year horizon. Ang and Bekaert state that the long-horizon predictability of the full sample is insignificant. The findings of Welch and Goyal (2008) are in line with the results of Ang & Bekaert (2007).

Studies for the US market dominate the extant literature of dividend yield predictability (Charles et al., 2017). The weak predictive power of the univariate dividend yield in the full sample might be caused by small sample phenomenon due to the very special nature of dividend yields in the US during the 1990s (Ang & Bekaert, 2007). Ang and Bekaert (2007) include data from the UK and Germany to test the robustness of their US results. Significant results of return predictability for the dividend yield are found for the UK in the one-year horizon. Germany’s dividend yield coefficients are of the same magnitude of the British, but insignificant (Ang & Bekaert, 2007).

International evidence from outside of the US markets produces more conclusive evidence of return predictability. Verdickt, Annaert & Deloof (2019) find evidence that dividend yields predict returns in Belgium during the period 1987-2015. Their study uses 165 years of data from the Brussels Stock Exchange. Verdict et al. (2019) do not find evidence of return predictability before 1987, which contrasts with US evidence. Verdickt et al. (2019) present possible reasons for this. Fama & French (2001) show that the dividend yield policy has changed in the US during the 1980-2000 period. Firstly, the fraction of dividend-paying firms has not dropped as much in Belgium relative to the US. Secondly, there is a difference in dividend smoothing between the US and Belgium (Verdickt et al., 2019).

A comprehensive study of the international stock return predictability is done by Charles, Darné, and Kim (2017). They use financial ratios to study return predictability in 16 Asia-Pacific countries (including US) and 21 European markets (including Finland). They use an augmented regression method and data sample that covers January 2000 until June 2014. Using the dividend yield as a predictor, they find that most of the markets show evidence of return predictability at the 5% significance level according to the F-test. The effect size results are however statistically insignificant in all countries, except Hong Kong, China and India. (Charles et al., 2017.)

Mcmillan (2014) studies the predictability of returns in 40 markets using the log dividend yield as a predictive variable. His results are particularly relevant to this study, as the markets in the study include both the US and Finland. His standard predictive regression gives varying results. Twelve of the 40 countries show a positive relation between the dividend yield and the market return at the 5 % significance level. Another 3 countries show significant predictability at the 10% level. For the US sample period of 1973-2010, the coefficient is positive but statistically insignificant. For the Finnish sample period of 1988-2010, the results are also statistically insignificant, but show a negative coefficient, contrary to the expected results. Three other countries, Italy, Cyprus, and Venezuela, also show a negative but insignificant coefficient. (Mcmillan, 2014.)

Golez and Koudjis (2018) study return predictability using a data sample covering four centuries. Their sample dates back to 1629 and uses a combination of data from the Netherlands, UK and the US. They find evidence for dividend yields predicting returns across different horizons. While this data sample is viewed as problematic by some (Verdickt et al., 2019) it shows that dividend yields have a long history in return prediction.

The historical evidence both in the US and internationally of dividend yields predicting stock market returns is the basis for the *H1* of this thesis. A clear difference between the US markets and European markets exists at least after the 1990s (Verdickt et al., 2019). By studying the US markets with the latest data and adding the less studied Finnish market as a comparison, this thesis will provide relevant results to the somewhat conflicting previous research results discussed in this sub-chapter.

2.2 Bear market predictability

Among the first studies done on bear market predictability S. S. Chen (2009) provided evidence that certain macroeconomic variables can predict bear markets accurately. These findings are confirmed by Nyberg (2013). Nyberg uses a binary time series model to predict bull and bear stock markets in the S&P 500 index during the time period 1957-2010 (Nyberg, 2013). Nyberg (2013) concludes that the dividend-price ratio and the term spread between long-term and short-term interest rates appear to be the best indicators of the future stock market state.

In their 2017 paper S.S. Chen together with N. K. Chen and Chou revisits bear market predictability using financial ratios instead of macroeconomic (N. K. Chen et al., 2017). N. K. Chen et al. (2017) choose financial variables that are particularly related to the presence of imperfect capital markets. This is motivated by the fact that imperfect capital markets play a role in the propagation mechanism of exogenous shocks during business cycles (N. K. Chen et al., 2017).

While the first paper by S. S. Chen published in 2009 did not use dividend yields as a predictive variable, the N. K. Chen et al. 2017 paper does. The data sample consists of monthly S&P 500 data ranging from January 1952 to December 2011. The results indicate that the in-sample predictability of the S&P 500 log dividend yield is statistically insignificant in all horizons. This is true for all valuation ratios, such as earnings-price and book-to-market ratios. In the out-of-sample tests dividend yield predicts future bear markets one and three months ahead. (N. K. Chen et al., 2017; S. S. Chen, 2009.)

These results of Nyberg (2013) and N. K. Chen et al. (2017) act as a motivation for the *H2* of this thesis. Nyberg (2013) finds evidence that supports the *H2*, while N. K. Chen et al. (2017) find only limited evidence. Similarly, as in the case for the return predictability, the results of the bear market predictability might also vary between US and Finnish markets due to the differences in dividend policies.

3 Efficient markets

This chapter will introduce the fundamental concept of efficient capital markets and the three different forms of it (Fama, 1970). The efficient market hypothesis is the basics of modern finance theory and allows us to study other theories and concepts that are based on it. Despite its evident influence, or perhaps because of it, the efficient market hypothesis has generated a lot of dispute. The hypothesis has inadequacies that allow deviations from the hypothesis in the form of excess returns (Jensen, 1978). Regardless of the ongoing dispute of the validity of the efficient market hypothesis, it is vital to explain it and understand the concepts.

3.1 Efficient market hypothesis

The efficient market hypothesis (EMH) states that all available information is at all times fully reflected on the security prices (Fama, 1970). This allows investors to make decisions on their capital allocation. Without the concept of "fully reflected information", the capital market would allow securities to be mispriced, and people with excess information would be able to make abnormal profits. This would lead to an anomaly within the capital markets.

This hypothesis that all asset prices fully reflect the available information is questionable. First of all, as Fama (1970) states, the definitional statement that all asset prices "fully reflect" the available information at all times is not empirically testable. Thus the EMH has three conditional assumptions (Fama, 1970):

(i) There are no transaction costs.
(ii) All available information is costlessly available to market participants.
(iii) All agree on the implications of current information for the current price and distributions of future prices of each security.

According to these assumptions, no excess returns could be made, so no anomalies in the markets could appear. Fama (1970) admits that a frictionless market where all information is freely available does indeed not exist in practice. Academics have studied and debated on the existence of several financial anomalies that exist in the markets. A few of these anomalies will be later discussed in this paper. The fundamental issue with testing the efficient market hypothesis is that it is not testable per se. In order to test the EMH, one must use a model of equilibrium, an asset pricing model. This leads to the *joint hypothesis* problem. Anomalies occurring might be caused by inaccurate pricing models of inefficient markets.

3.2 Forms of market efficiency

In his 1970 paper, Fama states that the studies around market efficiency have historically evolved to include three different forms of market efficiency; *weak*, *semi-strong,* and *strong*. These three forms of market efficiency are separated by the amount of information that they include. (Fama, 1970.)

3.2.1 Weak form of market efficiency

The weak form of market efficiency states that current stock prices only reflect the historical prices. All historical information on trading volumes and stock prices are included in the current price. The weak form of market efficiency is closely related to the *random walk* theory of early financial study. The random walk theory states that stock price changes are independent and identically distributed. If this were to be true, it would be simply impossible for anyone to predict future stock price movements, and thus earning excess returns compared to the market would be impossible. (Fama, 1970.)

In his 1991 paper, Fama takes on a new approach on the weak form of efficiency. Instead of solely focusing on predicting returns based on past returns, Fama (1991) takes a new view on return forecasting using variables like dividend yield, earnings-price ratios, and term structure. Empirical studies stating a clear pattern between dividend yield and stock price behavior (Cochrane, 2011; Shiller, 1984) do not work as evidence either for or against market efficiency (Fama, 1991). In an efficient market, the forecasting power of dividend yield states that when prices are high relative to dividends, expected returns are low (Fama, 1991). The informational value of the dividend yield is directly included in the price.

3.2.2 The semi-strong form of market efficiency

The semi-strong form of market efficiency states that new fundamental information is also included within the current stock price in addition to the historical prices. These include information such as earnings announcements, stock splits, and new security issues. This obviously public information would be included in all prices with right after it is released (Fama, 1970). This means that investors would not benefit from fundamental analysis in the search for excess profits. It is to be noted that these different forms of market efficiency are not independent of each other; if a market is semi-strongly efficient it must also be weakly efficient.

A way to test a market's semi-strong efficiency, according to Fama (1991), is by event studies. With new information regarding fundamental values, event studies allow us to measure the time it takes for the market to react. Some form of post-announcement lag or drift occurs within the market, but firm-specific announcements are usually adjusted to the price within a day. (Fama, 1991.)

3.2.3 The strong form of market efficiency

The last and most unrealistic form of market efficiency is the strong form, in which no market participant has any monopolistic knowledge that would able him to gain excess profits. Thus, it is the situation in which all available information is included within the prices. Any kind of fundamental analysis, event studies, or even insider trading would be impossible within the strong form of market efficiency. Insider trading, however, has been empirically proven to generate excess returns. Fama states that the strong form of market efficiency is best viewed as a benchmark against which deviations of market efficiency can be evaluated. (Fama, 1970.)

4 Asset pricing models

This chapter will discuss the relation of dividends to asset pricing. The irrelevance theorem of Miller and Modigliani (1961) states that dividends play no role in determining the price levels or returns of equities. The theorem does not take into account the usefulness of dividends in explaining these variables. It is important to understand the properties of dividends and dividend yield have in asset pricing. Researchers find dividends to be an important and useful variable when empirically characterizing asset pricing models (Campbell & Shiller, 1988; Fama & French, 1988). Since dividends are cashflows going to equity holders, their importance in asset pricing may feel intuitive, but academics have also made controversial views. This chapter will discuss the importance of dividends to the asset pricing theory.(Boudoukh et al., 2007.)

4.1 Capital asset pricing model

The capital asset pricing model, or CAPM, is perhaps the most fundamental and important asset pricing model in contemporary finance. The CAPM is a set of predictions concerning expected returns of risky assets (Bodie et al., 2014). The CAPM is based on the modern portfolio theory introduced by Markowitz (1952) and was developed by Sharpe (1964), Lintner (1965), and Mossin (1966). The CAPM is not empirically perfect, but provides an observable relationship between an asset's risk and expected return. Secondly, the model helps estimate the returns of an asset that has not yet been publicly traded in a market place. (Bodie et al., 2014.)

The CAPM states:

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] \tag{1}$$

Where $E(r_i)$is the expected return of asset *i*, r_f is the risk-free rate, β_i is the beta of asset *i*, and $E(r_m)$is the expected return of the market portfolio.

The CAPM has certain assumptions that are listed below (Bodie et al., 2014):

1. Investors are rational, mean-variance optimizers
2. The investor's planning horizon is a single period
3. Investors have homogeneous expectations
4. All assets are publicly held and traded on public exchanges, short positions are allowed and investors can lend at a common risk-free rate
5. All information is publicly available
6. No taxes or transactions costs

As we can observe, the assumptions are not realistic and provide more of an academic framework for asset pricing. Without taxes, the CAPM suggests that investors choose mean-variance efficient portfolios. In the realistic situation, with taxes existing, investors would be expected to choose portfolios that are mean-variance efficient in after-tax rates of return (Litzenberger & Ramaswamy, 1979). Brennan (1970) was the first to introduce an extended model of the single period CAPM that took into account the taxation of dividends. Assuming proportional individual tax rates, certain dividends and unlimited borrowing at the risk free rate Brennan derived the following equilibrium relationship (Brennan, 1970; R. H. Litzenberger & Ramaswamy, 1979):

$$E(\tilde{R}_i) - r_f = b\beta_i + \tau[d_i - r_f] \tag{2}$$

Where $\tilde{R}_i$ is the before-tax total return of security *i,* β_i is the systematic risk, r_f is the risk-free rate, d_i is the dividend yield of security *i* and τ is a positive coefficient that accounts for the taxation of dividends and interest as ordinary income and taxation of capital gains at a preferential rate.

Brennan's model as stated in equation 2, has had some criticism. Black and Scholes (1974) argue that it is impossible to demonstrate that the expected returns on high yield stocks differ from the low yield stocks either before or after taxes. However, in their tests, Black and Scholes (1974) were not able to reject the hypothesis that $\tau = 0$ either (Litzenberger & Ramaswamy, 1979). The Results of Litzenberger and Ramaswamy (1979) indicate that there is a positive correlation between before-tax expected returns and dividend yields of common stocks, verifying the model of Brennan (1970).

4.2 Dividend discount model

While the CAPM uses the systematic risk, the expected return of the market and the expected return of the risk-free asset to make an estimation of the expected return of a stock or portfolio, the dividend discount model uses the dividends paid to estimate a price for the stock. The dividend discount model, or DDM, is a fundamental method of valuating a stock by the sum of all the dividends it is going to pay in the future. In its most simplistic version, the DDM is simply:

$$P_0 = \frac{D_1}{r} \tag{3}$$

Where P_0 is the current price of the stock, D_1 is the future year's dividend, and r is the required rate of return for that company, which can be derived from the CAPM.

This restricted DDM model in equation 3 is quite limited, as it would price the stock only on the next year's dividend discounted by the cost of capital. In reality, the dividends would be paid yearly and most likely grow as time passes on. A more realistic assumption would be that the stock is held for several years, and thus the dividends should be summed up. This is presented in equation 4:

$$P_0 = \frac{D_1}{1+r} + \frac{D_2}{(1+r)^2} + \frac{D_3}{(1+r)^3} + \cdots \tag{4}$$

In equation 4, the stock price is the sum of all present values of future dividends. This equation is not practical to use as it requires making a dividend forecast for each year separately (Bodie et al., 2014). To make the equation more practical, we can assume that the dividends are growing with a stable growth rate each year.

In this case, the growth rate of the dividends should be taken into consideration. The Gordon growth model is perhaps the most widely used dividend discount model. The model simply adds the growth rate of the dividends, g, into the equation:

$$P_0 = \frac{D_1}{r-g} \tag{5}$$

This model (5) expects the dividend to grow each year at a steady rate. This is of course, an unrealistic assumption for most cases, as companies very seldomly are able to keep their dividend rising by a steady rate each year.

However, a small group of companies, called dividend aristocrats, have been paying an increasing dividend yearly for long time. The S&P Dividend aristocrat index currently holds 65 companies that have paid a growing dividend yearly for at least 25 consecutive years. However, even these 65 companies have had issues maintaining their aristocrat status under 2020 with the complications the COVID-19 pandemic has caused to the world. Only 10 companies out of the 65 announced a dividend increase in the second quarter of 2020, and about half of the companies were able to maintain their status by keeping the dividend unchanged. (Strauss, 2020.)

The Gordon growth model is widely used by stock market analysts. The model implies that a stock's value will be greater (Bodie et al., 2014):

1. The larger its expected dividend per share
2. The lower the market capitalization rate r
3. The higher the expected growth rate of dividends

Gordon growth model implies that the stock price will grow at the same rate as the dividend. This means that in the case of constant dividend growth, the price appreciation of the stock will be equal to the growth rate of the dividend g**.** This mean that the expected holding period return of the stock would be:

$$E(r) = Dividend\ yield + Capital\ gain\ yield \tag{6}$$

Which would be written as a formula:

$$E(r) = \frac{D_1}{P_0} + \frac{P_1 - P_0}{P_0} = \frac{D_1}{P_0} + g \tag{7}$$

This formula offers a means to infer the market capitalization of a stock. By viewing the dividend yield D_1/P_0 and estimating the growth rate of dividends, we can compute the value for r (Bodie et al., 2014).

5 Market trends and cycles

Now that we have looked at the theory of efficient markets and how assets are priced, it is relevant to look at how the market fluctuates. Markets tend to have different *trends*, also referred to as *cycles*. These can occur both in the short run as well as in the long run. In order to time the market, it is important to recognize different cycles. The performance of different investment strategies depends on the market cycle. A trend can be upward, referred to as "bull" or downward, referred to as "bear". Despite the common use of these two terms, there is no accepted definitions and almost no academic research regarding this subject (Gonzalez et al., 2006). The concepts of bull and bear markets are constantly used when describing the current trend in the stock market. Some practitioners use a rule of thumb that a market must fall or rise by over 20% before we can call it a bear or bull market, respectively (Biscarri & De Gracia, 2004; Sossounov & Pagan, 2003).

The time period for a certain trend within the market that determines the bull or bear market is not clear either. Usually, the trend needs to be occurring several months before a shift within the trend can be said to have happened. Gonzalez et al. (2006) identify bull markets as ongoing periods of higher than usual returns and bear markets as sustained periods containing lower than normal returns. The reason why a market trend is always only visible after a while is due to the different time frames of market trends. A *primary trend* is a long-period trend within the market. This can last several years. The *Secondary trend* is generally considered to last from a few weeks to several months. It is however, significantly shorter than the primary trend and moves against it. Secondary trends are corrections to the primary trends. The third trend, a *minor trend*, occurs within the secondary trend and lasts from days to a few weeks. It is generally considered unimportant as it has no real effect. (Fontanills & Gentile, 2001).

Bull or bear markets are always primary trends. A long-run bull market, as we have seen now in the US since 2009 can have several bearish secondary trends that are not considered to be a shift in the market cycle. Primary trends have usually been bullish; historically, the US stock market has been 90% a bull market (Maheu & McCurdy, 2000).

5.1 Shifts in market trends

Shifts in primary trends, bull and bear markets, always follow one after another. A bull market is followed by a bear market and vice versa. Several different things may cause shifts in market trends. Macroeconomic factors such as inflation, interest rates, and unemployment certainly affect investors' behavior (S. S. Chen, 2009). Fundamentally, the cause of market cycles is that stock values are either thought to be too high or too low relative to their actual value. This is known as investor sentiment (Brown & Cliff, 2004). The sentiment is the expectations market participants have, and expectations tend to change. This shift in investor sentiment can be caused by psychological factors (Hirshleifer, 2001). Overly optimistic sentiment within the markets may cause stock prices to be too high to be justified by fundamentals (Shen, 2003).

In the EMH it is assumed that the prices of securities are priced according to the fundamental values and that investors act rationally according to their information. In his 1986 article "Noise", Black suggests that investors sometimes make decisions based on noise as if it was information. The concept of noise is essential as it makes the markets possible, but imperfect and regarding the EMH also inefficient. The more noise trading, the more liquid the market will be (Black, 1986). Noise trading as a substantial dominating power of market movements is supported by Shiller (2003). Shiller Suggest that when speculative prices go up, creating profits for some heightens the expectations for further price increases. People who get feedback from others that a price is increasing start buying the stock themselves, thus further increasing the price (Shiller, 2003).

This effect of noise and positive feedback causes an irrational and unjustified market trend. If the noise on the market is positive, investor sentiment moves towards a bull market and thus causes the stock prices to rise too high compared to their fundamental values. This effect may lead to a bubble (Norman & Thiagarajan, 2009). Evidence that noise is highly correlated with changes in the fundamental values is presented by Campbell and Kyle (1993). They refer to this as over-reaction as this causes the stock price to react more to news about fundamentals than it would otherwise do. Noise has the effect of amplifying movements in fundamental values. Campbell and Kyle (1993) find that the magnitude of this movement is highly dependent on the interest rate.

Although strong evidence of the effects noise has on the markets, some controversy remains. As Brown & Cliff (2004) point out, noise is tough to measure. Brown & Cliff (2004) state that while past returns are an essential determinant of sentiment, investor sentiment has little predictive power for near-term future stock prices. Co-movement with the market is strongly evident; a bull market creates bullish investor sentiment and vice versa.

5.2 Identifying market cycles

As stated, primary market trends may be hard to identify unless they have already been ongoing for a more extended time period, usually several months. The duration of market trends can be identified as the time between peaks and troughs within the market (Kole & van Dijk, 2017). Empirical studies trying to identify bull and bear markets through these peaks and troughs have been made by Pagan & Sossounov (2003) and Lunde & Timmerman (2004).

Chen (2009) shows that several macroeconomic variables can identify market cycles. They use 3 different methods, both parametric and non-parametric to identify bear markets. The parametric model uses a markov-swithcing model similar to Maheu & McCurdy (2000), while the non-paramteric model uses a Bry-Boschan method. The third approach, and the one used in this study is a moving average approach (Chen, 2009). This approach identifies bull and bear markets by the moving average of the previous *k* months. As stated before, there is no specific value for *k,* which should be used in the identification, that academics would agree upon. To be identified as a primary trend, it could be assumed the period should be anywhere up from 3 months.

6 Value investing and company payouts

A dividend is a portion of a company's earnings paid back to its' shareholders. The profits that remain after taxation can be distributed either back to the shareholders as dividends or retained as equity on the balance sheet. Dividends can be paid whenever, although usually public companies follow a certain timetable, such as paying dividends quarterly or once a year. After the dividend is paid, the company's stock price usually should drop. This drop should equal the amount of the dividend. Dividends tend to be paid by large established companies, usually considered *value companies*.

Academic literature regarding dividends has a long history and has been widely discussed. Views on dividends' importance to the shareholder vary. According to the Miller-Modigliani theorem (Miller & Modigliani, 1961), dividends are irrelevant. It would be no difference between receiving a dollar in dividends or in capital gains for a rational investor. The return would be the same. This theorem assumes that investors are rational and there are no transaction costs or differences with taxation between dividends and capital gains.

Hakansson (1982) shows that the Miller-Modigliani theorem stands, and dividend payout serves no useful role in an efficient market with homogeneous investors. Under these assumed conditions, dividends could in fact be harmful to companies. Companies paying dividends could use the money to fund their investments, which would then increase the company value, thus creating more value for the investor. However, as Hakansson points out, in the more realistic situation with heterogeneous investors, imperfect market, and dividends having informative value, dividends actually have a positive effect on welfare (Hakansson, 1982).

Controversially to the Miller-Modigliani theorem, empirical studies have shown that there exists a relationship between the dividend yield of a company and its stock returns (Blume, 1980; R. Litzenberger & Ramaswamy, 1982; Naranjo et al., 1998). Investors seem to value dividends despite the proposed irrelevance that would fit the Miller-Modigliani theorem of rational investors. If dividends do affect future stock prices, their value of informational sources would be essential, as pointed out by Hakansson (1982).

6.1 Value investing

Fundamentally there are two approaches to stock investing, growth and value. Growth investing means investing in companies that are expected to grow both size and earnings. This means that very rarely growth stocks pay any dividends since all incoming profit is invested back into the company, allowing it to grow. It is common for growth stocks to experience two-digit growth percentages per year. Investors who buy growth stocks are expecting the price of the share to increase in the future. Usually, growth companies are relatively new and have a high price-to-earnings (P/E) ratio. Growth stocks are commonly considered riskier than value stocks since they are more likely to react heavily to any market changes. (Gitman, L. J., Joehnk, M. D. & Smart, 2011.)

Value stocks are usually blue-chip stocks that pay a steady dividend. Blue-chip stocks are stocks of large, well-established, and well-recognized companies. Compared to growth stocks, usually value stocks are stocks of companies that have operated a long time, are usually market leaders and have survived several market cycles. While a company doesn't need to pay a dividend to be called a blue-chip, this is often the case. (Gitman, L. J., Joehnk, M. D. & Smart, 2011.)

Value investment should not be confused with quality investment, although quality can be viewed as an alternative implementation of value (Novy-marx, 2014). High-quality stocks tend to be expensive, while value stocks are undervalued by their price-to-earnings or book-to-market ratios (Davydov et al., 2016; Fama & French, 1998; Novy-marx, 2014). The dividend aristocrats presented in chapter 4.2 can be seen as high-value quality stocks with a long history of steady (rising) dividends. They should not be interpreted as undervalued or as past losers, as discussed below.

Value stocks are proven to outperform growth stocks in markets worldwide (Fama & French, 1998). Multiple reasons for this exist. Value investing is a contrarian strategy that bases its performance mainly on the winner-loser effect. Choosing past losers tends to create excess returns compared to a portfolio of past winners. Loser stocks have a lower price than their underlying fundamental values and tend to grow in price when investors recognize this (Lakonishok et al., 1994). Value investing is also linked to the market sentiment and noise discussed in the previous chapter. Value investing is doing the opposite of what the masses are in the stock market, buying out-of-favor stocks with a low price relative to their fundamental value.

High book-to-market equity companies are viewed to be in greater risk of distress (Griffin & Lemmon, 2002). Studies show that high book-to-market companies display more fundamental risk as they react more negatively to economic shocks, tend to be less profitable, and are at a greater risk of default (Fama & French, 1992; Griffin & Lemmon, 2002; Tikkanen & Äijö, 2018).

De Bondt and Thaler (1985) studied the returns of the New York Stock Exchange (NYSE) from 1926 to 1982. They found that a portfolio of 35 loser stocks outperformed a portfolio that consisted of 35 winner stocks by 24,6% during the 3-year testing period. This is illustrated in Figure 1. Investors tend to overreact to negative news regarding loser stocks, thus creating excess losses artificially. Over time it becomes clear that the stock is not performing as poorly as it has been excepted and priced, and therefore it will rebound. On the other hand, the prices of winning stocks might have been inflated since investors believe that they will continue to perform as well as recently. Whether or not a company pays dividends is shown to matter on the performance in declining markets; however, the size of the dividend yield relating to the performance is questionable (Fuller & Goldstein, 2011).

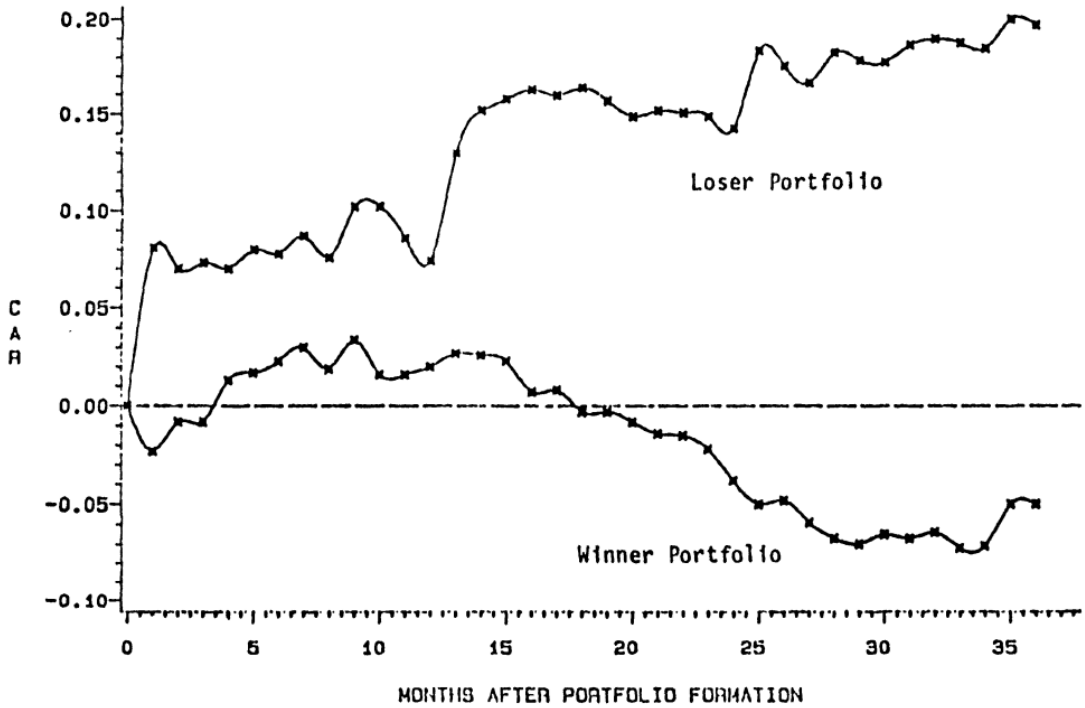


Figure 1. Cumulative average residual for 35 winner and loser portfolios of 35 NYSE stocks (Bondt & Thaler, 1985).

From figure 1 we can draw the conclusion that these heavily underpriced stocks will eventually become winners and that the former winners will then become the new losers. This is because the capital gains of the loser stocks will be much greater than those of the winner stocks.

6.2 Dividend yield

Dividends of companies are usually measured as a stock's dividend yield. Dividend yield measures the dividend on a relative basis and makes the evaluation of different companies' dividends easier than measuring dividends on an absolute basis. The dividend yield is calculated with the following formula:

$$Dividend\ yield = \frac{Annual\ dividends\ received\ per\ share}{Current\ market\ price\ of\ the\ stock} \tag{8}$$

When calculating dividend yields, it is important to notify that the current stock price can fluctuate significantly under a period of 1 year while the dividend remains the same. This means that the dividend yield can look very different at different points in time for the same company.

The monthly dividend yield for a stock is calculated as:

$$DY_t = \frac{\sum_{k=1}^{12} D_{i,t-k}}{P_{i,t-13}} \tag{9}$$

The dividend yield is a fundamental value and a source of information on the stock's performance for the investor. The dividend yield produces a cash flow that the investor receives from owning a stock and thus is a part of the total return in addition to the capital gain received. Capital gains produce returns only when a stock or security is sold. Dividend yields produce a quarterly or annual cash flow.

Dividend yield investment strategies are based on this cash flow. Compared to buying growth stocks with usually no dividends, investors buy stocks with high dividend yields. As stated before, these stocks have low prices compared to the dividends and are usually past losers overlooked by investors.

6.3 Stock repurchases

In addition to paying out dividends, companies have another option to distribute cash payouts to shareholders. As stated by Grullon & Michaely (2002), stock repurchases is becoming an increasingly popular method of distributing payouts in the US. During the period 1980-2000, the amount of stock repurchase programs increased from 4.8 % to 41.8 %. In 2000 industrial firms spent more money on stock repurchases than they did paying out dividends to shareholders (Grullon & Michaely, 2002). Companies buying back their own stocks lead to an increase in the stock price, leading to capital gains for the shareholders. However, capitalizing on this would require the investor to sell the stock.

Skinner (2008) states that repurchases are becoming a dominant form of payout. Companies are divided into three groups: companies that pay regular dividends and make regular repurchases, companies that make regular repurchases, and companies that make occasional repurchases. Companies that only pay dividends are largely extinct (Skinner, 2008). The decline in the incidence of dividend payers is partly due to the tilt toward the characteristics of firms that have never paid dividends – small size, low earnings and large investments relative to earnings (Fama & French, 2001).

This is true for the US companies, but Finnish companies still rely primarily on sole dividend payments. Evidently, it is an increasing trend that US companies are replacing regular dividends with stock repurchases (Skinner, 2008). This phenomenon diminishes the importance of the dividend yield as a predictor variable. It indicates that the total payout ratio might be a better way to capture the information components of payout ratios. The total payout ratio captures both the dividend payments and stock repurchases and is suggested as a substitute for the dividend yield by Boudokh et al. (2007).

6.4 Dividend smoothing

The concept of dividend smoothing dates to Lintner's 1956 article on the distribution of incomes of corporations (Lintner, 1956). Lintner states that both management and stockholders prefer a stable rate of payout and that the market puts a premium on the stability or gradual growth of payouts. This results in consistent patterns of behavior in dividend decisions. Companies avoid cutting dividends fearing the shareholders' reaction, even if the earnings would require a dividend adjustment. (Lintner, 1956.)

Linter's (1956) partial adjustment model was developed during a period when dividends were the dominant form of payout (Andres et al., 2015). However, this model is not necessarily appropriate when there is a strong shift towards repurchases. Andres et al. (2015) study how the authorization of repurchases affects the dividend yield and total payout policies in Germany. The perfect substitute hypothesis suggests that the introduction of repurchases should not alter total payouts. The results indicate that this hypothesis does not hold. The findings suggest that the dividend and total target payout ratios actually decrease when repurchases are allowed. (Andres et al., 2015.)

Dividend smoothing is still ongoing in the US despite the increasing role of stock repurchases (Skinner, 2008). Large, mature and profitable companies that make regular repurchases continue to pay dividends. Skinner (2008) suggests that these companies continue to pay dividends mostly because of their dividend history.

7 Data & methodology

The empirical part of this thesis will try to answer the following hypotheses:

H1: Dividend yields are able to predict market returns.

And

H2: Dividend yields can predict recessions in the stock market.

These hypotheses are based on literature (see Fama & French, 1988; Lewellen, 2004; Mcmillan, 2014) that the smaller the dividend yields, the more overpriced the stock. For this empirical study, two different markets will be studied. The markets chosen are the Finnish and the US stock markets. This is done so that two very different types of stock markets can be measured and see if the behavior of these markets mimics or differ from each other.

7.1 Dividend yield

The data is collected from Datastream and contains the monthly returns of both the price index and the total return index for both the S&P 500 composite and OMX Helsinki (OMXH) indices. The data ranges from January 1989 until March 2021 for S&P 500 and from January 1991 until March 2021 for OMXH. The values of the S&P 500 are in US dollars and Euros for the OMXH. Since these two are examined separately, there is no need to change the values into the same currency.

The return of the market indices is calculated as

$$r_t = \frac{I_t}{I_{t-1}} - 1 \tag{10}$$

Where I_t is the value of the index at time *t* and I_{t-1} is the value of the index at time *t-1,* respectively. Since the data is monthly, the return is simply dividing the monthly value of the index with the previous month's value and subtracting one to get the percentage.
To get the dividend yield of the index, we must first calculate a pre-dividend value of the total return index for period *t*:

$$I_{TRI,t}^{predividend} = I_{TR,t-1} * (1 + r_t) \tag{11}$$

In order to get the level of the total return index $I_{TR,t}$ at time *t* we before any dividends are accounted, we simply take the level of the total return index of the previous month and multiply it with the return of the price index. The to get the monthly dividend D_t we take the difference of the actual total return index value and the computed pre-dividend value:

$$D_t = I_{TR,t} - \ I_{TRI,t}^{predividend} \tag{12}$$

This gives the total dividend of the index for month *t*. To calculate the dividend yield, we follow the method of Lewellen (2004). The dividend yield DY is defined as the dividends paid over the prior year divided by the current level of the index. DY is thus based on a rolling window of annual dividends:

$$DY_t = \frac{\sum_{k=1}^{12} D_{I,t-k}}{I_{TRI,t}} \tag{13}$$

As such, equation 13 for the dividend yield of the index is almost identical to the equation 9 presented in chapter 6, which shows the method of calculating the dividend yield for a single stock. The only difference is that the nominator is the sum of the total dividend for the index 12 months prior to time *t,* and the denominator is the current value of the total return index.

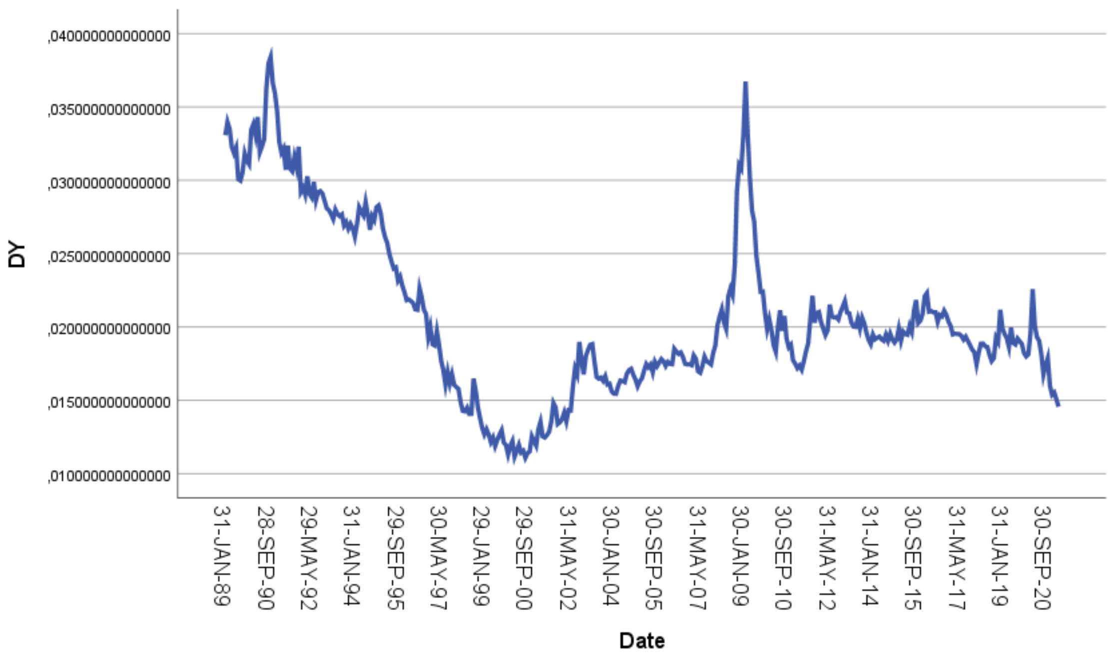


Figure 2. Dividend yield of S&P 500.

Figure 2 shows the dividend yield of the S&P 500 index for the evaluation period. A clear trend is visible in the level of the DY for the index. The DY was at its highest at the beginning of 1990 and at the beginning of 2009. The peak of the DY in 2009 is explained by the financial crisis, as it was a period when the stock prices were at a low, thus increasing the DY.

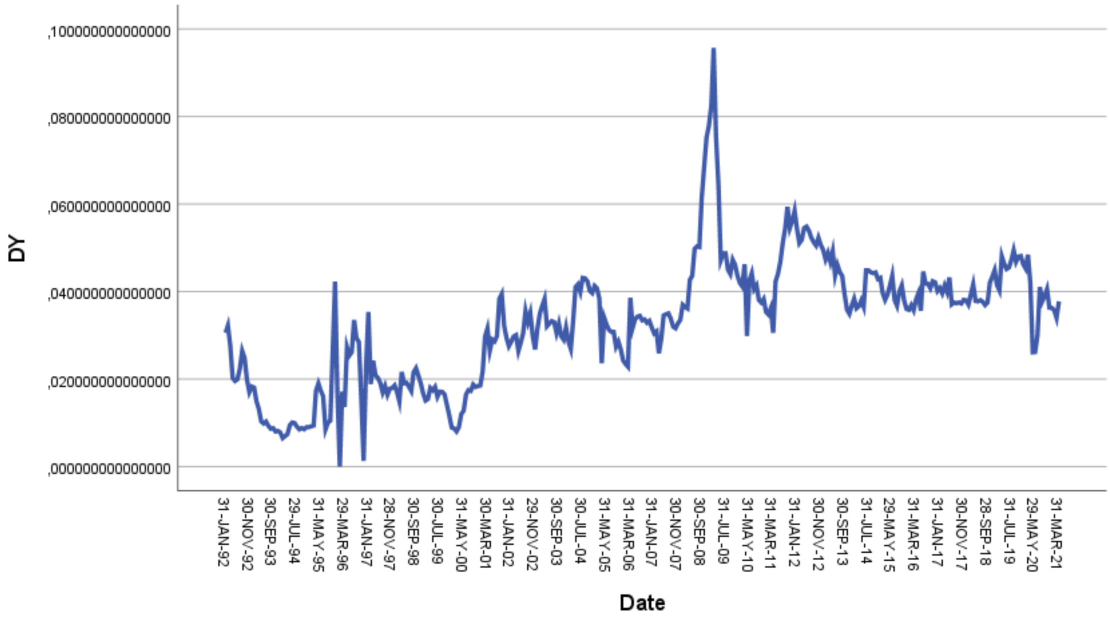


Figure 3. Dividend yield of OMXH.

Figure 3 shows the DY for the OMXH index. As we can see, the level of the DY is more fluctuating compared to the DY of the S&P 500. Similarly, as in the S&P 500, the DY of OMXH is at its highest in the beginning of 2009, also due to the financial crisis pushing stock values down.

The predictive regressions use the natural logarithm of the dividend yield since it should have better time-series properties. As Lewellen (2004) states, dividend yields tend to be positively skewed. This is confirmed in table 1. The DY of the S&P 500 is more positively skewed than the respective value for OMXH. Taking the logarithmic value decreases skewness, but the value for OMXH is extremely highly negatively skewed. This is because, in the data, there were a few months in December 1995 and January 1996 when the dividend yield of the OMXH index was practically zero. This causes the Log (DY) to be a very large negative value compared to the mean values of the Log (DY).

Table 1. Summary statistics of the return of the price index, dividend yield and natural logarithm of the dividend yield for S&P500 and OMXH. Observations are monthly. Note that the dividends have been summed over the past 12 months as shown in equation 13.

Variables	Mean	SD.	Skew.
S&P 500			
Sample period M1 1989 - M3 2021			
Return of PI	0.00779	0.04208	-0.561
DY	0.02074	0.00587	0.836
Log (DY)	-3.9132	0.27258	0.222
Number of observations	387		
OMXH			
Sample period M1 1992 - M3 2021			
Return of PI	0.01003	0.07324	0.165
DY	0.03280	0.01421	0.318
Log (DY)	-3.5565	0.68955	-5.001
Number of observations	351		

Table 1 presents the summary statistics for the price index returns, the dividend yield, and logarithmic dividend yield. The average monthly return of the S&P 500 for the analyzed period was 0.00779%, and the dividend yield was 2.07 %. Both the DY and the Log (DY) are positively skewed. OMXH returns on average 1.0% monthly with a dividend yield of 3.2%. The standard deviation for the DY of OMXH s higher than for the S&P 500 meaning that the dividend yield differs more monthly. This is visible in figures 2 and 3. This is understandable as stocks in the US usually pay dividends quarterly, while stocks in Finland usually pay only one dividend per year. This means that the dividend yield in OMXH is higher during the months of March and April when the dividends are paid out, while in the US, the dividends are distributed more evenly throughout the year. In order to run a meaningful regression, we must make sure that the dependent variables are stationary.

Table 2. Unit root test for variable *Log (DY)*. ADF is Augmented Dickey-Fuller and PP is Phillips-Perron test statistics. In both tests the null hypothesis is that the test has a unit root.

Variable: Log (DY)	
Test	p-values
S&P 500	
ADF	0.602
PP	0.741
OMXH	
ADF	0.01
PP	0.01

From table 2 we see that in the case of the Log (DY) of S&P 500, we cannot reject the null hypothesis that a unit root is present. We must conclude that in the case of the S&P 500 Log (DY), the values are non-stationary. For the Log (DY) of OMXH, we can reject the null and conclude that the values are stationary according to both the ADF and PP tests.

The non-stationarity of the Log (DY) is in line with the findings of Polimenis and Neokosmidis (2016). Their data ranges from 1926 until 2012 and shows similar non-stationary behavior of the dividend yield during that period. Researchers argue that the dividend yield is a stationary process based on an infinite sample. Still, our data clearly indicates the opposite within the finite data sample used in this study (Polimenis & Neokosmidis, 2016). Since the Log (DY) of the S&P 500 is still non-stationary, we must differentiate the variable. This is done by taking the first difference of the Log (DY) value. We can make sure that the variable is now stationary by comparing the plots.

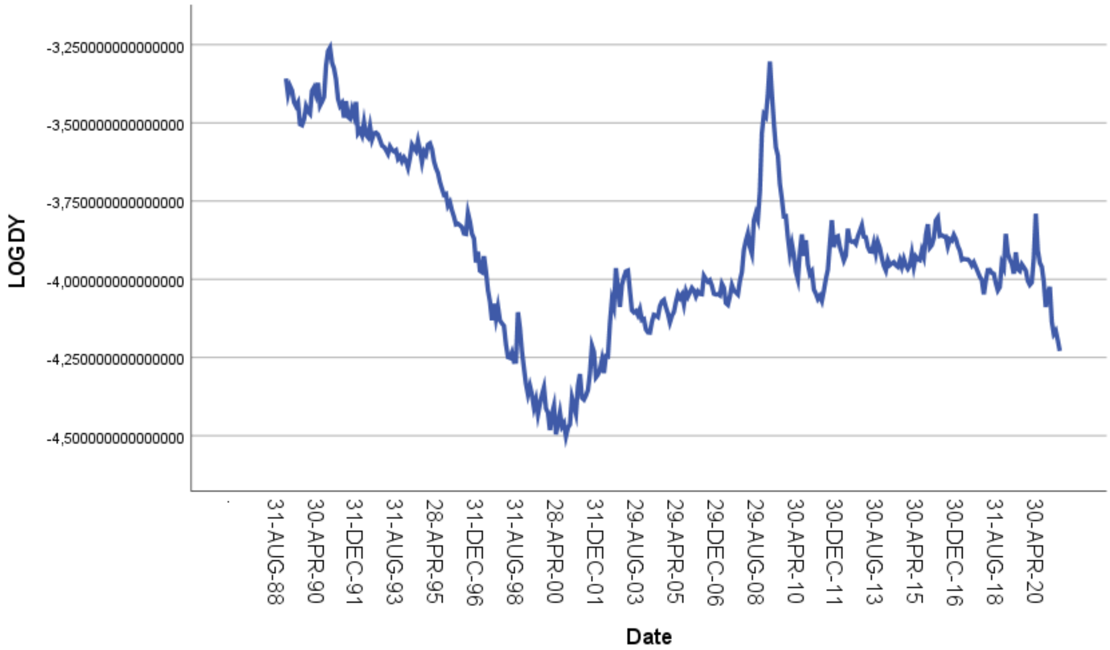


Figure 4. Log (DY) of S&P 500.

In figure 2 we see the plotted values of the Log (DY) variable of the S&P 500 index. Clear trends are visible, and the variable indicates non-stationarity. The Log (DY) plot follows almost identically the plot for the actual raw DY in figure 2.

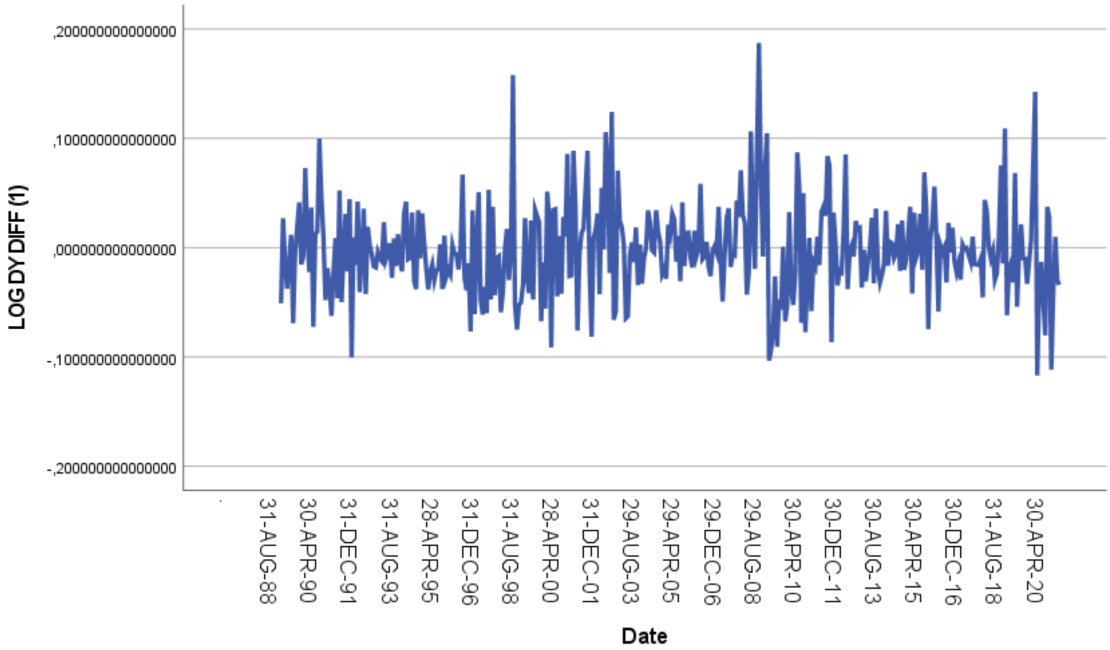


Figure 5. First difference of Log (DY) of S&P 500.

From figure 3 we can see that the variable is now stationary. We will use this new computed variable in our regression model. In order to find an answer to the first hypothesis, we test whether the dividend yield predicts market returns. The regression model is similar to that of Lewellen (2004).

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_t \tag{14}$$

Where r_t is the market return and x_{t-1} is the dividend yield of the index at $t-1$.

7.2 Market cycles

For us to be able to answer the second hypothesis, we must identify the different market cycles. Identification of bull and bear markets will be done as a *naïve moving average approach* similar to Chen (2009). In this model, the bull or bear market is decided as the mean return over the last couple of periods:

$$\bar{r}_t^k = \frac{r_{t-1} + r_{t-2} + \cdots + r_{t-k}}{k} \qquad (15)$$

Where $\bar{r}_t^k$ is the moving average of the last k values of the stock returns.

The dummy variable D_t is defined as follows:

$$D_t = \begin{cases} 1(bear\ market) if\ \bar{r}_t^k < 0 \\ 0\ (bull\ market) if\ \bar{r}_t^k > 0 \end{cases} \qquad (16)$$

Suppose the mean market return over the last k periods is negative. In that case, we identify the market as a bear market, and a bull market is defined as a positive mean return over the last *k* periods. The values for *k* will be 1, 3, 6, 12, and 24 months, respectively.

From equation 16 we obtain the binary variable, $D_t = 1$ indicates a bear market and $D_t = 0$ indicates a bull market. We then consider the following probit model similar to Chen (2009):

$$P(D_{t+k} = 1) = F(\alpha + \beta x_t) \qquad (17)$$

Where $\mathrm{P(D_{t+k}} = 1)$ is the probability of a bear market at time $t + k$ and x_t is the dividend yield. The data will show different periods for bear markets when different values of *k* is inserted into equation 15. Below, figure 4 shows how the price index of the S&P 500 composite has evolved during the evaluation period. The orange areas indicate bear markets when *k* is 12 months. We can see that the 2001-2002 and the 2007-2009 periods have seen more extended bear markets. These time periods are the dotcom-bubble and the financial crisis periods. Since the financial crisis, bear markets have been more seldom and not as long. Still, even during the long bull market period of the 2010's we have had periods when the average 12-month return has been negative.

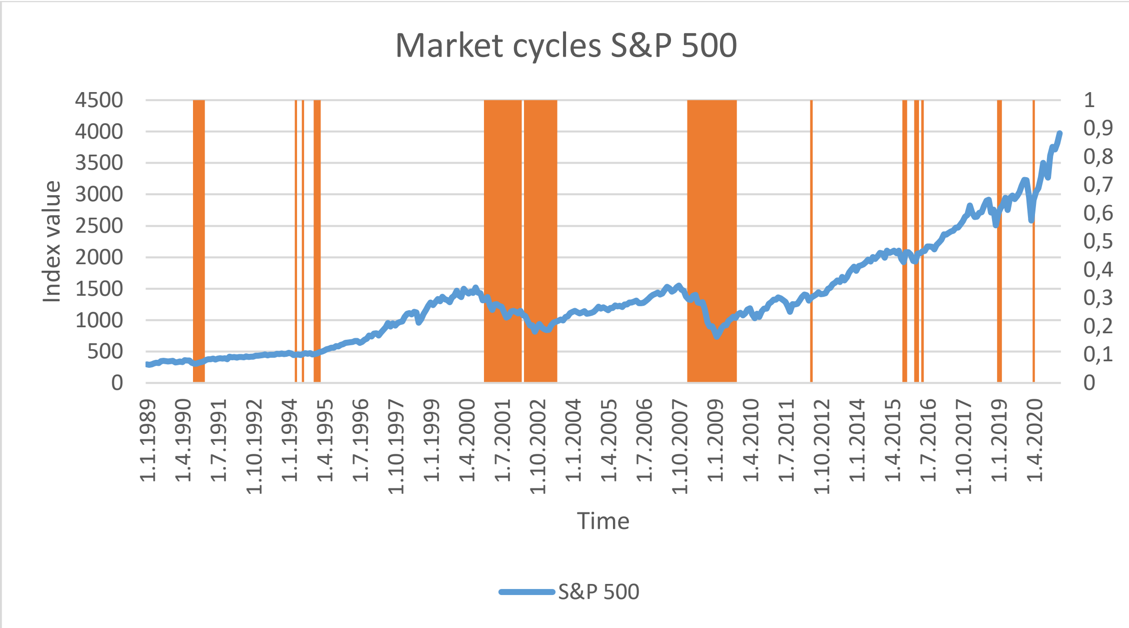


Figure 6. The evolution of S&P 500 and the bear market cycles. Orange areas indicate a period where the market return of the last 12 months has been negative on average.

Plotting a similar graph for the OMXH index shows that the stock market in Helsinki has seen a bit more drastic cycles during the last 30 years. Figure 5 shows that the period from 1996 to the early 2000s was an aggressive bull market period in Finland. During the dot-com bubble, the market crashed heavily, and the market entered the bear cycle similar to the US. The Financial crisis period was also a bear cycle in both countries, but Finland has not seen a comparable bull market period as the US during the 2010-decade. During the past 10 years, Finland has had three longer bear market cycles where the average return of the past 12 months has been negative.

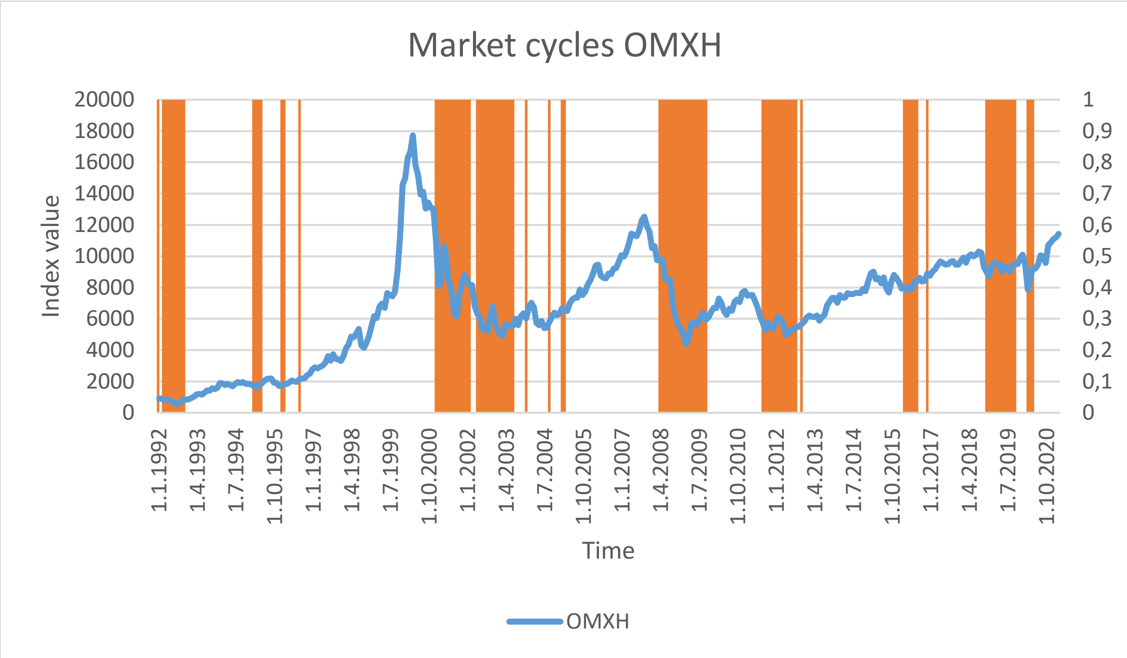


Figure 7. The evolution of OMXH and the bear market cycles. Orange areas indicate a period where the market return of the last 12 months has been negative on average.

The bear market cycles in figures 4 and 5 would look different with a different value for *k.* Figure 8 shows what the graph would look like when the bear markets are computed with the six-month average return:

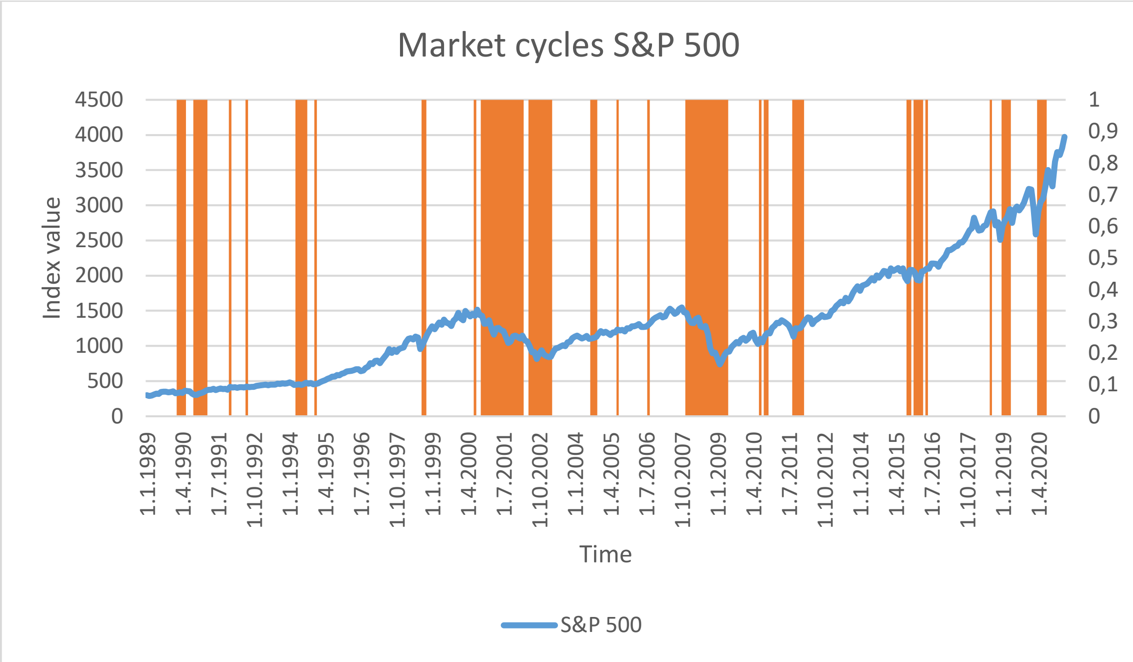


Figure 8. The evolution of S&P 500 and the bear market cycles. Orange areas indicate a period where the market return of the last 6 months has been negative on average.

When compared to figure 6 we can see that the way we define the periods of a bear market has a difference in the amount and the frequency of the bear periods. When k=6, periods specified as bear markets occur more often compared to periods of k=12. This is true for the OMXH index, as presented in figure 9:

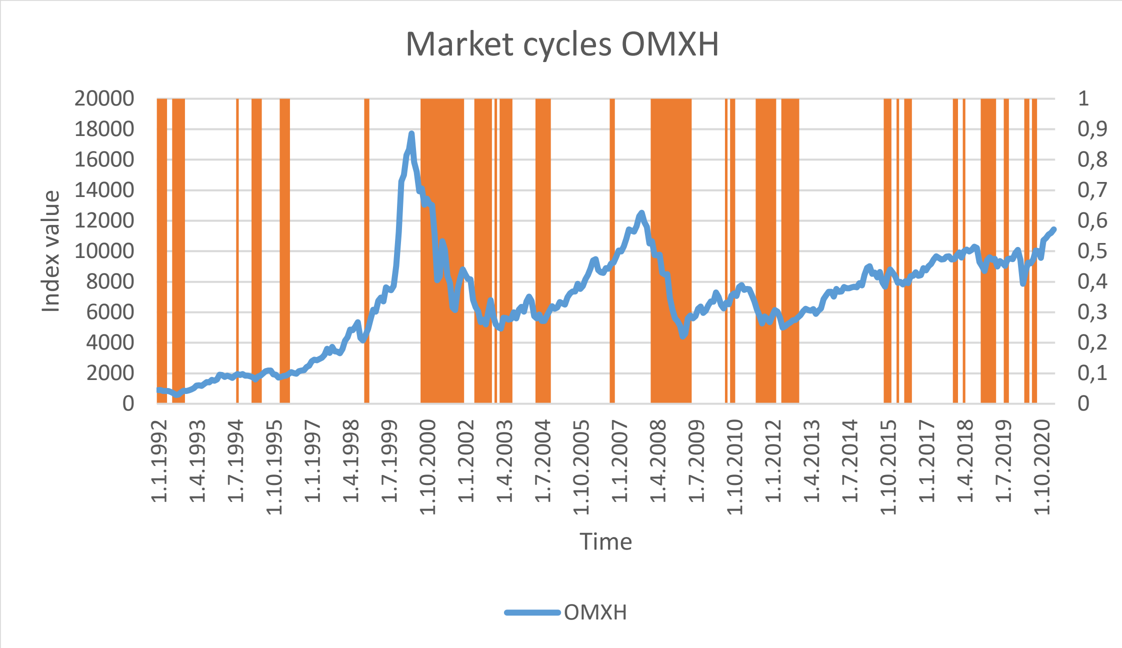


Figure 9. The evolution of OMXH and the bear market cycles. Orange areas indicate a period where the market return of the last 6 months has been negative on average.

To illustrate how the total time of the studied period is divided between bear and bull cycles, we show the percentages of the bear market cycles in table 3:

Table 3. The percentage of time in a bear market cycle during the studied period.

k	% of total time in bear markets	
	S&P 500	**OMXH**
1	36 %	43 %
3	29 %	34 %
6	25 %	32 %
12	18 %	30 %
24	15 %	30 %

As we can see, the amount of time spent in a bear market is lower as the value of *k* increases. Bear markets are identified here as periods with a negative cumulative return during *k* months. Table 3 shows us that OMXH has had more market periods with negative returns during the studied period than S&P 500. During the studied period, OMXH has had a negative return for at least 30% of the time, regardless of the *k* used to determine a bear cycle. If we consider the 24-month average return, S&P 500 has been in a negative return cycle only 15% of the time during the last 32 years.

8 Empirical results

This chapter will present and discuss the study's empirical results to find if dividend yields can predict market returns and cycles. Based upon previous literature and the methods introduced in chapter 7, the aim is to answer the two hypotheses presented earlier.

Literature presented in chapter 2 is not conclusive on the predictive power of the dividend yield. Studies have shown that several financial ratios and macroeconomic variables can predict returns and market cycles, but contrary views have been made as well. This study will extend the analysis of N.K Chen et al. (2017) by examining the ability to predict bear markets by using dividend yields. The results will also broaden the studies made by Fama (1970), Fama & French (1988), Campbell & Shiller (1988), Lewellen (2004), Cochrane (2008), Mcmillan (2014) and Charles et al. (2017), among others, by including a market that has not yet been studied extensively, the Finnish stock market. The majority of the studies made on the predictive power of dividend yields have been made using US data. Due to the apparent differences in dividend policy between these two markets, the results are expected to differ. This allows a wide-ranging examination of the different attributes between two very different stock markets.

Table 3 presents the results for the regression model shown in equation 14:

Table 4. OLS regression for the model $r_t = \alpha + \beta x_{t-1} + \varepsilon_t$. r_t is the return of the index at time t and x_{t-1} is the natural logarithm of the dividend yield at time t-1. Significance levels for levels 1%, 5% and 10% are indicated as ***, ** and * respectively.

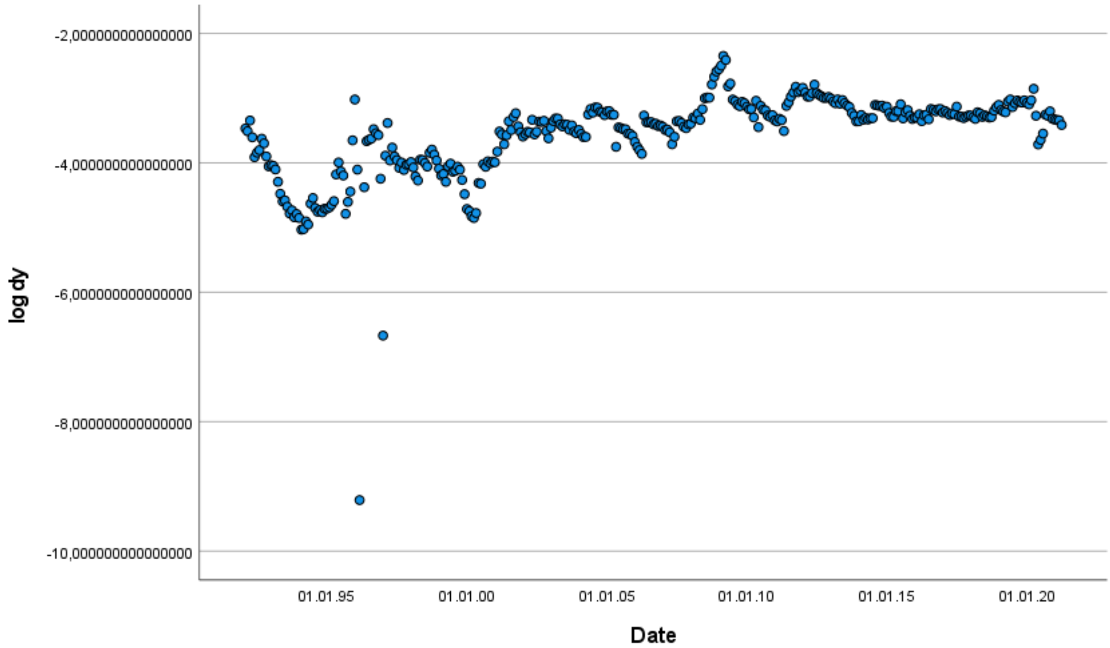
OLS	β	p-value	R^2	SE	Durbin-Watson
S&P 500					
Log (DY_{t-1})	0.008	0.422	0.002	0.010	1.946
OMXH					
Log (DY_{t-1})	-0.013**	0.032	0.013	0.006	1.590

The coefficient estimate (0.008) for the S&P 500 is not significant. The R-squared value (0.002) of the model indicates that the Dividend yields do not explain the changes in the index returns all that well. It is apparent that we cannot accept the hypothesis that Dividend yields predict changes in the market return for S&P 500. This result is contrary to the findings of Fama & French (1988) and Lewellen (2004), who find evidence that the log dividend yield would be capable of predicting market returns. However, their time period was longer, and the data set was not identical to this study. The Durbin-Watson test for autocorrelation signals slight positive autocorrelation.

For the OMXH, the coefficient estimate (-0.013) is significant at the 5% level. We can conclude that the stock market's dividend yield influences the market returns. However, the relation is opposite of what is expected. A negative coefficient implies that there is a negative relation between the dividend yield and the market return. This is against the results of Fama &French (1988) and Lewellen (2004), but in line with the results of Mcmillan (2014). Mcmillan's (2014) negative coefficient is statistically insignificant, while this test result shows statistical significance. The original hypothesis is that low dividend yields forecast future low returns. In the case of the OMXH the result implies that low dividend yield forecast future high returns. This forces us not to accept the hypothesis that dividend yield would have a positive correlation with market returns. However it appears that a contrary result to the initial hypothesis would be more applicable.

The R-squared value (0.013) indicates that the independent variable has better explanatory power than in the case of OMXH. For the case of the OMXH, there were some clear outliers in the dataset:

Figure 10. Plotted values for Log (DY) of OMXH.



In figure 8 we see that there are two clear outliers in the data for the dividend yield of the OMXH index. These occur during December 1995 and November 1996. It appears that during those two months, the dividend yield of the index was practically zero. No clear reason for this was found. We eliminate the two clear outliers and rerun the regression. This gives us the following results presented in table 4:

Table 5. OLS regression for the model $r_t = \alpha + \beta x_{t-1} + \varepsilon_t$ with the outliers of the OMXH Log (DY_{t-1}) eliminated. r_t is the return of the index at time t and x_{t-1} is the natural logarithm of the dividend yield at time t-1. Significance levels for levels 1%, 5% and 10% are indicated as ***, ** and * respectively.

OLS	β	p-value	R^2	SE	Durbin-Watson
OMXH					
Log (DY_{t-1})	-0.017**	0.015	0.017	0.007	1.589

As we see, controlling for the outliers increases the R-squared value and the significance of the model—the estimated coefficient changes from -0.013 in table 3 to -0.017 in table 4. No significant changes occur in the standard errors or the Durbin-Watson correlation value, which signals a positive autocorrelation in both table 3 and 4 for the Log DY.

Next, we will view the bear market predictability results:

Table 6. Predictability test results for predicting bear stock markets: Probit regression model $P(D_{t+k} = 1) = F(\alpha + \beta x_t)$, where D_{t+k} is a dummy variable so that $D_{t+k} = 1$ if in a bear market and $D_{t+k} = 0$ if in a bull market. The bear market is identified as described in equation 16. Significance levels for levels 1%, 5% and 10% are indicated as ***, ** and * respectively.

S&P 500

k	β	S.E.	p-value	Likelihood ratio Chi-squared	p-value
1	4.842	11.055	0.661	0.192	0.661
3	10.433	11.2925	0.356	0.852	0.356
6	16.826	11.4803	0.143	2.147	0.143
12	17.540	12.1378	0.148	2.081	0.149
24	-20.192	13.7153	0.141	2.222	0.136

OMXH

k	β	S.E.	p-value	Likelihood ratio Chi-squared	p-value
1	11.728**	4.7253	0.013	6.270**	0.012
3	18.819***	4.9815	0.000	15.042***	0.000
6	24.794***	5.2383	0.000	24.474***	0.000
12	35.994***	5.7995	0.000	45.686***	0.000
24	41.866***	6.1563	0.000	57.692***	0.000

Table 6 presents the results from the predictability test for predicting bear markets using the dividend yield. The results follow that of the return predictability test presented earlier. The dividend yield of the S&P 500 shows no statistically significant predictability values in any of the time horizons. The p-values drop as *k* increases but are still over the 10% significance level. All horizons except the 24-month horizon show a positive relation between dividend yields and the probability of a bear market. This is intuitive, as when the dividend yield increases, it is either due to the fall of the stock price or an increase in the payout ratio. The negative value for the coefficient in the 24-month horizon is curious as it signals that a fall in the dividend yield would result in an increased probability of a bear market. However, this is not statistically significant, and thus we will not evaluate the reasons further.

For the OMXH index, the results are more promising regarding the *H2* that dividend yield can predict market cycles. It appears that the dividend yield of the index has predictive power on possible bear markets in the future. Four out five coefficients are statistically significant at the 1% level, except the one-month horizon, which is significant at the 5% level.

The likelihood ratio Chi-squared value signifies the result of the Omnibus test, which compares the fitted model versus the null (intercept-only) model. The chi-square values of the OMXH are significant. We can interpret that the model was able to distinguish a relationship between the DY and the probability of a bear market. Comparing the chi-square values between S&P 500 and OMXH, we can conclude that the "goodness of fit" of the probit model was greater for OMXH than for S&P 500.

Similar to N. K. Chen et al. (2017), the focus of this study is to evaluate the capacity of the dividend yield to predict bear markets. No particular theoretical implication is to be tested for the value of β. What is important is the sign of the coefficient β. For the OMXH, all the values for β are positive, and we can state that there exists a positive relationship between the dividend yield and future recessions in the market. The dividend yield of OMXH has predictive power that seems to increase together with the horizon k. The results presented in table 6 allow us to accept the hypothesis *H2: Dividend yields can predict regressions in the stock market* for OMXH. For the case of S&P 500 we must reject it and conclude that dividend yield does not have any significant predictive power for the index.

9 Conclusions

Predicting return has been an extensively studied topic in finance. The ability to use financial variables to make reliable investment decisions continues to be the topic of academic papers. This study has provided a slight contribution to that field of literature. The purpose of this study was to find out if dividend yields have predictive power over market returns, and more importantly, whether dividend yields could be used to identify market cycles. The possibility of the next bear market is a continuous debate among investors and provides a relevant research topic. This study was done in the footsteps of Fama & French (1988) Campbell & Shiller (1988) Maheu & McCurdy (2000), Lewellen (2004), Mcmillan (2014) S. S. Chen (2009), and N. K. Chen et al. (2017).

Compared to the US, the different characteristics of the Finnish stock market gave varying results as expected. The observed period in this study, 32 years for the US data and 29 years for the Finnish, provided a study period that saw many changes that significantly affected the stock markets. This time frame includes the deep recession period during the early part of the 1990's in Finland, the booming dotcom-period in the early stages of the 21st century, the financial crisis that shocked the world in the end of the century's first decade and finally, the long bull market period in the US during the 2010-decade and eventually a glimpse of the effects of the Covid-19 pandemic during 2020. This provided an excellent premise to conduct this study.

The hypothesis of the thesis were that firstly, dividend yields are able to predict market returns. This hypothesis was rejected for the US data. Regarding the Finnish data, the results showed predictive ability, although not in the way it was hypothesized initially. This result leaves a possibility for future research as it is against the results of the majority of former studies.

Secondly, the other hypothesis was that the dividend yield would be able to predict market returns. This hypothesis was rejected for the US and accepted for the Finnish data. This happens primarily because of the different characteristics of the stock markets. As stated by Grullon and Michaely (2002), companies in the US prefer largely stock repurchases instead of dividends. This phenomenon essentially became popular during the period 1980-2000, which affects the early part of the data used in this study. Substituting repurchases to dividend payments decreases the relevance of the dividend yield as it simultaneously decreased the dividend and increases the stock price. The shift towards stock repurchases as a means to distribute cash flows would imply that instead of the dividend yield, one should use the total payout yield. (Grullon & Michaely, 2002.)

The early 2000s saw an increasing amount of new tech companies that started to grow into sizes to be incorporated into the S&P 500 index. Finland saw this occurring also, but the magnitude was different. The most notable tech company in Finland was Nokia. These new technology companies did not pay out dividends as they were focused on growing.

Dividends in the US are typically paid quarterly, while in Finland, it is usual to pay a single dividend during the spring. This evens out the dividends in the S&P 500 compared to the OMXH. This is visible when comparing the graphs of the dividend yields for each index. The monthly dividend yield in Finland varies more compared to the US. The regressions performed on bear market predictability in this study did show similar results for both stock markets, but statistical significance was present only in the data for the Finnish market.

To conclude this study, we can state that the value of dividend yields as a predictive variable for market returns is questionable. The significance is very much tied to the characteristics of the market. Clearly, the predictive power of the dividend yield in the S&P 500 is diminishing since earlier studies have found robust data that this has been present. The ability to detect market cycles is also included in the dividend yield, but again not for the S&P 500. This would lead to an assumption that perhaps the dividend yield works as a predictive variable in smaller markets, where stock repurchases are not as common as it is in the US. While the study was not able to fully verify the hypothesis, it can be seen as an essential addition to the long list of academic literature considering the dividend yield as a predictive variable for market returns.

Aspects to reduce the limitations in this study could have been using a more extended period of data. On the other hand, as we have now stated, the dividend yield characteristics have primarily changed in the US. Including the total payout ratio as a substitute for the dividend yield would be a further topic of interest when evaluating the ability to predict market returns.

References

Andres, C., Doumet, M., Fernau, E., & Theissen, E. (2015). *The Lintner model revisited: Dividends versus total payouts*. https://doi.org/10.1016/j.jbankfin.2015.01.005

Ang, A., & Bekaert, G. (2007). Stock Return Predictability: Is it There? *The Review of Financial Studies* 20(3). https://doi.org/10.1093/rfs/hhl021

Biscarri, J. G., & De Gracia, F. P. (2004). Stock market cycles and stock market development in Spain. *Spanish Economic Review*, *6*(2), 127–151. https://doi.org/10.1007/s10108-003-0078-7

Black, F. (1986). Noise. *The Journal of Finance*, *41*(3), 529–543. https://doi.org/10.2307/2328481

Black, F., & Scholes, M. (1974). The effects of dividend yield and dividend policy on common stock prices and returns. *Journal of Financial Economics*, *1*(1), 1–22. https://doi.org/10.1016/0304-405X(74)90006-3

Blume, M. E. (1980). Stock Returns and Dividend Yields: Some More Evidence. *The Review of Economics and Statistics*, *62*(4), 567. https://doi.org/10.2307/1924781

Bodie, Z., Kane, A., & Marcus, A. J. (2014). *Investments* (10th global). McGraw Hill Higher Education.

Bondt, W. F. M. De, & Thaler, R. (1985). Does the Stock Market Overreact? *The Journal of Finance*, *40*(3), 793–805. https://doi.org/10.2307/2327804

Boudoukh, J., Michaely, R., Richardson, M., & Roberts, M. R. (2007). On the importance of measuring payout yield: Implications for empirical asset pricing. *Journal of Finance*, *62*(2), 877–915. https://doi.org/10.1111/j.1540-6261.2007.01226.x

Brennan, M. J. (1970). Taxes, Market Valuation And Corporate Financial Policy. *National Tax Journal*, *23*(4), 417–427. https://doi.org/10.1086/ntj41792223

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, *11*(1), 1–27. https://doi.org/10.1016/j.jempfin.2002.12.001

Campbell, J. Y., & Kyle, A. S. (1993). Smart Money, Noise Trading and Stock Price Behaviour. *The Review of Economic Studies*, *60*(1), 1–34.

https://doi.org/10.2307/2297810

Campbell, J. Y., & Shiller, R. J. (1988). The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *Review of Financial Studies*, *1*(3), 195–228. https://doi.org/10.1093/rfs/1.3.195

Charles, A., Darné, O., & Kim, J. H. (2017). International stock return predictability: Evidence from new statistical tests. *International Review of Financial Analysis*, *54*, 97–113. https://doi.org/10.1016/j.irfa.2016.06.005

Chen, N. K., Chen, S. S., & Chou, Y. H. (2017). Further evidence on bear market predictability: The role of the external finance premium. *International Review of Economics and Finance*, *50*, 106–121. https://doi.org/10.1016/j.iref.2017.03.019

Chen, S. S. (2009). Predicting the bear stock market: Macroeconomic variables as leading indicators. *Journal of Banking and Finance*, *33*(2), 211–223. https://doi.org/10.1016/j.jbankfin.2008.07.013

Cochrane, John H. (2008). The dog that did not bark: A defense of return predictability. *Review of Financial Studies*, *21*(4), 1533–1575. https://doi.org/10.1093/rfs/hhm046

Cochrane, John H. (2011). Presidential Address: Discount Rates. *The Journal of Finance*, *66*(4), 1047–1108. https://doi.org/10.1111/j.1540-6261.2011.01671.x

Davydov, D., Tikkanen, J., & Äijö, J. (2016). Magic Formula vs. Traditional Value Investment Strategies in the Finnish Stock Market. *Nordic Journal of Business*, *65*(3), 38–54.

Dow, C. H. (1920). Scientific Stock Speculation. *Magazine of Wall Street*, 60.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance*, *46*(5), 1575–1617. https://doi.org/10.2307/2328565

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of Financial Economics*, *22*(1), 3–25. https://doi.org/10.1016/0304-405X(88)90020-7

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The*

Journal of Finance. 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1998). Value versus Growth: The International Evidence. *The Journal of Finance*, *53*(6), 1975–1999. https://doi.org/10.1111/0022-1082.00080

Fama, E. F., & French, K. R. (2001). Disappearing dividends: Changing firm characteristics or lower propensity to pay? *Journal of Financial Economics*, *60*(1), 3–43. https://doi.org/10.1016/S0304-405X(01)00038-1

Fontanills, G. A., & Gentile, T. (2001). *The Stock Market Course*. John Wiley & Sons, Incorporated.

Fuller, K. P., & Goldstein, M. A. (2011). Do dividends matter more in declining markets? *Journal of Corporate Finance*, *17*(3), 457–473. https://doi.org/10.1016/J.JCORPFIN.2011.01.001

Gitman, L. J., Joehnk, M. D. & Smart, S. B. (2011). *Fundamentals of investing* (11th ed.). Prentice-Hall.

Goetzmann, W. N., & Jorion, P. (1993). Testing the Predictive Power of Dividend Yields. *The Journal of Finance*, *48*(2), 663–679. https://doi.org/10.1111/j.1540-6261.1993.tb04732.x

Golez, B., & Koudijs, P. (2018). Four centuries of return predictability. *Journal of Financial Economics*, *127*(2), 248–263. https://doi.org/10.1016/j.jfineco.2017.12.007

Gonzalez, L., Hoang, P., Powell, J. G., & Shi, J. (2006). Defining and Dating Bull and Bear Markets: Two Centuries of Evidence. In *Multinational Finance Journal* 10(2), 81-116. http://doi.org/10.17578/10-1/2-3

Griffin, J. M., & Lemmon, M. L. (2002). Book-to-Market Equity, Distress Risk, and Stock Returns. *The Journal of Finance*, *57*(5), 2317–2336. http://doi.org/10.1111/1540-6261.00497

Grullon, G., & Michaely, R. (2002). Dividends, Share Repurchases, and the Substitution Hypothesis. *Journal of Finance*, *57*(4).

Hakansson, N. H. (1982). To Pay or Not to Pay Dividend. *The Journal of Finance*, *37*(2), 415–428. https://doi.org/10.2307/2327345

Hanna, A. J. (2018). A top-down approach to identifying bull and bear market states.

International Review of Financial Analysis, *55*, 93–110. https://doi.org/10.1016/j.irfa.2017.11.001

Hirshleifer, D. (2001). Investor Psychology and Asset Pricing. *The Journal of Finance*, *56*(4), 1533–1597. http://doi.org/10.1111/0022-1082.00379

Jensen, M. C. (1978). Some anomalous evidence regarding market efficiency. *Journal of Financial Economics*, *6*(2–3), 95–101. https://doi.org/10.1016/0304-405X(78)90025-9

Kole, E., & van Dijk, D. (2017). How to Identify and Forecast Bull and Bear Markets? *Journal of Applied Econometrics*, *32*(1), 120–139. https://doi.org/10.1002/jae.2511

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance*, *49*(5), 1541–1578. https://doi.org/10.2307/2329262

Lewellen, J. (2004). Predicting returns with financial ratios. *Journal of Financial Economics*, *74*(2), 209–235. https://doi.org/10.1016/j.jfineco.2002.11.002

Lintner, J. (1956). Distribution of Incomes of Corporations Among Dividends, Retained Earnings, and Taxes. In *Source: The American Economic Review* (Vol. 46, Issue 2).

Lintner, J. (1965). *The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets* 47(1).

Litzenberger, R. H., & Ramaswamy, K. (1979). The effect of personal taxes and dividends on capital asset prices. Theory and empirical evidence. *Journal of Financial Economics*, *7*(2), 163–195. https://doi.org/10.1016/0304-405X(79)90012-6

Litzenberger, R., & Ramaswamy, K. (1982). The Effects of Dividends on Common Stock Prices Tax Effects or Information Effects? *The Journal of Finance*, *37*(2), 429–443. https://doi.org/10.1111/j.1540-6261.1982.tb03565.x

Lunde, A., & Timmermann, A. (2004). Duration dependence in stock prices: An analysis of bull and bear markets. *Journal of Business and Economic Statistics*, *22*(3), 253–273. https://doi.org/10.1198/073500104000000136

Maheu, J. M., & McCurdy, T. H. (2000). Identifying bull and bear markets in stock returns. *Journal of Business and Economic Statistics*, *18*(1), 100–112. https://doi.org/10.1080/07350015.2000.10524851

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Mcmillan, D. G. (2014). Modelling Time-Variation in the Stock Return-Dividend Yield Predictive Equation. *Financial Markets, Institutions and Instruments*, *23*(5), 273–302. https://doi.org/10.1111/fmii.12021

Miller, M. H., & Modigliani, F. (1961). Dividend Policy, Growth, and the Valuation of Shares. *The Journal of Business*, *34*(4), 411. https://doi.org/10.1086/294442

Mossin, J. (1966). *Equilibrium in a capital asset market. Econometrica: Journal of the econometric society, 34(4), 768-783.*

Naranjo, A., Nimalendran, M., & Ryngaert, M. (1998). Stock Returns, Dividend Yields, and Taxes. *The Journal of Finance*, *53*(6), 2029–2057. https://doi.org/10.1111/0022-1082.00082

Norman, J. H., & Thiagarajan, S. R. (2009). Asset Bubbles and Market Crises. *The Journal of Investing*, *18*(4), 6–22. https://doi.org/10.3905/joi.2009.18.4.006

Novy-marx, R. (2014). Quality Investing. *Working Paper*, 1–37.

Nyberg, H. (2013). Predicting bear and bull stock markets with dynamic binary time series models. *Journal of Banking and Finance*, *37*(9), 3351–3363. https://doi.org/10.1016/j.jbankfin.2013.05.008

Polimenis, V., & Neokosmidis, I. M. (2016). The modified dividend-price ratio. *International Review of Financial Analysis*, *45*, 31–38. https://doi.org/10.1016/j.irfa.2016.01.019

Rozeff, M. S. (1984). Dividend Yields are Equity Risk Premiums. *Journal of Portfolio Management*, *Fall*, 68–75.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory Of Market Equilibrium Under Conditions Of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Shen, P. (2003). Market Timing Strategies That Worked. *The Journal of Portfolio Management*, *29*(2), 57 LP – 68. https://doi.org/10.3905/jpm.2003.319873

Shiller, R. J. (1984). Stock Prices and Social Dynamics. *Brookings Papers on Economic Activity*, *2*, 457–498. http://doi.org/10.0.9.3/2534436

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *The Journal of Economic Perspectives*, *17*(1), 83–104. http://doi.org/10.1257/089533003321164967

Skinner, D. J. (2008). The evolving relation between earnings, dividends, and stock repurchases. *Journal of Financial Economics*, *87*(3), 582–609. https://doi.org/10.1016/j.jfineco.2007.05.003

Sossounov, K., & Pagan, A. (2003). A Simple Framework for Analysing Bull and Bear Markets. *Journal of Applied Econometrics*, *18*(1), 23–46. https://doi.org/10.1002/jae.66

Strauss, L. C. (2020). These 10 Dividend Aristocrats Recently Raised Their Payouts. *Barron's*, *100*(29), 32.

Tikkanen, J., & Äijö, J. (2018). Does the F-score improve the performance of different value investment strategies in Europe? *Journal of Asset Management*, *19*(7), 495–506. https://doi.org/10.1057/s41260-018-0098-3

Verdickt, G., Annaert, J., & Deloof, M. (2019). Dividend growth and return predictability: A long-run re-examination of conventional wisdom. *Journal of Empirical Finance*, *52*, 112–127. https://doi.org/10.1016/j.jempfin.2019.03.002

Welch, I., & Goyal, A. (2008). *A Comprehensive Look at the Empirical Performance of Equity Premium Prediction*. *21*(4), 1455–1508. https://doi.org/10.1093/rfs/hhm014