A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

INVESTING IN DIVIDEND GROWTH STOCKS: ANALYSIS OF PORTFOLIO PERFORMANCE USING ASSET PRICING MODELS

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03-01-2021

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1. Abstract

By constructing dividend growth portfolios and comparing them to replicated value and equal-weighted S&P benchmarks, we find that the portfolios outperformed long-term in terms of both alpha and Sharpe Ratio. From the asset pricing model loadings, we find that a much higher profitability factor (RMA) is observed in a dividend raise portfolio. Another portfolio, holding stocks that kept dividends either constant or at a raise, has a much higher investment factor (CMW).

Key words (four): dividend growth investing, factor models, dividend aristocrats, asset pricing

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

1. Introduction and motivation

While dividend growth investing (or strategies) might be a familiar topic amongst investors, the subject is not extensively scientifically researched. Publications from Standard & Poor's (2020) interestingly highlights the Dividend Aristocrat Indexes as worthy competitors against the broader S&P in terms of both risk and returns since its launch date in 2005. "Dividend strategies have gained a foothold with market participants seeking potential outperformance and attractive yields, especially in the low-rate environment since the 2008 financial crisis and the even lower-rate environment we've seen in 2020 as the world deals with the economic fallout from COVID-19." (Standard & Poor's 2020, pp. 1)

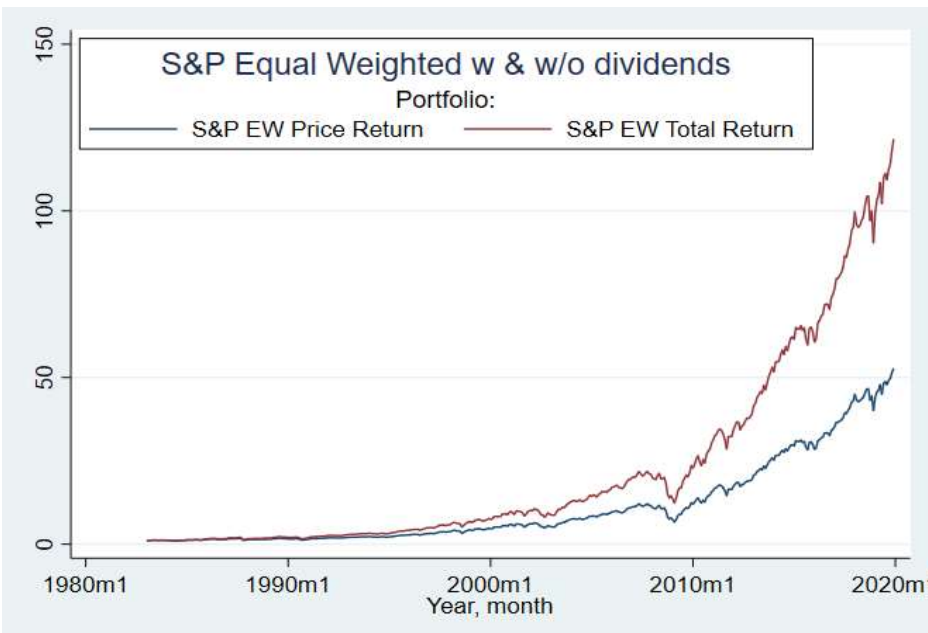


Figure 1. Source: WRDS (data collected and modified by writer)

Notes: the above graph displays how an equal-weighted replicated S&P500 performed with and without dividends reinvested starting at 1 from 1983 to 2019m1. It is apparent that cumulative returns, over time, are a quite substantial part of the total return even for a broad index.

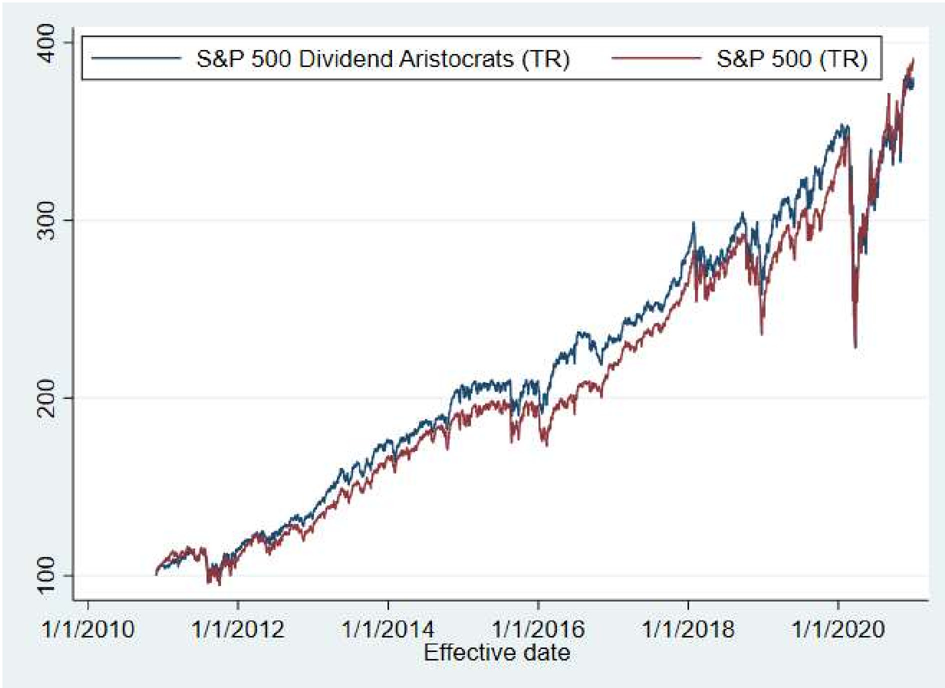


Figure 2. Source: S&P Dow Jones Indices

Notes: the above graph shows daily total returns of S&P500 Dividend Aristocrats versus the broader S&P500 from the past 10 years up until Dec. 31, 2020 starting at 100. The Dividend Aristocrat's 10-year average return was in this time period 13,68% and S&P500's was 13,88%.

This work project wants to focus on the long-term results of dividend growth strategies. How do dividend strategies compare to the broader benchmarks and can they perform even better over a longer time period? How can we explain the return drivers? The Dividend Aristocrat indices have approximately 15 years of historic data. By backtesting the broader S&P and constructing our own dividend portfolios, we can assess how similar investing strategies have performed even further back in time. Using COMPUSTAT and CRSP data, we obtain relevant data, starting our value date to observe dividends in the mid-1960's, which means that we could "launch" a dividend portfolio with 20 years of dividend history starting mid-1980's. If dividend investing strategies can prove to be less volatile and better earners, I believe the topic should be further investigated and researched.

2. Literature review

This Work Project aims to study the long-term characteristics of equal-weighted and value-weighted dividend growth investing strategy portfolios compared to an equal-weighted and value-weighted replicated S&P500. In doing so, regressions using well-renowned asset pricing models such as The Capital Asset Pricing Model by Sharpe (1964) and Litner (1965), Fama-French Three-Factor Model by Fama and French (1993), Carhart Four-factor Model Carhart (1997), and Fama-French Five-Factor Model will be utilized.

Extensively cited and still relevant on dividends is Miller and Modigliani (1961), introducing the Dividend Irrelevance theory suggesting that dividends do not affect a company's share price. Furthermore, Black and Scholes (1974) concluded in the abstract of their famous paper "The effects of dividend yield and dividend policy on common stock prices and returns" that "This paper suggests that it is not possible to demonstrate, using the best available empirical methods, that the expected returns on high yield common stocks differ from the expected returns on low yield common stocks either before or after taxes". The dividend's effect has been extensively researched throughout the years; however, few journals have covered dividend growth investing strategies' performance. Therefore, performing a literature review on this specific and somewhat narrow topic was quite hard due to few relevant scientific publications; thus, more general publications were reviewed. Standard and Poor's has published articles/reports quantifying the Dividend Aristocrats' performance and characteristics compared to the broader S&P500.

Standard & Poor's introduced in 2005 the Dividend Aristocrats, an index essentially consisting of those S&P500 stocks that raised dividends for 20 or more years consecutively. Standard and Poor's (2008) compared the quality rankings of the S&P500 constituents to those of the Dividend

Aristocrats and looked at the compositions of value vs. growth stocks for the two indices. The report suggested that the Dividend Aristocrats consisted of higher-quality companies and a higher relative portion of growth stocks than the broader S&P500. Furthermore, it reported returns, standard deviations, and Sharpe ratios on a 3, 5, 10, and 15-year basis for both indices, mostly in favor of the Dividend Aristocrat index. “In todays’ low-interest climate, investors need to take on bigger risk to receive the same return as when rate rates were higher. In 2007, dividend income comprised 6.7% of per capita personal income in the United States, compared to 4.8% ten years prior and 2.8% twenty years prior” (Standard & Poor’s 2008). In Standard & Poor’s (2020) report “A Case for Dividend Growth” strategies, which again examined returns and other characteristics, they argued that dividend growing companies are better quality companies in terms of earnings quality and leverage. Mostly using data 10 years prior, S&P had similar findings as to the aforementioned 2008 publication. “There are clear distinctions that set dividend growers apart from other dividend stocks. Dividend growers, which tend to be quality companies, have generally shown greater resilience in unsteady markets and could address concerns about dividend stocks in a rising-rate environment, to some extent. This argument not only applies to the U.S. large-cap space, but it also extends to small- and mid-cap segments and international markets” (Standard & Poor’s 2020).

As the title might suggest, “Investing in Dividend Growth Stocks: Analysis of Portfolio Performance Using Asset Pricing Models”, this project is focused on analyzing how each of our constructed portfolios performs using relevant and efficient measures. Given the past impressive performance and characteristics of the Dividend Aristocrat portfolios, we want, ultimately, to answer if dividend growth investing serves as an adequate investment choice and if it could outperform indexing.

3. Data and data manipulation

In essence, this chapter reports the main adjustments, decisions, and calculations made to generate our relevant variables as accurately as possible.

4.1 Data sets and adjustments

We have gathered a security price dataset from Wharton Research Data Services containing CRSP (The Center for Research in Security Prices) and COMPUSTAT data merged for our data. It contains monthly individual security prices and other relevant variables ranging from 1962-01 until 2019-12. Initially, the dataset had almost 4 million observations containing trusts, stocks, indices, and funds currently and previously listed on AMEX/Nasdaq/NYSE. To narrow the dataset to relevant constituents, we are merging with an Index Constituents dataset from COMPUSTAT. Unfortunately, some of the Index Constituents did not match, which means that our attempt at replicating S&P500 will miss out on some companies. In attempting to compensate for the missing companies, we will be using S&P500 constituents from 1961-01 through 1991-05, then the 500 largest (by market capitalization) S&P Composite 1500 constituents from 1991-06 until 2019-12. For our research, we will also need to import data on risk-free rate (one-month Treasury bill rate (from Ibbotson Associates)), HML (high minus low), SMB (small minus big), and MOM (momentum factor), RMW (on profitability), and CMA (on investments) accomplished by merging in a monthly Fama-French factor dataset from WRDS and French's website on the relevant months.

After matching our constituent list with the dataset process, the remainder of the company observations in the dataset used to be or are currently constituents of the S&P500. The Index Constituents dataset contained "from" and "thru" variables, with dates of the constituents' possible addition and deletion dates, which we will use at a later stage to drop the companies who used to be a constituent.

4.2 Definitions, portfolio construction, and more adjustments

The datasets' monthly observations in the 1960's, '70s, and '80s often have a missing Shares Outstanding variable, making errors in calculations for our market capitalization variable (mcap). Furthermore, from the 80's and onward, Shares Outstanding are reported only quarter-wise. As monthly mcap is needed monthly to account for index weights, our alternative solution is to operate with a average monthly shares outstanding on a year-basis variable for the Market Capitalization calculations. N is the number of shares outstanding observations within a year (mostly 4, 2 or 1).

(1) $Market\ Capitalization_t = \left(\frac{\sum_{n=1}^{N} shar\quad outstanding}{N}\right) * Price\ per\ share_t$

For the security price monthly returns, we are using arithmetic returns, denoted by:

(2) $Arithmetic\ return_t = \left(\frac{Price\ per\ share_t}{Price\ per\ share_{t-1}}\right) - 1$

In this work project, we will be dealing with arithmetic returns including dividends reinvested. We use the Total Return if the company pays dividend that month (and if not, we use the arithmetic return), denoted by:

(3) $Total\ return_t = \left(\frac{Dividend\ per\ share_t + Price\ per\ share_t}{Price\ per\ share_{t-1}}\right) - 1$

In constructing a dividend growth portfolio, we would need to know if a specific company stopped, raised, or lowered their dividends from time *t* to time *t+12* (*t+12* being the first month in the following year), as a dividend grower must raise dividends each year. An obstacle when generating a code for this occurs as some companies pay dividends once a year, some semiannually, and others quarterly. The suggested solution is, therefore, to operate with an average dividend per month on a year-basis.

In this paper, two portfolios with somewhat similar strategies are constructed. The first portfolio, Dividend Constant 20 (DC20), must either keep dividends constant or raise them for 20 consecutive years to become a constituent. The second, Dividend Raise 10 (DR10), must raise dividends for 10 consecutive years. For DC20, if the year-average dividend payouts are lowered compared to the previous year, the company is dropped from the portfolio. For DR10, if the year-average dividend payout is lowered or constant relative to the previous year, the company is dropped from the portfolio. It is not feasible to replicate the exact addition criteria strategy of S&P500 Dividend Aristocrats as that will give us some years with alarmingly few constituents. The Dividend Aristocrat portfolio from Standard & Poor's (2020) operates with a 20 consecutive year dividend raise criteria.

We are generating a counter for the constituent selection, which counts the "dividend streak" for each company. If the dividend streak is higher than the rule (of 10 or 20 years), the observation gets a dividend dummy = 1, thus signaling that it should be a constituent for our portfolios.

All companies are dropped before their addition date and after their deletion date as an S&P500 constituent, giving us the end constituents of our replicated S&P500 portfolio. The WRDS constituent dataset provides these dates. The average number of constituents per month for the time series is 478.

S&P500 uses a float-adjusted market capitalization to solve for their weights. However, we have to settle with standard market capitalization due to restrictions in our dataset. We are denoting the weights like the following:

(4) $Weights\ in\ Value\ Weighted\ portfolio_t = \frac{Market\ Capitalization\ Stock_{t-1}}{Index\ Market\ Capitalization_{t-1}}$

In solving for our dividend portfolio weights, we cannot use data before 1983 because it takes 20 years to know if a company met the criteria to become an addition to the second portfolio (20 years of raised or constant dividends). From 1983 until 2019, we have, on average, 21 constituents per month using the 20-year rule and 10 constituents using the 10-year rule of raised dividends. To solve for our equal-weighted portfolios, we only need to know the number of constituents each month to solve for the weights:

(5) $Weights\ in\ Equal\ Weighted\ Portfolio_t = \frac{1}{N\ Constituents_t}$

4. Method and Empirical Analysis

With the research question in mind, it is essential to assess, compare, and explain both the S&P and dividend portfolios' performance using adequate and relevant measurements. This first part will look at average returns, Sharpe Ratio, and other metrics. In part two, we will dive into the asset pricing models and time-series regression.

5.1 Portfolio metrics: theory

In William Sharpe's (1966) paper, he utilized the reward-to-variability ratio, more commonly known as the Sharpe Ratio. The Sharpe Ratio is a profitability measure per unit of standard deviation. As the dataset has monthly returns, the annualized Sharpe Ratio is denoted:

(6) $Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} * \sqrt{12}$

With R_p: portfolio return, σ_p: portfolio standard deviation of excess returns, and R_f: risk-free rate of return

Summary statistics in from the dataset in Stata will give us the monthly average return for each portfolio, monthly standard deviations, and monthly risk-free rate. Although we are using monthly returns, we are achieving annual portfolio return and risk-free rate of return defined as such:

$$(7)\ Return\ Annu. = (1 + r_{monthly})^{12} - 1$$

5.2 Portfolio metrics: results

Table 1: Metrics

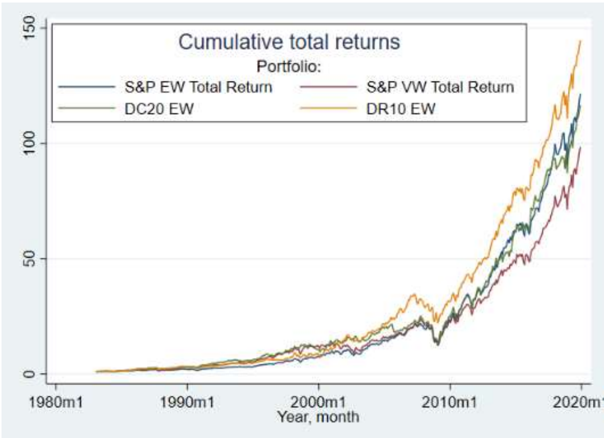
1983-2019				
Portfolio	Return mth.	Return annu.	Yield annu.	Sharpe Ratio
S&P EW	1,19 %	15,28 %	2,30 %	0,68
S&P VW	1,15 %	14,72 %	2,85 %	0,63
DC20 EW	1,17 %	14,93 %	4,92 %	0,72
DC20 VW	1,21 %	15,47 %	4,85 %	0,75
DR10 EW	1,23 %	15,79 %	3,87 %	0,71
DR10 VW	1,21 %	15,49 %	4,18 %	0,67

Source: WRDS (data collected and modified by writer)

Notes: the above portfolios consist of the replicated equal-weighted and value-weighted S&P, Dividend Constant 20 years, and Dividend Raise 10 years. All returns are based on total returns (returns with dividends monthly reinvested).

The most interesting metric is the Sharpe Ratio, which looks at excess portfolio return relative to its standard deviation. Even though the DR10 equal-weight and value-weight received the highest average returns, DC20 has the higher Sharpe Ratio. S&P displayed the lowest Sharpe Ratio in almost all cases.

Dividend portfolios will, by construction, have a significantly higher yield than the S&P portfolios. Between the dividend portfolios, the Dividend Constant 20 gave the highest yield. With its criteria of holding both companies keeping and companies raising dividends, the portfolio is prone to hold high-yield dividend companies keeping high dividends at a constant. Whereas the Dividend Raise 10 misses out on companies maintaining such dividend policies. S&P (2020) displayed that their Dividend Aristocrat index holds a much higher portion of growth stocks relative to a normal high dividend portfolio. Growth stocks generate substantial revenue and would tend to be more mature companies. The same logic could apply to our portfolios with the DR10, having only dividend growers having a higher percentage of growth companies relative to the DC20. The bigger portion of growth stocks should make our portfolio less volatile and more robust in downturns; however, and interestingly, the DR10 has the higher standard deviation. This was somewhat unexpected and could be attributed to the fact that DR10 has clearly on average fewer constituents.



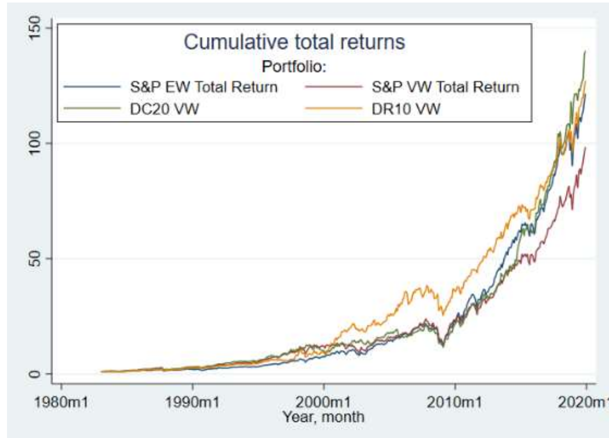
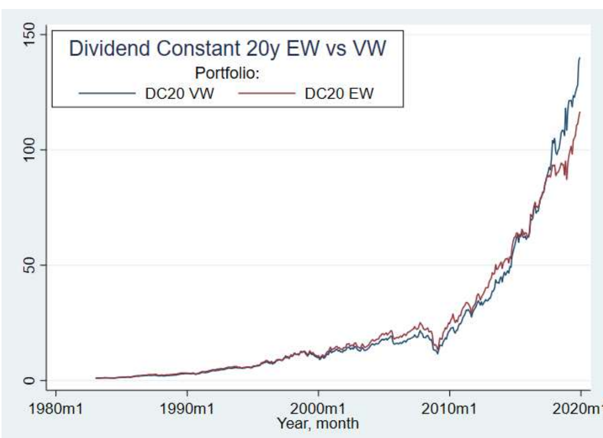


Figure 3 & 4. Source: WRDS (data collected and modified by writer)

The DR10 portfolio (both EW and VW) delivered strong results, especially during the 90's, while also showing remarkable resilience during the 2008 recession and the dot-com bubble. However, the DR10 portfolio does not have the highest Sharpe Ratio.



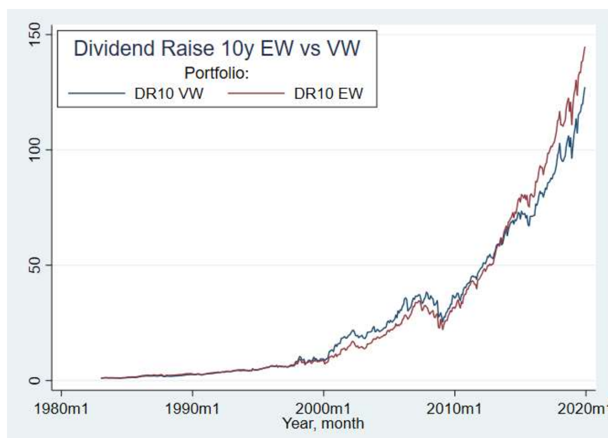


Figure 5 & 6. Source: WRDS (data collected and modified by writer)

The equal-weighted dividend portfolios did not outperform the value-weighted ones in both cases the same way the S&P did. For the Dividend Constant portfolio, it was the other way around. Historically, broader equal-weighted portfolios have tended to outperform value-weighted ones as smaller stocks with a larger expected return have relatively bigger portfolio weights. Smaller companies yielding higher returns is essential in explaining portfolio returns and also a factor we will look further into through some of the asset pricing models.

5.3 Asset pricing models: theory

Our second form of measurements will focus on asset pricing models, and firstly, the Capital Asset Pricing Model (CAPM). “The CAPM explains the tradeoff between assets’ returns and their risks, measuring the risk of an asset as the covariance of its returns with returns on the overall market” (Rossi 2016, pp. 605). We are performing regressions to assess the excess returns of our desired portfolio on the market risk premium. This specific type of regression is also called the Sharpe-Litner CAPM, denoted (in this case) as:

(8) $E(R_p) - R_f = \alpha_p + \beta_p\big(E(R_m) - R_f\big) + \varepsilon_p$

With α_p: portfolio alpha, β_p: portfolio beta, R_m: return market, and ε_p: error-term

The β_p is a portfolio coefficient estimated through the regression and serves as the portfolio risk versus the market. If beta (or MKTRF through the regression) > 1, the portfolio tends to be more volatile than the market, and if beta < 1, it tends to be less volatile. Furthermore, the closer beta is to 1, the more correlated the given portfolio is with the market. Our constant or α (alpha) coefficient is more famously known as Jensen’s alpha. Jensen’s alfa demonstrates “the ability to earn results which are higher than those we would expect given the same level of risk of each of the portfolios” (Jensen 1967, pp. 390). With “the portfolios” being our constructed portfolio and the market return variable. Epsilon (ε) is a value that expresses average standard errors between our observations and the regression model line.

Fama and French (1993) presented the Three-Factor Model, expanding on the CAPM. They found that adding explanatory variables of a size premium (small market cap stocks minus big market cap stocks) and a value premium (high book-to-market ratio minus low book-to-market ratio) could better explain the variation in the return of risky assets. “At a minimum, our results show that five factors do a good job explaining (a) common variation in bond and stock returns and (b) the cross-section of average returns. We think there is appeal in the simple way we define mimicking returns for the stock-market and bond-market factors. But the choice of factors, especially the size and book-to-market factors, is motivated by empirical experience" (Fama and French 1993, pp. 53).

(9) $E(R_p) - R_f = \alpha_p + \beta_1\big(E(R_m) - R_f\big) + \beta_2(SMB) + \beta_3(HML) + \varepsilon_p$

The Carhart Four-Factor Model (Carhart 1997) adds the momentum variable, which was at first presented by Jagadeesh and Titman (1993). The momentum variable is a one-year momentum in the markets' stocks, covering long positions in the previous years' winning stocks and short positions in the previous years' losing stocks. Momentum-based

(10) $E(R_p) - R_f = \alpha_p + \beta_1\big(E(R_m) - R_f\big) + \beta_2(SMB) + \beta_3(HML) + \beta_4(MOM) + \varepsilon_p$

The Fama-French Five-Factor Model (2013) added RMW and CMA as new factors to their already well-renowned Three-Factor Model. "RMW is the difference between returns on diversified stock portfolios of stocks with robust and weak profitability, and CMA is the difference between returns on diversified portfolios of the stocks of low and high investment firms, which we call conservative and aggressive." (Fama and French 2013, pp. 5).

(11) $E(R_p) - R_f = \alpha_p + \beta_1\big(E(R_m) - R_f\big) + \beta_2(SMB) + \beta_3(HML) + \beta_4(RMW) + \beta_5(CMA) + \varepsilon_p$

5.4 Asset pricing models: results

Using the above defined factor models, we want to run time series regressions to estimate the intercepts (α), and estimate the coefficients (β). The α serves as the Jensen's Alpha previously mentioned and the coefficients will tell us the exposure the portfolios have to each factor in each model. Ultimately, we want to use both the factor loadings and the metrics from the first part of the method chapter to reach conclusions for our research question.

Table 2: Factor loadings w/ annu. alphas						
	S&P EW	S&P VW	DC 20 EW	DC20 VW	DR10 EW	DR10 VW
CAPM						
ALPHA	**2,31 %**	1,74 %	**5,72 %**	**6,58 %**	**5,21 %**	**5,75 %**
	2,91	*1,75*	*2,85*	*3,20*	*2,69*	*2,54*
MKTRF	**1,01**	**1,01**	**0,58**	**0,54**	**0,73**	**0,63**
	67,23	*54,05*	*15,50*	*14,19*	*20,18*	*15,08*
R-SQUARED	91,09 %	86,86 %	35,22 %	31,29 %	47,94 %	33,96 %
FF3						
ALPHA	**1,70 %**	0,90 %	3,46 %	**4,67 %**	**3,89 %**	**4,81 %**
	2,28	*0,98*	*1,91*	*2,44*	*2,08*	*2,15*
MKTRF	**1,02**	**1,06**	**0,67**	**0,62**	**0,78**	**0,68**
	69,34	*58,95*	*19,02*	*16,81*	*21,33*	*15,70*
SMB	**0,09**	**-0,15**	-0,07	**-0,13**	-0,04	-0,12
	4,03	*-5,51*	*-1,31*	*-2,31*	*-0,58*	*-1,82*
HML	**0,16**	**0,18**	**0,52**	**0,42**	**0,30**	**0,20**
	7,22	*6,87*	*9,99*	*7,72*	*5,59*	*3,13*
R-SQUARED	92,22 %	88,98 %	47,66 %	40,56 %	51,52 %	36,03 %
Carhart 4						
ALPHA	**2,45 %**	**2,10 %**	**3,71 %**	**4,68 %**	2,92 %	3,46 %
	3,33	*2,40*	*2,02*	*2,41*	*1,55*	*1,55*
MKTRF	**1,00**	**1,03**	**0,66**	**0,62**	**0,81**	**0,72**
	68,24	*59,05*	*18,24*	*16,27*	*21,57*	*16,23*
SMB	**0,09**	**-0,14**	**-0,07**	**-0,13**	-0,03	-0,12
	4,23	*-5,81*	*-1,30*	*-2,31*	*-0,61*	*-1,87*
HML	**0,13**	**0,13**	**0,51**	**0,42**	**0,34**	**0,25**
	5,85	*5,19*	*9,49*	*7,47*	*6,18*	*3,90*
UMD (MOM)	**-0,08**	**-0,13**	-0,03	0,00	**0,10**	**0,14**
	-5,78	*-7,88*	*-0,78*	*-0,03*	*2,92*	*3,38*
R-SQUARED	92,77 %	90,35 %	47,73 %	40,56 %	52,44 %	37,66 %
FF5						
ALPHA	0,34 %	-0,04 %	0,95 %	2,28 %	1,47 %	1,90 %
	0,47	*-0,05*	*0,53*	*1,18*	*0,79*	*0,85*
MKTRF	**1,06**	**1,09**	**0,74**	**0,69**	**0,84**	**0,76**
	69,29	*56,25*	*19,82*	*17,45*	*21,69*	*16,40*
SMB	**0,14**	**-0,13**	0,01	-0,06	0,09	0,00
	6,29	*-4,40*	*0,19*	*-0,95*	*1,57*	*-0,02*
HML	**0,07**	**0,09**	**0,32**	**0,23**	**0,19**	0,02
	2,33	*2,61*	*4,65*	*3,17*	*2,60*	*0,19*
RMW	**0,19**	**0,09**	**0,30**	**0,28**	**0,41**	**0,41**
	6,65	*2,48*	*4,23*	*3,67*	*5,56*	*4,68*
CMA	**0,13**	**0,17**	**0,33**	**0,32**	0,09	**0,25**
	3,08	*3,15*	*3,18*	*2,95*	*0,89*	*1,99*
R-SQUARED	93,02 %	89,34 %	50,43 %	43,18 %	54,73 %	39,28 %
N (months)	444					

Source: WRDS (data collected and modified by writer)

For table 2, alphas are annualized. T-stats are in italic, and significant regression outputs at a 95% significance level are in bold (P-value < 0.05). Our replicated S&P portfolios performs better than the market return variable (obtained from Kenneth R. French's data library, which comes from NYSE/AMEX/NADAQ security prices); hence, they have positive alphas.

The factor loadings should allow us to explain what drives the dividend portfolio returns and to what extent the returns are unexplainable. Less focus will be attributed to the CAPM model, as the other models have been proven to explain stock returns better. Initial observations are that the alphas are much higher for the dividend portfolios than for the constructed S&P portfolios. Thus, the dividend portfolios have a higher excess return in which cannot be predicted by the given asset pricing model than both the market and S&P. The loadings on MKTRF are slightly higher than 1 for the S&P portfolios, which tells us that the S&P portfolios are highly correlated with the market and slightly more volatile than the market. All dividend portfolios have MKTRF lower than 1, which means that they have a lower correlation with the market. Another way to explain the dividend MKTRF coefficients is that the portfolios tend to go down less when the market goes down and does not tend to go up as much when the market goes up. R-squared values tell us how much of the variation in the excess market return is explained the given portfolio through the model. Table 2 shows that all models have a high goodness-of-fit for the S&P portfolios (between 87% and 93%). While on the other hand, much lower for the dividend portfolios (between 31% and 50% for DC20, between 34% and 55% for DR10). The Fama-French Three-Factor Model loadings, adding HML and SMB as factors, gives lower alphas for all portfolios while also rendering S&P VW and DC20 EW's alphas non-significant. When looking at the MKTRF coefficient, they are all significant and higher than those displayed from the CAPM regression. The SMB loadings, which captures the size premium following smaller companies, is only positive for the S&P EW, while negative for the others. We can infer that, partially, the returns from S&P EW can be explained by smaller-cap companies. Dividend growing stocks tend to be more mature in their life cycle and are often characterized as growth stocks; thus, being more likely to have large-cap stocks. Receiving positive SMB coefficients from the regressions means that the portfolio tends to hold low market capitalization companies contributing to the returns. By construction, the value-weighted S&P portfolio has and should have a negative SMB coefficient due to the low weights of smaller cap stocks. On the other hand, we would expect equal-weighted portfolios to have positive SMB, which is not the case for the dividend portfolios. They are negative and insignificant. The HML factor, which is buying high book-to-market stocks and shorting low book-to-market stocks, will help explain the portfolio's exposure to "cheap" or "expensive" stocks defined by the book-to-market ratio, and can help us explain spread in returns coming from companies' low or high book-to-market ratio. In all factor models, we see a clear difference between S&P and the dividend portfolios. The HML coefficient is mostly significant, and much bigger for the dividend portfolios than for the S&P portfolios. In other words, both a dividend raise and a dividend constant portfolio will tend to have a higher exposure to "cheap" stocks than both the market and our S&P portfolios. The S&P portfolios also have a slightly positive HML coefficient, which can be because S&P companies have a profitability criterion to be met for inclusion. The market data comes from the factor dataset, consisting of data gathered from companies from several exchanges, which does not have the profitability criteria. Introduced in the Carhart Four-Factor Model, the momentum (UMD) factor loading is low but insignificant for DC20 and positive for the DR10. For the S&P portfolios, the momentum factor is negative. The momentum (UMD) factor corresponds to buying previous years' winners and shorting previous years' losers. A positive and significant MOM coefficient for the DR10 portfolios means that some of the portfolio return comes from holding previous years' winners and, therefore, also more trendy stocks. It is reasonable to say that dividend growers could be momentum stocks as a dividend raise is considered positive company news; thus, the stock continues to generate positive returns and stay relevant. Moving on to the Fama French Five-Factor Model, factors for robust vs. weak profitability firms (RMW) and conservative investing vs. aggressive investing firms (CMA) are added to their previous three-factor model. Dividend-paying stocks are often profitable companies, and we can expect 10-year dividend raisers to be even more profitable. The RMW factor is positive and significant for all portfolios; however, bigger for dividend portfolios than for the S&P's. The DR10 portfolios have the biggest RMW loading, which can be accredited to a better profitability than other dividend-paying companies. "Dividend growth stocks tend to be of higher quality than those of the broader market in terms of earnings quality and leverage. Quite simply, when a company is reliably able to boost its dividend for years or even decades, this may suggest it has a certain amount of financial strength and discipline" (Standard & Poor's 2020, pp. 2). The estimated CMA coefficient is positive for all but much higher for the DC20 and insignificant for DR10 EW. As aggressive investing contributes to returns more for DC20 constituents than for S&P and DR10 companies, this one is interesting. To a more prominent degree, the DC20's could have policies to re-invest their revenue rather than raising dividends, which again should give a better return on investment than paying shareholders.

5.5 Analysis wrap-up

The apparent "winner" from the analysis section is the value-weighted Dividend Constant 20. It had the lowest significant MKTRF among the portfolios and maintained a high alpha through the different models. Furthermore, it held the lowest standard deviation and the highest Sharpe Ratio. The equal-weighted Dividend Raise 10 had the highest average return but was outperformed on

Sharpe Ratio and after considering the alpha loadings. Unfortunately, the alphas under the Fama French Five-Factor Model were all insignificant.

5. Critique and weaknesses

The constructed dividend and S&P portfolios are not an exact science and are reflecting a hypothetical historical performance. Even though they are replicated using commonly used data, tweaks and preconditioning were necessary to obtain necessary data for certain variables on older dates, i.e., average yearly shares outstanding, which was necessary to solve for the monthly value weights. The dividend portfolios did, on average, have a decent number of constituents. However, in some the months in 1992 and 1993, the DR10 portfolio had as few as three constituents but gradually increasing afterward. Performance for the portfolio was exceptional in the '90s, but the lack of consistent constituents does make it less suited for comparisons.

The dividend portfolios constructed immediately drop stocks who did not raise (for DR10) or keep dividends constant or raise (for DC20) from the portfolio. An investor in the real world cannot consistently drop a stock exactly before/when it changes its dividend policy. Therefore, it would probably be a more realistic portfolio if we held on to the stock one more month after the policy changed (as we are using monthly returns).

As addressed earlier, our S&P portfolio used the constituent lists of S&P500 and S&P1500. However, when merging security datasets by the commonly used company identifiers, some companies did not match from the constituent list, leaving us with fewer companies (478 on average). Which companies we are missing and how the lack of constituents implicates the results is not clear.

7 Open questions/future research

Quality Minus Junk (2019) found that investors should pay a higher price for quality (profitability, safety, and higher growth) in a stock. It proved that a long quality and short low quality stocks yielded higher risk-adjusted returns in 24 countries. Accounting for quality factors when analyzing dividend growth stock returns would certainly be interesting and a value-adding feature.

Standard and Poors (2020) did find that a dividend aristocrat index could hypothetically have beaten its relevant benchmark on a global scale and in most countries tested in 15 years. In proving and analyzing the added value in which dividend growth strategies can serve, one could perform long-term backtesting with asset models and metrics similar to this work project. With large datasets, more constituents would be possible, making a similar work project more reliable. Furthermore, a similar project could gather data for a wide range of countries.

7. Conclusion

This work project has demonstrated how well four different dividend investing strategies would have hypothetically performed against its relevant benchmarks. We found through the analysis that, given our sample, the constructed dividend portfolios tended to outperform both in terms of Sharpe Ratio and Jensen's Alpha, with the Dividend Constant 20-year portfolio yielding a 4,86% annual alpha under Carhart Four-Factor assumptions and a Sharpe Ratio of 0,75. The dividend portfolios tended to be less volatile and show resilience during economic downturns (see Appendix A). Our factor loadings gave us insight into what drives the dividend portfolio returns. The drivers of the excess dividend portfolio return were, through time-series regressions, explained by a tendency to hold higher book-to-market stocks and investing more aggressively. The Dividend Raise 10 portfolios received much better and significant RMA loadings than other portfolios, resulting from a bigger share of high profitability stocks and a lower share of low profitability stocks. The Dividend Constant 20's returns, which is the "best" portfolio, is driven by and stands out by its ability to invest aggressively. Ultimately, given findings in this work project and other research, dividend growth investing strategies look like a viable investment option compared to indexing.

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