Much Ado About Dividends

Gabriel Rambanapasi[a]

[a]*Stellenbosch University, Cape Town, South Africa*

Abstract

Investors deploy capital in equity markets to search for return that beats a market index. To acheive this, its important for practioners to identifyinvestement strategies and rules that can best deliever consistent outperformance. In this study, we assess globally dividend portfolios and determine that despite their value proposition, there exists great inconsistency in acheiving positive excess returns. We construct dividend investment strategies by considering high yield and dividend growth as signals and backtest performance of constituents throughout differing interest rate regimes against the JSE Top 40 Index. Such trading stratgeies have been successfully internationally, we test this for South Africa.

1. Introduction

This study provides an extensive investigation into the return signaling of dividend portfolios. Firstly, we address the question of when dividend portfolios work. The analysis delves into the performance and risk attributes of globally traded dividend portfolios across different geographical regions, market cycles, and interest rate regimes. We find that return characteristics of dividend portfolios vary greatly, with advanced economy high-yield portfolios returning multiples during the sample period, whilst emerging market and South African dividend portfolios fail to deliver stratifying excess return over the same period. More broadly, dividend portfolios, whether high yield (HY) or dividend growth (DG), all offer downside protection during periods

*Corresponding author: Gabriel Rambanapasi
Email address: `gabriel.rams44@gmail.com` (Gabriel Rambanapasi)

of high market volatility.

Taking the analysis a step further, we observe that dividend portfolios provide the best returns during periods of interest rate hiking cycles. We note that because dividend yield is categorized as a proxy for value, such assets are primed to outperform growth stocks as investors move away from risky assets within asset classes.

Next, the study also evaluates the consistency of performance among dividend portfolios using a rolling information ratio. From this dynamic measure, we note the inherent lack of consistency in all dividend portfolios. However, coupled with drawdowns experienced in different jurisdictions, we acknowledge that advanced market dividend portfolios experience the least variation in drawdowns compared to emerging markets. The results indicate that both growth and high-yield dividend portfolios tend to under perform relative to their benchmarks, raising questions about their consistency in delivering positive returns.

We then move on to how dividend portfolios work, with the goal of constructing a portfolio that can best harness the existing premium. We use share data from the Johannesburg Stock Exchange (JSE), with our benchmark being the JSE Top 40 index. We construct four portfolios varying in complexity, with the most advanced accounting for price momentum and dividend payout sustainability.

2. Problem Statement

As summarized by Vanguard (2017) succinctly, “the focus of high dividend-yielding equities is often their income potential, but higher yields do not necessarily translate into higher returns. This is because, for all companies, whether or not to pay a dividend is a capital budgeting decision. When a stock goes ex-dividend, its price falls by the same amount as the dividend payment. Therefore, no wealth is created through paying a dividend; rather, the payment reduces retained earnings. This means that share price should decrease accordingly thus share holders should be worse off.

Thus, brings in the question of why dividend strategies provide for a return signalling cue. First, there should exists a rationale beyond dividend payment effect on share price, perhaps in line with theories regarding dividend relevance. Second, if the signals provide some type excess return beyond their market index, does it continuously provide the premium to be harvested by a systematic investment strategy.

3. Research Aim

The aim of this study is to test whether and why dividend payout strategies contain a profitable investment signal to potential investors. There exists various international studies testing this hypothesis across geographies, underscoring that dividend can be used as a profitable future return signal. Studies conducted for the South African market employ methodologies that do not inform readers on mechanisms behind why the dividend signal works or provide an indication of returns for a systematic dividend investment strategy. We aim to fill this gap by testing various portfolios constructed based on dividend information in South Africa.

4. Literature Review

4.1. What are dividends

Dividends constitute a form of capital distribution by corporations towards shareholders. They exist in various forms, such as cash, stock, liquidating, scrip, or property dividends Baker & Powell (1999), of which cash dividends and share repurchases being the most commonly used in practice. Within cash dividends, regular dividends are widely used by corporations and payment frequency across jurisdictions. The decision to issue dividends is typically made by the board of directors, and approved by shareholders, however practiced more in Europe and less so in the United States. The payout policy policy of a corporation, which are guiding principles for management and board of directors towards capital distributions considers company investment and is closely watched by investors and analysts. As such, management strives to grow or maintain a certain level of dividend payouts as this signals firm growth and investors share of profitability in the company.

4.2. Theorectical Arguments on Dividend Payments

Given the apparent decrease in shareholder value, the logical question has encouraged a long running debate on dividend relevance and irrelevance. In 1961, Miller & Rock (1985) opined that dividends are irrelevant (MM theory), he argued that shareholders are indifferent to dividend payments, thus implying that there is no optimal dividend policy and that all dividend policies are equally good and payments of dividends could easily be reinvested in shares and make no difference to share holder wealth. However, the MM theorem fails to consider real-world market imperfections that may give relevance to dividend payments. The bird in the arguments opposes the MM theory, suggesting that investor would prefer to receive less risky cash flow in the form of dividends instead of potential capital gains at some point in the future (Gordon, 1962). This permeates to the cost of equity, since dividends are less risky, companies that issue more dividends should have higher share prices. However, propoents of the MM theory contend this suggesting the risk of future cash flow is affected by the payment of dividend, leading to negative effects on share prices after the ex-dividend date. The dividend puzzle considers real world constraints and gives an interesting take on its relevance and irrelevance, by suggesting that dividends reduce equity value and make investors worse off; however, are a reward to investors who bear the risk associated with their investments as it provides an additional source of return on investment from a share Black (1996). Various literature has made convincing arguments for corporations to pay dividends which include tax considerations, dividend signalling and agency costs in issuing dividends .

Taxe considerations argue in favor for dividend relevance. Across jurisdiction dividends have different tax treatments to capital gains and often tax at a higher income tax rate, thus investors that have higher tax rates choose stocks with lower dividend payouts and transversly pushes up the stock price, this is called the clientele effect Baker & Powell (1999). However a major pushback emanates from proponents of the MM theory, that suggest the client effect causes major substitution effect, meaning that if companies change their dividend policy, investors with preferential tax treatment will simply allocate more capital to that stock and those out of favor will sell their shares. Given the large number of investors versus listed companies the process is instantaneously causing a net zero effect on prices(Baker & Powell, 1999). Second, flotation costs refer to the opportunity costs incurred by a firm when paying dividends. Through distributing dividends, companies forego opportunities to expand their operations using retained earnings. In a world without flotation costs, as suggested by the MM theorem, management would be indifferent between issuing dividends and borrowing from the market thus have no effect on shares prices. However, in reality, external financing comes at a higher cost, leading to trade-offs in dividend policy decisions and ultimately share prices.

Information asymmetry between shareholders and managers is another factor that gives relevance to dividend payments. Managers of businesses have greater knowledge of operations thus value of a business at any given point more than shareholders. As such, investors rely on dividend announcements to assess a company's valuation. Dividend signaling conveys information about the company's quality Baker & Powell (1999). Investors compare dividend announcements to historical levels while considering company fundamentals. However, a major concern towards its ability to be "gamed' by management, making the dividend signal imperfect for determining share prices. Principal agency issues may give another reason for issuance of dividends. The free cash flow hypothesis suggests that dividend payments force management to raise capital from external sources, which increases borrowing costs and scrutiny from capital markets. This, in turn, reduces management's ability to make sub optimal investments and aligning management and shareholder objectives (**baker2009understanding?**). Supporters of this theory ascertain that dividends payments by the mechanism encourage good business practices.

4.3. Investment Strategies from Dividend signals

The amount of literature regarding dividend relevance leaves readers wiser. Thus, it can be reasonably concluded that the past performance of dividend-based portfolio strategies could be understood by using proxy arguments (as opposed to it being considered an attractive feature in itself). For example, high dividend-paying companies could proxy for the quality of management structures over time (through their ability to consistently afford dividend payments) or similarly point to prudent cash-flow management capabilities. Therefore, from the perspective of an investor, the dividend yield can be used as a signal in constructing an investment strategy. O'higgins & Downes (1991) proposed an investment strategy which used companies included in the Dow Jones Industrial Average (DJIA) called the "Dogs of the Dow" (DOD). By ranking 30 companies by dividend yield and including only the 10 highest-yielding shares in a portfolio, this achieved a return higher than the DJIA (16.6% per annum versus the DJIA's 10.4%). This had lower risk than the DJIA, thus achieving a higher Sharpe Ratio. Testing O'higgins & Downes (1991)'s strategy resulted in "Beat the Dow 5," which involved annually investing in only the five lowest-priced of the HY10 shares each year, in other words, high dividend yield. This strategy gave superior returns of 19.4% versus the DJIA. As opined by Gardner, Gardner & Maranjian (2002), this strategy leverages the fact that low-priced stocks experience the most volatility, by courting future volatility in the 10 stocks that have some potential upside, expecting their stock prices to rise in return.

Many more studies emerged examining the DOD strategy or similar high-yield dividend strategies, in different time periods and regions, consistently showing superior risk-adjusted returns compared to the market index. Examples of such studies include Lemmon & Nguyen (2015) in Hong Kong, Brzeszczyński & Gajdka (2007) in Poland, Visscher & Filbeck (2003) in Canada, Filbeck & Visscher (1997) in Britain, and Wang, Larsen, Ainina, Akhbari & Gressis (2011) in China. More recently, Filbeck, Holzhauer & Zhao (2017) investigated the performance of DOD against a high-yield portfolio of Fortune Most Desired Companies (MAC) compared to the Dow Jones Industrial Average and the S&P 500. The study found significantly higher risk-adjusted returns for the DOD strategy. In South Africa, Fakir & others (2013) employs a parametric approach to investigate dividends as an investment strategy. However there are issues with such methodology.First, on the JSE the signal-to-noise ratio on regressed stock returns is low, implying that the modeler's ability to accurately attribute return differences to a variable of interest (e.g., DY) is severely undermined. This is often rectified by considering returns at a lower frequency (e.g., monthly or even annually) to partially control for noise. Also, studies using parametric techniques seek to infer statistical significance, often leaving the more applied reader with limited knowledge gained as to the actual profitability of considering said signal from a portfolio context. Secondly, returns tend to be non-normally distributed and have large outliers. The combination of these problems can easily lead to a small sample size, non-normally distributed, and noisy inference series (especially in a local application) with limited practical application. In practice, subset portfolios are used, which are compared in-sample performances. While not necessarily providing readers with a parametric significance test, portfolio risk and return measures based on systematically constructed portfolios serve to provide valuable insights. Various such applications exist in the literature. Damodaran (2004) constructs top decile portfolios based on trailing DY at the beginning of each year from 1952 to 2001. For the last sample period (1991 - 2001), it is found that the highest dividend-yielding portfolio outperformed the lowest by about 3%. Conover, Jensen & Simpson (2016) find that portfolios constructed from high-dividend payers return over 1.5% more per year than non-dividend payers, in addition to having lower risk.

Dividend signaling can be catergorized in two forms, namely high yield (HY) or dividend growth per share (DG). Whereas HY confirms is typically used as a value proxy, it's a poor proxy given its relation to price if we consider a constant payout ratio. For this reason, the use of DGPS provides attributes that aim to curtail negative aspects of HY. That is, DGPS for corporations, and unlike the dividend yield, it is not affected by price but maintains properties that allow for inference into management quality. As management is aware of the signaling effect of dividends, this may induce the value trap, forcing management to continually increase dividends to maintain a certain valuation. However, such companies are more vulnerable to facing financial distress.

5. Methodology

5.1. Introduction

We employ dividend signals to rank our assets within our selected universe to construct portfolios that offer higher risk adjusted return than the market index. We consider a dividend yield ranking selecting the top 20 stock, dividend growth per share and selecting the top 20 stock, an extension of the dividend portfolios by adding a price momentum filter and a sustainability portfolio that aims penalizes stock that have unsustainable dividend practices.

Optimizing an asset portfolio involves carefully calibrating the trade-offs between risk and expected returns. In achieving the ultimate goal of the study, we aim to investigate how different risk models can provide significant cues in forming dividend strategies. To this end, we employ Minimum Variance, Equal Risk Contribution, and Minimum Volatility. Additionally, this study incorporates more refinements models like Risk Efficiency and makes use of proprietary software-based approaches, specifically drawing upon the Barras risk model.Unique to the Barras model is the introduction of the Max Utility Operator, which allows for a more sophisticated interpretation of risk by focusing not only on the total risk but also the active risk associated with each asset. This dual perspective enables the construction of a more versatile covariance matrix, thereby enriching the portfolio optimization process. The following sections analytically describes the optimization problem and risk models used in the study.

6. Security Selection Methodology

We will employ a practical approach in evaluating dividend signals that involves constructing subset portfolios and compare in sample performance as suggested by Damodaran (2004) .We will rank stock within our selected universe by dividend signals, namely dividend yield (DY) and dividend growth per share (DGPS). First, we rebalance at the end of March and September and construct fully invested, long only portfolios. On each re balancing date, we take the top 100 stocks by market capitalization (MC), and then select the top quintile (20 stocks) based on the our signal scores. We then apply 25 basis trading costs to both buying and selling of stocks, and we will then use total return values, adjust for stock splits and other distorting effects on prices to calculate portfolio returns. We also carefully apply back-dated adjustments to dividends paid to accurately arrive at on-the-day dividends and actual closing prices when calculating our Dividend Yield and Dividend Per Share Growth measures.

We also apply at each re balancing on the risk models mentioned previously. The optimization are constrained to have minimum and maximum weight exposure of 0.5 and 1.5 times the equal weighted alternative. With our quintile portfolios, this implies weights ranging between 2.5% and 7.5%. For the Barra Max utility model with we use a risk aversion parameter of Common Factor Risk Aversion ratio we'll use will be: 0.0075 & asset specific R.A ratio of 1

Following this we will construct back-tests on the subset of dividend signal portfolios.

The Standard portfolios considered as follows

The Standard Dividend Yield Portfolio: uses the 12 month mean trailing dividend yield measure in its construction. - This avoids biasing to stocks that experienced recent share price declines (negative momentum), as would be done when considering on the day DY values; - This will be treated as the vanilla DY signal portfolio.

The DPSG signal portfolio is constructed by considering the growth of company dividends mentioned above on a 1, 3 and 5 year basis.

- For the three and five year measure, we only consider stocks that had positive share payment growth over the period considered.
- E.g., if a stock had a DPS decrease in year 2, even if it has an increased dividend payment over three years
- we set this value to zero.
- This has the effect of rewarding consistency, but also reduces the sample set substantially if the period under consideration increases

Momentum Adjusted DY and DPSG portfolios extend both our DY and DPSG portfolios by applying a momentum adjusted filter for each. We use the following approach to make the adjustments:

- Step 1: Rank our sample (top 100 by MC) by risk-adjusted price momentum and consider the top half.
- Note that we do not use the "traditional" definition of momentum (12 - 1 month return as introduced by Jegadeesh and Titman), but rather use a risk-adjusted measure for

momentum. Here we consider the 90 day moving average return series to the same 90 day standard deviation for each stock.

- Step 2: Rank our sample by either the DY or DPSG measure, and pick the top 20 stocks.

Sustainability Adjusted DY and DPSG portfolios extend our DY and DPSG signals by considering dividend payout ratios (DPR). DPR measures how much of a company's profit is paid out in dividends. We construct this signal by removing from the top 100 companies the 20 with the highest DPR scores. The aim of this filter is simply to avoid the most unsustainable stocks from a dividend payment perspective - thus systematically avoiding stocks that are most likely to cut dividends in the future, leading to a reactionary capital gain loss (as commonly experienced in practice). - Step 1: Rank our sample (top 100 by MC) by the payout ratio using normalized earnings and consider only the bottom 80 (lower DPR is more sustainable). This measure is calculated by considering the fraction (percentage) of net income a firm pays to its shareholders in dividends, calculated as: Total Common Cash Dividends / Normalized Earnings. - Step 2: Rank our sample by either the DY or DPSG measures, and pick the top 20 stocks for each.

For completeness we compare the performance of these constructed portfolios to a standard value signal (PE) and a momentum signal, constructed as a composite 60, 120 and 240 day risk-adjusted momentum score for each stock. We next compare the absolute returns as well as the risk-adjusted performance and drawdowns of each of these portfolios. We then consider turnover and tracking error, before briefly showing the sector exposure of some of the different strategies.

7. Portfolio Optimization

Portfolio optimization consists of determining a set of assets, and their respective portfolio participation weights, which satisfy the investor concerning the combination of risk-return trade-off. Markowitz (1959) proposed the Mean-Variance (MV) model in which the expected return is given by the a measure of the historical data of the stock's return. For our study we geometrically chain return to measure true effects on portfolio returns overtime. The risk is calculated by the variance of these returns. The MV model treats returns of individual assets as random variables and to adopt the value of expected return and variance in order to quantify the return and investment risk, respectively (Zhang, Li & Guo, 2018).

$$\begin{aligned} \mu &= w^T R \\ \sigma^2 &= w^T \sum w \end{aligned}$$

The resulting objective function is to maximize return given a certain level of risk and constraint:

$$Maximise\ w^T R \sum w <= \sigma^2\ and\ \sum_{i=1}^{N} w_i = 1$$

Linear constraints are generally included in MV portfolio optimization. Optimization typically assume that portfolio weights sum to 1 and are non negative. This defines a linear equality constraint on the optimization. Another constraint typically used is no-short-selling condition is a set of sign constraints or linear inequalities. This reflects avoidance of unlimited liability investment often required in institutional contexts.

This study will use a an extension of the MV that uses risk preferences to determine optimum allocation of assets within a portfolio. Barra definition of portfolio risk extends that from the Modern Portfolio theory. It defines risk as the decomposition of the variance of returns. Using Barra multifactor model, the return (r) of a portfolio can be decomposed into both a common factor return (Xf) and asset specific return (u) components as:

$$r = X_F + u$$

The multi-factor approach entails the creation of a factor covariance matrix. This is a short term risk forecast that describes trade off of each common factor within the model. This approach requires periodic return calculation to these exposures. The upshot is that the methodology provides an forecast of each assets specific risk.

The covariance matrix is defined as:

$$XFX^T + D$$

where X = n x k matrix of asset exposures to the factors. F = k x k positive semi-definite factor covariance matrix, and D = n × n positive semi-definite covariance matrix representing a forecast of asset specific risk.

Expressing portfolio risk in decomposition allows for portfolio manager to optimize portfolio from either a total risk perspective or an active risk perspective. In total risk, portfolio holdings are only considered, and the benchmark holdings are treated as irrelevant for optimization purposes. Whereas in active risk, the tracking error in which the difference between the portfolio holdings and those of the benchmark is given primary consideration in the optimization problem.

$$Total\ Risk: h^T(\lambda_F XFX^T + \lambda_D)h$$
$$Active\ Risk: (h - h_B)^T(\lambda_F XFX^T + \lambda_D D)(h - h_B)$$

where

$$\lambda_f = common\ factor\ risk\ aversion\ parameter,$$
$$\lambda_d = specific\ risk\ aversion\ parameter,$$
$$h = n * 1\ vector\ of\ managed\ portfolio's\ holdings,$$
$$and$$
$$h_B = vector\ normal\ (benchmark)\ portfolio's\ holdings$$

The introduction of risk aversion parameters into Barra's portfolio optimization is a form of a max utility operator that allows the portfolio managers to incorporate a numeric representation of personal risk preferences into the portfolio optimization process[1]. It also provides the opportunity to quantify relative aversion to common factor risk vis-à-vis specific risk. Consequently, these risk aversion parameters are important tools that are available to assist the portfolio manager in the construction of an optimal portfolio that is consistent with their goals.

7.1. Equal Risk Contribution (ERC)

Equal risk contribution is a return free approach that seeks to equalize risk contributions from the universe of selected assets thus ensuring it is fully diversified from a risk perspective. Let sigma measure portfolio risk and C(x) defined to be the risk contribution of asset i. If the portfolio risk is measured as by the variance of its return then is;

$$\sigma^2 = x^T Qx$$

$$and\ C_i(x) = x_i(Qx)_i$$

$$where\ (Qx)_i = \sum_{i=1}^{N} Q_i jxj$$

$$x^{ERC}\ satisfies\ C_i(x^{ERC}) = (R(x^{ERC})/N)\ for\ i = 1, ..., N.$$

[1]see https://www.sciencedirect.com/science/article/pii/S1057521921002556 for a detailed explanation on advantages of using maximum utility operators to efficiently factor investor risk preferences

From this we conclude that the variance and standard deviation measures are the same for and when can then only the variance risk measure appreciating that all results apply equally to standard deviation.

8. Tax considerations

Portfolio theory was developed in a perfect world without friction. In practice, frictions need to be considered and in portfolio construction this often entails considering the effect of taxes on income and capital gains as they can erode returns and significantly alter risks and return characteristics of shares. The contribution of dividends and capital gains to total return can lead to varying tax inefficiencies for shares as most jurisdictions imposed higher taxes than on capital gains. Therefore shares with higher contribution of dividends will be less tax efficient than those with a higher capital gains component and with timing most jurisdictions tax dividends in the year that they are receive[2].

Jurisdictional laws can also affect the distribution of taxable returns amongst shares depending on their class namely ordinary shares or preferred shares. Preferred shares are viewed as a substitute for bonds and income from preferred shares are often given tax at a lower rate than those from dividends from ordinary shares.

We will not survey global tax regimes or incorporate all potential tax complexities into the portfolio construction but assume a high level commonalities exists amongst all jurisdictions

[2]See Deloitte's tax guides and country highlights: https://dits.deloitte.com/#TaxGuides

this study uses. This is a reasonable assumption considering the summary of taxes on dividends and capital gains from major economies. For simplicity, we will assume a basic tax regime includes the key elements of investment-related taxes that are representative of what a typical taxable asset owner of a global portfolio will contend with. The proposed methodology to employ on the dividend portfolios use the following methodology.

$$r_{at} = p_d r_{pt} \left(1 - t_d\right) + p_a r_{pt} \left(1 - t_{cg}\right)$$

where r_{at} the after tax return, p_d= the proportion of r_{pt} attributed to dividend income, p_a= the proportion of r_{pt} attributed to price appreciation, t_d= the dividend tax rate and t_{cg}= the capital gains tax rate

9. Data

The data used for this research is sourced from Bloomberg with the sample period from 04/01/01–06/30/23. We collected daily price levels for various indices and benchmarks[3], share prices for stock listed on the Johanesburg Stock Exchange (JSE) to construct our own portfolios. We also retrieved data on indices on volaitility and interest rates to segment some of our analysis to reflect market cycles and interest rate regimes performane. That is, Chicago Board of Options Exchange (CBOE) VIX Index for the US and EM, V2X for Europe, IVUK for UK and JALSH VR for SA volatility proxies. For interest rate data we considered policy rates for central banks for instruments geography within our study, thse are the Federal Fund rate for the US and EM, Minimum Deopsit Financing Rate for the EU, Bank of England Bank Rate and the South African Reserve Bank Repo rate.

To calculate our excess returns, we geometrically chain the excess returns for the different periods before annualizing. This produces comparable cumulative annualized excess return (CAER) results, defined as:

$$CAER = \left[\prod_{t=1}^{n} (1 + ER_t)\right]^{\frac{222}{n}} - 1$$

Our rule to identifying volatility periods either high volatility (Hi-vol) or low volatility (Lo-vol) is achieved by computing the top and bottom quantile in standard deviation for our respective proxies. We then pull the dates corresponding to the periods, and compute annualized returns

[3] see **??** for a detailed guide to indices used and codenames used later in the results and analysis

after geometrically chaining the monthly returns. The amount of daily data for the respective interest rate cycles is large enough to annualized, however, when the VIX, V2X or JALSH RV breach the top or bottom quintile for less than 50 trading days, the period is excluded in order to avoid annualizing small samples. To stratifying between Hiking, Cutting and Neutral interest rate cycles we define these periods as either 5 quarters of changes (upwards for Hiking and downwards for Cutting) or otherwise if central bank held interest rates constant.

9.1. When Do Dividend Strategies Work

The data presented in Table 9.1 presents the excess cumulative returns of our globally traded dividend portfolios of which cumulative returns are indexed and start from value 1. On an aggregate level, most portfolios yield a positive premium but below their starting point in comparison to their corresponding market indices. Nevertheless, a nuanced examination reveals a discernible variance in performance between the high yield (HY) and dividend growth (DG) strategies. From the EM proxy for dividend strategies, the EM_HY surpasses its comparables, delivering a cumulative return of 1.2 times the initial investment over the sample period. In other regions, most high yield and growth strategies fail give consistent cumulative returns from the inception. It's pertinent to underscore, however, that these represent marginal gains when contextualized within a 20-year investment horizon.

Upon assessing the cumulative returns, it becomes evident that there is not a consistent indication that dividend strategies, irrespective of their specific approach or geographical orientation, can consistently procure a premium that, over time, translates into substantive value for investors.

	Regions	Start Date	Total Years	Median	Cumulative Excess R
1	Cumulative_Excess_of_EM_HY	1060300800.00	20.00	0.73	
2	Cumulative_Excess_of_EU_DG	1060300800.00	20.00	0.82	
3	Cumulative_Excess_of_EU_HY	1060300800.00	20.00	0.98	
4	Cumulative_Excess_of_JP_DG	1060300800.00	20.00	0.92	
5	Cumulative_Excess_of_JP_HY	1060300800.00	20.00	0.68	
6	Cumulative_Excess_of_SA_DG	1060300800.00	20.00	1.05	
7	Cumulative_Excess_of_SA_HY	1060300800.00	20.00	1.14	
8	Cumulative_Excess_of_UK_HY	1060300800.00	20.00	2.38	
9	Cumulative_Excess_of_UK_HY_B	1060300800.00	20.00	1.41	
10	Cumulative_Excess_of_US_DG	1060300800.00	20.00	0.73	
11	Cumulative_Excess_of_US_HY	1060300800.00	20.00	0.92	
12	Cumulative_Excess_of_W_HY	1060300800.00	20.00	0.96	

Table 9.1: Cumulative Excess Return

By stratifying these samples according to distinct interest rate regimes and equity market stability cycles, a more refined understanding emerges regarding the efficacy of dividend signals. Initially, interest rates are categorized into two distinct cycles: the “cutting” cycle and the “hiking” cycle. These cycles are defined by periods wherein sustained rate changes (a minimum of three alterations) manifest at intervals of at least every five quarters. Moreover, both implied and realized equity market volatilities are leveraged to represent various episodes of market stability. Subsequent to this stratification, we engage in the geometric chaining of the excess returns across these varied periods, which are then annualized. The resultant metric provides a comparative framework for cumulative annualized returns.

Table 9.2 shows performance in periods of heightened volatility (Hi Vol) or subdued (Lo vol) market cycles. We immediately notice higher annualized excess returns in Lo vol over Hi vol periods. Specifically, within regions, SA_HY in Hi Vol , UK_HY_B in Lo Vol , US_DG in Lo Vol , EM_HY in Lo Vol , EU_HY in Lo Vol , JP_HY in Lo Vol give the highest annualized excess returns. That is, HY strategies in advanced economies give higher annualized excess returns in low volatile markets over SA. We note that SA and Japan make up the highest returns over the period in either HY or DG.

Name	Market Period	Days	Annualized Return (%)
SA_HY	High Vol	113	309.87
JP_HY	Low Vol Period	179	198.25
SA_DG	High Vol	113	120.41
SA_DG	Low Vol Period	125	94.44
JP_DG	High Vol	179	45.47
SA_HY	Low Vol Period	125	34.05
US_DG	Low Vol Period	179	26.41
EM_HY	Low Vol Period	179	21.01
EU_HY	Low Vol Period	221	12.94
EU_HY	High Vol	224	7.22
EU_DG	Low Vol Period	221	6.76

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Name	Market Period	Days	Annualized Return (%)
US_DG	High Vol	179	-0.60
EU_DG	High Vol	224	-2.49
JP_HY	High Vol	179	-3.35
JP_DG	Low Vol Period	179	-10.74
EM_HY	High Vol	179	-17.66
W_HY	Low Vol Period	179	-20.81
US_HY	Low Vol Period	179	-23.45
UK_HY_B	Low Vol Period	221	-35.57
US_HY	High Vol	179	-39.44
W_HY	High Vol	179	-43.17
UK_HY_B	High Vol	224	-68.32
UK_HY	Low Vol Period	221	-77.77
UK_HY	High Vol	224	-93.26

Table 9.2: Volatility Stratification

Table 9.3 presents the performance metrics of various dividend portfolios across different interest rate regimes, encompassing Hiking, Cutting, and Neutral phases. The Federal Reserve Funds Rate serves as a representative metric for the interest rate regime in emerging markets, given the recognition that interest rate shifts in the US influence risk appetites, thus determining capital flows between advanced and emerging economies. For other indices, the local central bank interest rate cycles are employed to ascertain their corresponding interest rate regimes. Japan stands as an anomaly among these economies; absent distinct hiking or cutting cycles, its central bank largely maintained constant rates. Consequently, we assess its performance exclusively within the confides of a neutral interest rate cycle.

Name	Market Period	Days	Annualized Return (%)
EM_HY	Neutral	20	-99.47
EM_HY	Cut	15	-82.92
EM_HY	Hiking	36	485.38
EU_DG	Neutral	29	729.52
EU_DG	Cut	14	4393.91
EU_DG	Hiking	27	103.77
EU_HY	Neutral	29	-49.52
EU_HY	Cut	14	-42.57
EU_HY	Hiking	27	-72.61
JP_DG	Neutral	49	125.72
JP_HY	Neutral	49	227.97
SA_DG	Neutral	3	1891830094068994539520.00
SA_DG	Cut	27	-98.86
SA_DG	Hiking	39	100.61
SA_HY	Neutral	3	-99.85
SA_HY	Cut	27	-99.30
SA_HY	Hiking	39	200.41
UK_HY	Neutral	22	-100.00
UK_HY	Cut	19	-100.00
UK_HY	Hiking	30	-100.00

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Name	Market Period	Days	Annualized Return (%)
UK_HY_B	Neutral	22	-84.83
UK_HY_B	Cut	19	-99.99
UK_HY_B	Hiking	30	-100.00
US_DG	Neutral	20	-88.38
US_DG	Cut	15	302657.58
US_DG	Hiking	36	641.26
US_HY	Neutral	20	-99.72
US_HY	Cut	15	3.43
US_HY	Hiking	36	-80.18

Table 9.3: Performance in Interest Rate Regimes

Within geographies then, EM_HY (Hiking), EU_DG (Cutting), JP_HY (Neutral),SA_DG (Hiking), UK_HY_B(Hiking), US_DG(Hiking), perform well in Hiking periods but their strategies are evenly split given our sample. Therefore, there is no clear indication of which strategy works best given the interest rate regime.

Figure 9.1 illustrates the consistency in the performance of dividend portfolios by employing the rolling information ratio. The information ratio serves as a measure of a portfolio's performance relative to a market benchmark. It is frequently used in the industry to gauge a manager's proficiency in generating excess returns and the consistency with which these returns are achieved. Thus, our objective is to assess the capacity of our dividend portfolios to achieve such excess returns. We have adopted a rolling 60-month information ratio as a metric to evaluate long-term performance consistency. This ratio is computed by determining the rolling excess return of the index relative to its benchmark and then dividing this by the volatility of those excess returns.

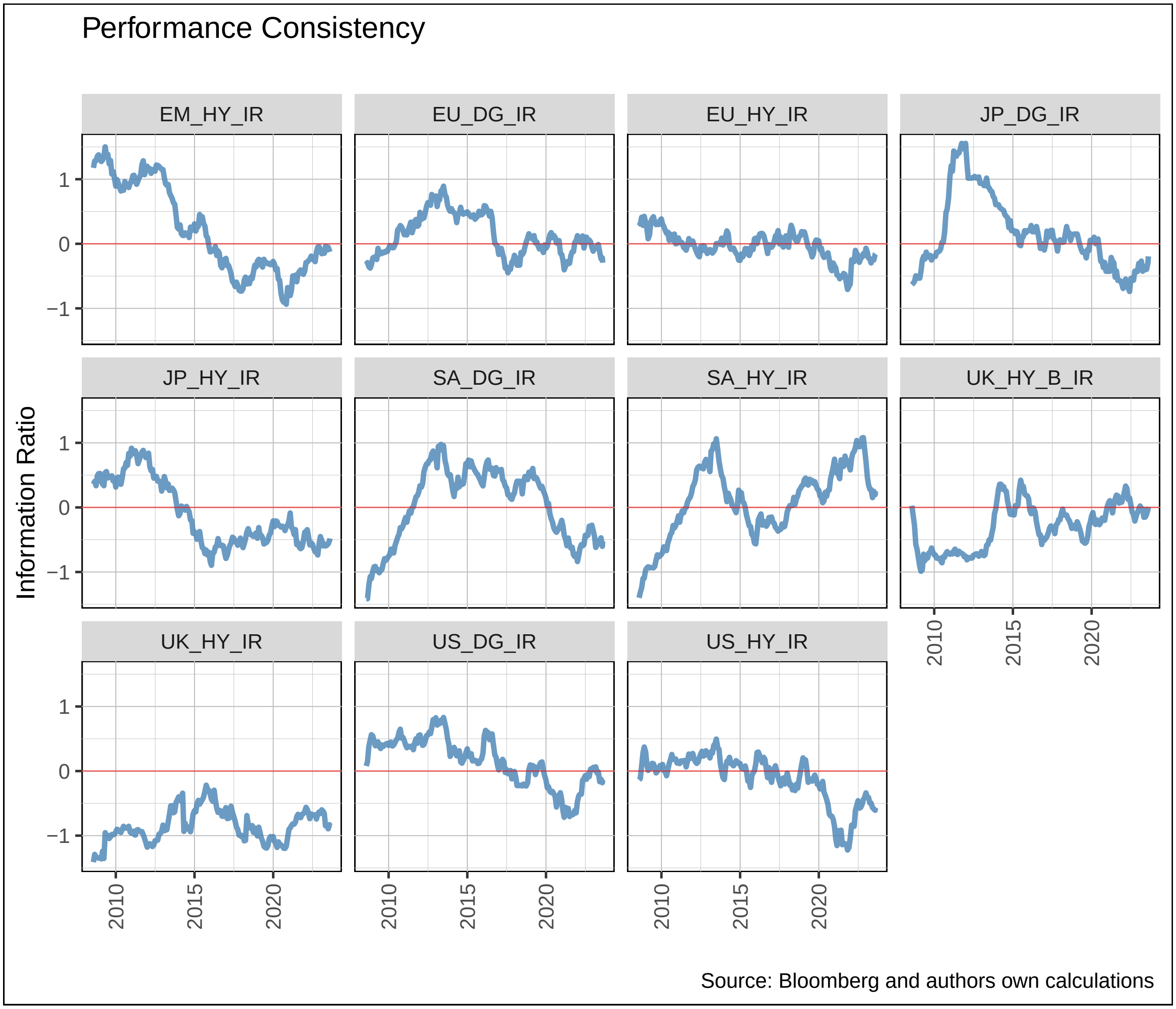

Figure 9.1: Rolling 3 Year Returns

- but having said that, lets consider the redline to be a measure of strategy working or not.

- The UK_HY stands out as one that has struggled to give that bang for buck effect.
- EM and JP HY and JP DG from 2005 to 2015 return positive IR then since then until the start of 2022 its been negative.
- SA indexes , a tale of two have shown 2010 to 2020 in positive for DG but the SA HY IR from 2017 to date for HY
- US indexes have been mirroring each other. However difficult to conclude.

We notice that UK HY portfolios have not been working. Whilst SA HY has deliverd some respectable consistency for several years. However EM _HY like the UK since 2015 has delivered negative information ratio.

Figure 9.1 demonstrates that, when assessed on a rolling 60-month basis, both growth and high-yield dividend indexes display varying levels of consistency in delivering returns, i.e, difficult for strategies to consistently deliever IR above zero across markets present in our sample period. When we broaden our analysis to encompass 24 and 36 month rolling periods, the results appear even more volatile. However, if we consider the horizontal red line at zero as a mark that defines a startegy working or not we uncover interesting results. One, SA indexes have shown since 2010 to 2020 a positive turn in information ratios for SA_DG but the SA HY IR from 2017 to date for HY. Two, EM and JP HY and JP_DG from 2005 to 2015 return positive IR then since then until the start of 2022 its been negative. Three, The UK_HY stands out as one that has struggled to give that bang for buck effect. Finally, US and EU exhibit similar trends, most notable that is that over the past few years have given negative information ratios.

In line with the results from our stratification based on market cycles and interest rate regimes, we observed that the majority of HY experienced declines in rolling information ratios, while DG portfolios incurred losses. This trend was particularly evident during the period following the global financial crisis in late 2008 to late 2009. This period was characterized by high volatility and falling interest rates. Conversely, the subsequent crisis, which occurred after the COVID-19 pandemic and was marked by rising interest rates, favored SA , JP and EM, a (SA). These observations align with the major findings on the influence of interest rates from the previous section.

9.2. Index Drawdowns

Drawdowns give a more detailed picture of the risk attributes of the constituents of a data series. Their importance for our study is to uncover latent relationship between performance and drawdown.

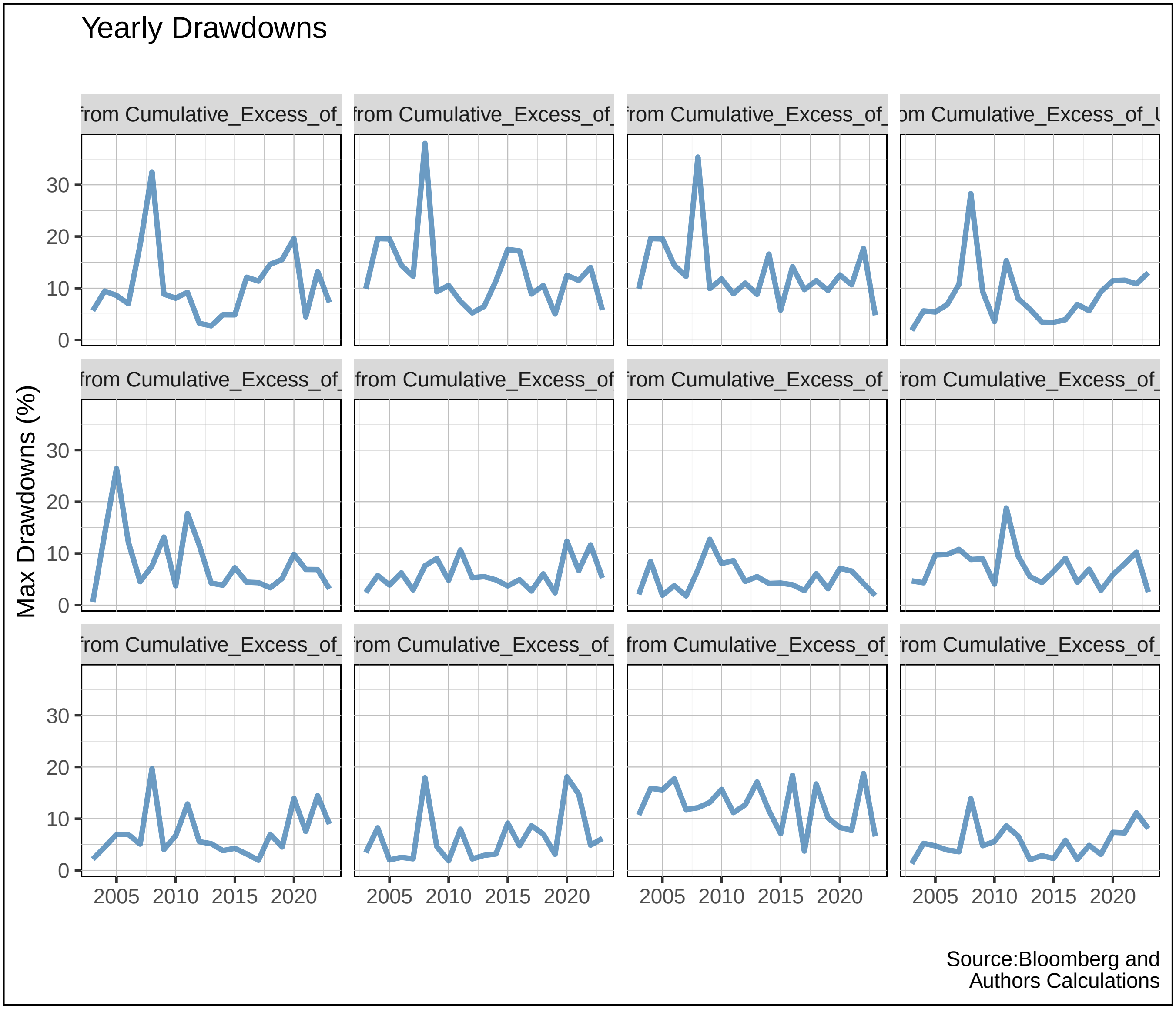

Figure 9.2: Rolling 3 Year Returns

Our analysis in ??fig2] defines as the disparity between the peak and trough values of cumulative excess returns within a specified time frame. When scrutinizing our dividend portfolios, a pattern of similarity emerges both geographically and across varied strategies.The SA portfolios were markedly volatile, displaying the most pronounced draw downs visually and more concretely by value from the beginning of the sample period. This is closely followed by the UK High Yield (HY) strategies. In contrast, portfolios associated with the EU and US exhibit relatively milder draw downs. Yet, when the focus shifts from mere magnitude to the distribution or dispersion of these drawdowns, the narrative undergoes a transformation. The UK High Yield and Japan High Yield strategies are revealed to be more volatile, being susceptible to significant fluctuations. In juxtaposition, emerging markets, with South Africa as a case in point, manifest a more stabilized profile, evidenced by diminished variation in their drawdowns.

9.3. Conclusion

Over time, dividend portfolios, whether HY or DGPS, have exhibited positive excess returns as indicated by cumulative returns. While the UK_HY index has shown the highest cumulative return, this trend is not consistently observed across other regional indexes. Consequently, when assessing the aggregate perspective on investor portfolio value, dividend portfolios may not offer a reliable means to capture the value premium consistently. However, upon stratifying these portfolios according to different periods of market volatility, it becomes evident that during low volatility periods, the primary determinant of performance is not the geographical region but rather the specific investment strategy employed. In this case, HY strategies. Surprisingly, portfolios based in South Africa (SA) tend to perform well during these high volatility periods, which is somewhat unconventional as such times are typically associated with a flight to safety, and Emerging Markets (EM) and, by extension, South Africa, are considered riskier. When extending our analysis to encompass interest rate cycles, we observe a contrasting effect compared to the volatility-based stratification. We find that all strategies appear to give the highest return in hiking cycles.

In assessing consistency, we employ the information ratio. Initially, we discern that, at a broad level, dividend portfolios do not consistently maintain a positive ratio over an extended investment horizon. However, disparities in performance emerge. Notably, South African (SA) and dividend indexes have consistently delivered positive ratios over the past decade. In contrast, Emerging Markets (EM) and Japanese (JP) indexes have experienced substantial declines in their information ratios, despite seemingly consistent performance prior to 2015. Meanwhile, the United States (US), European Union (EU), and United Kingdom (UK) indexes have exhibited unpredictable performance over the sampled period.

When we integrate our information ratio findings with drawdown analysis, we observe that advanced economies have experienced the fewest drawdowns over the sample period, with the exception of the UK. This could suggest a relatively lower level of systematic risk in these economies. Conversely, South African (SA) and Emerging Market (EM) drawdowns have exhibited a declining trend, possibly indicating a reduced perception of risk in emerging markets over time.

10.

11. Results and Analysis

12. Discussion

12.1. Limitations of the study

13. Conclusion

14. References

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15. Appendix

TICKER	NAME	Codename	Inception Date
FUDP	FTSE UK Dividend+ Index	UK_HY	
M2EFDY	MSCI EM HY Gross Total Return USD Index	EM_HY	
M2GBDY	MSCI UK HY Gross Total Return USD Index	UK_HY	
M2JPDY	MSCI Japan HY Gross Total Return USD	JP_HY	
M2USADVD	MSCI USA HY Gross Total Return USD Index	US_HY	
M2WDHDVD	MSCI World HY Gross Total Return Total Return USD Index	W_HY	
SPDAEET	S&P EU 350 Dividends Aristocrats Total Return Index	EU_DG	
SPJXDAJT	S&P/JPX Dividend Aristocrats Total Return Index	JP_DG	
SPDAUDT	S&P 500 Dividend Aristocrats Total Return Index	US_DG	
SPSADAZT	S&P South Africa Dividend Aristocrats Index ZAR Gross TR	SA_DG	
TJDIVD	FTSE/JSE Dividend+ Index Total Return Index	SA_HY	
M2EUGDY	MSCI Europe Ex UK HYGross Total Return USD Index	EU_HY	
TUKXG	FTSE 100 Total Return Index GBP	UK	
GDUEEGF	MSCI Daily TR Gross EM USD	EM	
GDDUUK	MSCI UK Gross Total Return USD Index	UK_B	
TPXDDVD	Topix Total Return Index JPY	JP	
GDDUUS	MSCI Daily TR Gross USA USD	US	
GDDUWI	MSCI Daily TR Gross World USD	W	
SPTR350E	S&P Europe 350 Gross Total Return Index	EU_2	
SPXT	S&P 500 Total Return Index	JP	
SPXT	S&P 500 Total Return Index	US_2	
JALSH	FTSE/JSE Africa All Share Index	SA	
JALSH	FTSE/JSE Africa All Share Index	SA	
GDDUE15X	MSCI Daily TR Gross Europe Ex UK USD	EU	

Table 15.1: Index Description