A Dive into Dividend Portfolios, When and How to They Work

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Abstract

Dividend paying stock offer an additional componenet to otherwise non dividend paying stock. This paper studies the return signalling cue from dividend portfolio. We find that dividend portfolios around the around offer downside protection. However emerging market portfolios have positive return during market turmoil which is considerably above returns from advanced economy portfolios.

1. Introduction

2. Problem Statement

Dividend yield is a poor proxy for stock returns, as it doesn't distinguish itself from price effects of a stock. Unfortunately, practice in industry when constructing dividend portfolios fails to recognize this flaw thus leading to sub optimal allocation within portfolio.

3. Research Aim

We propose to enhance the dividend signalling by considering price changes and dividend payment sustainability offered by stock. Our solution corrects for this oversight by using price momentum filters and adjusting for unsustainable payout ratios in portfolio construction to offer superior risk adjusted return overtime. We will consider multiple back testing samples and highlight periods in which strategies offer diversification benefits to portfolio construction.

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

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(**baker2009understanding?**), 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. Various liertature has covered the effect of dividend announcements before and after ex -dividend dates. Figure 1 shows a clear and direct relation with a decrease in share value to the proportionate to the dividend announcement.

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 tranversly pushes up the stock price, this is called the clientele effect (**baker2009understanding?**). Proponents of the MM theory suggest that the client effect causes major substitution effect, suggesting 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(**baker2009understanding?**). 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 Al-Najjar & Kilincarslan (2018) and Baker & Powell (1999). Investors compare dividend announcements to historical levels while considering company fundamentals. However, there is a risk of manipulation 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.

4.2. Empirical review

The various methods of capital distributions have varying impact on financial statements which is summarized in Table of the appendix. From the perceptive of an investor or analyst the dividend yield metric helps show the additional return dividends paying securities could add to a portfolio. Consider that describes the fundamentals that influence the dividend yield. Assuming a constant payout ratio, dividend yield is a function of earnings yield. shows the correlation between DY and Price overtime for various securities. Various studies have identified a predictive power of dividend yield thus confirm the existence of a value signal. Also, another signal for dividends is dividend growth per share for corporations, and unlike the dividend yield, it is not affected by price but maintain properties that allow for inference into management quality. As managemnet is aware of the signalling effect of dividends, this may induce the value trap, that forces management to continually increase dividends to maintain a certain valuation. However such companies are more vulnerable to facing financial distress.

Cash dividends, although widely used, are not as tax-efficient as share buybacks. In this form of capital redistribution, a firm exchanges assets for outstanding shares, which shrinks the company's assets by the amount of cash paid out. This action too reduces both its borrowing base and the shareholders' aggregate equity (**baker2009understanding?**). A clear benefit to the company is that it is more flexible when compared to the rigid dividend payout structures. To most higher net worth investors, tax benefits in the form of lower capital gains taxes result in greater preference for share buybacks. Surprisingly, their adoption has been relatively slow in some emerging economies. According to a study by Wesson, Muller & Ward (2014), there were only 195 open market share repurchases announced in South Africa from 1999 to 2009. In comparison, Manconi, Peyer & Vermaelen (2014) estimated that share repurchases constituted approximately 58% of total announcements in the United States, 15% in Canada, and 11% in Japan over the same period, indicative of a significant disparity in the adoption of share buybacks across the world, despite their popularity in the United States.

Dividend payments and growth in dividends per share provides a return cue and over the years studies on dividend signaling studies can be categorized into academic and practitioner-oriented studies. Academic studies, such as Fama & French (1988), found a positive correlation between increasing predictive power and longer forecast horizons. However, subsequent studies like Ang & Bekaert (2007) found no evidence of long-term predictability in stock returns when considering finite sample influence. This suggests that dividend yield may not be a reliable predictor of subsequent returns. One possible reason for this declining predictive power is the increasing use of share buybacks as an alternative means for capital distribution, which reduces the contribution of dividend yield to total return (Robertson & Wright, 2006).

On the other hand, practitioner-oriented literature focuses on the long-term returns of systematic dividend portfolios. One popular strategy is the "Dogs of the Dow (DOD)," which involves constructing a portfolio of the top 10 highest-paying dividend stocks on the Dow Jones Industrial Index at the beginning of the year based on the dividends paid in the previous 12 months, therefore this entail deploying a high yield strategy (McQueen, Shields & Thorley, 1997). Various studies have examined 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 Britian, 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.

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

A widely used approach to evaluate dividend signals is to construct subset portfolios and compare in sample performance. This methodology does not provide parametric significance test, however, portfolio risk and return measures are based on systematically constructed portfolios and 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.

Following a similar approach 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 4.1 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 4.2. 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).

$$\begin{aligned} \mu &= w^T R \\ \sigma^2 &= w^T \sum w \end{aligned} \tag{7.1}$$

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.

$$\begin{aligned} Total\ Risk : h^T(\lambda_F XFX^T + \lambda_D)h \\ Active\ Risk : (h - h_B)^T(\lambda_F XFX^T + \lambda_D D)(h - h_B) \end{aligned} \tag{7.2}$$

where, =

$$\lambda_f \quad = \quad common\ factor\ risk\ aversion\ parameter, \tag{7.3}$$

$$\lambda_d \quad = \quad specific\ risk\ aversion\ parameter,$$

$$h \quad = \quad n\ddot{O}1\ vector\ of\ managed\ portfolio's\ holdings, \tag{7.4}$$

$$and$$

$$h_B \quad = \quad vector\ normal\ (benchmark)\ portfolio's\ holdings$$

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

[1]see https://www.sciencedirect.com/science/article/pii/S1057521921002556 for a detailed explanation on advantages of

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;

$$\sigma^2 = x^T Qx \tag{7.5}$$

$$and\ C_i(x) = x_i(Qx)_i \tag{7.6}$$

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

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

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.

7.2. Minimum Volatility (MinVol)

Minimum-variance similar to ERC do not require return forecasts, there can be in some cases they may be more efficient than strategies that trade off expected risk and return.

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

using maximum utility operators to efficiently factor investor risk preferences 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 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.

$$r_{at} = p_d r_{pt} \left(1 - t_d\right) + p_a r_{pt} \left(1 - t_{cg}\right) \tag{8.1}$$

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

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

9. Data Source and Stratification

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, share prices for stock listed on the Johanesburg Stock Exchange (JSE) to construct our own portfolios. To capture the dynamic nature of financial markets in our stratification, we segmented the data using proxies that reflect market cycles and interest rate regimes. For volatility we used Chicago Board of Options Exchange (CBOE) VIX Index for the US indexes and emerging market indexes, V2X for Europe, FTSE IVUK for UK and SATITOP40 for SA volatility proxies fo and data from the Federal Reserve Bank of the United States. These metrics served as our stratifying variables, allowing us to categorize our sample across different market and interest rate cycles. For interest rate regimes, we use central bank interest rate schedules from the geographies we study.

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 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.

10. When Do Dividend Strategies Work

The data presented in Table 10.1 delineates the excess cumulative returns of our globally traded dividend portfolios. On an aggregate level, these portfolios yield a positive premium 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 UK-centric proxies for dividend strategies, the UK_HY notably surpasses its counterparts, delivering a cumulative return of 3.5 times the initial investment over the sample period. In other regions, high yield strategies have manifested returns exceeding 1x from the inception of the period. It's pertinent to underscore, however, that these represent marginal gains when contextualized within a 16-year investment horizon. In stark contrast, dividend growth strategies have under performed, yielding diminished excess returns since the onset of the period.

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 Return
1	EM_HY	1199232000.00	16.00	0.83	0.85
2	EU_DG	1199232000.00	16.00	0.76	0.82
3	EU_HY	1199232000.00	16.00	1.08	1.13
4	JP_DG	1199232000.00	16.00	0.70	0.70
5	JP_HY	1199232000.00	16.00	0.99	1.26
6	SA_DG	1199232000.00	16.00	0.46	0.40
7	SA_HY	1199232000.00	16.00	0.56	0.40
8	UK_HY	1199232000.00	16.00	1.71	3.52
9	UK_HY_B	1199232000.00	16.00	1.37	1.47
10	US_DG	1199232000.00	16.00	0.76	0.74
11	US_HY	1199232000.00	16.00	0.90	1.04
12	W_HY	1199232000.00	16.00	1.07	1.20

Table 10.1: 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 epochs 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 10.2 delineates performance across diverse market cycles. An immediate observation is that, on average, the various geographies experience more periods characterized by market volatility than they do periods of low volatility. In these heightened volatility epochs, the annualized returns for most portfolios, be they HY or DG, tend to outstrip those seen during low volatility phases. This observation suggests that dividend portfolios might exhibit inherent defensive qualities during phases of market instability. It is especially noteworthy that the UK_HY portfolio registers the most substantial returns during both high and low volatility phases.

Index	Market Period	Months	annualized_return
SA_DG	Low Vol Period	82	-0.13
SA_HY	Low Vol Period	82	-0.09
SA_HY	High Vol Period	63	-0.09
JP_HY	Low Vol Period	80	-0.08
JP_DG	Low Vol Period	80	-0.07
US_DG	Low Vol Period	80	-0.05
JP_DG	High Vol Period	77	-0.05
SA_DG	High Vol Period	63	-0.05
US_DG	High Vol Period	77	-0.05
EU_DG	Low Vol Period	86	-0.03

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Index	Market Period	Months	annualized_return
EM_HY	Low Vol Period	80	-0.03
JP_HY	High Vol Period	77	-0.03
EU_DG	High Vol Period	93	-0.03
EM_HY	High Vol Period	77	-0.02
US_HY	Low Vol Period	80	-0.01
US_HY	High Vol Period	77	-0.00
EU_HY	Low Vol Period	86	0.01
EU_HY	Low Vol Period	86	0.01
EU_HY	Low Vol Period	86	0.01
EU_HY	High Vol Period	93	0.02
UK_HY_B	High Vol Period	93	0.11
UK_HY_B	Low Vol Period	86	0.14
UK_HY	High Vol Period	93	0.18
UK_HY	Low Vol Period	86	0.18

Table 10.2: Performance in Market Cycles

Table 10.3 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 confines of a neutral interest rate cycle.

The high yield portfolios, with the exception of SA, typically register superior annualized returns across all interest rate cycles. Several portfolios, including EU_DG, JP_DG, JP_HY, SA_DG, and SA_HY, consistently report negative annualized returns regardless of the prevailing interest rate regime. Meanwhile, the UK_HY_B index exhibits a negative return in neutral phases, and the US_DG portfolio underperforms during both cutting and hiking phases. The index that emerges with the highest annualized excess return across these cycles is UK_HY. Notably, the UK_HY_B portfolio demonstrates commendable excess returns, realizing a 0.54% gain during cutting cycles.

Index	Market Period	Months	annualized_return
SA_HY	Hiking	30	-0.27
SA_DG	Hiking	30	-0.23
EU_DG	Hiking	14	-0.19
US_DG	Cut	12	-0.14
SA_HY	Cut	24	-0.11
JP_HY	Neutral	58	-0.09
SA_DG	Cut	24	-0.08
EU_DG	Cut	20	-0.08
JP_DG	Neutral	58	-0.06

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Index	Market Period	Months	annualized_return
EU_DG	Neutral	28	-0.05
SA_HY	Neutral	8	-0.05
US_HY	Cut	12	-0.03
UK_HY_B	Neutral	28	-0.03
EU_HY	Hiking	14	-0.03
US_DG	Hiking	22	-0.03
SA_DG	Neutral	8	-0.02
US_HY	Hiking	22	0.01
EM_HY	Neutral	28	0.02
EU_HY	Cut	20	0.02
US_DG	Neutral	28	0.02
US_HY	Neutral	28	0.03
EM_HY	Cut	12	0.04
EU_HY	Neutral	28	0.05
EM_HY	Hiking	22	0.07
UK_HY_B	Hiking	18	0.11
UK_HY	Neutral	28	0.22
UK_HY	Hiking	18	0.44
UK_HY_B	Cut	16	0.54
UK_HY	Cut	16	0.78

Table 10.3: Performance in Interest Rate Regimes

10.1. Performance consistentcy

Figure 10.1 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.

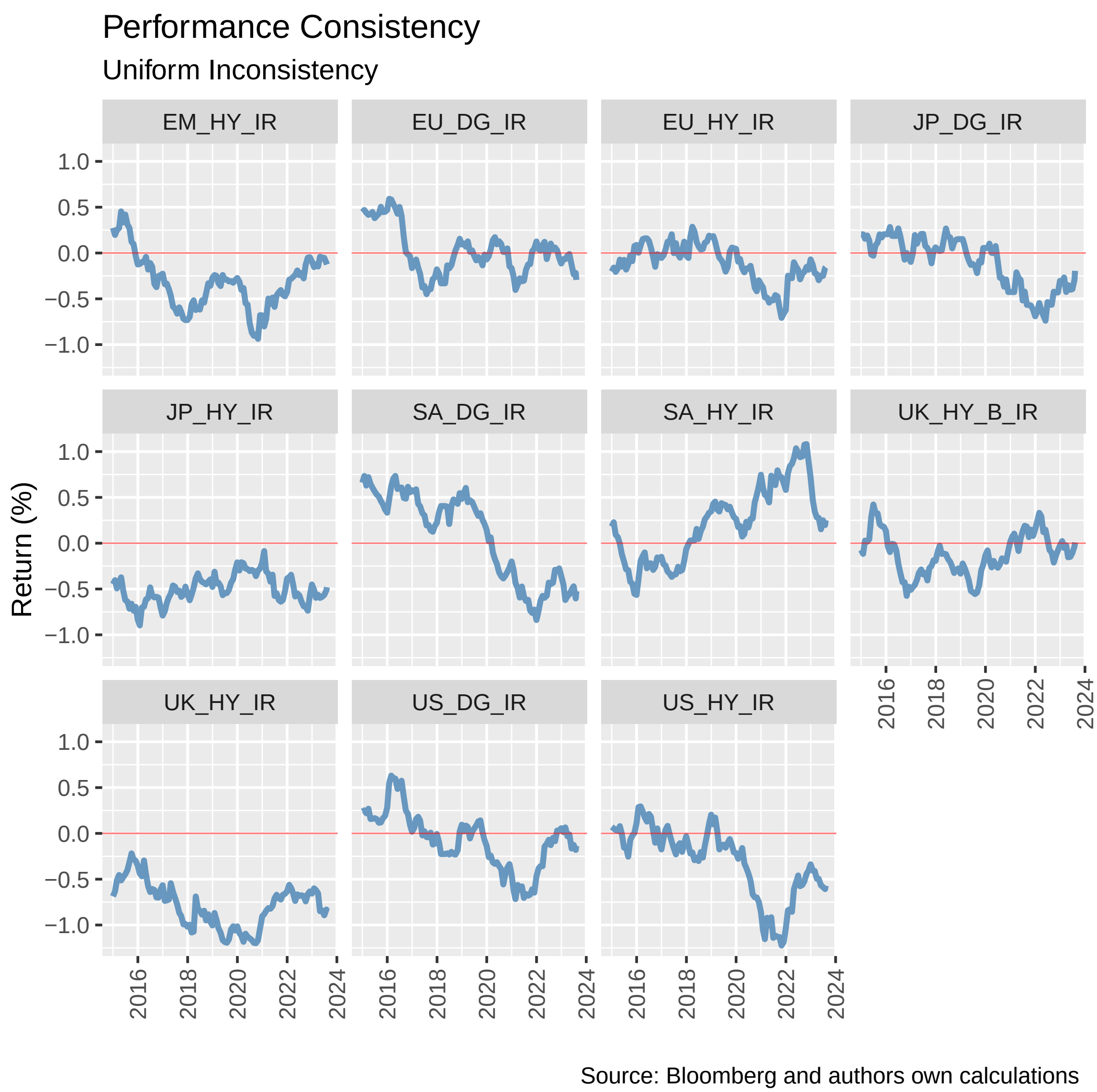

Figure 10.1: Rolling 3 Year Returns

The findings presented here illuminate the sporadic performance of dividend strategies, further highlighting the challenges inherent in securing high returns in asset markets. In an ideal scenario, an information ratio exceeding 0 is preferred, with most industry strategies typically averaging around 0.3. However, Figure 10.1 demonstrates that, when assessed on a rolling 60-month basis, both growth and high-yield dividend portfolios tend to underperform relative to their benchmarks.Upon broadening our evaluation to encompass 24 and 36-month periods, the results appear even more volatile. Notably, SA indices consistently demonstrate commendable performance, with the SA_HY standing out particularly. Within the domain of advanced markets, the dividend portfolios of both the EU and Japan exhibit a modicum of consistency in positive returns initially, only to later deteriorate.

It is imperative to note that despite their capacity to deliver decent cumulative returns and exhibit defensive characteristics across stratified periods, these indices, when gauged on a relative basis, still leave much to be desired in terms of consistent performance.

10.2. Drawdowns

A trailing return provides insights into the performance of an investment over a specified period, measured between two distinct dates. As the name suggests, it essentially “trails” the investment from a starting point to an end point, effectively capturing the point-to-point returns. This tool offers a concise snapshot of, for instance, a mutual fund’s performance at a specific juncture in its trajectory.

The utility of the trailing return metric is multi-faceted. For one, it can gauge returns over varying durations, such as year-to-date, over one year, three years, and so forth. Furthermore, it is feasible to compute trailing returns by referencing the current date back to the fund’s very inception. Such an analysis proves invaluable when attempting to discern how varying inception dates might influence the performance of a fund.

Delving deeper into the realm of risk assessment, drawdowns provide a comprehensive view of the risk attributes of the data series’ constituents. In the context of our study, the relevance of drawdowns is underscored by their capacity to unveil latent correlations between performance and drawdown. Essentially, by analyzing drawdowns, one can ascertain the maximum potential loss an investment has experienced, thereby providing insights into the inherent risks and vulnerabilities associated with said investment.

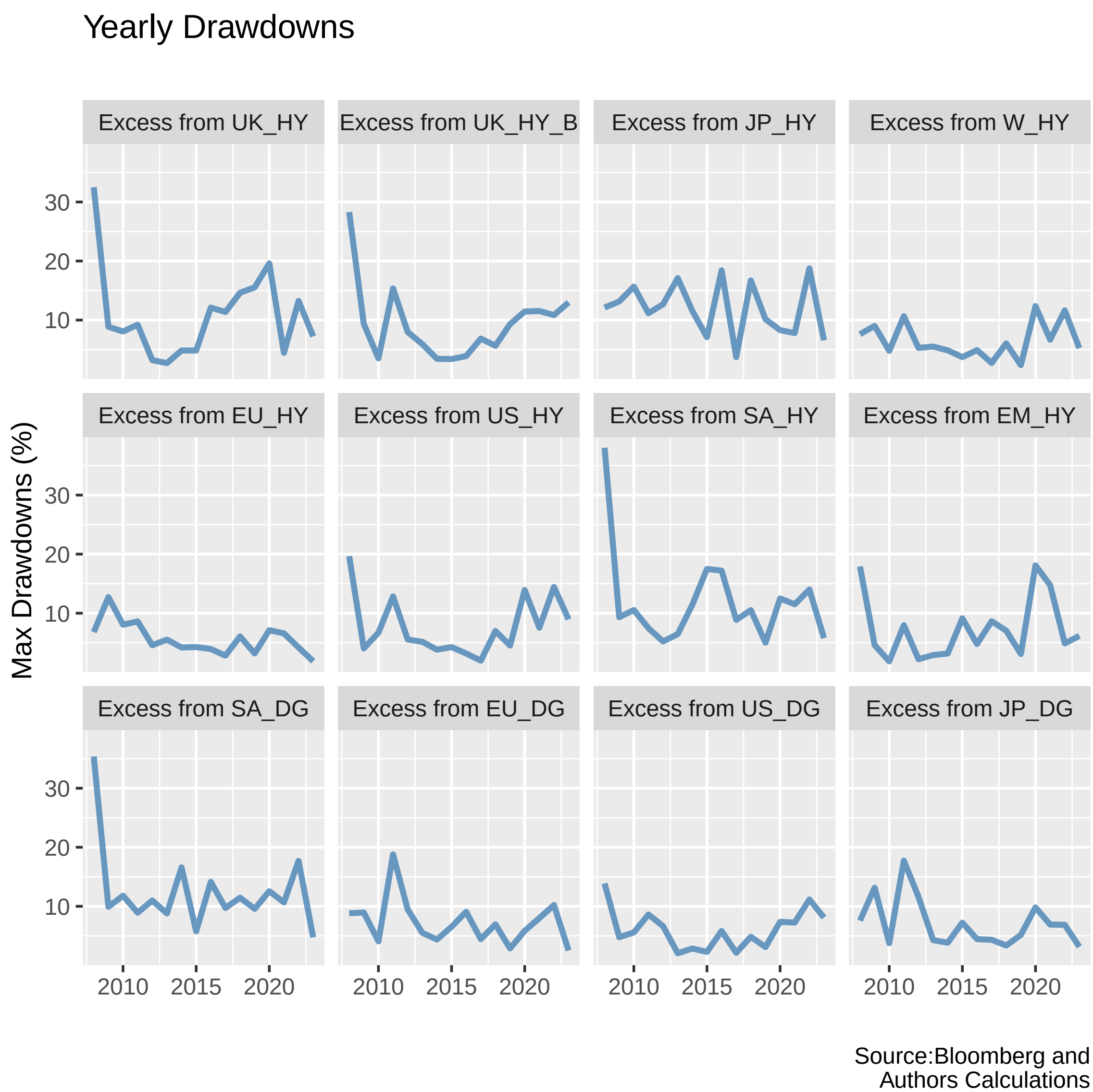

Figure 10.2: Rolling 3 Year Returns

In this analysis, drawdowns are delineated 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 are markedly conspicuous, displaying the most pronounced drawdowns by value. This is closely followed by the UK High Yield (HY) strategies. In contrast, portfolios associated with the EU and US exhibit relatively milder drawdowns.

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.

10.3. Wrapping it up

- I did a PCA which tries to link all these together. Partcilarly which risk attributes link the performance of dividend portfolios and how these can be accounted for by designing a partcilar portfolio.

In the extensive evaluation of globally dividend portfolios across varied market cycles and interest rate regimes, it's evident that while dividend strategies offer additional return offered by their income componenet, their performance remains notably inconsistent. The challenges in obtaining high returns in asset markets come to the fore, with dividend strategies across various geographies and timelines exhibiting uneven returns. The impact of interest rate cycles, plays a decisive role in portfolio performance, a fact made salient by Japan's unique neutral rate cycle. Adding another layer of depth to our analysis, rolling informatio ratios offer periodic snapshots of performance consistency, noting that most strategies fail to give performance postive ratios but it's the drawdowns, defined by the discrepancies between peak and trough values of cumulative excess returns, that reveal the underlying risk attributes. Geographically, while South African portfolios record pronounced drawdown values, closely trailed by UK High Yield strategies, portfolios in regions like the EU and US demonstrate relative stability.

11. Which Dividend Signals Matter in South Africa?

We assessed dividend portfolio performance in different geographies and # Results and Analysis # Discussion

11.1. Limitations of the study

Could not get constituent data for the indices that had superior performance within the sample period. This would have been help in constrcuting more representative indices and unpacking why it was that dividend yield and or grow signals were more effective in that portfolio.

12. Conclusion

13. References

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14. Appendix