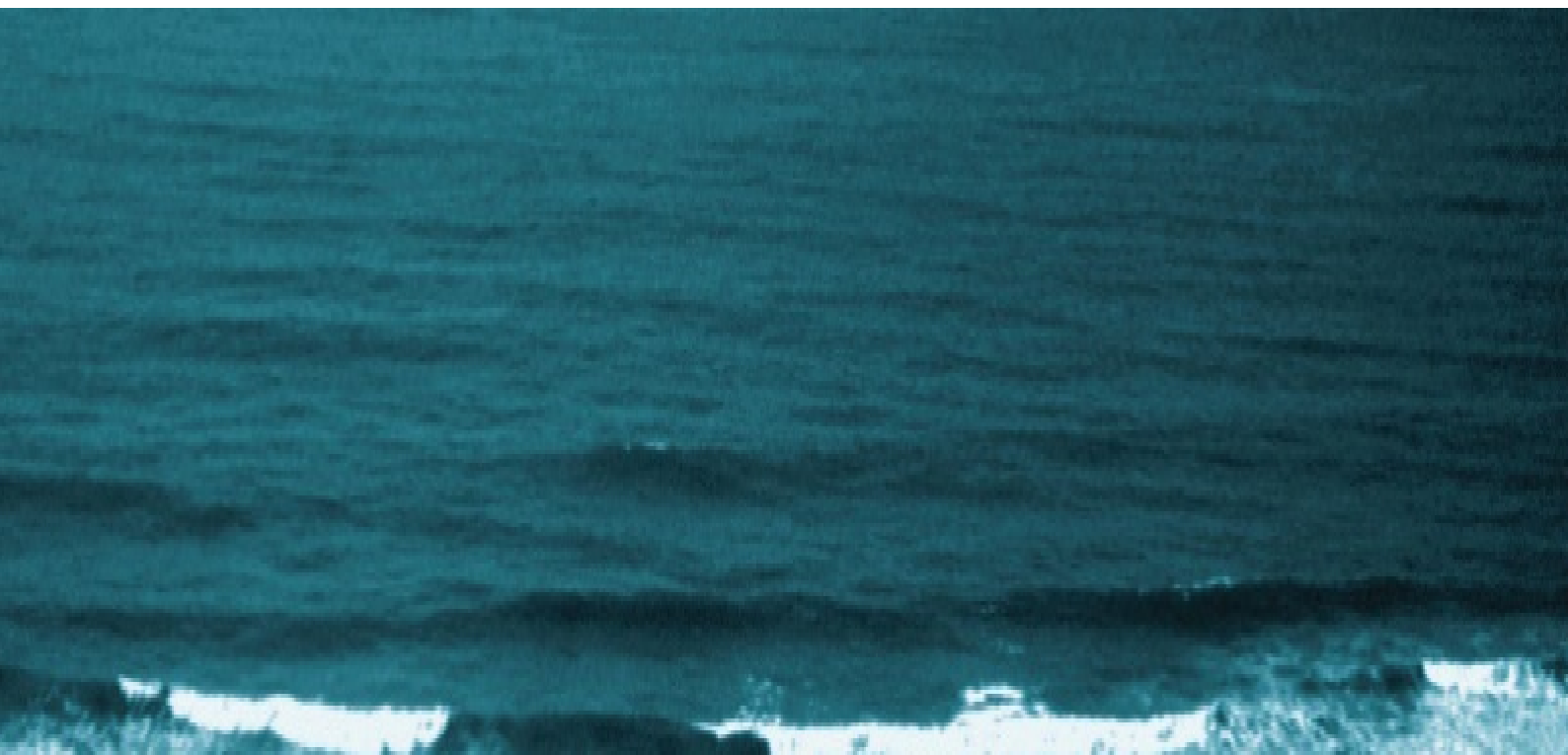


OSSIAM RESEARCH TEAM

## Equity duration: a dividend yield approach

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## Abstract

We look at the exposure of stock portfolios - sorted by dividend yields - to interest rate risk and determine if this can explain differences in risk and risk-adjusted performances between low and high dividend yield portfolios over a 25-year period for US equities. As for volatility sorted portfolios, we do find small but positive duration for high dividend yield portfolios. Nevertheless, the addition of the interest rate factor brings little explanatory power to the 4-Factor model and does not explain the alphas away. Because of the similarities in the results between volatility and dividend yield sorted portfolios with respect to interest rate risk, we try to highlight any potential overlap between the two. More precisely, we build double sorted volatility portfolios in a way that neutralizes the dividend yield difference between them. The model now fits the portfolios' returns better than the pure volatility sorted case. The duration for lower (double sorted) volatility portfolios is almost 38% lower than the pure case, although the alphas are not explained away and remain significant. These findings shed light on the existing link between low volatility and high dividend yield portfolios, for which there is a substantial overlap. As such, a significant portion of low volatility duration can be attributed to their high dividend yield characteristic.

**JEL Classification:** : C41, C52, G11, G12

**Key words:** CAPM; Dividend investing; Equity duration; Fama-French equity model; Low volatility investing;

## 1 Introduction

With the US interest rates at their lowest over the latest 50 years, the search for yield has oriented many investors towards stocks with high dividend yields. As a matter of fact, several strategies focusing on dividend yields are now available to investors in an index format, but not only. One possibility for investors could be to gain exposure to dividend paying stocks in order to monetize a portion of their portfolio's value while keeping their exposure to equity market. In this sense, investors actually keep their exposure until the company pays its dividend and then decide to keep or remove it from their allocation. Different reasons can be advocated to explain such investment strategies, among which tax-related issues or the need for regular cash-flows. On the other hand, dividend yield has been used in the literature as a forward-looking measure of equity premium. This problem has been extensively studied and goes beyond the scope of this paper. We refer to the seminal works in Fama and French (1988), Fama and French (1988b) and references therein for the dividend yields predictive power of the equity premium. Together with default spread and term spread, it has been one of the economic variables used to explain variations in stocks expected returns. Campbell and Shiller (1988) instead look at the relationship between historical earnings and real dividend, and as a consequence, to the relation between dividend yields and expected future returns. A second possibility for investors, following this approach, could then be to gain exposure to high dividend yield stocks in order to improve their portfolio's expected return. In this sense, they do not need to wait until the company actually pays the divi-

dend before removing the stock from their portfolio: provided that today's dividend gives information about future prices, this type of strategy mostly looks at the potential of upward price movements carried by dividend figures. It seems that modern theories have reached a sort of consensus on the fact that dividend yield is one of the quantitative measure to be looked at when it comes to set equity valuation models<sup>1</sup>. However, as an indicator, the dividend yield is particularly business-cycle related. Its forecasting power varies across the business cycle (Rozeff, 1984): it tends to correlate with the expected returns in strong economic conditions and worsen in restrictive economic conditions (Jensen and Johnson, 1995). As a consequence, the relation between expected returns and dividend yields weakens or strengthens, *inter alia*, according to the monetary policy (Rozeff, 1974). More precisely, actual dividend yields can forecast expected returns conditionally to the monetary policy and interest rate movements (Jensen et al., 1996).

In this paper we focus on the empirical relationship between dividend yields and interest rates. Specifically we look at the relationship between expected returns of portfolios based on different levels of dividend yields and interest rate movements. Although the literature on the dividend yield puzzle is an old and well documented topic, very little has been said over the relation between interest rates and equity dividend yields. Cohen (2003) studies the relationship between dividend yield, empirical durations and forward-looking measures

<sup>1</sup>The position has changed since the seminal works in Modigliani and Miller (1958), in which dividends, and more generally capital structure, should not be accounted for when investors value equities.

of equity premium from the perspective of equity valuation. According to his conclusions, the equity duration has an impact on future returns, but *historical and forward-looking equity premium should never expect to converge as long as market and, subsequently, interest rates behave erratically*. As pointed out in De Franco et al. (2015), measuring empirical equity duration for equity is a complex operation. With respect to fixed income securities, duration, defined as the sensitivity of the security price to interest rate movements, is not easily computed. The reason stands behind the risk associated with expected cash flows linked to the type of security. For fixed income securities, cash-flows are known and there is little risk that these cash-flows are impacted by macro-economic factors. So the only risk investors carry when investing in fixed income securities is the time they need to recover the investment<sup>2</sup>. Mechanically, the longer the investor needs to wait, the more the security price is impacted by movements in interest rates. On the other side, for equities, the puzzle is complicated by the fact that cash-flows (dividends) are not known in advance and can change according to future macro-economic conditions. Company management can decide to reduce the dividend if economic conditions worsen, or can decide to pay a dividend to maintain flows from investors or attract new investors. Dividend is also a choice of opportunity for a company, who may decide to distribute to its investors if the management does not believe in the investment opportunities available to the company within some specific market conditions. These few examples show how dif-

ficult can be to forecast the equity cash-flow streams since they strongly depend on the economic conditions (Jensen and Johnson, 1995). Both components (time and amount) of equity cash flows have then different impacts on equity prices. For low duration stocks, the equity risk is mainly short-term - as by definition they are supposed to repay the investors in the short term. As a consequence, the equity risk is driven by market shocks on the cash-flows (expected or unexpected), such as profit warning or dividend below market consensus. For these stocks, the interest rate risk is secondary as the total risk is captured by market risk and company's specific idiosyncratic risk. For high duration stocks the picture is somehow symmetric: short-term conditions should have relatively small impact as the expected cash flows are scheduled in the long term. In this case, market shocks have less impact on the stock prices but future movements in interest rates impact future cash-flows and, mechanically, today's valuations. In distressed market conditions, low duration stocks should appear riskier than high duration ones, as today's cash flows are impacted. On the other side, in growing market conditions coupled with increasing rates, high duration stocks should appear riskier than low duration stocks. This mechanism remains valid as long as the dividend stream is constant (or at least predictable). Since companies can manage their dividend policy and determine if, when and how to distribute, the relation between market conditions, interest rates and dividend yields becomes rapidly complicated. In this paper we will not review or introduce new models that may mimic the relationship between interest rates, dividend yields and market conditions. We will rather concentrate on

<sup>2</sup>We do not consider here the credit risk associated with fixed income securities, which of course plays a role in the total risk investors carry

two specific questions that can give an idea of the type of relationship we may expect from the data:

**Statement 1** Do high dividend yield stocks carry a hidden interest rate risk?

**Statement 2** Can the differences in dividend yields across volatility-sorted portfolios explain the small but positive duration for low volatility stocks found in De Franco et al. (2015)?

Using US market data over the period 1990-2014, we build ten portfolios based on dividend yields and run classical regression over a 4-Factor model (Market, Size, Value and Momentum) with the addition of an interest rate risk factor. We show that when it comes to fit the historical data, the addition of the interest rate risk factor does not bring significant explanatory power to the 4-Factor model and fails to explain the alphas away. In contrast, with the same exercise with volatility (De Franco et al., 2015), we find here the 4-Factor model good enough to explain the cross-sectional equity total variance. High dividend yields portfolios show significant positive alphas and a small but positive duration (around 2). We recall it was between 1.5 and 1.8 for low-volatility portfolios in De Franco et al. (2015). For the first statement then we do not see from the data a significant interest rate risk for high dividend yields portfolios. Even if duration is found positive and significant, the majority of portfolios' risk is explained by the 4-Factor model. Durations are similar to those found for low volatility portfolios, but we have here a model with a sufficient explanatory power. In the second part of the paper we look into the relationship between low volatility and high dividend yields portfolios. They both

show small but positive durations; mid-high dividend yields portfolios show lower volatility compared to low dividend yields portfolios; similarly, low volatility portfolios show higher dividend yields compared to high volatility ones. As pointed out in De Franco et al. (2015), one of the reasons for the small but positive duration of low volatility portfolios is their historical high exposure to the Utility sector. Here we propose a second approach by testing whether the low volatility portfolios inherit duration because of their high dividend yields. More precisely we show that duration for low volatility portfolios decreases from 1.8 to 1.1 (38% circa in relative terms) when we neutralize the dividend yield components. In other words, a substantial proportion of the empirical duration of low volatility stocks comes from the fact that, historically, they have also been high dividend yields stocks.

## 2 Description of the investment universe

The dataset is the same as defined in De Franco et al. (2015). Portfolios are built with US stocks belonging to the S&P 500 Index from January 1990 to December 2014. The 4-Factor time series (Market (MKT), Size (SMB), Value (HML) and Momentum (UMD)) are taken from the Kenneth French website. We refer to Fama and French (1993) and Carhart (1997) for further details on the construction and properties of these factors. The Interest Rate risk factor is proxied by the 10-year US Treasury bond yields, specifically the Generic United States on-the-run government (annual) yield on 10Y maturity instruments (Bloomberg ticker *USGG10YR Index*). Starting from the set of stocks in



	Annualized Return	Annualized Volatility	Max Drawdown	Sharpe ratio	CAPM Beta	CAPM Alpha	Dividend yield
Decile1	12.34%	23.97%	-65.44%	0.38	1.36	-2.17%	0.12%
Decile2	12.86%	20.88%	-61.15%	0.46	1.26	-0.86%	0.30%
Decile3	13.64%	18.67%	-57.96%	0.55	1.12	1.08%	0.87%
Decile4	12.92%	16.86%	-51.23%	0.57	1.02	1.15%	1.34%
Decile5	13.41%	16.49%	-54.85%	0.61	0.97	2.12%	1.75%
Decile6	13.47%	17.10%	-59.28%	0.59	0.98	2.05%	2.04%
Decile7	13.98%	15.84%	-47.12%	0.67	0.91	3.11%	2.45%
Decile8	13.97%	15.11%	-39.13%	0.70	0.85	3.61%	2.92%
Decile9	12.49%	16.42%	-63.39%	0.56	0.92	1.54%	3.51%
Decile10	12.50%	16.07%	-62.47%	0.57	0.73	3.15%	4.88%

Table 1: Performance statistics of dividend yields portfolios. *Source S&P, Datastream. Data from Jan, 31, 1990 to Dec, 31, 2014. The Sharpe Ratio is computed with a risk-free rate over the period of 3.34%.*

the S&P 500 Index, we build ten equally-weighted portfolios based on stock dividend yields. To avoid jumps in yields when the dividend is paid, we adjust dividend yields on a daily basis, as if the company would pay a (small) amount of dividend each day. More in details, for a given stock, let  $P_t$  be the stock price at time  $t$ , and define  $(t_k, D_k)$  the sequence of all dividends amounts  $D_k$  paid by the company at time  $t_k$ . We define then the daily dividend yield as follows

$$dY_t := \frac{D_k}{P_{t_k}} \frac{1}{n_k}$$

where  $t_k$  is chosen to verify  $t_k \leq t < t_{k+1}$  and  $n_k$  is the number of business days between  $t_k$  and  $t_{k+1}$ . Even if this measure depends on  $t_{k+1}$ , i.e. the next dividend date, it is not completely forward-looking: for the majority of companies, next dividend dates are known in advance. Should this not be the case, using  $n_k = \text{constant}$  could be an alternative, if we assume that, for the US large cap stocks, quarterly dividend payments is the standard. The annual dividend yield is then computed as the sum

of the past 250 daily yields:

$$DY_t = \sum_{u=t-249}^t dY_u$$

Under this measure, the stock's dividend yield is smoothed over time. Stocks that have not yet paid any dividends are assigned  $dY_t = 0$ . The first portfolio (Decile 1) contains those stocks that have not paid regular dividends or have done so only as special dividends (those for which  $DY_t = 0$ ). Decile 2 contains stocks with the lowest dividend yields and Decile 10 with the highest dividend yields. Portfolios are re-balanced monthly, each third Friday of the month. Net dividends are invested in each portfolio following S&P methodology. Table 1 collects basic portfolios' statistics over the last 25 years. We do not notice any clear pattern in the ex-post returns when sorting stocks by dividend yields, even if mid-high dividend yields portfolios (Decile 6, 7, and 8) show higher returns than low dividend yields or no paying portfolios (Decile 1 or 2). Deciles 7 and 8 show the lowest volatility, although volatility levels are quite stable from Decile 4 to 10.

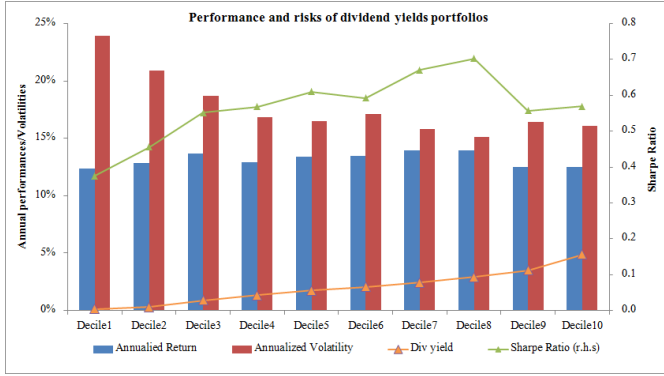


Figure 1: Performance statistics of dividend yields deciles. Source *S&P, Datastream*. Data from Jan, 31, 1990 to Dec, 31, 2014. The Sharpe Ratio is computed with a risk-free rate over the period of 3.34%.

Sharpe ratio is almost monotonically increasing from Decile 1 to Decile 8 where it peaks and then decreases. The fact that Sharpe ratio is at its highest in the mid-high deciles (Figure 1) is partially expected. In general low dividend paying companies are more of growth stocks with high volatility. On the other side, in higher deciles we potentially include troubled companies, showing high dividend yields because of severe drops in their prices. This is because in our calculation we do not include forward looking dividend yield. As a result, the deciles at both ends shows lower Sharpe ratios. By sorting stocks according to their past volatility, De Franco et al. (2015) found a decreasing relationship between volatility and dividend yields: low volatility portfolios showed 2.71% annual dividend yield compared to only 0.39% for the high volatility one. To a lesser extent, this is confirmed in Table 1, where volatility decreases (even if not monotonically) while dividend yields increase.

	MKT	SMB	HML	UMD
SMB	0.25***			
HML	-0.25***	-0.33***		
UMD	-0.25***	0.05	-0.14***	
IR	-0.10*	-0.20***	0.04	0.19***

Table 2: Correlation matrix of the factors in the regression model (3.1). *Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = correlation not significant*

### 3 Multi-factor model description

To assess potential relationship between dividends and interest rate risk, we use the 4-Factor Fama-French-Carhart (FFC) model completed with the interest rate factor:

$$r_t^{Decile_i} = \alpha + \beta^{MKT} MKT_t + \beta^{SMB} SMB_t + \beta^{HML} HML_t + \beta^{UMD} UMD_t + \beta^{IR} IR_t + \epsilon_t \quad (3.1)$$

The portfolio returns  $r^{Decile_i}$  together with the FFC factors are observed monthly at the last business day.  $IR$  is the monthly time series of 10-Year US Treasury bond yields variations.

Since we want to interpret the loading  $\beta^{IR}$  as an empirical equity duration, we multiply yield changes by -1:

$$IR_t = US10Y_{t-1} - US10Y_t;$$

Consequently positive loading means that the portfolio return decreases when interest rates increase.

The correlation matrix of our explanatory factors is given in Table 2. Note that the factors show significant correlation during the time period of our analysis. In particular, the SMB and HML factors, designed to



be weakly correlated, show significant negative correlation. Moreover, our proxy for the interest rate factor has significant negative correlation of -0.20 to the SMB factor, significant positive correlation of 0.19 with the UMD factor and significant, even if with less precision, negative correlation of -0.10 with the market factor.

Thus, the model can potentially suffer from multicollinearity, which can result into artificially high loadings for some factors. We will address these issues in the following sections.

## 4 Empirical results

We start by testing the explanatory power of the FFC model. Table 3 collects the results of a classical linear regression for the dividend-deciles monthly returns over the FFC model without the addition of the interest rate risk factor (i.e. model (3.1) with  $\beta^{IR} = 0$ ) over the last 25 years.

Compared with volatility portfolios in De Franco et al. (2015), we notice that the 4-Factor model is able to explain the majority of the risks and the performances of our ten portfolios based on dividend yields. As a matter of fact,  $R^2$  is above 80% for all deciles except for Decile 10 (74.84%). Low dividend yields deciles are characterized by market beta higher than 1 and tend to be Small (positive exposure to SMB). High dividend yields deciles instead have market beta lower than 1, they are negatively exposed to Size and positively exposed to Value. They tend to be large and value companies with stable dividend yields. As we already explained, Decile 10 may contain distressed companies that show abnormal high dividend yields. For these companies, the idiosyncratic risk is quite significant and this can partially explain why the

$R^2$  is lower than the other deciles. We then add the interest rate risk factor to the 4-Factor model and regress monthly returns of the ten portfolios according to (3.1). Table 4 shows the first set of results. We first notice that, as in De Franco et al. (2015), there is no significant increase in the goodness of fit.  $R^2$  slightly increases for Deciles 2, 9 and 10, and remains almost unchanged for the other deciles. Moreover, the addition of the interest rate factor fails to explain the alphas away. Deciles 7 to 10 still show residual alphas of similar magnitude with or without the interest rate factor. Finally, high dividend yields portfolios exhibit significant positive duration, while the lowest dividend decile has negative duration.<sup>3</sup> Positive duration for high dividend yields stocks may be explained by the fact that these stocks are usually seen as substitutes for fixed income products in a low rate environment. Previous research (Stone, 1974; Chance and Lane, 1980) already showed that negative duration is expected for growth stocks and a more bond-like duration for dividend paying stocks. We notice that the interest rate sensitivity structure is very similar to what was found in De Franco et al. (2015), that we report for the sake of clarity in Table 5. On the one hand we do not find any increase in the explanatory power of the model when adding interest rate factor; on the other hand, high dividend yields deciles (like low volatility deciles) show small but positive duration (between 1 and 2.6 for dividend yields Deciles 8, 9 and 10 and between 1.5 to 1.8 for low volatility-sorted Deciles 1 and 2). Similarly Decile 2, with the lowest dividend yield, shows negative duration of -1.3 as the high volatility-sorted Decile 9 which

<sup>3</sup>We recall that Decile 1 contains all non paying stocks.

Bucket	Alpha	MKT	SMB	HML	UMD	R <sup>2</sup>
Decile 1	0.002**	1.22***	0.336***	-0.369***	-0.282***	88.15%
Decile 2	0.001	1.2***	0.136***	0.118***	-0.209***	86.03%
Decile 3	0.001	1.138***	0.035	0.236***	-0.07***	83.84%
Decile 4	0.002	1.044***	0.009	0.34***	-0.066***	85.33%
Decile 5	0.003*	1.005***	-0.045	0.447***	-0.08***	83.48%
Decile 6	0.003*	1.028***	-0.034	0.505***	-0.112***	84.27%
Decile 7	0.004***	0.957***	-0.08**	0.48***	-0.109***	85.08%
Decile 8	0.003***	0.883***	-0.09***	0.472***	-0.135***	83.40%
Decile 9	0.003**	0.959***	-0.101***	0.55***	-0.166***	85.96%
Decile 10	0.002**	0.788***	0.034	0.778***	-0.166***	74.84%

Table 3: 4-Factor model regression of dividend yields deciles. *Source S&P, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

Bucket	Alpha	MKT	SMB	HML	UMD	IR	R <sup>2</sup>
Decile 1	0.003**	1.22***	0.331***	-0.369***	-0.279***	-0.267	88.15%
Decile 2	0.002	1.2***	0.114***	0.117***	-0.194***	-1.3***	86.34%
Decile 3	0.001	1.138***	0.028	0.235***	-0.066**	-0.407	83.88%
Decile 4	0.002	1.044***	0.013	0.34***	-0.069***	0.251	85.35%
Decile 5	0.003*	1.005***	-0.043	0.447***	-0.081***	0.068	83.48%
Decile 6	0.003*	1.028***	-0.035	0.505***	-0.112***	-0.02	84.27%
Decile 7	0.004***	0.957***	-0.08**	0.48***	-0.109***	0.008	85.08%
Decile 8	0.003***	0.884***	-0.072**	0.472***	-0.146***	1.049***	83.79%
Decile 9	0.002*	0.96***	-0.067**	0.551***	-0.189***	2.012***	87.15%
Decile 10	0.003*	0.789***	0.077*	0.779***	-0.194***	2.562***	76.86%

Table 4: 5-Factor model regression of dividend yields deciles. *Source S&P, Bloomberg, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

Bucket (Volatility)	Alpha	MKT	SMB	HML	UMD	IR	R <sup>2</sup>
Decile 1	0.004***	0.559***	-0.194***	0.433***	0.039	1.824***	55.23%
Decile 2	0.003***	0.783***	-0.193***	0.321***	-0.025	1.598***	74.51%
Decile 3	0.003***	0.818***	-0.171***	0.351***	-0.057**	0.697*	79.28%
Decile 4	0.002	0.958***	-0.111***	0.406***	-0.088***	0.321	82.93%
Decile 5	0.003**	0.984***	-0.019	0.425***	-0.115***	0.03	84.94%
Decile 6	0.001	1.06***	0.004	0.497***	-0.135***	0.161	88.56%
Decile 7	0.003**	1.079***	0.05	0.39***	-0.19***	-0.323	87.67%
Decile 8	0.001	1.17***	0.148***	0.314***	-0.173***	-0.553	89.46%
Decile 9	-0.001	1.364***	0.243***	0.103**	-0.336***	-1.445***	89.20%
Decile 10	0.002	1.613***	0.654***	-0.275***	-0.587***	-0.369	85.84%

Table 5: Source: De Franco et al. (2015). 5-Factor model regression of volatility-sorted deciles, from low to high. *Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

has significant duration of -1.445.

## 5 Interest rate exposure of dividend yields deciles: different model specifications

In this section we test different specifications of the model in 3.1 to see if the factor colinearity in Table 2 may have affected the deciles' loadings on the 4-Factor with interest rate model. We will focus on Deciles 8, 9 and 10, for which we found significant positive duration. The first model specification is given by the Market factor together with the interest rate factor (i.e.  $\beta^{SMB} = \beta^{HML} = \beta^{UMD} = 0$ ). This model specification gives significantly lower  $R^2$  statistics for high dividend yields deciles. For Decile 10, the  $R^2$  dramatically drops from 76.86% to 44.29%. Duration for Decile 8 is no longer significant, while it was 1.049 within the 5-Factor model. As the duration appears only when we add the SMB, HML and UMD factors, we can argue that the duration for Decile 8 is likely the product of factors' colinearity rather than

a significant and distinguishable measure of interest rate exposure. For Deciles 9 and 10 (Tables 7–8), the empirical duration coefficients are always significant, even if magnitudes and estimation errors strongly depend on the model specifications. We notice that the inclusion of the Momentum factor (UMD), whose loading always appears significant and negative, automatically increases the magnitude of the empirical duration, for both Deciles 9 and 10. Table 7 extends our analysis on Decile 9. Each row contains the loading of the model (3.1) where only some factors are included. First row, for example, tests the model where  $\beta^{SMB} = \beta^{HML} = \beta^{UMD} = 0$ ; second row the model where  $\beta^{HML} = \beta^{UMD} = 0$  and so on.

## 6 Interest rate exposure: dividend yield and volatility

According to De Franco et al. (2015), low volatility deciles show small but significant positive duration when monthly portfolio returns are regressed over the 4-Factor

Bucket	Alpha	MKT	IR	R <sup>2</sup>
Decile 1	-0.001	1.416***	-1.891***	80.52%
Decile 2	0.001	1.25***	-2.13***	83.42%
Decile 3	0.002	1.118***	-0.64	81.58%
Decile 4	0.002*	1.004***	0.055	79.89%
Decile 5	0.003**	0.939***	-0.025	73.11%
Decile 6	0.003**	0.962***	-0.221	71.56%
Decile 7	0.005***	0.886***	-0.089	70.62%
Decile 8	0.004***	0.826***	0.817	66.72%
Decile 9	0.002	0.9***	1.65***	66.98%
Decile 10	0.005**	0.715***	1.902***	44.29%

Table 6: 2-Factor model regression of dividend yields deciles. *Source S&P, Bloomberg, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

Decile9: Model	Alpha	MKT	SMB	HML	UMD	IR	R <sup>2</sup>
IR-MKT	0.003	0.901***	-	-	-	1.651***	66.98%
IR-MKT-SMB	0.003*	0.946***	-0.263***	-	-	1.088*	70.03%
IR-MKT-HML	0.001	1.013***	-	0.637***	-	1.563***	83.47%
IR-MKT-UMD	0.005***	0.829***	-	-	-0.275***	2.497***	74.37%
IR-MKT-SMB-HML	0.001	1.025***	-0.097***	0.608***	-	1.36***	83.85%
IR-SMB-HML-UMD	0.013***	-	0.168**	0.25***	-0.433***	1.956**	23.44%
IR-MKT no intercept	-	0.913***	-	-	-	1.741***	84.50%

Table 7: Interest rate loadings across various regression models. *Source S&P, Bloomberg, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

Decile10: Model	Alpha	MKT	SMB	HML	UMD	IR	R <sup>2</sup>
IR-MKT	0.005**	0.716***	-	-	-	1.903***	44.29%
IR-MKT-SMB	0.005**	0.747***	-0.182***	-	-	1.515**	45.81%
IR-MKT-HML	0.001	0.861***	-	0.823***	-	1.789***	73.10%
IR-MKT-UMD	0.007***	0.638***	-	-	-0.298***	2.82***	53.34%
IR-MKT-SMB-HML	0.001	0.856***	0.049	0.838***	-	1.89***	73.20%
IR-SMB-HML-UMD	0.011***	-	0.272***	0.532***	-0.396***	2.516***	31.97%
IR-MKT no intercept	-	0.735***	-	-	-	2.049***	74.94%

Table 8: Interest rate loadings across various regression models. *Source S&P, Bloomberg, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

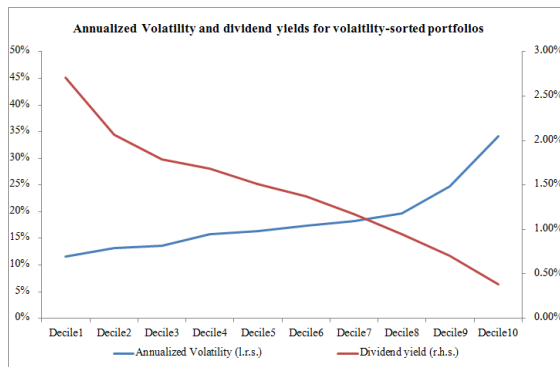


Figure 2: Annualized volatility and dividend yield for volatility-sorted portfolios.  
Source De Franco et al. (2015)

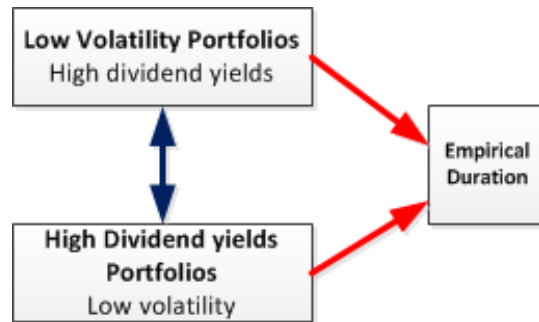


Figure 3: Relation between low volatility-sorted and high dividend yields-sorted portfolios

model completed with interest rates as in 3.1. Moreover, according to their ex-post performances (Table 1 in De Franco et al. (2015)), the low volatility portfolios show higher dividend yields than high volatility portfolios (Figure 2)

On the other hand, according to Table 1, high dividend yields portfolios show lower volatility than low dividend yields portfolios. Finally, both low volatility and high dividend yields portfolios show small but significant positive duration. The goal of this section is to see if a link appears between low volatility-sorted and high dividend yields-sorted portfolios (Figure 3).

For this, we build ten portfolios, sorted by volatility, but in a way that they all show similar dividend yields, so as to neutralize this component when it comes to regress their monthly returns on our model in (3.1). We start by considering the ten portfolios built by sorting the stocks in S&P 500 Universe according to their dividend yields as explained in section 2. Within each decile<sup>4</sup>, we rank the stocks accord-

ing to their volatility and we build ten volatility-based sub-portfolios within each decile. The double sorted decile  $i$  will then be the union, across dividend deciles, of sub-portfolios  $i$  in each decile (Figure 4).

Stocks in double-sorted portfolios (DS Deciles) are equally weighted and are rebalanced each third Friday of the month. Volatility is computed over 500 business days ending 3 days before the Rebalancing date. Net dividends are reinvested in each double sorted portfolio according to the S&P methodology.

Two different double-sorted deciles are then union of ten sub-portfolios - horizontally in Figure 4 - such that

- Pairwise, sub-portfolios in the same dividend yields decile have different volatilities - vertical sorting in Figure 4
- Pairwise, sub-portfolios in the same dividend yields decile have similar dividend yields - vertical sorting in Figure 4

<sup>4</sup>We recall that Decile 1 contains non paying stocks, Decile 2 the stocks with the lowest divi-

dend yield and Decile 10 the ones with the highest dividend yield.

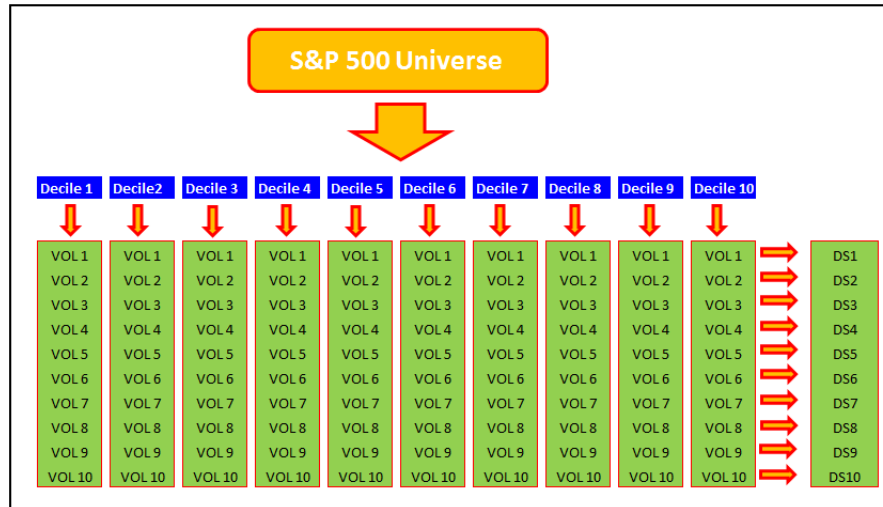


Figure 4: The construction of double sorted portfolios at each rebalancing. Within each dividend yields decile (boxes in blue) we consider ten sub-portfolios by ranking stocks according to their volatilities (boxes in green - vertical sorting). The Double sorted deciles are the union of similar volatility sub-portfolios (horizontal aggregation).

- Sub-portfolios in the same line have the same rank in volatility - horizontal sorting in Figure 4

The dividend yield for this ten double sorted deciles is expected to be the same, as Figure 5 confirms.

By using double-sorted deciles instead of volatility deciles, we neutralize the dividend component effect when it comes to assess the relation between volatility and interest rates. Table 9 collects basic performance statistics for our double sorted deciles over the period January 1990 - December 2012. From Figure 6 we notice how the double sorting technique still allows us to distinguish between low and high volatility stocks. When comparing with the volatility results in De Franco et al. (2015), we only notice a minor increase in the volatility for DS Decile 1 versus the

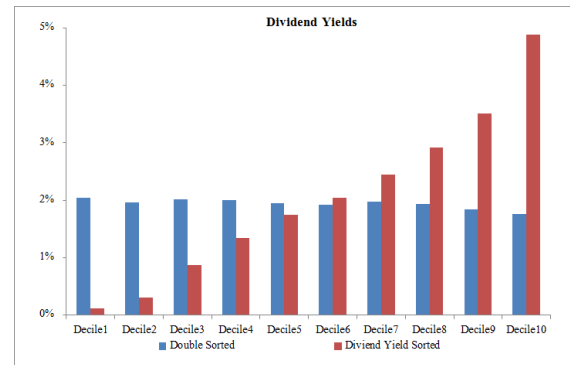


Figure 5: Dividend yields for double sorted deciles. Source S&P, Datastream. Data from Jan, 31, 1990 to Dec, 31, 2014.



Double Sorted	Annualized Return	Annualized Volatility	Max Drawdown	Sharpe ratio	CAPM Beta	CAPM Alpha	Dividend yield
DS Decile1	14.35%	12.19%	-37.08%	0.90	0.28	8.56%	2.05%
DS Decile2	12.90%	13.06%	-38.81%	0.73	0.34	6.54%	1.96%
DS Decile3	14.10%	13.93%	-43.81%	0.77	0.39	7.28%	2.02%
DS Decile4	13.74%	15.17%	-48.90%	0.69	0.44	6.52%	2.00%
DS Decile5	11.09%	16.13%	-52.99%	0.48	0.50	3.33%	1.95%
DS Decile6	11.93%	17.16%	-58.35%	0.50	0.55	3.72%	1.93%
DS Decile7	13.57%	19.16%	-56.13%	0.53	0.63	4.67%	1.98%
DS Decile8	11.57%	21.48%	-63.93%	0.38	0.72	1.85%	1.93%
DS Decile9	13.01%	23.17%	-66.34%	0.42	0.78	2.74%	1.84%
DS Decile10	12.21%	27.26%	-76.23%	0.33	1.00	0.00%	1.76%

Table 9: Performance statistics of double sorted. *Source S&P, Datastream. Data from Jan, 31, 1990 to Dec, 31, 2014. The Sharpe Ratio is computed with a risk-free rate over the period of 3.34%.*

pure (low) volatility Decile 1 (12.19% vs. 11.64%, see Figure 2) and a significant reduction in the volatility of the DS Decile 10 versus the pure (high) volatility Decile 10 (27.26% vs. 34.10%, see Figure 2). For the rest, the differences in annualized volatilities between volatility-sorted and double sorted deciles are really small. We do not notice any clear pattern in the ex-post returns of double sorted deciles, while the Sharpe Ratio declines as the volatility increases, and, by construction, the dividend yield is stable across double sorted deciles. We start by testing the explanatory power of the classical 4-Factor model without interest rate factor for the set of double sorted deciles. Table 10 collects regressions loadings of double sorted monthly returns over the model (3.1) without interest rates ( $\beta^{IR} = 0$ ) over the period January 1990 to December 2014.

Compared to the pure volatility deciles in De Franco et al. (2015), the 4-Factor model has a better explanatory power for the double sorted deciles, especially for the DS Decile 1, for which the  $R^2$  is 67.84% (vs. 53.27% for the pure (low) volatility decile),

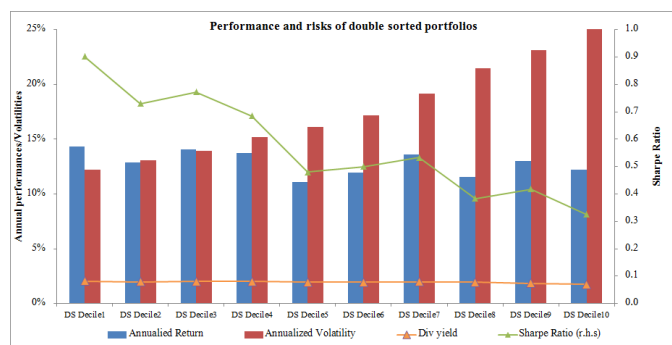


Figure 6: Performance statistics of dividend yields deciles. *Source S&P, Datastream. Data from Jan, 31, 1990 to Dec, 31, 2014. The Sharpe Ratio is computed with a risk-free rate over the period of 3.34%.*

Bucket	Alpha	MKT	SMB	HML	UMD	R <sup>2</sup>
DS Decile 1	0.003***	0.703***	-0.195***	0.271***	0.028	67.84%
DS Decile 2	0.002*	0.777***	-0.141***	0.272***	-0.028	75.53%
DS Decile 3	0.002**	0.874***	-0.129***	0.326***	-0.025	83.67%
DS Decile 4	0.002	0.943***	-0.07**	0.291***	-0.046**	83.96%
DS Decile 5	-0.001	0.998***	-0.088***	0.309***	-0.116***	87.95%
DS Decile 6	0.001	1.029***	0.072**	0.258***	-0.171***	89.69%
DS Decile 7	0.002	1.114***	0.124***	0.307***	-0.247***	90.11%
DS Decile 8	-0.001	1.249***	0.16***	0.311***	-0.288***	91.32%
DS Decile 9	-0.001	1.313***	0.262***	0.351***	-0.32***	90.45%
DS Decile 10	-0.001	1.422***	0.409***	0.274***	-0.474***	87.47%

Table 10: 4-Factor model regression for double sorted deciles. *Source S&P, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

Bucket	Alpha	MKT	SMB	HML	UMD	IR	R <sup>2</sup>
DS Decile 1	0.004***	0.703***	-0.175***	0.271***	0.015	1.13***	68.53%
DS Decile 2	0.001*	0.778***	-0.121***	0.272***	-0.041*	1.176***	76.18%
DS Decile 3	0.002**	0.874***	-0.122***	0.326***	-0.03	0.404	83.73%
DS Decile 4	0.002	0.943***	-0.052	0.292***	-0.058***	1.084***	84.37%
DS Decile 5	-0.001	0.998***	-0.085***	0.309***	-0.118***	0.219	87.97%
DS Decile 6	0.001	1.028***	0.066**	0.257***	-0.168***	-0.327	89.72%
DS Decile 7	0.002	1.114***	0.12***	0.307***	-0.244***	-0.268	90.13%
DS Decile 8	0	1.248***	0.145***	0.311***	-0.279***	-0.861**	91.45%
DS Decile 9	-0.001	1.313***	0.255***	0.351***	-0.315***	-0.429	90.48%
DS Decile 10	-0.001	1.422***	0.406***	0.273***	-0.472***	-0.172	87.48%

Table 11: 5-Factor model regression for double sorted deciles. *Source S&P, Bloomberg, Datastream, Kenneth French website. Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

as showed in Table 10. We notice how the market beta for the DS Decile 1 is significantly higher than the one for the pure low volatility decile (0.703 vs. 0.559).

We can now add the interest rate factor and perform the same type of regression to assess the differences in the empirical duration between the double sorted and the volatility sorted deciles. Table 11 collects regressions loadings of double sorted monthly returns over the model (3.1) completed with the interest rate factor. We also report the results in De Franco et al. (2015) relative to the regressions of volatility sorted deciles to make comparisons easier (Table 12). We remark that the double sorted Deciles 1 and 2 have a significant positive duration (resp. 1.13 and 1.176), as was the case for pure volatility sorted portfolios. But the magnitude is significantly lower, as showed in Table 12: the (low) volatility Decile 1 showed duration of 1.824 while the double sorted Decile 1 has 1.13 duration ( 38% reduction). Similarly, the volatility Decile 2 has 1.598 empirical duration while double sorted Decile 2 only 1.176 ( 26% reduction). Interestingly, DS Decile 2 has higher duration than DS Decile 1: when neutralizing the dividend yield component, the relation between volatility and empirical duration is not monotone anymore. Going down with the deciles, we notice how DS Decile 3 has no longer significant duration - it was 0.697 for the volatility sorted Decile 3, although with 10% significance. On the other side, DS Decile 4 has significant duration of 1.084 while the corresponding volatility sorted Decile 4 has no significant duration. Again, DS Decile 4 duration is higher than DS Decile 3 as it was the case for the couple DS Decile 1/DS Decile 2. For the high volatility deciles, we notice how DS Decile 9 has no significant

	IR		R <sup>2</sup>	
	VS	DS	VS	DS
Decile 1	1.824***	1.13***	55.23%	68.53%
Decile 2	1.598***	1.176***	74.51%	76.18%
Decile 3	0.697*	0.404	79.28%	83.73%
Decile 4	0.321	1.084***	82.93%	84.37%
Decile 5	0.03	0.219	84.94%	87.97%
Decile 6	0.161	-0.327	88.56%	89.72%
Decile 7	-0.323	-0.268	87.67%	90.13%
Decile 8	-0.553	-0.861**	89.46%	91.45%
Decile 9	-1.445***	-0.429	89.20%	90.48%
Decile 10	-0.369	-0.172	85.84%	87.48%

Table 12: 5-Factor model regression for volatility sorted (VS) versus double sorted (DS) deciles. *Source S&P, Bloomberg, Datastream, Kenneth French website and De Franco et al. (2015). Data from Jan, 31, 1990 to Dec, 31, 2014. Significance: \*\*\* = 1% \*\* = 5% \* = 10%. No stars = loading not significant*

duration, unlike is the case for its volatility sorted counterpart.

## 7 Conclusions

We estimated the empirical duration of portfolios with different levels of dividend yields, using a linear 4-factor model completed with 10-year nominal rates that proxy the interest rate risk factor. Despite the potential issues with model specification using interest rate factor together with Fama-French-Carhart factors (market, size, value and momentum), we find several robust results. It turns out that portfolios with low dividend yields tend to have small but significant negative duration, meaning that they tend to respond positively when interest rates rise. On the other hand, higher dividend yields deciles have a positive duration meaning that they have an inverse relation with interest rates, more in line with bonds. However, the inclusion

of the interest rate factor does not bring any significant explanatory power, neither explains away the alphas of high dividend yields portfolios, even when controlling for Fama-French risk factors. These results match the conclusions for volatility sorted portfolios in De Franco et al. (2015). We find several striking similarities between the two distinct datasets:

- Both volatility and dividend yields sorted portfolios'  $R^2$  show almost no improvement when we add the interest rate factor, although the model does a better job in the dividend sorted portfolios.
- The alphas remain significant
- Both low volatility and high dividends yield portfolios have small but positive duration.
- Low volatility portfolios show high dividend yields, while high dividend yields are generally associated with low volatility.

To see if any potential links underlies these similarities, we build a dataset of ten volatility-sorted portfolios while controlling for dividend yields. This double sorting method is very standard when it comes to neutralize some specific characteristics, similar to the one used by Kenneth French to build his factors. This should allow us to see if the relation between interest rate sensitivity and volatility still holds under equal dividend yields condition. We compare our results with the ones obtained by De Franco et al. (2015) in the case of pure volatility sorted portfolios. We find that the 4-Factor model does a better job for the double-sorted volatility portfolios, at least for the lowest deciles. But the

addition of the interest rate in the model does not explain the alphas for the lowest (double-sorted) deciles. And finally, although the lowest double-sorted decile still has small but significant duration, its magnitude is reduced by almost 38%. Furthermore, the monotonic relation between volatility and duration does not hold anymore. In other words, it seems that part of the duration of low volatility portfolios comes from their overlap with high dividend paying portfolios.

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### Endnote

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