The Valuation of Future Dividends in Cross-Sectional Models of Stock Returns

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Abstract

The valuation of future dividends as implied in option prices adds to the understanding of cross-sectional stock returns. I consider portfolios sorted by the difference between the valuation of future dividends and actual dividends. If it is fast, such implied dividend growth coincides with high stock returns but is followed by low stock returns, particularly if dividend yields are low. Explaining returns of portfolios sorted by implied dividend growth and accounting variables challenges the value effect and casts light on a possible origin of the profitability effect and the investment effect: a stock's return history associated with implied dividends.

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1 Introduction

Dividends are a key ingredient to the valuation of stocks and contain predictive power for stock returns. Canonical research shows that returns are predicted at the index level by actual dividends, particularly for longer returns horizons (Campbell and Shiller, 1988, Fama and French, 1988, Cochrane, 2011). More recent research draws attention to the valuations of future dividends, implied from option prices, as a predictor for index returns (Bilson et al., 2015, Golez, 2014)[1]. Actual dividends are also informative about the cross-sectional returns among portfolios of stocks, but authors report a premium of only 0.10% to 0.20% per month for portfolios of stocks paying a high dividend relative to their price over those paying a small one (Fama and French, 1993, Conover et al. 2016). Compared to other well known factors such as *Book-to-Market* this does not appear to be large. In fact, variation in dividend yields appears to be related to other factors to a point that it is omitted in return predicting models by several authors (for example Fama and French, 2015, Asness et al., 2014)

In view of this research and the perhaps unexpectedly weak performance of dividends in this regard, I investigate the area that has been missed out thus far: do the valuations of future dividends implied from option prices predict returns cross-sectionally? To visualize where this question stands in the literature, I draw the following quadrant:

Return prediction	Actual dividends	Valuation of future dividends, as implied by option prices
Index	Campbell and Shiller (1988) Fama and French (1988) Cochrane (2011)	Golez (2014) Bilson et al. (2015)
Cross-section	Fama and French (1993) Conover et al. (2016) Maio and Santa-Clara (2015)	This paper

In the previous Chapter, I exploit the price data of options traded on US stocks to find implied dividends for individual companies. A Cox, Ross and Rubinstein (1973) binomial tree prices a pair of otherwise equal put and call options and is solved simultaneously for implied dividend and implied volatility, both of which refer to the same stock. The approach results in a data set of term structures of implied dividends for all firms that have options

[1] Other authors focus on implied dividends of the S&P 500 index too, notably Binsbergen, Brandt and Koijen (2012), but they apply these data to other purposes than return predictions.

traded on their stocks from 1996 onward. Implied dividends have forecasting power for actual dividends being paid later. Implied dividends also reflect that, if market participants are wrong about the implied values by not anticipating an actual dividend cut later, the element of surprise bears strongly on the stock price.

In this Chapter, this implied information about future dividend valuation is tested for its relevance to stock returns more generally. The analysis is presented in two parts. First, I investigate the relation between implied dividends and stock returns contemporaneously and sequentially. Second, implied dividends are used to sort portfolios of stocks and to construct a factor which is put to work as an add-on to a CAPM and a five-factor model.

Portfolios of stocks with fast dividend growth, defined as a high valuation of future dividends relative to current dividends, show high returns. In the 12 months *prior* to sorting, the fastest quartile portfolio returns are about 0.90% per month above those of the slowest quartile portfolio. If a stock moves up or down in portfolio quartile rankings, that explains a return of 0.72% in the same quarter.

Future returns, however, paint the opposite picture. In fact, in the year following sorting, portfolios of fast dividend growth stocks underperform those with slow dividend growth by 0.30% per month. Low returns following an expected increase in dividend may seem to be counter-intuitive, but if the earlier coincidence of high implied dividends and high returns is a stock price overreaction, perhaps low returns afterwards is merely a reversal in the stock price.

The dividend yield premium (documented by among others Fama and French (1993) and Conover et al., (2016)) may be a consequence of the reversal phenomenon. Fast dividend growth causes a stock to rise, which in turn reduces the dividend yield if this rise is larger than the actual dividend increase. An anticipated increase in dividends, when dividend growth is positive, will not necessarily materialize in an actual dividend increase. Low returns following fast dividend growth and a low dividend yield may thus be one and the same: a consequence of a high stock price rather than of a low dividend.

The effect of a change in dividend growth on returns appears to depend on the level of dividend growth. When it is fast or slow, a change in dividend growth down or up matters significantly more to returns than when dividend growth falls into one of two middle quartiles. This is also true for the reversal pattern after portfolios are sorted. For example, when dividend growth is fast, stock prices respond stronger to a decrease in dividend growth because there is a larger potential for a reduction in dividend growth.

Next, I document that future dividends matter to expected returns as measured in a CAPM setting enhanced by dividend yield and dividend growth used to build factor portfolios. The regression intercept of a standard CAPM model decreases once the two factors are added. Moreover, there are two types of interactions between the two dividend factors. Portfolios of stocks with a low dividend yield respond stronger to the returns of the dividend growth factor than high dividend yield portfolios. And portfolios of stocks with slow dividend growth respond stronger to the returns of the dividend yield factor than fast dividend growth portfolios. The interaction indicates that the extent of return effects from dividend growth depends on the actual dividend itself.

Such dependency results exist also when portfolios are controlled for the Fama and French variables. In the latest version of their 1993 model, Fama and French (2015), further referred to as FF, introduce *Operating Profitability* (*OP*) and *Investment* (*Inv*) as variables along which to construct portfolios of companies. In line with the present value accounting identity, they show that portfolios consisting of companies with high *OP* and low *Inv* outperform subsequent to sorting, even if controlled for by *Book-to-Market* (*B/M*) and *Size*.

The authors use current observable values of these variables in their tests to proxy for their expected future values, which are required in present value thinking. Total dividends paid is the difference between *OP* and *Inv* and implied future dividends can thus step into the gap between the theoretically intended expected values and empirically applied actual values of these variables. The implied valuations of future dividends can be found within the horizon of the expiry dates of options, but they remain unobservable for longer horizons. Implied dividends thus cannot close, but can still reduce the gap between the actual data as applied and the expected values intended.

Average returns of portfolio sorted by one of the FF variables show that several of the effects found by FF are in trouble when dividend growth comes into play as a second sorting variable. The value effect is lost entirely on such portfolios, while the relevance of profitability and investment to stock returns depends on the speed of dividend growth. The profitability effect only survives when dividend growth is slow. Earlier results show that returns are poor in the run-up to slow dividend growth, and a stock may have become cheap. A combination of good profitability and slow dividend growth induced cheapness underpins good future returns. Portfolios of high investment companies show lower returns than average (FF). This effect only survives when dividend growth is fast. A stock's relative expensiveness due to fast dividend growth in the past may be a main cause of the investment effect.

I further calculate the alpha's and the loadings of portfolios double-sorted by FF variables and dividend growth on FF factors. Adding a factor formed from the returns of portfolios of fast dividend growth minus slow dividend growth consistently reduces the unexplained abnormal returns of portfolios relative to applying only one or more of the FF factors.

The returns from this *Fast minus Slow* dividend growth factor behave quite different from other FF factors. It correlates positively with the *Market* and the *Size* factor, and negatively with factors based on accounting variables B/M, OP and Inv. The signs of dividend growth factor correlations are the exact opposite of those of the accounting variables. Regressions on other factors confirm that the dividend growth factor is not well explained by them, which justifies its inclusion in a five-factor model.

The dividend growth factor plays a part in the transmission of these company accounting variables into returns. Portfolio returns are more susceptible to dividend growth factor returns when OP or Inv are high. These sensitivities seem to depend on the sustainability of future dividends as they, in turn, depend on profits and investment.

This paper has three main sections. The subsequent section describes the contemporaneous and forecasting relationship between implied dividends and stock returns. The implied dividend data are then deployed to portfolios sorted by dividends in a CAPM setting enlarged by dividend growth and dividend yield as factors. The closing section investigates the returns of portfolios of companies sorted by the growth in implied dividends in the framework of the Fama and French (2015) five-factor model extended by a dividend growth factor.

2 Portfolio returns conditional on dividends

The central item of investigation in this paper is the relationship between the valuation of future dividends and expected returns in a cross-section of stocks. Following the introduction to dividend growth as a concept, this section discusses the average portfolio returns in relation to dividend growth, as well as to the combination of dividend growth and dividend yield and closes with cross-sectional regressions of returns on dividend growth. This discussion serves as a prelude to the following two sections, in which dividends are introduced as factors in other models.

The relevance of future dividends to stock prices is evident in the standard dividend discount model (DDM):

$$S_t = \sum_{n=1}^{\infty} PV_t(D_{t+n}), \tag{1}$$

which simply equates the value of a stock S_t to the sum of the present value PV_t of all dividends D_{t+n} that it is expected to pay at $t+n$. To assess the level of a future dividend's valuation, I construct dividend growth rate $DG_{t,n}$ which relates its present value to the actual dividend D_t, paid at the moment of observation t:[2]

$$DG_{t,n} = \frac{PV_t(D_{t+n})}{D_t} \tag{2}$$

As is standard, the economic interpretation of dividend growth is the rate $g_{t,n}$ at which dividends are objectively expected to grow, discounted by the time value of money $y_{t-1,n}$ and risk-adjusted by risk premium $\theta_{t,n}$, all over the same horizon until $t = n$:

$$DG_{t,n} = \frac{1 + g_{t,n}}{1 + y_{t-1,n} + \theta_{t,n}}. \tag{3}$$

In the framework of the DDM, cash returns on a stock R_{t+1} follow from the dividend yield and from price changes, and the latter is linked to actual dividends and the growth rate of future dividends:

$$R_{t+1} = D_{t+1} \sum_{n=1}^{\infty} DG_{t+1,n} - D_t \sum_{n=1}^{\infty} DG_{t,n} + D_{t+1}. \tag{4}$$

Consequently, whether dividends are valued to grow fast or slowly does not necessarily influence returns. If growth rates and dividends remain unchanged from one period to the next, cash returns equal the dividend paid and the stock's price remains unchanged. Only if the dividend growth rate or the actual dividend changes can a stock's price change.

2.1 Portfolio returns before and after monthly single-sorting

A first step to investigate the claim that dividend growth affects returns is to visualize stock returns as a function of the valuation of future dividends. I use the implied dividends discussed in the second Chapter of this thesis for this purpose. From July 1997 to June 2015, portfolios of stocks are sorted each month by implied dividend growth into quartiles. The horizon for implied growth is 5 to 7 months following the sorting month[3]. Returns are then calculated for the months surrounding the sorting month, from 12 months prior to sorting to 12 months following sorting. Portfolio returns are value-weighted. The data set contains only stocks for which dividend growth rates can be found. This means that stocks on which no options are traded and stocks of companies that pay no dividends are excluded. In the

[2]Note that the infinite sum of dividend growth rates equals the price-dividend ratio:

$$\sum_{n=1}^{\infty} DG_{t,n} = \frac{\sum_{n=1}^{\infty} PV_t(D_{t+n})}{D_t} = \frac{S_t}{D_t}.$$

[3]Other horizons do not materially change the estimation outcomes.

early years of the data period the returns of about 500 companies are available, by the end of the data period this has increased to over 1,000 companies.

In the first DG quartile, future dividends are valued consistently well below actual dividends at -26% and in the fourth quartile they are consistently valued above actual dividends at $+41\%$[4]. Such growth rates are large enough that objective growth $g_{t,n}$ in equation (3) should play a part. Very slow DG cannot reasonably be expected to be caused by high discounting values $r_{t,n} + \theta_{t,n}$ alone in the case of first quartile DG and very fast DG cannot reasonably be expected to be caused by low discounting values for the high DG quartile. Broadly speaking, dividends are expected to be cut in the first quartile and to be raised in the fourth quartile at an objective measure.

The main message emerging from this exercise is the return reversal at the point of sorting. Returns before sorting are low for slow DG stocks and high for fast DG stocks, which fits in with the DDM as anticipated in equation (4). Following sorting, however, the pattern is reversed (Figure 1, (a) and (d) respectively).

In the sorting month itself, stocks of which dividends are expected to be cut show average returns, but in the run-up to that point returns are poor. The average monthly return in the 12 preceding months is 0.66%, against 1.10% in the 12 months following sorting. A mirrored pattern is clear in the returns of the fast DG portfolio, showing an average of 1.57% before sorting and 0.80% after sorting. Second and third quartile DG portfolios return closer to average both before and after sorting.

The data shown in Figure 1 suggests that the relationship (4) between returns and dividends occurs throughout the preceding year, and in particular in the second to fourth month before sorting[5]. In the year-long run-up to sorting, high/low DG stocks outperform/underperform the market average by a cumulative $6.33\%/-4.53\%$. This excellent/ dismal performance of high/low DG stocks before sorting suggests that such stocks may have become expensive/cheap by some measure by the time of sorting. This raises the question whether the reversal pattern is a correction of irrational overshooting in the price of the stock, of which a discussion follows below.

2.2 Portfolio returns before and after monthly double-sorting

The dividend yield DY can be regarded as a measure of the expensiveness of a stock. Portfolios double-sorted on dividend growth and dividend yield shed some light on their interaction

[4]Both on a average in the data set and at a horizon of 6 months. See Chapter 2 for further reference.

[5]The size of a dividend payment is often announced in the month preceding it. If an announcement is made to change dividends, then the stock has normally undergone the returns associated with the change in dividends in the month immediately before sorting. During second to fourth month before sorting, first quartile DG stocks return as little as 0.35% per month, whereas fourth quartile DG stocks return 1.69%.

as relevant to returns and thus on reversal patterns. Figure 2 shows value weighted monthly returns of the first and fourth quartiles of DG/DY sorted portfolios. The low DY and fast DG portfolio returns in the months preceding sorting are substantial (1.81%) and they fall to below average following sorting (Panel (b)). Such return reversal does not appear for a high DY/fast DG portfolio (Panel (d)). If anything, this portfolio has somewhat higher returns following sorting.

The high DY/slow DG portfolio in Panel (c) shows a similar but opposite reversal pattern. Before sorting it performs poorly at only 0.20% per month and it reverses to a slightly above average return in the period following sorting. Again this contrasts starkly to slow DG portfolios that start from a low dividend yield (Panel (a)). Their returns are above 1.50% in months 12 to 6 preceding sorting, then drop to less than 0.50% in the remaining months up to sorting to bounce back to slightly above average in the period following sorting.

The return patterns found in the first and fourth quartile portfolios sorted by DG only in the previous subsection are sharpened when they are sorted by DY as well. If dividends are expected to fall/rise, this negatively/positively influences returns contemporaneously, but much more so if dividend yield is high/low. The level of the dividend yield thus clearly matters to returns associated with fast or slow dividend growth.

A possible interpretation is that the potential for gains or losses in dividends influences returns. For example, a portfolio of high DY has more return from dividend to lose than a low DY portfolio. When market expectation is for dividends to fall, then returns are lower in the run-up to sorting of stocks with high dividend yields that have more to lose than of stocks with low dividend yields.

But this mechanism may be blurred: high DG stocks that are expensive, as measured by a low dividend yield, show strong returns in the run-up to sorting which cause them to stay expensive and remain or end up in the low DY quartile[6]. In such instances, actual dividends may have risen less, if at all, than stock prices gained. If that happens, their subsequent returns are low. The opposite is true for high DG stocks that are cheap as measured by a high dividend yield, and mutatis mutandis for low DG portfolios. Changes in dividend growth may cause stock prices to overshoot due to such prior returns. The tendency towards fair pricing following such a move is the reversal found.

Portfolios sorted by dividend yield alone produce future excess returns. (Fama and French 1993, Conover et al., 2016). Along the line of reasoning above, it may be not the dividend itself that affects subsequent returns, but irrational prior returns associated with dividend growth being at least partly reversed. If a stock rises in conjunction with fast dividend growth, the dividend yield falls if this rise is larger than the actual dividend increase. A

[6]In the months preceding sorting these stocks did not necessarily fall in the low DY quartile.

low return following a low dividend yield might thus be nothing other than a reflection of a stock's expensiveness. This is not to rule out a rational explanation for the phenomenon, although that requires large moves in risk premiums.

2.3 Cross-sectional regressions

When investors change the valuation of expected dividends, the stock price as a present value of future dividends should change too if markets are efficient (4). As an introduction to the factor analysis in subsequent sections, I investigate empirically the connection between dividend growth and returns as well as its predictive power for future returns in a cross-sectional setting.

Stocks are sorted each quarter into 4 portfolios by the growth rate from actual dividends to implied dividends at a horizon of 6 months, as before. I refrain from using dividend growth rates per stock as regressors because the implied dividend data are noisy. The indicator for dividend growth change $I_{\Delta DG_{j,t}}$ is defined as a change in dividend growth quartile of stock j. Its value equals 1 if $DG_{j,t}$ increases in its quartile ranking from quarter $t-1$ to quarter t, it is -1 if the ranking decreases and is zero otherwise. The equation to test is as follows:

$$R_{j,t+i} = \alpha_t + \beta_t I_{\Delta DG_{j,t}} + \epsilon_{j,t+i}, \tag{5}$$

where $R_{j,t+i}$ are quarterly returns of stock j in quarter $t+i$ in excess of the data set average. This regression is run for each quarter in the data set from 1996 to 2015. The β_t and its t-statistic are calculated following the Fama-Macbeth method.

The contemporaneous return ($i = 0$) of an individual stock explained by a change in $DG_{j,t}$ quartile amounts to 0.72% during a quarter (Table 1, model (5a)) and this coefficient is highly significant. This result confirms that stock prices respond to implied dividends in line with the dividend discount model (4).[7]

That can not be said for the power of a stock return prediction by the same variable. Dividend growth has a small impact on stock returns two quarters ahead ($i = 2$) with a coefficient not significantly different from zero (Table 1, model (5b)).

I continue by differentiating the sensitivities of returns to up and down dividend growth. Work with this data set in Chapter 2 suggests that downward and upward changes in DG produce different effects on stock returns, notably as a response to a dividend announcement. When companies announce a dividend cut, on average stock prices fall by more than 2%. However, if a cut is anticipated as measured by implied dividends, the stock does not respond

[7] At 1.3% the R^2 seems low, but this is quite reasonable given the large dispersion in individual stock returns and the measurement error in the regressor.

by much at all. It is useful to investigate whether returns respond symmetrically to dividend changes or not.

To distinguish between up and down moves, I introduce dummies which capture upward, downward and zero changes in the DG quartile: $I_{\Delta DG_{j,t}>0} = 1$ if the DG quartile indicator increases from quarters $t-1$ to t, $I_{\Delta DG_{j,t}<0} = 1$ if it decreases and $I_{\Delta DG_{j,t}=0} = 0$ if remains unchanged[8]. The following model reflects this distinction:

$$R_{j,t+i} = \beta_{1,t} I_{\Delta DG_{j,t}>0} + \beta_{2,t} I_{\Delta DG_{j,t}<0} + \beta_{3,t} I_{\Delta DG_{j,t}=0} + \epsilon_{j,t}. \tag{6}$$

The regression results of this model indicate a similar relationship to stock returns regardless of whether dividends are implied to increase or to decrease. Both sensitivities are 0.72%, highly significant and very close to the coefficient in model (5a) that does not make the distinction (Table 1). The quarters in which the dividends growth quartile does not change constitute about 60% of the data set. The dummy for these instances attracts a coefficient that is close to zero, which is as expected.

This symmetric connection between future dividend valuations and stock prices can be reconciled with the result in Chapter 2 that stocks hardly respond to the announcement of a change in dividends if they are predicted by implied dividends but react strongly to an unanticipated cut and much less so to a raise. If a dividend raise/cut is correctly anticipated and the stock price has turned upwards/downwards correspondingly, the shock of the dividend raise/cut once announced has by that time abated since the raise/cut is already reflected in the stock price[9].

Lastly, I combine levels and changes in implied dividends as explanatory variables of stock returns to test whether the impact of a change in dividend growth depends on the level of dividend growth. The following model serves this purpose:

$$\begin{aligned} R_{j,t+i} = \alpha_t + \beta_{1,t} I_{\Delta DG_{j,t}} \times I_{DG=1} + \beta_{2,t} I_{\Delta DG_{j,t}} \times I_{DG=2} + \\ \beta_{3,t} I_{\Delta DG_{j,t}} \times I_{DG=3} + \beta_{4,t} I_{\Delta DG_{j,t}} \times I_{DG=4} + \epsilon_{j,t}. \end{aligned} \tag{7}$$

$I_{\Delta DG_{j,t}}$ is the quarterly change in the DG of stock j from $t-1$ to t, as before. $I_{DG=q}$ takes on the value 1 if DG falls in quartile q.

The results in Table 1 (model (7a)) show the differentiation in the sensitivities to the different levels of dividend growth as measured by quartiles for contemporaneous stock returns ($i = 0$). If it is either low or high (quartiles 1 or 4), the price response to a change in

[8]Increases and decreases in dividend growth each account for 20% of a total of 46,564 dividend growth quarters in the data set.

[9]Practitioners capture this phenomenon by the phrase: "Buy the rumor, sell the fact."

dividend growth is just under 1.00. If dividend growth is more muted (quartiles 2 and 3), the response is on average 0.40 smaller.

The interpretation of these results is as follows. Dividend growth in quartile 1 tends to be negative and in quartile 4 it tends to be positive. If dividend growth moves up ($\Delta DG_{j,t} > 0$) from a decreasing path ($DG_{j,t} = 1$), at least its decrease lessens, and if it moves down ($\Delta DG_{j,t} < 0$) from an increasing path ($DG_{j,t} = 4$), at least its increase lessens[10]. If either happens, stock prices react more strongly than when dividend growth is closer to unchanged in quartiles 2 and 3. Consequently, stock prices respond more sharply to a change in dividend growth when there is high dividend growth to be lost or low dividend growth to be increased[11].

To connect with the earlier findings about reversal, the same model is tested for its predictive power ($i = 2$). This regression shows the opposite relationship suggested by reversal, but it is weaker (Table 1, model (7b)). The sensitivity of stock returns in quartiles 1 and 4 have the expected negative sign and returns are reversed by about 0.15% per quartile indicator over two quarters. In comparison to the contemporaneous regression (model (7a), $i = 0$), this sensitivity is a relevant proportion of the difference between their coefficients (0.94 and 0.97) and those of quartiles 2 and 3 (0.48 and 0.62). A meaningful degree of reversal thus appears to exist, although the coefficients of the first and fourth quartile regressors are not significant[12].

An et al. (2014) report that portfolios sorted by implied volatilities produce excess returns. They find that stocks with call/put options that have experienced increases in implied volatilities tend to have high/low future returns, which is attributed to informed traders. I suggest a different explanation for the phenomenon. These authors apply implied volatility data provided by OptionMetrics, which are calculated under the assumption that future dividends as inputs to the option pricing model are fixed and equal to actual dividends. As shown in the previous chapter and by other authors (for example Binsbergen et al., 2013), implied dividends often differ drastically from actual dividends. All other things equal, a price increase in a call option may be caused by an increase in implied volatility when implied dividends are fixed, or by a decrease in implied dividends when implied volatility is fixed. The results in this section are that future returns are high when implied dividends are low, which is therefore close to the results of An et al. (2014), albeit labeled differently[13]. But since they

[10] Note that $\Delta DG_{j,t}$ cannot be positive in quartile 4 and cannot be negative in quartile 1.

[11] A similar response is found when dividend yield replaces dividend growth as an interaction term in each of the regressors.

[12] Regressions including lagged returns as explanatory variables do not find cross-sectional relevance (not shown here).

[13] The authors strictly apply changes in implied volatility as a return predictor, not levels.

fix implied dividends, I argue with their interpretation that the return relationship to option prices is a consequence of a preference among informed investors to trade in option markets first, which then leads stock returns[14]. I contend that no inefficiency between markets is required for a predictive capacity of options: my results show that the relationship may run past implied dividends. Stock options contain information about dividends which drive returns, and are not necessarily a channel for returns themselves.

3 The CAPM extended by dividends

Dividends play a minor part in the literature using factors for understanding cross sectional stock returns. Well known factors, such as those discussed by Fama and French (2015, further referred to as FF), consist of company accounting fundamentals known to influence stock prices. It seems obvious to construct a factor from dividends as well, if only as a transmission of such fundamentals into cash. Indeed, average stock returns of firms with high dividend yields are somewhat higher than those with low dividend yields (Fama and French, 1993, Keim, 1988). High dividend stocks do even better in down markets (Fuller and Goldstein, 2011). But since the cash payoff from dividends is a substantial part in the evaluation of share prices, the question is whether the risk premium associated with dividends shouldn't be more influential to stock returns. I will pursue this question first by investigating a Sharpe-Lintner CAPM model expanded with actual and implied dividends. In section 4 a similar exercise is performed for the Fama and French five factor model, to which I add implied dividends as a factor.

3.1 The present value of stocks derived from dividend yields and dividend growth

A rational motivation for dividends as priced risk factors starts with the present value relationship in (1). In this identity, share price S_t at time t equals the sum of the present values of dividends $PV_t(D_{t+n})$. Part of the present values are observable from implied dividends, which are those up to and including $t+n$. Dissecting the identity into observable and non-observable present values then renders:

$$S_t = \sum_{i=1}^{n} PV_t(D_{t+i}) + \sum_{i=n+1}^{\infty} PV_t(D_{t+i}). \tag{8}$$

Observable dividends are depicted as their implied growth rate from D_t to $PV_t(D_{t+n})$

[14]Cremers and Weinbaum (2010) make a similar claim.

while unobservable dividends beyond n are approached by their expected value $E_t(D_{t+n})$ discounted at r:

$$S_t = D_t \sum_{i=1}^{n} \left(\frac{PV_t(D_{t+i})}{D_t} \right)^i + \sum_{i=n+1}^{\infty} \frac{E_t(D_{t+i})}{(1+r)^i}. \tag{9}$$

This depiction of the present value relationship motivates to consider the growth in the implied valuation of dividends $PV_t(D_{t+n})/D_t$ and dividend yields D_t/S_t as systematic risk factors for stock returns in addition to the market factor. The CAPM attributes returns to non-diversifiable exposure to the market and this decomposition does not preclude the validity of CAPM. As to the expected effects from risk factors, Fama and French (1993, 2015) make the case for what happens to returns if all variables are fixed except a particular variable and returns. Applied to (9) this ceteris paribus reasoning provides the following return relationships. If everything in (9) is fixed except dividend yields and the expected stock return r, then higher dividend yields imply higher expected returns. The dividend growth path can change shape without necessarily affecting returns at all. Faster dividend growth upto $i = n$ then merely implies slower dividend growth beyond $i = n$. However, a change in short term dividend growth is an anticipation of a higher dividend level in the near future that may leave the growth path beyond $i = n$ unchanged. In that case faster dividend growth upto $i = n$ implies higher expected returns. The test results discussed in the second section indicate a clear relationship between returns and short term dividend growth, but in the opposite direction as returns are below average following fast dividend growth. Tests in the context of a CAPM confirm this conclusion and provides some interpretation.

3.2 Dividend yield and dividend growth added to the CAPM

An additional motivation to extend the CAPM by dividend growth and dividend yield as factors stems from their interaction with stock returns. The earlier results show that portfolios sorted by dividend growth vary in returns. An irrational interpretation for the interaction is that dividend growth stands in for overshooting returns which are subsequently reversed. Dividend yield also provides a basis for adding a factor to the CAPM, as the impact of dividend growth on returns depends on dividend yields.

The analysis pursued here closely follows the procedure in FF. They analyze the average returns of portfolios and test the sensitivity of portfolio returns to risk factors. The model tested is the Sharpe-Lintner CAPM, expanded by the two dividend risk factors:

$$R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + p_j PMF_t + f_j FMS_t + \epsilon_{j,t}, \tag{10}$$

where $R_{j,t}$ is the return on (a portfolio of) stocks j for period t, $R_{F,t}$ is the risk-free return, $R_{M,t}$ is the return on the market portfolio and $\epsilon_{j,t}$ is a residual with zero mean. The two dividend related factors are *Prodigal minus Frugal* (*PMF*) and *Fast minus Slow* (*FMS*). *PMF* is the return of a portfolio of high dividend yield stocks minus the return of a portfolio of low dividend yield stocks. *FMS* is the return of a portfolio of companies with fast growing dividends minus the return of a portfolio of companies with slow growing dividends. The definition of growth in dividends is given in (2), making use of the implied dividends found in Chapter 2. Further discussion of these factors follows in a subsection below.

The empirical tests investigate the explanatory power of the model in two parts. The first is a check on the average returns of quartiles of portfolios, sorted along the dimensions above. The second part of the analysis focuses on the time series characteristics of the factors.

3.3 Average portfolio returns

Portfolios for calculating returns are constructed by sorting the companies into quartiles for both dividend growth (DG) and dividend yield (DY) in the second quarter of a calendar year[15]. Dividend growth is defined as the dividends implied for the two quarters following the sorting quarter relative to the actual dividend in the sorting quarter[16]. Returns are then calculated for the subsequent year starting at the third quarter, which is the quarter following the sorting quarter, up to and including the second quarter of the next calendar year. As before, the data set contains only stocks for which dividend growth rates can be found, which excludes stocks without options and companies that do not pay dividends.

Table 2 demonstrates the average monthly value weighted returns of these portfolios sorted on implied dividend growth and dividend yield in excess of the one-month Treasury bill rate. First of all, the higher return for higher dividend yield companies documented in the literature (Fama and French, 1993) clearly emerges. The difference in average return between the highest and the lowest DY quartile is 0.25% per month. More particularly, frugal companies return less than companies in the other DY portfolios. At the same time, fast DG firms return less than slow DG firms. This difference is of a similar magnitude at – 0.30% per month.

Portfolios double-sorted on DG and DY may provide insight into the interaction between these dividend variables, but patterns of excess returns are not consistent within DY

[15]The second quarter of the calendar year is used as the moment to sort portfolios in both this extended CAPM and the FF five factor model discussed in the following section. FF consistently use the second quarter as the moment of sorting and I benchmark the two extended models tested in this paper against theirs.

[16]The data set allows for sorting on the first, the first two and the first three quarters following the sorting quarter. Although the results for returns differ, the general conclusions remain the same. Using LEAPS for this purpose would extend the horizon out to two years, but reduce the size of the data set more drastically.

portfolios and DG portfolios. Among frugal companies, the effect of higher dividend growth is substantial, but in the other groups the effect is not clear. Likewise is the pattern of increasing returns as DY rises not consistent within DG groups. The picture emerging from Table 2 is that the sensitivity of average stock returns to dividend growth highly depends on the level of dividends. When the dividend yield is high, there is less potential for it to rise than when it is low. Fast DG portfolios anticipate a dividend increase and their returns are high before sorting and show a low return reversal afterwards.

This interpretation matches the data while the ceteris paribus reasoning followed in the subsection 3.1 does not. If all variables are fixed except for DG, DY and expected stock returns, then if both DG and DY are small, expected returns should be small as well. I find the opposite, with the slow and frugal quartile returning the best of all 16 portfolio. This result suggests that such reasoning is not appropriate for the purpose of relating expected returns to other elements of present value identity (9). More specifically, the data show that short term dividend growth and the stock price move together. Assuming that the stock price remains fixed within (9) while dividend growth is varied will dilute a conclusion for expected returns. In fact, if it is correct to characterize the stock price response to an upward change in dividend growth as irrational overshooting, then future expected returns will drop, which agrees with the data. It appears that ceteris paribus is not a reasonable imposition for anticipating conclusions about expected returns from the present value identity.

3.4 Factor definitions

The next step is to construct factors for dividend yield and dividend growth and let them perform as regressors of portfolio returns.

Next to market return $R_M - R_F$, the two factors capturing the defining inputs to the share price in equation (10) are *Fast minus Slow (FMS)* for dividend growth and *Prodigal minus Frugal (PMF)* for dividend yield. Similar to constructing portfolios, for calculating the returns of *FMS* I apply dividend growth for two quarters ahead of the sorting quarter.[17] The DG sorting variable is thus the growth rate from the dividend paid in the second quarter to the option implied dividend for the fourth quarter[18], and it is calculated for each company. The DY sorting variable is the dividend actually paid in the second quarter of the year, divided by the average share price in the second quarter.

[17]The choice to use dividends two or three quarters ahead does not bear materially on the results. For limiting space, the results of three quarters ahead dividend growth is omitted here.

[18]For recollection, quarterly periods for the purpose of sorting are defined as the first trading day of the third Friday of the last month of the calendar quarter up to and including the third Friday of the last month of the next calendar quarter. This definition shifts from a calendar quarter by on average just under two weeks. The shift serves to correspond to the expiry schedule of the options used to find implied dividends.

Factor portfolio returns are constructed at each second quarter of the calendar year by forming three groups of firms demarcated at the 30^{th} and the 70^{th} percentile of the sorting variable. *DG* factor *FMS* is then defined as the returns of the fast *DG* group minus the returns of the slow *DG* group. Similarly, *DY* factor *PMF* is defined as the returns of the prodigal *DY* group minus the returns of the frugal *DY* group. Returns are expressed at monthly rates. Annual rebalancing of portfolios in the second quarter is less frequent than feasible since quarterly data are available, but it is chosen to stay close to the methodology applied by FF.

3.5 Factor summary statistics

Table 3 contains the statistics of factor returns. The *FMS* portfolio returns are negative on average, which matches the earlier finding that fast *DG* firms return measurably less than slow growing ones. Slow dividend growth companies return 0.40% per month more than fast *DG* companies, with a standard deviation of 2.81. At a t-stat close to 2 this mean return is just about significantly different from zero at the 5% confidence level.

The average return of *PMF* is 0.22%, which is somewhat higher than 0.12% found over the FF data period of 1963 to 2013. There are several reasons for this difference apart from the length of the data period. FF calculate the returns for the year starting at the third calendar quarter for portfolios of dividend yields which are sorted at the end of the previous calendar year, instead of in the second quarter. FF returns thus refer to a period that is further removed from the moment of sorting than is applied here. Moreover, my data set contains fewer companies (see Table 1 in the previous Chapter). The standard deviation of *PMF* is 3.90, which is too volatile for its returns to be different from zero at reasonable significance levels.

The correlation between the two dividend factors is strongly negative and significant at -0.42. They also show opposite correlation with the market factor, *FMS* correlates positively with market excess returns, but the *PMF* factor correlates negatively (Table 3). The p-values of these correlations are less than 0.01 (not shown here). Regression of one factor on the others provides further insight in their interaction (Table 4). Returns of the *PMF* factor show substantial and significant negative slopes on both market excess returns and *FMS* returns.

The dividend growth factor does not load on market excess returns once PMF is included in the regression. The correlation matrix in Panel B of Table 3 reveals some correlation between *FMS* and the market, but in regressions (Table 4) this turns out to be superseded by the strong relation between *PMF* and market returns. This remarkable difference among

FMS and *PMF* in exposure to the market corroborates the impression that portfolios sorted by dividend growth and sorted by dividend yield are different in nature, which furthers their relevance as part of an extended CAPM.

3.6 Portfolio regression intercepts

Portfolios are constructed by double-sorting along DG and DY and forming quartiles out of the data set at each second quarter of the calendar year, similar to the construction of the factors. The 4×4 portfolio returns are regressed on the three factors as described in the dividend-extended CAPM (equation 10).

We are interested in the ability of the model to explain average returns of the 4×4 portfolios. For this, the alphas of the portfolio regression need to be statistically zero individually and jointly. The top Panel in Table 6 describes the alphas of all 4×4 sorted portfolios. About half of them attain an absolute value of 0.20 or more. Nonetheless, none of them is significant at the 10% level. The average absolute alphas of these portfolio regressions is 0.18 (Table 5) against 0.29 in the base CAPM regressions. The inclusion of each dividend factor individually materially improves the performance of the CAPM too judged by their alphas.

In order to establish the validity of the model in explaining excess return, the intercepts in (15) should be jointly zero across portfolios. Table 5 shows the GRS-statistic of Gibbons, Ross and Shanken (1989) that tests the zero-intercept hypothesis for each set of 16 portfolios and factors. The joint-zero hypothesis is tested by means of the GRS-statistic and its p-value. The GRS-statistic improves a lot from the inclusion of either dividend growth or dividend yield as regressors to test model (10). Its p-value triples, primarily due to the addition of *FMS*. Overall, the model does a good job in explaining portfolios sorted by both dividend variables.

The average value of the intercept also decreases relative to the difference of the average return on portfolio j and the average of all portfolio returns when *FMS* and *PMF* are added as factors[19]. This is true both when they are considered as absolute values and as squared

[19]FF assess the extent to which returns are left unexplained by the competing models. They divide the average (of 16 portfolios) absolute estimated intercept $A(a_j)$ by the average absolute deviation $A(\bar{r_j})$ of the time-series average return of each portfolio R_j from their cross-sectional average $A(\bar{R_j})$. This measure shows the proportion of excess portfolio returns that is left unexplained by a given model. Measurement error causes these estimates to be exaggerated, which can be adjusted for by focusing on squared intercepts and squared errors. Since α_j is a constant, the expected value of the square of its estimate is the squared value of the true intercept plus the sampling variance of the estimate, $E(a_j^2) = \alpha_j^2 + E(e_j^2)$. The estimate $\hat{\alpha_j}^2$ of the square of the true intercept, α_j^2, is the difference of the intercept and its standard error. Similarly, defining the estimate of realized deviation of returns of portfolio j as $\bar{r_j} = \bar{R_j} - A(\bar{R_j})$, the estimate of $\bar{r_j}^2$ is the difference between its square and the square of its standard error. The ratio of averages $A(\hat{\alpha_j}^2)/A(\hat{\bar{r}}_j^2)$ then

values, corrected for sampling error. Although both measures decrease a lot, they remain high. The reason is that the deviation in average returns of individual portfolios is small at 0.12%. With absolute alphas at 0.18%, their ratio is about 1.5 and the ratio of their squares is barely less than one. But, as FF point out as well, I am primarily interested in whether these statistics point to an improvement relative to the CAPM, which they do.

3.7 Portfolio regression slopes

Table 6 further contains the slopes of $R_M - R_F$ and the two dividend factors. The slope to the *Market* is measured with small errors and they are usually close to one. Nevertheless, for some portfolios they are significantly different from one and they often do not show a consistent pattern.

Slopes for *FMS* and *PMF* have the expected increasing pattern for rising *DG* and *DY* respectively. There is, however, a notable difference between the steepness of this pattern among portfolios. When dividend yields are low, the difference in loadings between fast and slow *DG* portfolios on *FMS* (0.48 and −0.41 respectively) is about twice as large as it is among the average of the other higher *DY* portfolios. On the *PMF* factor, this difference is also larger for low *DY* portfolios. The interpretation is that firms with low dividend yields are more susceptible to the risk premiums associated with the dividend factors, which is consistent with the reversal phenomenon. Consider for example the *PMF* coefficients of the two portfolio groups with the highest dividend yield. Whether these firms portray slow or fast dividend growth hardly matters to their exposure to the dividend yield risk premium. This lack of distinction agrees with intuition as it indicates that, once dividends are high and further increases may be a stretch, the sensitivity to the dividend yield risk premium does not change with dividend growth projections. But when they are low, there is a lot of room to move from low to high dividend yield due to an adjustment towards fast dividend growth and for the share price to attain positive abnormal returns in conjunction.

4 The five-factor model extended by dividend growth

The results of the double-sorting on dividend yield and dividend growth provides guidance on the workings of these variables for returns. Furthermore, dividends are a channel transmitting company fundamentals into tangible returns on stocks. It is therefore useful to investigate the interaction between them in the light of returns of stock portfolio. This section discusses dividend growth in the context of accounting variables in the manner proposed

reflects the proportion of the variance of *LHS* returns that is not explained by the model.

by FF. It follows their analysis with dividend growth added to their model as a factor.

4.1 The present value of stocks by company accounting fundamentals

Companies generally pay dividends out of operating profitability, while the non-distributed remainder of profits is added to the capital base of the company. Stimulated by the results of Novy-Marx (2013) in particular, FF identify profitability and investment within the DDM (1), using:

$$S_t = \sum_{n=1}^{\infty} PV_t(D_{t+n}) = \sum_{n=1}^{\infty} \frac{E(D_{t+n})}{(1+r)^n}, \tag{11}$$

to pursue a route at the level of company cash flows. Total expected dividend pay-out can be replaced by the difference between profits and investment, analogous to Modigliani and Miller (1961). The market capitalization M_t (the number of shares outstanding times their price S_t) of a company then equals its discounted future balance of profit and capital growth:

$$M_t = \sum_{n=1}^{\infty} \frac{E(Y_{t+n} - dB_{t+n})}{(1+r)^n}. \tag{12}$$

The difference between total earnings Y_{t+n} and the change in total book equity dB_{t+n} both for period t to $t+n$ fulfills the role of payout to shareholders in (1). FF contend that dividing (12) by book equity B_t

$$\frac{M_t}{B_t} = \frac{\sum_{n=1}^{\infty} E(Y_{t+n} - dB_{t+n})/(1+r)^n}{B_t}, \tag{13}$$

provides a positive relationship between both the book-to-market equity ratio and total expected future earnings and expected stock return r, as well as a negative relationship between the total expected future change in book equity and expected stock return, under ceteris paribus reasoning.

As market expectations for future values of Y_{t+n} and dB_{t+n} are not observable, Fama and French use their current values in the five-factor-model as proxies for testing (13). The approximation puts drawing conclusions from ceteris paribus reasoning at some risk. For example, if a relationship between current total earnings Y_t and expected returns is found that fits such reasoning, then that result hinges on the assumption that the proxy is reasonably accurate. There is no way of knowing that proxying for expectations actually does work, so the relationship, although empirically valid, may follow from another mechanism.

Despite that expected future values are missing elements in the transition from equation (13) into an estimable model, future dividend valuation is an observable variable, at least up to the maturity of the options from which future dividends can be implied. I therefore propose to consider the growth in the implied valuation of dividends as an explanatory factor for stock returns. Deployed next to the FF factors, equation (13) is matched closely by adding dividend growth as defined in (3) and rewriting it to:

$$\frac{M_t}{B_t} = \frac{Y_t - dB_t}{B_t} \times \sum_{n=1}^{\infty} \left(\frac{1 + g_{t,n}}{(1 + y_{t,n-1})(1 + \theta_{t,n})} \right)^n = \frac{Y_t - dB_t}{B_t} \times \sum_{n=1}^{\infty} \left(\frac{PV_t(D_{t+n})}{D_t} \right)^n , \quad (14)$$

in which $(1 + y_{t,n-1})(1 + \theta_{t,n})$ equals $(1 + r)$ in (13). The first term on the right hand side equals dividends and the second terms equals the divided growth rate.

It is clear from (14) that dividend growth steps into the void between current values for earnings and investment and the expectations about their future values, even if it is measured only for a limited horizon. It can do so as a factor in its own right, but also as a term interacting with current payoffs captured by the FF accounting factors.

4.2 Dividend growth added to the five-factor model

Motivated by the role of dividend growth shown in (14), I test the five-factor model deployed in FF, enlarged by a dividend growth factor:

$$\begin{aligned} R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + \\ r_j RMW_t + c_j CMA_t + f_j FMS_t + \epsilon_{j,t}. \end{aligned} \quad (15)$$

$R_{j,t}$, $R_{F,t}$, $R_{M,t}$ and $\epsilon_{j,t}$ reflect the same variables as those in the dividend-extended CAPM discussed in the previous section. The five anomaly factors are the difference in returns between diversified portfolios of companies with, for *SMB*, small and big market capitalization, for *HML*, low and high book-to-market, for *RMW*, robust and weak profitability, for *CMA*, conservative and aggressive investment and, for *FMS*, fast and slow growth in dividend valuations, the latter of which is the focus of this paper. The analysis pursued here closely follows the approach and methodology in FF, as before. I omit the dividend yield factor *PMF* as it is strongly correlated to *HML*, of which some discussion follows further below. A key test is whether coefficients $b_j, s_j, h_j.r_j, c_j$ and f_j capture all variation in the expected returns of portfolio j such that the intercept a_j is zero for all portfolios.

Dividend growth takes the role as a gauge of future dividends, forward-looking as it is. At the same time, *DG* has a substantial effect on stock returns and FF and Novy-Marx (2013) show that current profitability and investment do so as well. The research question pursued is whether the proxy seen in *OP* and *Inv* for future stock behavior holds up next to a variable which actually is forward looking by construction.

The tests hereafter investigate the explanatory power of the model in two segments. The first empirical test is a check of the average returns of quartiles of portfolios, sorted along the dimensions of *DG* on the one hand and each of the three FF accounting[20] anomaly variables on the other. I investigate to what extent dividend growth returns can be explained by these variables and whether their own effects on portfolio returns prevail when dividend growth comes into the equation. The second part of the analysis focuses on the time series regressions of portfolios on the factors. I analyze how dividend growth affects regression intercepts and document the slopes of the coefficients, looking in particular at the sensitivity of portfolio returns to the dividend growth risk factor depending on their profitability and investment groups.

4.3 Average portfolio returns

Table 7 contains the average returns in excess of the one-month U.S. Treasury bill rate of the value weighted double-sorted quartile portfolios over the period July 1996 to June 2015. The details of all sorting are consistent with FF. The breakpoints for the quartiles for book-to-market (*B/M*), (operating) profitability (*OP*) and investment (*Inv*) are sourced from the website of Ken French[21]. Quartiles are formed at the end of June for the three accounting factors and in the second quarter for dividend growth. Returns refer to the year immediately following sorting, as before. The quartile breakpoints use only NYSE stocks, but the sample includes all NYSE, AMEX and NASDAQ stocks in both CRSP and Compustat with share codes 10 or 11.

An ideal disentanglement of variables in (14) would sort portfolios jointly for all variables at the same time. As FF point out, this would produce many poorly diversified portfolios that have low power in tests of asset pricing models. They compromise on sorts of *Size* and pairs of the other three variables. In view of the small number of small sized companies in the dividend growth data set, no sort along the *Size* dimension is made here[22]. Instead, the focus will be on pairwise independent sorts of *DG* with each of the other three accounting anomaly variables *B/M*, *OP* and *Inv*.

[20] The term accounting refers to the variables that appear in equation (14), which excludes *Size*.

[21] Not shown in this paper is how factor effects hold up in this data period (1996-2015) relative to the longer period that FF (2015) deploy (1963-2013). As an overall judgment call, the anomaly factors documented by FF hold up in the period 1996-2015, albeit not as well as in their longer data period.

[22] Sorting portfolios on *Size* reveals that the number of companies in the data set under investigation falling in the smallest *Size* group represents only 18% of the universe in the FF data set. This "tiny" group is actually over-represented in numbers as FF do not calculate breakpoints of their universe but of NYSE. The largest *Size* group in this data set overlaps that of FF by about 80%.

DG-B/M portfolios in Panel A show that the value effect is in trouble among portfolios sorted by growth in dividends. Returns of the highest *B/M* portfolios average less than 0.10% more than the lowest, and a consistent value effect does not exist for any of the *DG* portfolios. For portfolios formed on *DG-OP* sorts, the picture is not much better. The slowest dividend growth portfolio increases returns for higher profitability, but faster growing portfolios do not. Portfolios sorted on *DG-Inv* picture the opposite. Here fast growing portfolios show the expected pattern of declining returns for high *Inv* portfolios, whereas there is no clear picture for portfolios with slow dividend growth.

The effect on portfolio returns from profitability and investment found by FF are clearly related to the valuation of future dividends as measured by dividend growth. For average portfolio returns, the investment effect is largely gone when *DG* is slow, and when it is fast, the profitability effect is largely gone. When *DG* is slow, stocks are cheap and future returns are high. Returns are particularly high if a firm's high profitability coincides with slow dividend growth (Panel B). In such circumstances a stock is cheap and its past profits have been good, which underpins returns. But the investment effect is found among stocks with fast *DG*, when stocks are expensive and future returns are low. Returns are particularly low if a firm's high investment coincides with fast dividend growth. In such circumstances a stock is expensive and its pay-out is small, which hurts returns. Both the profitability and the investment effect may thus be primarily transmitted to returns via their relationship to a stock's pricing level. Such transmission may well underlie the success of the ceteris paribus reasoning pursued by FF.

How do the accounting variables and the dividend growth effect interact? Expressed as lower returns subsequent to higher dividend growth, the effect is maintained when portfolios are constructed based on *OP* and *Inv*. Like the combination with *DY*, however, when combined with *B/M* the *DG* effect is largely lost, except for low *B/M* portfolios[23].

The reason for the weak performance of *B/M* may be found in its similarity to *DY*. Both *B/M* and *DY* relate rather stationary values for B_t and D_t to the volatile market capitalization of a company. When the stock price is high, both *B/M* and *DY* are low and subsequent returns are low. This simple mechanism may be influential for the value effect and the dividend yield effect to be similar in nature. Moreover, the prevalence of market prices in both parameters may limit the effect from *DG* on average returns since, as we have seen in the single sorted portfolios, high dividend growth coincides with high returns and is followed by low returns. Sorting portfolios by dividend growth thus introduces pricing that is correlated to stock prices into these portfolios as well. The data bear out that sorting portfolios twice on market pricing, once directly by *B/M* or *DY* and once indirectly by *DG*,

[23]Notably, FF consider *HML* redundant next to *RMW* and *CMA*, which is investigated further below.

causes the expected effects to mostly disappear from view[24].

4.4 Factor definitions

FF pursue several definitions for portfolio sorts and conclude that the choice between them seems inconsequential to the results, and that they are led back to the following method to calculate factors[25]. Portfolios are sorted in June of each year for *Size* at the NYSE median market cap and the breakpoints for B/M, *OP*, *Inv* and *DG* are the 30^{th} and 70^{th} percentiles of their respective values for NYSE stocks, except for *DG* where percentiles are taken for all stocks in the data set and sorting occurs per the second quarter of the calendar year.

The *Size* factor is calculated by first taking the average of the returns of the three small portfolios for B/M and deducting the returns of their counterparts of the big portfolios. The same is done for *OP* and *Inv*. Next the resulting three returns are averaged to produce the returns of size factor *SMB*.

Value factor *HML* is the average of the return of the two small and big high B/M portfolios minus the average of the return of the two small and big low B/M portfolios. Profitability and investment factors *RMW* (robust minus weak profitability) and *CMA* (conservative minus aggressive investment) are constructed in the same way. The data used are from Ken French's website[26].

Dividend growth factor *FMS* (fast minus slow dividend growth) is constructed by deducting the average returns of the portfolio with slow dividend growth from the portfolio with fast dividend growth during the two quarters following the quarter of sorting[27]. As before, returns refers to the subsequent 12 months, a period chosen to stay close to the FF methodology.

4.5 Factor summary statistics

The summary statistics of factor returns are shown in Panel A of Table 3. The period over which these values are calculated refers to 1996-2015 and they deviate from the values of the same variables shown in FF (data period of 1963-2013). The mean return of *RMW* is somewhat higher, but other FF factor returns are smaller and their standard deviations are

[24] Recall that *OP* and *Inv* are both scaled by book equity.

[25] FF label these as 2×3 factors.

[26] Note that, where factors B/M, *RMW* and *Inv* are calculated for the universe including stocks on which no options are traded and can be sourced from Ken French's website, the factor *FMS* and all *DG* double-sorted portfolio returns, stem from the smaller universe of stocks that have traded options.

[27] Recall that the lack of small companies in the data set for dividend growth precludes a distinction along the *Size* dimension.

larger for the more recent data period. The general picture for these values, however, is the same for both periods.

Panel B of Table 3 contains the correlation matrix of the six factors. In particular the *RMW* factor stands out, as its correlations with the other factors are considerably stronger than in the longer FF data period. Its negative correlations with the *Market* factor (-0.46) and the *SMB* factor (-0.53) are stronger (FF: -0.21 and -0.36 respectively), while its correlation with *HML* is 0.52 (FF: 0.08) and the correlation with *CMA* is 0.26, switching signs (FF: -0.10). All other correlations change by less than 0.10. Arguably, the interaction of *RMW* with the other variables is not stable over time and depends on the data period.

The *FMS* factor correlates positively with the *Market* and the *SMB* factor and negatively with the factors composed of portfolios sorted by company accounting variables. This pattern is the opposite of the accounting factors, which correlate positively among themselves and negatively with *Market* and *Size*. As the average return of the *FMS* factor is negative, this is perhaps not surprising. All *FMS* correlations are more than three standard errors from zero, except for correlation with *SMB*. Correlations of the dividend yield factor *PMF* shows the opposite pattern, much like *HML*.

In Table 8 the results of multivariate regressions of individual factor returns on the other factors are shown. *Market* factor $R_M - R_F$ has negative coefficients for both *RMW* and *CMA*, the *SMB* factor is strongly negatively correlated to *RMW*, but not to any other, and *RMW* and *CMA* are negatively dependent[28][29].

Turning to the two dividend factors, their dependence on the FF factors differs markedly from each other. *PMF* has a substantial negative coefficient for $R_M - R_F$ and a large but positive one for *HML* as well. A negative coefficient to the *Market* factor implies that the risk premium for high dividend companies goes down in positive markets. Such a pattern fits the view that high dividend companies are defensive (Asness, Frazzini and Pedersen, 2014). The positive relationship between *PMF* and *HML* is discussed earlier. The other three FF factors play much less of a part, to the point of no significance at 5% for any of their coefficients. The intercept is equal to the time-series average at 0.22%. But once *FMS* is added as a factor to the *PMF* regression, it drops to 0.10%. The *FMS* coefficient is strong

[28]Regression coefficients largely show the same pattern as found by FF for the period of 1963-2013, but the *HML* factor stands out. FF find that it is explained by the other factors to the point where its intercept is close to zero. The authors conclude that *HML* is redundant in their five-factor model for describing average returns since its variation is captured by the exposure to primarily *RMW* and *CMA*. In the data period of 1996 to 2015, however, its regression intercept is -0.34 and significant at 5%. It would be interesting to investigate whether this reduction in the value premium is related to the initiation of value investing following the publication of Fama and French (1993) in which it was first described.

[29]The regression results shown in Table 8 include *FMS* and *PMF* as regressors, without them, the intercept for *HML* is -0.32.)

and significant, which matches the pattern found in the extended CAPM (10). In the case of *PMF*, the inclusion of *FMS* as a regressor increases the R^2 by more than 8%, while it barely moves the needle for the other factors. The reason is that *FMS* returns are explained to some degree by the other factors. The intercept of the FMS factor is not significantly different from zero, but at –0.22%, it equals about half of its time-series mean of –0.40% (Table 3, Panel A). The coefficients of the FF factors are relatively small, with a t-statistic around 2. The $R_M - R_F$ and *SMB* coefficients are close to zero. When *FMS* is added in the RHS, the intercepts of all FF factor regressions change by less than 0.04%. *FMS* average return is not strongly captured by the factors of the five-factor-model, while it correlates less strongly with them than these factors correlate among themselves. The conclusion of these results is supportive for viewing dividend growth as a force in its own right in the estimation of model (15).

4.6 Portfolio regression intercepts

The excess returns of the portfolios regressed on the factors are the next subject of investigation. The five-factor model enhanced by dividend growth is tested next to guises from which one ore more factors are omitted. Note that the *Market* and *SMB* factors are included as regressors in all cases.

The average absolute alpha's decrease for all models when *FMS* is added as a factor (Table 9). Alpha's improve most for $DG - Inv$ portfolios (5 basis points) and typically by 2 to 3 basis points for portfolios sorted by one of the other three variables. However, *FMS* never reduces the alpha's by more than the other factors do, when applied on their own (next to *Market* and *SMB*).

The GRS-statistic and its p-value do not reject most model specifications. Portfolios double-sorted by *B/M* or *Inv* show similarly good values, but those of *DG-OP* portfolios fare less well. The original five-factor model without *FMS* does well for *DG-DY* portfolios. When factors are removed or added, the difference in these values among portfolios remains similar. This conclusion is not in line with the results from FF's tests of *Size* sorted portfolios. They find that statistics sometimes deteriorate when a factor is added. The more consistent result found here suggests that portfolio returns sorted along *DG* are more easily explained than along *Size*.

The GRS values found in the elaborate CAPM enhanced by dividends *PMF* (10) in Table 5 attain values in the same range as those calculated for the five-factor model without *FMS* (15). If both models are about as strong, then it makes sense that the inclusion of *FMS* on the right hand side of the five-factor model further improves the regressions results. The p-values of the GRS-statistic improve substantially in whichever combination of portfolios and regressors *FMS* is added. For example, in *DG-OP* and *DG-Inv* sorted portfolios, adding *FMS* often doubles the p-values of the GRS-statistic[30].

Abnormal returns of *DG-DY* portfolios are explained similarly well by the five-factor model and the dividend-extended *FMS*, whether *FMS* is included as a factor or not. But for all other portfolio specifications returns unexplained by the fully specified five-factor are reduced once dividend growth comes into play as a factor. These improvements confirm that dividend growth addresses risk characteristics in portfolio returns which are not contained in the five-factor model.

Tables 10 to 13 contain the coefficients of the regressions of *DG* and *FF* variable double-sorted portfolio returns. The intercepts vary quite a lot, with several portfolios in difficulty due to values above 0.30% and below −0.30%, levels at which they attain significance at 5% confidence. Perhaps surprisingly, these larger values do not appear in the same *DG* quartiles. Nevertheless, with 18 out of 64 portfolio regression intercepts more than one standard error away from zero, proportionately this is a better result than the intercepts in the FF regressions of returns of portfolios sorted by *Size* and another factor in which 46 out of 75 intercepts are more than one standard error away from zero (not shown here). The betas to the *Market* factor are close to one, although high *DG* portfolios often attract values near and below 0.90, which is significantly different from one due to the small standard errors of the estimated coefficients.

4.7 Portfolio regression slopes

The loadings on the risk factors further cast light on the transmission mechanism through which dividend growth matters to portfolio returns. Before focusing on the dividend growth factor, it is worth noticing that the FF factors associated with the tested portfolios sorted by *DG* show the expected slopes. *HML* coefficients rise strongly as *B/M* rises in *DG-B/M* sorted portfolios and so do *RMW* coefficients in *DG-OP* portfolios. The slopes for *CMA* fall for higher *Inv* portfolios, which is also in line with expectations.

On average, *FMS* slopes do not change much for rising *B/M*, *OP* and *Inv*, but their values are quite different within these groups. Moving from low to high *DG* within *DG-B/M*

[30] Overall, both $A|a_j|/A|\bar{r}_i|$ and $A(\hat{\alpha_j}^2)/A(\hat{\bar{r}}_i^2)$ measures are higher than in FF's larger data period, leaving a weaker impression of these models for the 1996-2015 data period (Table 9). The absolute levels of intercepts and the variance of their estimates are again often larger than those of return deviations, in which cases the dispersion of the intercepts is the larger of the two. For example in *DG-B/M* portfolios the average return deviation is less than 0.10%, while among *Size-B/M* sorted portfolios this value equals almost 0.20% (FF, 2015). It is a harder job to explain these smaller deviations, which is reflected in these statistics. Nevertheless, in most cases the addition of *FMS* as factor on the *RHS* of the regressions improves these measures.

portfolios, the increase falls as *B/M* increases. The lowest *B/M* quartile *FMS* slopes differ nearly 1.00, while for the largest *B/M* quartile this difference is only 0.10. Returns of *DG-DY* portfolios regressed on the extended CAPM also show such patterns for *FMS* slopes, which confirms the overlapping characteristics of *DY* and *B/M* for returns.

In *DG-OP* sorted portfolios the *FMS* slopes of the two high *OP* category portfolios both increase by more than 1.00 from slow to fast *DG* portfolios and these slopes for the low portfolios differ much less. Although more moderate, this pattern shows again in *DG-Inv* portfolios. Here the highest *Inv* portfolios attract a difference between fast and slow growing portfolios for *FMS* of nearly 1.00, while this is 0.38 for low *Inv* portfolios.

Susceptibility to *FMS* returns appear to increase for high *OP* and *Inv* portfolios and to decrease for high *B/M* and *DY* portfolios. When *OP* is high it stands to reason that portfolios sorted by this variable and dividend growth are more susceptible to *FMS* when dividend growth is high. High profitability gives more scope for dividend increases to materialize than low profitability, a group in which companies are often loss-making, so when *DG* is fast such stocks respond more strongly to the *FMS* premium. If companies have low profits, but nonetheless pay dividends, there is no consistent *FMS* effect. Many companies in these portfolios have negative *OP* at least temporarily. Given that they do pay dividends, they then deplete their capital. It makes sense that sustainable higher dividends increasing the sensitivity to *FMS* emerges only among companies with profitability of some magnitude. Earlier findings in this paper are that fast dividend growth is generally followed by low returns and high profitability increases average returns much more when dividend growth is slow (Table 7). These findings concern average portfolio returns and do not stand in the way of this interpretation of *FMS* slopes, which represent sensitivity to the dividend growth risk premium.

In the case of *DG-Inv* double sorted portfolios, a similar argument for the ability to increase dividends and an associated decreasing effect on returns can be made for a longer horizon. When companies invest, it takes some time for revenues to come to fruition. While the *FMS* coefficient moves up from low to high *DG* for high *Inv* groups, the pattern is also found in low *Inv* but to a lesser degree at about half of the increase in higher *Inv* portfolios. Future profitability due to larger investment gives more scope for a sustainable *FMS* impact on returns. But probably low investment companies are sufficiently profitable on average for dividend growth to matter still to show an effect in both *DG-OP* and *DG-Inv* portfolios.

Portfolios sorted by *B/M* and *DY* have similar return characteristics and *FMS* loadings. Both groups show high sensitivity to *FMS* when they are low and *DG* is slow, with returns decreasing for faster *DG*. This sensitivity is lost for high *B/M* and *DY*. The returns from factors based on these variables strongly correlate. The difference in sensitivity to *FMS* among *DG* sorted portfolios decrease as *B/M* and *DY* rise.

Both *B/M* and *DY* are fractions with the price of the stock as their denominator. Strong susceptibility to *FMS* factor returns of a portfolio of highly priced stocks measured as low *B/M* or *DY* implies that an adjustment in future dividend valuations weighs heavily on such stocks. Such a response is commonplace among investors; a stock's high price is supported by an anticipated future rise in dividends. Once that anticipation fades, stocks that depend for their expensiveness on this dividend outlook are punished more harshly than stocks that are cheaper relative to book value or dividends. Such stock pricing aligns with the below average future returns of high *DG* and low *B/M* or *DY* portfolios (Table 2, Panel A).

Lastly, *SMB* coefficients are significantly different from zero in 19 out of 48 portfolios, without a clear tendency. However, for rising *DG*, two patterns can be found. Among *DG-B/M* portfolios, *SMB* coefficients increase for higher *B/M*, while they fall for higher *Inv* in the case of *DG-Inv* sorted portfolios. Double-sorting with *DG* does not interfere with this finding, high *B/M* and low *OP* remain positively associated with the *Size* effect.

5 Conclusion

Market participants adjust the prices of options to reflect their valuations of future dividends. This paper investigates how stock prices adjust in conjunction with changes to these valuations and whether their future returns are impacted.

A high valuation of future dividends explains higher returns during the time when the valuation is made and lower returns afterwards. The results in this paper suggest that this sequence constitutes a reversal to overshooting stock prices. A portfolio sorted by fast dividend growth stocks outperforms a slow growing portfolio by 0.90% per month in the year preceding sorting, but underperforms it by 0.30% per month in the subsequent year.

Portfolios sorted on well known accounting variables do not show a consistent return pattern when sorted by dividend growth as well. The profitability effect only prevails when dividend growth is slow, while the investment effect depends on fast dividend growth. The value effect appears to be lost altogether on dividend growth portfolios.

The returns of a factor based on portfolios of dividend growth are not very dependent on factors returns based on accounting variables. Nonetheless, high profitability and investment increase the susceptibility of portfolio stock returns to dividend growth, a phenomenon which may serve as the transmission mechanism for company accounting fundamentals into returns.

Dividend growth correlates with stock prices and changes to it will thus influence the expensiveness of a stock. The evidence presented here suggests that relationships between stock returns and variables such as dividend yield, *Book-to-Market*, profitability and investment may be caused by a stock's pricing relative to its fundamentals.

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Table 1: **Cross-sectional regressions of excess returns on dividend growth.**

Each quarter in the period 1996-2015 portfolios are formed by sorting stocks on dividend growth (DG). Excess returns $R_{j,t}$ are defined as their returns above the quarter average. These excess returns are regressed on DG in three equations, in which $I_{\Delta DG_{j,t}}$ is a change in the DG quartile ranking equal to 1 if the change from quarter $t-1$ to t is upward and -1 if it is downward, $I_{\Delta DG_{j,t}>0}$ equals 1 if $\Delta DG_{j,t}$ is positive, $I_{\Delta DG_{j,t}<0}$ equals 1 if $\Delta DG_{j,t}$ is negative and $I_{\Delta DG_{j,t}=0}$ equals 1 if ΔDG is unchanged. Regressions are performed each quarter. The coefficients reported are calculated as the average of the quarterly coefficients, the t-statistics are averaged multiplied by the square root of the number of regressions performed (78 for $n = 0$) (Fama and MacBeth, 1973). The R^2 reported are the average of the quarterly R^2.

$$R_{j,t+i} = \alpha_t + \beta_t I_{\Delta DG_{j,t}} + \epsilon_{j,t} \tag{5}$$

$$R_{j,t+i} = \beta_{1,t} I_{\Delta DG_{j,t}>0} + \beta_{2,t} I_{\Delta DG_{j,t}<0} + \beta_{3,t} I_{\Delta DG_{j,t}=0} + \epsilon_{j,t} \tag{6}$$

$$\begin{aligned} R_{j,t+i} = \alpha_t + \beta_{1,t} I_{\Delta DG_{j,t}} \times I_{DG=1} + \beta_{2,t} I_{\Delta DG_{j,t}} \times I_{DG=2} + \\ \beta_{3,t} I_{\Delta DG_{j,t}} \times I_{DG=3} + \beta_{4,t} I_{\Delta DG_{j,t}} \times I_{DG=4} + \epsilon_{j,t} \end{aligned} \tag{7}$$

	(5a)	(5b)	(6a)	(6b)	(7a)	(7b)
	$i = 0$	$i = 2$	$i = 0$	$i = 2$	$i = 0$	$i = 2$
Intercept	-0.001	-0.001			0.001	-0.013
	(-0.33)	(-0.32)			(0.01)	(-0.10)
$I_{\Delta DG_{j,t}}$	0.718	-0.067				
	(13.08)	(-1.39)				
$I_{\Delta DG_{j,t}>0}$			0.716	-0.052		
			(11.45)	(-0.97)		
$I_{\Delta DG_{j,t}<0}$			-0.724	0.083		
			(-12.13)	(1.43)		
$I_{\Delta DG_{j,t}=0}$			0.004	-0.018		
			(0.19)	(-0.68)		
$\Delta DG_{j,t} \times (DG_{j,t} = 1)$					0.935	-0.148
					(9.07)	(-1.59)
$\Delta DG_{j,t} \times (DG_{j,t} = 2)$					0.483	-0.068
					(6.90)	(-0.86)
$\Delta DG_{j,t} \times (DG_{j,t} = 3)$					0.618	0.061
					(7.8)	(0.84)
$\Delta DG_{j,t} \times (DG_{j,t} = 4)$					0.975	-0.162
					(8.25)	(-1.43)
R^2	0.013	0.003	0.015	0.005	0.020	0.009

Table 2: **Value-weight portfolios formed on dividend growth and dividend yield.**

Panel A: Average monthly percent returns in excess of the one-month Treasury bill rate for portfolios formed on dividend growth (DG) and on dividend yield (DY). At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to four DG groups and four DY groups independently at their quartile breakpoints of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. DG Average and DY Average are the returns of single-sorted portfolios.

Panel B: The average number of firms per DG-DY portfolio throughout the period 1996-2015.

DY	Low	2	3	High	DY Average
Panel A: Average excess returns					
Slow DG	0.93	0.79	0.92	0.56	0.84
2	0.47	0.72	0.68	0.70	0.57
3	0.63	0.52	0.72	0.75	0.65
Fast DG	0.27	0.74	0.65	0.66	0.54
DG Average	0.43	0.66	0.75	0.68	
Panel B: Average number of companies					
Slow DG	40	42	45	43	
2	22	46	60	52	
3	41	54	46	38	
Fast DG	87	38	24	27	

Table 3: **Summary statistics of monthly factor returns in the period 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015). The data are sourced from Ken French's website.
At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three DG groups and three DY groups independently with breakpoints at the 30^{th} and 70^{th} percentile of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of fast DG group minus the returns of the slow DG group and *PMF* is the returns of prodigal DY group minus the returns of the frugal DY group.

Panel A: Average monthly returns (Mean), the standard deviations of monthly returns (St dev.) and the t-statistics for the average returns.

Panel B: the correlations of the factors among themselves.

	$R_M - R_F$	SMB	HML	RMW	CMA	FMS	PMF
Panel A: Mean returns, standard deviations and t-statistics							
Mean	0.58	0.25	0.22	0.34	0.30	-0.40	0.22
St dev	4.62	3.34	3.35	2.90	2.24	2.81	3.90
t-stat	1.89	1.13	0.98	1.75	2.00	-2.13	0.86
Panel B: Correlations between factors							
$R_M - R_F$	1	0.22	-0.23	-0.46	-0.36	0.20	-0.46
SMB	0.22	1	-0.20	-0.53	-0.03	0.10	-0.18
HML	-0.23	-0.20	1	0.52	0.65	-0.16	0.55
RMW	-0.46	-0.53	0.52	1	0.26	-0.22	0.40
CMA	-0.36	-0.03	0.65	0.26	1	-0.23	0.51
FMS	0.20	0.10	-0.16	-0.22	-0.23	1	-0.42
PMF	-0.46	-0.18	0.55	0.40	0.51	-0.42	1

Table 4: **Regressions of factor returns used in the dividend-extended CAPM (10) on each other for the period 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three DG groups and three DY groups independently with breakpoints at the 30^{th} and 70^{th} percentile of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of fast DG group minus the returns of the slow DG group and *PMF* is the returns of prodigal DY group minus the returns of the frugal DY group. *Int* is the regression intercept.

	Int	$R_M - R_F$	PMF	FMS	R^2
$R_M - R_F$					
Coef	0.70		-0.54	0.01	0.21
t-stat	(2.54)		(-6.97)	(0.09)	
	0.70		-0.54		0.21
	(2.55)		(-7.74)		
	0.71			0.33	0.04
	(2.32)			(3.04)	
PMF					
Coef	0.22	-0.33		-0.48	0.33
t-stat	(1.03)	(-6.97)		(8.53)	
	-0.01			-0.59	0.18
	(-0.04)			(-6.95)	
	0.45	-0.39			0.21
	(1.92)	(-7.74)			
FMS					
Coef	-0.33	0.00	-0.30		0.18
t-stat	(-1.91)	(0.09)	(-2.00)		
	-0.33		-0.30		0.18
	(-1.93)		(-6.95)		
	-0.47	0.12			0.04
	(-2.51)	(3.04)			

Table 5: **Summary statistics for tests of CAPM extended by dividend growth and dividend yield.**

Test portfolios are 4 × 4 sorted by dividend growth and dividend yield. The *GRS*-statistic tests whether the expected values of all 16 intercept estimates are zero, the average absolute value of the intercepts, A$|a_j|$, A$|a_j|/|\bar{r_j}|$, the average absolute value of the intercept a_j over the average absolute value of $\bar{r}_j$, which is the average return on portfolio i minus the average of the portfolio returns, and $A(\hat{a}_i^2)/A(\hat{\mu}_j^2)$, which is $A(\hat{a}_j^2)/A(\hat{\mu}_j^2)$ the average squared intercept over the average squared value of $\bar{r}_j$, corrected for sampling error in the numerator and denominator.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + d_j PMF_t + f_j FMS_t + e_{j,t}$

	GRS	pGRS	A$\|a_j\|$	$\frac{A\|a_j\|}{A\|\bar{r_j}\|}$	$\frac{A(\hat{a_j}^2)}{A(\hat{\mu_j}^2)}$
16 DG-DY portfolios					
$R_M - R_F$	1.30	0.20	0.29	2.48	2.80
$R_M - R_F$ FMS	0.90	0.57	0.22	1.86	1.61
$R_M - R_F$ PMF	1.07	0.39	0.19	1.63	1.49
$R_M - R_F$ PMF FMS	0.83	0.65	0.18	1.52	0.97

Table 6: **Regressions for 16 value-weighted *DG-DY* portfolios: 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three DG groups and three DY groups independently with breakpoints at the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentile of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor FMS is the returns of fast DG group minus the returns of the slow DG group and PMF is the returns of prodigal DY group minus the returns of the frugal DY group.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + d_j PMF_t + f_j FMS_t + e_{j,t}$

DY	Low	2	3	High	Low	2	3	High
	a				t(a)			
DG Slow	0.32	0.21	0.31	-0.22	1.39	1.01	1.40	-1.09
2	-0.02	0.15	0.13	0.00	-0.09	0.71	0.74	0.03
3	0.26	-0.02	0.23	0.27	1.00	-0.10	1.36	1.67
DG Fast	-0.08	0.24	0.22	0.19	-0.62	1.11	1.01	0.98
	b				t(b)			
DG Slow	0.96	0.82	0.87	1.02	17.37	16.36	16.48	21.15
2	0.93	0.87	0.84	1.04	16.73	16.79	19.95	27.08
3	0.91	0.88	0.85	0.79	14.87	18.92	20.74	20.64
DG Fast	1.03	0.93	0.89	0.90	34.13	17.82	16.81	19.42
	f				t(f)			
DG Slow	-0.41	-0.31	-0.18	-0.24	-4.64	-3.84	-2.07	-3.08
2	-0.09	-0.08	-0.05	0.17	-1.05	-0.94	-0.76	2.76
3	-0.09	-0.05	0.17	0.15	-0.96	-0.69	2.63	2.49
DG Fast	0.48	0.13	0.07	0.28	9.88	1.57	0.87	3.73
	p				t(p)			
DG Slow	-0.54	0.05	0.25	0.61	-7.65	0.79	3.71	9.93
2	-0.27	0.17	0.20	0.85	-3.72	2.64	3.77	17.36
3	-0.06	0.11	0.35	0.64	-0.75	1.93	6.66	12.96
DG Fast	-0.12	0.23	0.31	0.71	-3.22	3.48	4.64	12.09

Table 7: **Average monthly percent returns in excess of the one-month Treasury bill rate for portfolios formed on dividend growth and accounting variables.**

Portfolios are 4 × 4 sorted by dividend growth (*DG*) and *Book-to-Market* (*B/M*), *DG* and *Operating Profitability* (*OP*), *DG* and *Investment* (*Inv*) and *DG* and dividend yield (*DY*): 1996-2015. At the end of each June, stocks are allocated to four *B/M* groups using NYSE market cap breakpoints, to four *OP* groups using accounting data for the fiscal year ending in year $t-1$ (revenues minus cost of goods sold, minus SG&A and interest expenses all divided by book equity) and to four *Inv* groups using the change in total assets from the fiscal year ending in $t-1$, divided by $t-2$ total assets. At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to four *DG* groups and four *DY* groups independently at the quartile breakpoints of that quarter. *DG* is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. *DY* is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Returns are value-weighted.

	Low	2	3	High
Panel A: 16 DG-B/M portfolios				
Slow DG	0.97	0.61	0.79	0.60
2	0.57	0.83	0.68	0.89
3	0.65	0.71	0.66	0.71
Fast DG	0.40	0.62	0.69	0.51
Panel B: 16 DG-OP portfolios				
Slow DG	0.71	0.52	0.70	1.32
2	0.70	0.68	0.85	0.51
3	0.71	0.74	0.59	0.76
Fast DG	0.40	0.60	0.40	0.43
Panel C: 16 DG-Inv portfolios				
Slow DG	0.87	0.97	0.89	0.77
2	0.73	0.65	0.55	0.65
3	0.77	0.74	0.66	0.47
Fast DG	0.56	0.45	0.58	0.29
Panel D: 16 DG-DY portfolios				
Slow DG	0.93	0.79	0.92	0.56
2	0.47	0.72	0.68	0.70
3	0.63	0.52	0.72	0.75
Fast DG	0.27	0.74	0.65	0.66

Table 8: **Regressions of factor returns in the dividend extended five-factor model (15) regressed on each other for the period 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015). The data are sourced from Ken French's website. At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three DG groups and three DY groups independently with breakpoints at the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentile of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of fast DG group minus the returns of the slow DG group and *PMF* is the returns of prodigal DY group minus the returns of the frugal DY group. *Int* is the regression intercept.

	Int	$R_M - R_F$	*SMB*	*HML*	*RMW*	*CMA*	*PMF*	*FMS*	R^2
$R_M - R_F$									
Coef	1.01		-0.03	0.58	-0.75	-0.70	-0.40		0.40
t-stat	(4.06)		(-0.30)	(5.20)	(-6.49)	(-4.69)	(-5.11)		
	1.05		-0.01	0.45	-0.82	-0.88		0.07	0.32
	(3.97)		(-0.12)	(3.87)	(-6.72)	(-5.63)		(0.71)	
SMB									
Coef	0.44	-0.02		0.06	-0.68	0.14	-0.04		0.30
t-stat	(2.21)	(-0.30)		(0.70)	(-7.75)	(1.17)	(-0.60)		
	0.43	-0.01		0.05	-0.68	0.13		0.00	0.30
	(2.16)	(-0.12)		(0.54)	(-7.68)	(1.08)		(-0.03)	
HML									
Coef	-0.34	0.19	0.03		0.49	0.76	0.21		0.63
t-stat	(-2.34)	(5.20)	(0.70)		(7.74)	(10.41)	(4.79)		
	-0.31	0.14	0.03		0.55	0.91		0.05	0.59
	(-2.01)	(3.87)	(0.54)		(8.29)	(12.78)		(0.92)	
RMW									
Coef	0.52	-0.21	-0.32	0.43		-0.25	0.00		0.56
t-stat	(3.92)	(-6.49)	(-7.75)	(7.74)		(-3.10)	(-0.07)		
	0.49	-0.21	-0.31	0.43		-0.28		-0.09	0.57
	(3.67)	(-6.72)	(-7.68)	(8.29)		(-3.39)		(-1.84)	
CMA									
Coef	0.31	-0.13	0.04	0.43	-0.16		0.07		0.52
t-stat	(2.81)	(-4.69)	(1.17)	(10.41)	(-3.10)		(1.99)		
	0.29	-0.14	0.04	0.47	-0.18			-0.09	0.53
	(2.67)	(-5.63)	(1.08)	(12.78)	(-3.39)			(-2.46)	
PMF									
Coef	0.22	-0.27	-0.04	0.44	-0.01	0.25			0.43
t-stat	(1.04)	(-5.11)	(-0.60)	(4.79)	(-0.07)	(1.99)			
	0.10	-0.25	-0.04	0.47	-0.08	0.14		-0.40	0.51
	(0.52)	(-5.19)	(-0.65)	(5.47)	(-0.78)	(1.16)		(-5.76)	
FMS									
Coef	-0.22	-0.05	-0.02	0.22	-0.18	-0.20	-0.33		0.21
t-stat	(-1.20)	(-1.16)	(-0.26)	(2.71)	(-2.00)	(-1.84)	(-5.76)		
	-0.29	0.03	0.00	0.08	-0.17	-0.29			0.09
	(-1.50)	(0.71)	(-0.03)	(0.92)	(-1.84)	(-2.46)			

Table 9: **Summary statistics for tests of the Fama and French five-factor model extended by dividend growth.**

Test portfolios are 4 × 4 formed on dividend growth (*DG*) and *Book-to-Market*, *DG* and *Operating Profitability*, *DG* and *Investment* and *DG* and dividend yield. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015). The data are sourced from Ken French's website. All regressions include $R_M - R_F$ and *SMB* and the factors indicated. The first line of each Panel reflects regressions on $R_M - R_F$ and *SMB* only.
The *GRS*-statistic tests whether the expected values of all 16 intercept estimates are zero, the average absolute value of the intercepts, A$|a_j|$, A$|a_j|/|\bar{r_j}|$, the average absolute value of the intercept a_j over the average absolute value of $\bar{r}_j$, which is the average return on portfolio j minus the average of the portfolio returns, and $A(\hat{a}_j^2)/A(\hat{\mu}_j^2)$, which is $A(\hat{a}_j^2)/A(\hat{\mu}_j^2)$ the average squared intercept over the average squared value of $\bar{r}_j$, corrected for sampling error in the numerator and denominator.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + r_j RMW_t + c_j CMA_t + f_j FMS_t + e_{j,t}$.

	GRS	pGRS	A$\lvert a_i \rvert$	$\frac{A\lvert a_i\rvert}{A\lvert\bar{r_i}\rvert}$	$\frac{A(\hat{a_i}^2)}{A(\hat{\mu_i}^2)}$
Panel A: 16 DG-B/M portfolios					
	1.11	0.35	0.27	2.80	3.17
HML	0.99	0.47	0.12	1.24	2.13
HML RMW	0.98	0.48	0.13	1.38	1.68
HML CMA	0.87	0.60	0.11	1.09	1.96
RMW CMA	1.21	0.26	0.24	2.49	2.95
HML RMW CMA	1.08	0.38	0.15	1.58	1.66
FMS	0.73	0.76	0.22	2.30	2.47
HML FMS	0.67	0.82	0.12	1.24	1.32
HML RMW FMS	0.73	0.76	0.11	1.16	0.96
HML CMA FMS	0.64	0.85	0.11	1.14	1.27
RMW CMA FMS	1.04	0.42	0.20	2.11	2.46
HML RMW CMA FMS	0.93	0.53	0.12	1.26	1.27
Panel B: 16 DG-OP portfolios					
	1.94	0.02	0.25	1.78	2.74
HML	1.87	0.03	0.20	1.38	2.40
RMW	1.43	0.13	0.22	1.51	1.63
HML RMW	1.44	0.13	0.21	1.47	1.61
HML CMA	1.68	0.05	0.17	1.21	2.18
RMW CMA	1.44	0.13	0.24	1.71	2.04
HML RMW CMA	1.18	0.28	0.19	1.36	1.40
FMS	1.51	0.10	0.23	1.58	2.14
HML FMS	1.49	0.10	0.18	1.29	1.76
RMW FMS	1.17	0.30	0.18	1.24	1.31
HML RMW FMS	1.18	0.29	0.17	1.19	1.33
HML CMA FMS	1.41	0.14	0.17	1.16	1.63
RMW CMA FMS	1.26	0.23	0.21	1.48	1.40
HML RMW CMA FMS	1.03	0.42	0.17	1.19	1.10
Panel C: 16 DG-Inv portfolios					
	1.25	0.23	0.28	1.91	2.50
HML	1.12	0.34	0.19	1.34	1.37
CMA	0.86	0.61	0.15	1.03	0.90
HML RMW	0.88	0.59	0.17	1.19	1.44
HML CMA	0.95	0.51	0.15	1.06	0.92
RMW CMA	0.77	0.72	0.19	1.31	1.33
HML RMW CMA	0.69	0.80	0.15	1.07	0.95
FMS	0.84	0.63	0.21	1.47	1.42
HML FMS	0.77	0.72	0.13	0.90	0.76
CMA FMS	0.61	0.88	0.09	0.64	0.86
HML RMW FMS	0.64	0.85	0.13	0.88	0.50
HML CMA FMS	0.69	0.80	0.10	0.67	0.86
RMW CMA FMS	0.62	0.87	0.14	0.94	0.77
HML RMW CMA FMS	0.56	0.91	0.12	0.83	0.51
Panel D: 16 DG-DY portfolios					
	1.42	0.13	0.32	2.66	3.46
HML	1.26	0.22	0.19	1.64	1.62
CMA	1.09	0.37	0.17	1.45	1.40
HML RMW	1.06	0.40	0.14	1.22	1.39
HML CMA	1.12	0.34	0.18	1.55	1.43
RMW CMA	1.14	0.32	0.17	1.43	1.85
HML RMW CMA	0.99	0.47	0.16	1.31	1.51
FMS	1.01	0.45	0.24	2.04	2.16
HML FMS	0.90	0.57	0.17	1.42	0.99
CMA FMS	0.82	0.66	0.15	1.26	1.07
HML RMW FMS	0.80	0.68	0.12	1.03	1.15
HML CMA FMS	0.85	0.62	0.16	1.36	1.03
RMW CMA FMS	0.97	0.49	0.16	1.32	1.78
HML RMW CMA FMS	0.84	0.63	0.14	1.22	1.40

Table 10: **Regressions for 16 value-weighted *DG-B/M* portfolios: 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015). The data are sourced from Ken French's website.
At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three DG groups and three DY groups independently with breakpoints at the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentile of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of the fast DG group minus the returns of the slow DG group and *PMF* is the returns of prodigal DY group minus the returns of the frugal DY group.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + r_j RMW_t + c_j CMA_t + f_j FMS_t + e_{j,t}$.

B/M	Low	2	3	High	Low	2	3	High
		a				t(a)		
DG Slow	0.08	-0.31	-0.23	-0.15	0.60	-1.70	-1.28	-0.60
2	-0.22	0.19	-0.19	0.23	-1.80	1.10	-1.06	1.22
3	-0.04	0.03	-0.07	-0.01	-0.26	0.17	-0.38	-0.07
DG Fast	-0.09	-0.02	-0.04	-0.12	-0.75	-0.09	-0.20	-0.47
		b				t(b)		
DG Slow	1.03	1.00	1.10	0.92	33.22	22.06	24.36	14.41
2	0.99	0.98	1.04	0.81	32.84	23.10	24.05	17.68
3	0.86	1.05	1.10	0.96	25.12	25.65	24.33	19.22
DG Fast	1.10	1.03	0.92	1.02	36.22	20.05	17.33	16.66
		s				t(s)		
DG Slow	-0.10	0.07	0.09	0.16	-2.34	1.19	1.55	1.86
2	-0.26	0.01	-0.14	0.05	-6.38	0.24	-2.42	0.85
3	-0.17	-0.20	-0.01	0.07	-3.75	-3.69	-0.17	1.10
DG Fast	-0.09	0.01	0.19	0.18	-2.29	0.14	2.67	2.16
		h				t(h)		
DG Slow	-0.09	0.22	0.66	0.80	-1.66	2.69	8.26	7.11
2	-0.06	0.57	0.65	1.12	-1.19	7.58	8.56	13.77
3	-0.06	0.31	0.60	0.82	-1.02	4.34	7.49	9.28
DG Fast	-0.10	0.38	0.55	0.78	-1.95	4.24	5.84	7.25
		r				t(r)		
DG Slow	0.27	0.41	0.13	-0.14	4.37	4.58	1.44	-1.09
2	0.45	0.09	0.20	-0.21	7.56	1.07	2.38	-2.28
3	0.28	0.16	0.32	-0.01	4.14	1.94	3.62	-0.13
DG Fast	0.34	0.32	0.20	0.19	5.60	3.16	1.88	1.58
		c				t(c)		
DG Slow	0.12	0.24	0.20	0.15	1.62	2.14	1.77	0.96
2	0.39	-0.06	0.00	-0.19	5.24	-0.58	-0.01	-1.69
3	0.46	0.34	0.04	0.09	5.51	3.45	0.35	0.78
DG Fast	0.17	0.09	0.07	0.01	2.25	0.75	0.51	0.04
		f				t(f)		
DG Slow	-0.49	-0.25	-0.30	-0.01	-11.15	-3.82	-4.71	-0.12
2	-0.10	0.01	-0.15	-0.16	-2.26	0.24	-2.40	-2.52
3	-0.05	0.16	0.20	0.05	-0.98	2.71	3.10	0.69
DG Fast	0.50	0.27	0.07	0.09	11.65	3.76	0.88	1.06

Table 11: **Regressions for 16 value-weighted *DG-OP* portfolios: 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015. The data are sourced from Ken French's website.
At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three *DG* groups and three *DY* groups independently with breakpoints at the 30^{th} and 70^{th} percentile of that quarter. *DG* is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. *DY* is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of the fast *DG* group minus the returns of the slow *DG* group and *PMF* is the returns of prodigal *DY* group minus the returns of the frugal *DY* group.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + r_j RMW_t + c_j CMA_t + f_j FMS_t + e_{j,t}$.

OP	Low	2	3	High	Low	2	3	High
		a				t(a)		
DG Slow	0.25	-0.34	-0.17	0.36	0.62	-1.30	-0.59	1.95
2	-0.30	0.10	0.04	-0.32	-0.95	0.37	0.20	-2.02
3	0.02	0.19	-0.02	-0.04	0.06	0.73	-0.12	-0.24
DG Fast	-0.16	-0.32	0.24	-0.02	-0.43	-1.19	0.95	-0.10
		b				t(b)		
DG Slow	0.96	1.07	1.04	0.87	9.83	16.42	14.42	18.97
2	1.18	0.99	1.06	0.91	15.29	14.70	20.92	23.33
3	1.03	0.94	0.97	0.91	13.88	14.57	20.04	20.48
DG Fast	1.13	1.06	1.10	1.01	12.60	16.14	17.96	22.76
		s				t(s)		
DG Slow	0.17	0.13	0.06	-0.02	1.27	1.48	0.64	-0.33
2	0.36	-0.12	0.01	-0.19	3.46	-1.30	0.22	-3.66
3	0.13	-0.08	-0.06	-0.16	1.24	-0.87	-0.91	-2.70
DG Fast	0.25	0.30	-0.09	0.06	2.02	3.32	-1.06	1.03
		h				t(h)		
DG Slow	0.25	0.34	0.18	-0.21	1.45	2.99	1.46	-2.63
2	0.50	0.12	0.41	-0.04	3.64	1.04	4.63	-0.63
3	0.47	0.05	0.28	-0.03	3.60	0.47	3.24	-0.42
DG Fast	0.65	0.31	0.17	-0.07	4.12	2.68	1.61	-0.86
		r				t(r)		
DG Slow	-0.03	0.36	0.09	0.47	-0.13	2.80	0.61	5.17
2	0.32	-0.05	0.47	0.51	2.06	-0.39	4.71	6.58
3	0.08	-0.18	0.15	0.45	0.54	-1.44	1.53	5.09
DG Fast	-0.19	0.55	0.05	0.53	-1.09	4.24	0.44	5.98
		c				t(c)		
DG Slow	-0.20	0.22	-0.36	0.43	-0.81	1.36	-2.04	3.83
2	0.07	0.12	-0.08	0.40	0.37	0.72	-0.64	4.22
3	-0.01	0.54	0.23	0.44	-0.06	3.41	1.98	4.07
DG Fast	-0.10	0.15	-0.43	0.14	-0.46	0.95	-2.88	1.31
		f				t(f)		
DG Slow	0.30	-0.12	-0.71	-0.49	2.18	-1.32	-6.96	-7.56
2	-0.02	-0.05	0.01	-0.17	-0.19	-0.56	0.08	-3.03
3	0.06	0.00	0.21	-0.10	0.60	0.01	3.01	-1.65
DG Fast	0.34	0.02	0.76	0.64	2.69	0.18	8.77	10.19

Table 12: **Regressions for 16 value-weighted *DG-Inv* portfolios: 1996-2015.**

$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015. The data are sourced from Ken French's website.
At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three *DG* groups and three *DY* groups independently with breakpoints at the 30^{th} and 70^{th} percentile of that quarter. *DG* is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. *DY* is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of the fast *DG* group minus the returns of the slow *DG* group and *PMF* is the returns of prodigal *DY* group minus the returns of the frugal *DY* group.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + r_j RMW_t + c_j CMA_t + f_j FMS_t + e_{j,t}$.

Inv	Low	2	3	High	Low	2	3	High
		a				t(a)		
DG Slow	0.14	-0.12	0.16	-0.21	0.68	-0.55	1.05	-0.96
2	-0.11	-0.15	-0.23	0.12	-0.62	-1.06	-1.33	0.58
3	-0.01	0.03	-0.04	-0.17	-0.04	0.18	-0.22	-0.83
DG Fast	-0.18	-0.13	-0.02	-0.04	-0.93	-0.76	-0.10	-0.22
		b				t(b)		
DG Slow	0.95	1.01	1.03	1.08	18.37	19.38	28.05	20.19
2	1.04	1.04	1.00	0.93	23.52	30.03	23.34	18.40
3	1.03	0.91	0.92	1.05	20.03	25.08	22.23	21.33
DG Fast	0.99	1.01	1.00	1.14	20.34	24.32	26.06	23.31
		s				t(s)		
DG Slow	-0.06	-0.03	-0.11	0.16	-0.81	-0.49	-2.30	2.15
2	-0.02	-0.18	-0.27	-0.31	-0.27	-3.84	-4.69	-4.45
3	-0.18	-0.08	-0.17	-0.17	-2.65	-1.64	-3.05	-2.59
DG Fast	0.05	0.08	-0.09	-0.09	0.76	1.44	-1.80	-1.38
		h				t(h)		
DG Slow	0.24	-0.22	0.20	0.14	2.65	-2.39	3.16	1.48
2	0.03	0.14	0.32	0.35	0.44	2.34	4.28	3.93
3	0.13	0.19	0.24	0.40	1.44	2.93	3.27	4.56
DG Fast	0.19	0.20	0.14	0.26	2.26	2.79	2.00	2.98
		r				t(r)		
DG Slow	0.11	0.18	0.16	0.45	1.10	1.74	2.22	4.25
2	0.49	0.27	0.28	0.21	5.63	3.89	3.28	2.08
3	0.05	0.28	0.27	0.26	0.45	3.83	3.30	2.64
DG Fast	0.16	0.31	0.24	0.13	1.63	3.83	3.22	1.33
		c				t(c)		
DG Slow	0.15	1.04	-0.24	-0.16	1.19	8.14	-2.64	-1.24
2	0.64	0.27	0.22	-0.22	5.93	3.24	2.15	-1.75
3	0.71	0.39	0.34	-0.04	5.62	4.40	3.39	-0.35
DG Fast	0.62	0.11	0.16	-0.31	5.17	1.10	1.75	-2.60
		f				t(f)		
DG Slow	-0.23	-0.43	-0.34	-0.39	-3.18	-5.86	-6.62	-5.19
2	0.11	-0.10	-0.13	0.03	1.71	-2.09	-2.09	0.45
3	0.02	0.00	0.05	0.16	0.22	0.08	0.79	2.22
DG Fast	0.15	0.39	0.20	0.59	2.20	6.69	3.76	8.53

Table 13: **Regressions for 16 value-weighted *DG-DY* portfolios: 1996-2015.**

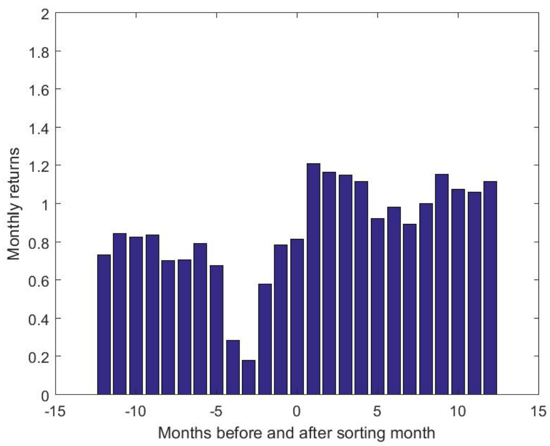
$R_M - R_F$ is the value-weighted return on the market portfolio of all stocks in the sample of Fama and French (2015) minus the one-month Treasury bill rate. Factors *SMB* for *Size*, *HML* for *Book-to-Market*, *RMW* for *Operating Profitability* and *CMA* for *Investment* are all defined as described in Fama and French (2015. The data are sourced from Ken French's website.
At the second quarter of each calendar year in the period 1996-2015, stocks are allocated to three DG groups and three DY groups independently with breakpoints at the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentile of that quarter. DG is defined as the growth rate of the average of the implied dividend in the third and the fourth quarter of the calendar year relative to the dividend paid in the second quarter. DY is the dividend paid in the second quarter relative to the average daily share price in the second quarter. Factor *FMS* is the returns of the fast DG group minus the returns of the slow DG group and *PMF* is the returns of prodigal DY group minus the returns of the frugal DY group.

The regression equation is: $R_{j,t} - R_{F,t} = a_j + b_j(R_{M,t} - R_{F,t}) + s_j SMB_t + h_j HML_t + r_j RMW_t + c_j CMA_t + f_j FMS_t + e_{j,t}$.

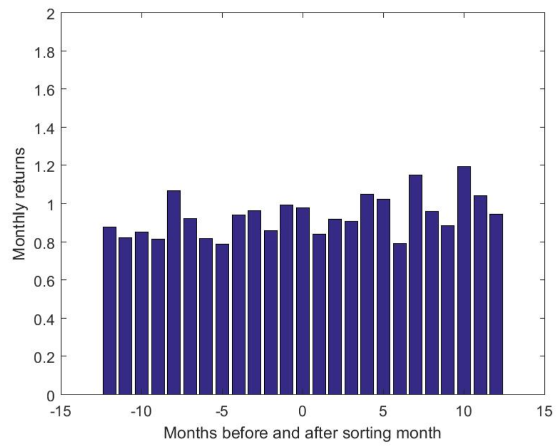
DY	Low	2	3	High	Low	2	3	High
	a				t(a)			
DG Slow	0.22	-0.15	0.01	-0.42	0.82	-0.77	0.03	-2.02
2	-0.19	-0.25	-0.04	0.07	-0.82	-1.43	-0.32	0.32
3	0.08	-0.30	0.05	0.18	0.33	-1.78	0.29	1.12
DG Fast	-0.18	-0.08	-0.08	0.14	-1.39	-0.42	-0.39	0.70
	b				t(b)			
DG Slow	1.10	0.98	1.02	1.00	16.74	20.84	20.55	19.57
2	1.14	1.07	0.97	0.86	19.49	24.85	28.68	16.74
3	1.05	1.03	0.91	0.74	16.80	25.20	23.19	18.68
DG Fast	1.16	1.02	0.94	0.78	35.91	21.43	19.17	15.51
	s				t(s)			
DG Slow	0.08	0.03	-0.12	0.01	0.85	0.47	-1.86	0.07
2	-0.29	-0.07	-0.24	-0.10	-3.67	-1.19	-5.29	-1.42
3	-0.12	-0.12	-0.11	-0.12	-1.38	-2.26	-2.03	-2.15
DG Fast	-0.06	0.14	0.20	0.02	-1.44	2.13	2.95	0.36
	h				t(h)			
DG Slow	0.10	0.09	-0.01	0.40	0.87	1.09	-0.06	4.46
2	0.05	0.03	0.14	0.65	0.53	0.45	2.35	7.14
3	0.16	0.14	0.20	0.49	1.43	1.99	2.86	6.97
DG Fast	0.10	0.38	0.37	0.72	1.74	4.57	4.25	8.12
	r				t(r)			
DG Slow	0.09	0.43	0.47	0.27	0.72	4.60	4.76	2.71
2	0.13	0.63	0.37	0.03	1.15	7.39	5.56	0.27
3	0.08	0.33	0.32	0.12	0.64	4.03	4.07	1.52
DG Fast	0.19	0.31	0.35	0.15	2.93	3.27	3.59	1.52
	c				t(c)			
DG Slow	-0.42	0.20	0.56	0.38	-2.61	1.77	4.59	3.01
2	0.07	0.42	0.24	-0.04	0.48	3.99	2.87	-0.34
3	0.38	0.33	0.22	0.24	2.47	3.35	2.35	2.47
DG Fast	0.00	0.18	0.21	-0.22	0.05	1.56	1.72	-1.75
	f				t(f)			
DG Slow	-0.24	-0.37	-0.12	-0.31	-2.55	-5.51	-1.68	-4.32
2	-0.06	-0.06	0.00	-0.10	-0.72	-1.00	-0.06	-1.40
3	0.06	-0.05	0.06	-0.02	0.66	-0.91	1.06	-0.35
DG Fast	0.54	0.01	0.00	-0.03	11.89	0.09	-0.04	-0.46

Figure 1: **Monthly value-weighted returns of portfolios of stock sorted at month = 0 by dividend growth implied 6 months ahead of the sorting month.**

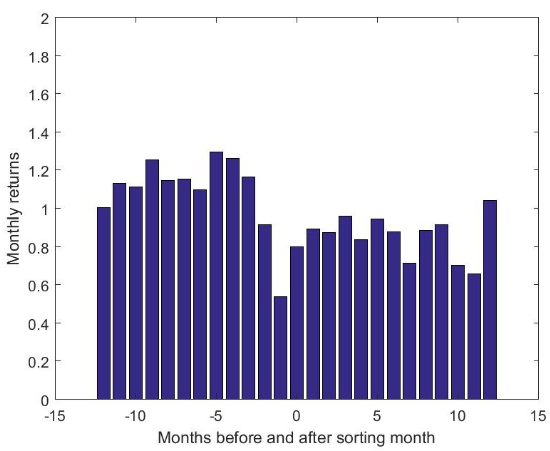
Returns refer to the 12 months before and after the sorting month. Stocks are sorted each month. Period: July 1997 – June 2015.



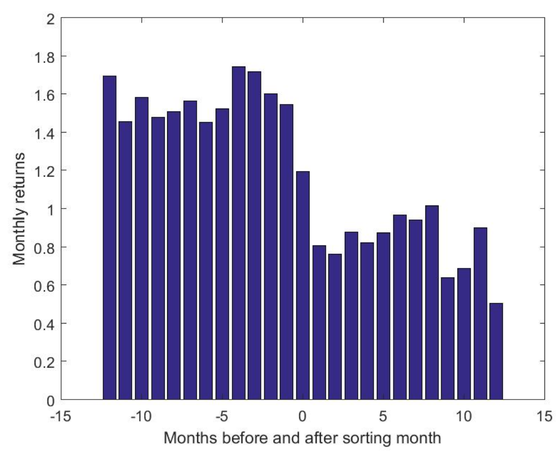
(a) 1^{st} quartile dividend growth



(b) 2^{nd} quartile dividend growth



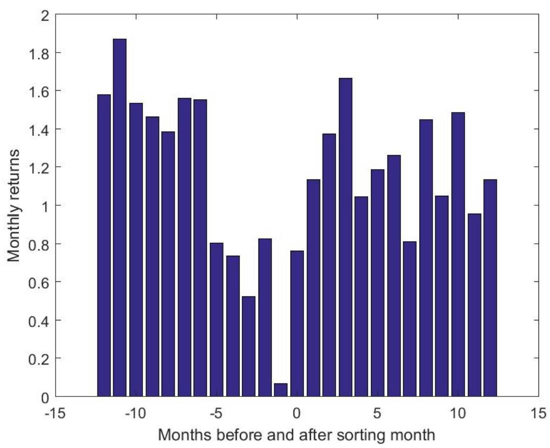
(c) 3^{rd} quartile dividend growth



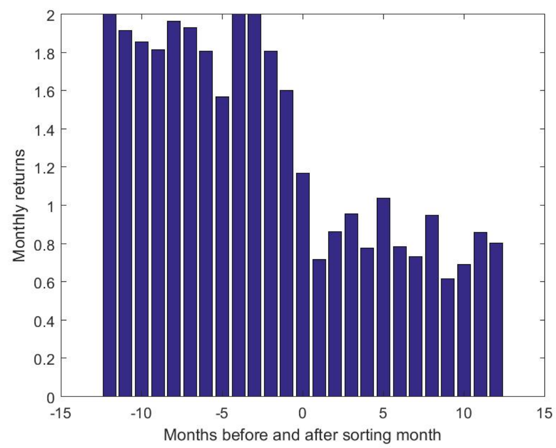
(d) 4^{th} quartile dividend growth

Figure 2: **Monthly value-weighted returns of portfolios of stock double-sorted at month = 0 by dividend yield and by dividend growth implied 6 months ahead of the sorting month.**

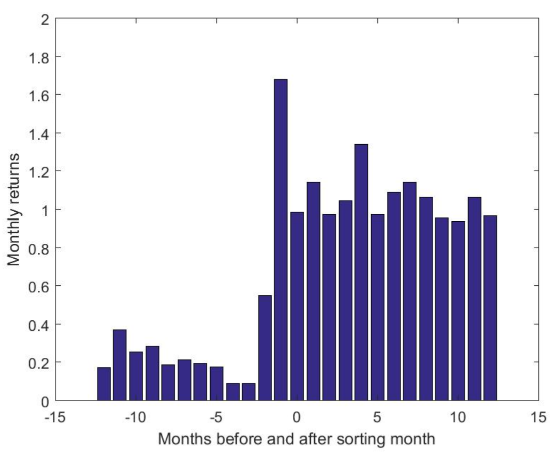
Low dividend yield and slow dividend growth refer to the first quartile and high dividend yield and fast dividend growth to the fourth quartile. Returns refer to the 12 months before and after the sorting month. Stocks are sorted each month. Period: July 1997 – June 2015.



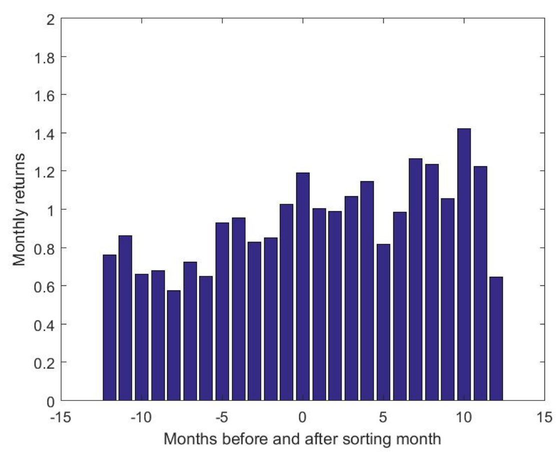
(a) Low dividend yield and slow dividend growth



(b) Low dividend yield and fast dividend growth



(c) High dividend yield and slow dividend growth



(d) High dividend yield and fast dividend growth