Profitability, R&D Investments and the Cross-Section of Stock Returns

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Abstract

In this paper, after controlling for the level of R&D expenditures, I find that profitability of R&D intensive firms is more important for subsequent returns than the R&D intensity (measured with R&D-to-market value or R&D-to-assets) and past performance. In a sample of firms where I am able to compute abnormal returns around quarterly earnings announcements R&D-to-market value variable becomes insignificant even when not controlling for the firm's profitability. Since quarterly profits are reported by big firms this suggests that R&D anomaly is driven by small stocks. Big firms with high R&D-to-market value earn lower not higher subsequent returns, once I control for the level of R&D expenditures and firm's profitability. The previously recorded anomaly, namely that R&D intensive firms earn positive abnormal returns, seems to be driven by the level of R&D investment, its profitability and small stocks.

1. Introduction

Why are expected returns of firms which invest heavily in R&D so low? Or put differently, what is driving positive abnormal returns of firms with large R&D outlays and low market value? In the cross-section of stock returns asset pricing models systematically underprice firms with large R&D outlays and low market value. To explain these abnormal returns, Chan et al. (2001) make use of behavioral arguments. They argue that, on one hand, managers are investing large R&D outlays despite poor past performance because they are relatively optimistic about the firm's future prospects. On the other hand, however, market participants discount poor past performance too heavily and are sluggish in revising their expectations. Therefore, returns of high R&D-to-market value firms are lower in the beginning and reverse in long-term. This patter is similar to long run reversals uncovered by De Bondt and Thaler (1985). After controlling for book-to-market and size firms which commit to large R&D outlays, with high R&D-to-market value (RDM), have positive abnormal returns which are associated but not subsumed by poor past performance.

Since profitability is known to be persistent and a robust predictor of future returns (Novy-Marx, 2013, Fama and French, 2015), Novy-Marx (2013) investigates how important is gross

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profitability for explaining positive abnormal returns of high R&D-to-market value firms. He finds that gross profits-to-assets variable retains power after controlling for R&D-to-market value but it does not subsume it.

My first contribution is to test if (gross) profitability subsumes the power of R&D-to-market value (RDM) to predict future returns once I control for R&D-to-profits and past performance. I disentangle how much of profit firm invests into R&D from firm's profitability using a twofold decomposition of R&D-to-assets variable which is similar to Du Pont's decomposition of return on investment into an asset turnover and profit margin.[2] In particular, I test whether abnormal returns to firms with a high R&D-to-market are driven by the effect R&D has on future profitability, or if power of R&D to predict future returns derives from share of the profit invested into R&D, firm's past performance, or both. In cross-sectional regressions I control for the book-to-market and size.

If market participants are slow in recognizing management's signals, profitability should not predict subsequent returns in cross sectional regressions once I control for the R&D-to-market value, the R&D-to-profits and firm's past performance. However, if gross profitability preserves its significance after controlling for R&D-to-profits and firm's past performance, while R&D-to-market value does not, it is the firm's profitability which matters for asset pricing, and the market distinguishes between firms which are driven by profitability motives when committing to high R&D investments from those firms which are unprofitable. This is my main finding.

In the second part of the paper I focus on earnings momentum. Novy-Marx (2015) shows that strategies based on the earnings momentum are explaining the performance of the price momentum. Stocks which were performing well over the prior year will continue to outperform stocks which have performed poorly over the prior year due to momentum in earnings. Returns of firms with higher profitability and positive earnings surprises are on average higher than firms with the weak profitability which have recently announced below

[2] Soliman (2008) finds that DuPont analysis represents incremental information about the firm's operating performance.

expected earnings. Novy-Marx (2015) shows that major part of price momentum is concentrated around days when firms are reporting quarterly earnings.

My second contribution is to test if R&D-to-market value and past performance retain power to predict subsequent returns in cross-sectional regressions, after controlling for earnings momentum, gross profitability, and the level of R&D. Chan et al. (2001) find that R&D intensive firms (measured with R&D-to-market value) have lower current profitability than firms doing no R&D. On the contrary, future growth in earnings of high R&D-to-market value firms is higher. Therefore, since available at a yearly frequency, gross profitability could be a poor signal for future profitability of R&D intensive firms. Additionally, since positive abnormal returns to high R&D-to-market value (RDM) firms, are more likely to be associated but not completely driven by firms with poor past performance, I test if earnings momentum subsumes poor past price performance, predicts subsequent returns, and therefore provides an early signal for improvements in profits of R&D intensive firms.

However, even when not controlling for earnings momentum and gross profitability the average coefficient estimated on the R&D-to-market value is not significant in a sample where I am able to compute earnings momentum variables. The number of firms which report quarterly profits and nonzero R&D expenditures is lower, and firms are on average bigger than firms with non-zero R&D expenditures. That is why I investigate how important are small stocks for explaining the R&D anomaly. In a subsample of big firms, with above median market capitalization, the average coefficient estimated on the R&D-to-market value variable becomes negative (changes direction) and significant at 10% level, once I control for gross profitability and the level of R&D expenditures. That is, once I control for R&D-to-gross profits, big firms with higher gross profitability have higher average returns, whereas the R&D-to-market value variable seems to be picking up the effect of past losers which continue to loose.

The paper is organized as follows. Section 2 presents findings on R&D investments and subsequent stock returns. Section 3 presents the sample and the data. Section 4 presents main asset pricing results. Section 5 investigates the importance of small stocks for R&D anomaly. Section 6 concludes.

2. R&D Investments and Subsequent Stock Returns

Chan et al. (2001) test the relation between R&D intensity and future excess returns by sorting firms based on the R&D-to-market value (RDM), defined as:

$$\frac{Annual\ R\&D\ Expenditures_{i,t}}{Market\ Value_{i,t}} = RDM_{i,t} \tag{1}$$

Chan et al. (2001) argue that firms which spend heavily on R&D despite poor past performance represent instances where managers are relatively optimistic about the firms' future prospects. Firms with high R&D-to-market value (RDM) earn average abnormal return of 6.12 percent in three years after portfolio formation. Each stock is matched with a control portfolio based on size and book-to-market. Abnormal return is the difference between the stock's annual buy-and-hold return and the return on the control portfolio.

Despite their poor performance, firms in the top quintile of R&D-to-market value (RDM) portfolios spend a substantial portion of sales (in excess of 11 percent) on R&D. They argue that management beliefs are credible since R&D spending needs to be expensed immediately (FAS No. 2, 1974) while benefits of R&D spending accrue to a firm over several years in the future. Annual earnings growth over 5 post formation years for firms which are in the top quintile of R&D-to-market value (RDM) portfolio is 17.13 percent, compared to 10.15 percent for firms with no R&D. Firms in the top quintile portfolio have a lower earnings-to-price, 0.0311, compared to low quintile portfolio firms, 0.0651. Therefore, high RDM firms have depressed current but higher future earnings and sales growth. These findings suggest that simply observing current profitability (net income before extraordinary items) represents an insufficient proxy for improved prospects about future profitability of R&D intensive firms (measured with R&D-to-market value).

In double sorts on R&D-to-sales and past returns, abnormal performance is concentrated in portfolios with relatively low past returns. After controlling for lower past performance the high minus low R&D investment spread in average annual abnormal return in the first three years following portfolio formation decreases from 7.83 to 5.09 percent. Since portfolio sorts are directly conditioned on past returns, R&D intensity is measured with R&D-to-sales. Chan et al. (2001) find that positive abnormal returns to R&D intensive firms (measured with

R&D-to-market value) are more likely to be associated, but not completely driven by firms with poor past performance. The authors argue that positive abnormal returns to high R&D-to-market value firms emerge since market participants discount poor past performance too heavily and are sluggish in revising their expectations.

However, this is to some extent tautological, as the factor model's failure to price a strategy is used as the defining characteristic of an anomaly. Another argument would be to say that factors driving asset prices insufficiently sum the information in the conditional set. To explain positive abnormal returns to high R&D-to-market value (RDM) firms, Lin (2012) proposes a model where technological progress is endogenously driven by R&D investment. Part of the firm's technological progress is devoted to new products, whereas the rest increases the *productivity* of physical investment. Successful innovations increase the productivity of equipment and machines and reduce the cost of production process. This generates the necessary contemporaneous positive covariation between R&D investment and future stock returns and a negative covariation between physical investment and future stock returns.

In this model a firm's expected return on physical investment is increasing in R&D investment but decreasing in physical investment. All else being equal, on the one hand, R&D investment increases the expected marginal benefit of physical investment. On the other hand, R&D investment decreases the marginal cost of physical investment. These two effects reinforce each other and imply that R&D investment increases expected returns on a physical investment. Since more of physical investment, ceteris paribus, is eventually decreasing marginal benefits while increasing marginal costs (law of diminishing returns), stock returns are increasing in R&D investment but decreasing in physical investment.

The second implication is that high R&D intensive firms have higher, while high physical investment intensive firms have lower expected returns. The model generates high minus low R&D investment spread equal to 8.75 percent in the first year after portfolio formation, which is similar to the one observed in the data, 12.06 percent. Stock returns are adjusted for book-to-market and size characteristics. Lin (2012), however, does not control for past performance, which according to Chan et al. (2001) is associated with mispricing of R&D intensive firms.

Besides Lin (2012) no study up to now proposed a *rational* expectations explanation of positive abnormal returns to high R&D-to-market value firms. In this paper I build upon the intuition presented by Lin (2012), namely that high subsequent returns to R&D intensive firms accrue on the basis of higher average productivity and not a mispricing of R&D intensive firms. I build upon the profitability factor of the Fama and French (2015) five factor model. Specifically, Novy-Marx (2013) proposes gross profitability as a priced risk factor in a cross section of stock returns.[3] As he notices, since R&D expenditures need to be expensed immediately, gross profits (revenues minus costs of goods sold) better gauge the underlying profitability of R&D intensive firms than net income. I use Novy-Marx's (2013) gross profitability to explain abnormal returns of R&D intensive firms recorded by Chan et al. (2001) once I condition on the *level* of R&D investment.

Net income is reduced by any investments that are treated as expenses, such as research and development (R&D). R&D investments are associated with higher future economic profits and dividends and therefore increase book equity, but are expensed in the current period, and therefore directly reduce earnings (net income before extraordinary items). On the other hand, gross profitability measures a firm's earnings before items such as R&D expenditures. Since a firm's earnings should represent true economic profitability, gross profitability should be a better proxy for the profitability of the firm with large R&D outlays. Novy-Marx (2013) finds that gross profitability retains power but does not subsume the power of R&D-to-market value to predict future returns. In cross-sectional regressions of future returns, Novy-Marx (2013) finds that the estimated coefficients on both, gross profits-to-assets, and R&D-to-market value, are statistically significant after controlling for past returns, book-to-market, and size. This presents evidence against the hypothesis that gross profitability is subsuming the full effect of R&D, or that R&D alone can fully explain why profitable firms which are intensive in R&D earn higher expected returns. Therefore, R&D-to-market value presents additional information to gross profitability for subsequent returns of R&D intensive firms.

[3] Novy-Marx (2013) tests the power gross profits-to-assets (GPA) variable has in predicting subsequent returns, which is defined as $\frac{\text{Gross profits}_{i,t}}{\text{Total assets}_{i,t}} = GPA_{i,t}$.

However, cross sectional regressions with gross profitability and R&D-to-market value (RDM) do not disentangle the level of R&D investments from a firm's profitability. While preserving its significance when controlling for gross profitability, a more interesting question is whether market participants are able to disentangle the level of R&D investment from the firm's profitability, and reward firms which commit to a high level of R&D expenditures, and are profitable, from those which are not. Latter firms could continue to invest high proportions of the firm's gross profits in R&D due to management's stubbornness.

Chambers et al. (2002) find that monthly high minus low R&D investment spread in abnormal returns of portfolios ranked on R&D-to-assets is of similar magnitude to R&D-to-sales (0.44 compared to 0.26 percent). To test the relationship between R&D, profitability and past performance I decompose R&D-to-asset variable as follows:

$$RDA_{i,t} = \frac{Annual\ R\&D\ Expenditures_{i,t}}{Total\ Assets_{i,t}} = \underbrace{\frac{Annual\ R\&D\ Expenditures_{i,t}}{\boldsymbol{Gross\ profits_{i,t}}}}_{\textbf{Level of R\&D}} \times \underbrace{\frac{\boldsymbol{Gross\ profits_{i,t}}}{Total\ Assets_{i,t}}}_{\textbf{Firm's gross profitability}} = RDGP_{i,t} \times GPA_{i,t} \tag{2}$$

This decomposition of the R&D-to-assets variable disentangles the level of R&D spending from profitability of R&D intensive firms. The first part, RDGP, measures how much of gross profits managers are investing into R&D, whereas the second part, GPA, measures the firm's (gross) profitability. The first hypothesis which I am testing is:

> *H_1: R&D intensity (RDM) predicts subsequent returns once controlled for the level of R&D spending (R&D-to-gross profits), gross profitability, and past performance.*

If market participants are sluggish in revising their expectations, they cannot disentangle the level of R&D spending (R&D-to-gross profits) from gross profitability (GPA) of R&D intensive firms. Once they observe R&D intensity (RDM) and past performance they do not impute the information about a firm's profitability after controlling for the amount spend on R&D. The second hypothesis which I am testing is:

H_2: Gross profitability predicts subsequent returns once controlled for the level of R&D spending (R&D-to-gross profits), R&D intensity (RDA or RDM), and past performance.

If Chan et al. (2001) are correct and managers are investing a substantial proportion of earnings in R&D since they are optimistic about the firm's future prospects, despite the firm's low profitability, and market participants are sluggish in revising their expectations, then the R&D-to-gross profits and gross profitability should not be significant in a cross-section of stock returns, while R&D intensity (RDM) should preserve power in predicting subsequent returns. If RDM variable preserves its significance after controlling for gross profitability, R&D-to-gross profits, and past performance, Chan et al. (2001) argument is supported by the data. Market participants should not distinguish between level of R&D spending (R&D-to-gross profits) and gross profitability of R&D intensive firms, so both should become insignificant for the cross-section of stock returns.

If gross profitability subsumes the effect of the level of R&D spending, R&D intensity (measured with R&D-to-market value) and past performance, then R&D spending predicts subsequent returns because of the increased (gross) profitability of R&D intensive firms. Market participants can distinguish between firms which are investing large R&D outlays despite being unprofitable and firms which are driven by the profitability motive in their R&D decisions. Novy-Marx (2013) controlled for R&D intensity (R&D-to-market value) when testing the predictive power of gross profitability. His focus was not on detecting the source of predictability for subsequent returns of R&D intensive firms. By adding to the regression R&D-to-gross profits, I test if RDM variable retains predictive power once I control for the level of R&D spending and the firm's profitability or high R&D spending predicts higher subsequent returns only when firm is profitable.

Earnings momentum

In cross-sectional regressions of monthly returns on past performance and earnings surprises, earnings surprises largely subsume the power of past performance to predict future monthly returns. When earnings surprises are added as explanatory variables in cross-sectional regressions the coefficient on past performance becomes insignificant. Past performance leaves estimated coefficients on earnings surprises unchanged. Novy-Marx (2015) argues past performance predicts cross-sectional variation in average stock returns because strong past performance is a signal of positive moves in fundamentals. He concludes that after controlling for fundamentals, past performance does not provide significant additional information in the cross-section of expected returns. It is robust vis-à-vis weak profitability (SUE) and above vis-à-vis below expected announced earnings (CAR3) which are driving the momentum anomaly. Table 1 summarizes these findings.

Table 1: Fama and MacBeth (1973) regressions of monthly stock returns on past performance, measured over the preceding year skipping the most recent month ($r_{2,12}$) and firms' most recent earnings surprises, measured using both standardized unexpected earnings (SUE) and the cumulative three day abnormal returns around the most recent earnings announcement (CAR3). Regressions include controls for the log of firms' market capitalizations (ln(ME)), the log of firms' book-to-market (ln(B/M)), gross profitability (GP/A) and stocks' prior month returns ($r_{0,1}$). Independent variables are trimmed at the 1% and 99% levels. The sample covers January 1975 through December 2012, with the dates determined by the data requirements for making the SUE and CAR3 categories (Novy-Marx, 2015, p. 6).

Independent variable	Estimated coefficient (t statistic in parenthesis) (1)	Estimated coefficient (t statistic in parenthesis) (2)	Estimated coefficient (t statistic in parenthesis) (3)
$r_{2,12}$	0.59		0.15
	(2.84)		(0.70)
SUE		0.27	0.26
		(17.0)	(19.2)
CAR3		5.84	5.75
		(19.7)	(20.4)
log(ME)	-0.06	-0.08	-0.08
	(-1.39)	(-1.69)	(-1.93)
log(B/M)	0.44	0.30	0.32
	(5.96)	(3.82)	(4.47)
GP/A	0.91	0.76	0.75
	(6.82)	(5.58)	(5.60)
$r_{0,1}$	-4.66	-5.83	-6.00
	(-10.2)	(-11.9)	(-12.9)

Novy-Marx (2015) defines two earnings surprise measures, *standardized unexpected earnings* (SUE) and *cumulative three day abnormal return* (CAR3). SUE is defined as the most recent year over-year change in quarterly earnings per share, scaled by the standard deviation of the earnings innovations over the last eight announcements, subject to a requirement of at least six observed announcements over the two year window (t represents quarters and not years):

$$SUE_{i,t} = \frac{EPSPXQ_{i,t} - EPSPXQ_{i,t-4}}{\sigma\left(EPSPXQ_{i,t\to(t-6,t-7,t-8)}\right)} \quad (3)$$

Where

$EPSPXQ$ – Quarterly earnings per share (basic) / excluding extraordinary items

CAR3 is defined as the cumulative return in excess of that earned by the market over the three days starting the day before the most recent earnings announcement and ending at the end of the day following the announcement.

Past performance is significant predictor of future returns (specification 1, Table 1). However, specification 3 shows earnings surprise variables subsume power of past performance to predict monthly returns. Besides becoming insignificant average coefficient on past performance shrinks by three quarters, while the coefficients on the earnings surprise variables are unchanged. Novy-Marx's (2015) finding suggests that the power of past performance to predict cross-sectional variation in expected returns derives from its correlation with earnings surprises. Additionally, SUE correlates stronger with $\mathrm{r}_{2,12}$ than with CAR3. This indicates that more of the information regarding the change in earnings per share is incorporated into prices before announcements than in the days immediately surrounding the announcements.

Stocks which have experienced long periods of underperformance tend to have low valuations as well. Novy-Marx (2015) argues that the correlation between fundamental and market valuation drives subsequent stock returns. Therefore, poor (long-run) past performance can represent a signal for value in markets where direct measures of fundamentals are unavailable. In case of firms with high RDM, fundamentals are easily observable, but the relationship between R&D and future benefits (profitability) is not. While on one hand Sougiannis (1994) and Lev and Sougiannis (1996, 1999) find positive relationship between R&D outlays and future benefits, standard setters argue that an association between R&D expenditures and subsequent benefits is not clear (FAS No. 2, 1974).

I add earnings momentum variables to current gross profitability. In particular, first group of firms has low current gross profitability and quarterly earnings which are decreasing (SUE) while companies disappointed market with most recent earnings announcement (CAR3). On the contrary, second group of firms is on a rebound, invests heavily into R&D despite low current gross profitability but has positive change in quarterly earnings and earnings surprises. In most recent earnings announcements firm surprised market positively when harvesting first benefits of undergone R&D projects. These are early signals of improved (long-run) profitability.

Past performance does not fully reveal the relationship between R&D and market valuations. I test if positive abnormal returns to R&D intensive firms are due to earnings momentum after controlling for the gross profitability and the level of R&D (R&D-to-gross profits). Put differently, I test if R&D-to-market value (R&D-to-assets) retains predictive power after controlling for the gross profitability, R&D-to-gross profits and earnings momentum:

> *H_3: Earnings surprises and the gross profitability subsume the power of past performance and R&D-to-market value (R&D-to-assets) to predict subsequent returns once controlled for the level of R&D spending (R&D-to-gross profits).*

3. Sample Construction

I follow Fama and French (2006) in constructing book-to-market (BM), market capitalization (MC) and cleaning the sample. B_t, book equity, is total assets (AT) minus liabilities (LT) plus balance sheet deferred taxes and investment tax credit (TXDITC), if available, minus preferred stock liquidating value (PSTKL) if available, or redemption value (PSTKR) if available, or carrying value (PSTK). Book equity in the regression for July of year $t+1$ is for fiscal year ending in calendar year t. The size variable, MC_t, is measured at the end of June of year $t+1$. When constructing B_t/M_t, M_t is measured at the end of December of year t.

I drop financial firms (Standard Industrial Classification codes between 6000 and 6999) and small firms with total assets less than or equal to $25 million, or book equity less than or equal to $12.5 million in year t to mitigate in sample small firm effect. I exclude firms with negative book equity or price in period t. Additionally, to be included in the sample a firm must have Compustat data for year t on book equity, revenues, costs of goods sold, R&D expenditures, shares outstanding, and assets. A firm must have market cap (price times shares outstanding) available in the Center for Research in Security Prices (CRSP) database for December of t and June of $t+1$. A firm must have quarterly data item EPSPXQ (Earnings Per Share (Basic) / Excluding Extraordinary Items) to compute SUE, and announcement dates RDQ available to compute CAR3. Additionally, firm must have returns over the three days starting the day before the most recent earnings announcement and ending at the end of the day following the announcement date available in daily CRSP database. Market return which is subtracted in computation of CAR3 is from Ken French's data library.[4]

Finally, firm must have dependent variable, monthly return, available in CRSP monthly database. Construction of $r_{0,1}$ and $r_{2,12}$ demand that firm in period t has prices for $t, t-1, t-2$ *and* $t-12$ available in CRSP monthly database. In construction of return variable I use price returns without dividends (computed as either change in price from period t *to* $t-\tau$, or RETX variable as given in CRSP database). I *do not* drop observations of firms with

[4] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

negative R&D (Compustat data item XRD) following Wharton Compustat editors' FAQ 63.[5] I drop firms with zero R&D expenditures.

4. Main Asset Pricing Results

This section tests if current gross profitability subsumes the power of R&D intensity (measured as either R&D-to-assets or R&D-to-market value) to predict cross-sectional variation in expected returns after controlling for past performance and level of R&D investments. Table 2 reports results of Fama and MacBeth (1973) regressions of monthly stock returns on the R&D-to-assets, R&D-to-market value, past performance ($r_{2,12}$), gross profitability (GPA) and R&D-to-gross profits (RDGP). Regressions include controls for size (ln(MC)), book-to-market (BM) and short horizon past performance ($r_{0,1}$). Independent variables are trimmed at the 1% and 99% levels. The full sample covers December 1975 through June 2014 when FAS no. 2 (1974) came into effect.

[5] "As explained by the data vendor (also confirmed by our internal investigation), the cases of negative XAD and XRD are very rare. However, these are NOT data errors. For example, if you take a look at the following company (Energy Focus - GVKEY=030614), you will see that it did report two consecutive years of negative R&D expenses. You will need to dig into the actual filing itself to see why this is the case. Most likely, the negative R&D expenses reflect adjustments of funds allocated in the earlier years." Available at https://wrds-web.wharton.upenn.edu/wrds/support/Additional%20Support/WRDS%20Knowledge%20Base%20with%20FAQs.cfm?folder_id=658&article_id=5724

Table 2: Fama and MacBeth (1973) regressions of monthly stock returns on past performance ($r_{2,12}$), R&D-to-assets, R&D-to-market value, R&D-to-market value lagged for one year (both numerator and denominator), gross profitability (GPA) and R&D-to-gross profits. Regressions include controls for the log of market capitalization (ln(ME)), the log of book-to-market (ln(B/M)) and prior month returns ($r_{0,1}$). Independent variables are trimmed at the 1% and 99% levels. The sample covers December 1975 through June 2014 the year when FAS No. 2 (1974) came into effect. Slope coefficients are scaled by factor 100. Slope coefficients with p-values bellow 0.10 are in bold. Regressions use Newey-West standard errors (lag 12).

Average R^2	0.043	0.047	0.053	0.056	0.051	0.057	0.059
Average number of firms	920	920	920	920	920	920	920
Number of time periods	451	451	451	451	451	451	451
Independent variable	Estimated coefficient (p-values in parenthesis) (1)	Estimated coefficient (p-values in parenthesis) (2)	Estimated coefficient (p-values in parenthesis) (3)	Estimated coefficient (p-values in parenthesis) (4)	Estimated coefficient (p-values in parenthesis) (5)	Estimated coefficient (p-values in parenthesis) (6)	Estimated coefficient (p-values in parenthesis) (7)
$r_{2,12}$	**0.44**	**0.42**	0.37	0.36	0.40	0.36	0.35
	(0.079)	**(0.098)**	(0.131)	(0.145)	(0.106)	(0.147)	(0.162)
R&D-to-market		**1.19**	**1.01**	0.18			
		(0.012)	**(0.039)**	(0.696)			
R&D-to-assets					**3.72**	**3.38**	1.90
					(0.009)	**(0.025)**	(0.294)
GPA			**0.83**	**0.92**		**0.92**	**1.08**
			(0.007)	**(0.003)**		**(0.002)**	**(0.001)**
RDGP				**1.03**			0.63
				(0.086)			(0.240)
log(ME)	**-0.15**	**-0.14**	**-0.14**	**-0.14**	**-0.12**	**-0.11**	**-0.11**
	(0.013)	**(0.016)**	**(0.019)**	**(0.017)**	**(0.025)**	**(0.032)**	**(0.034)**
log(BM)	**0.16**	0.09	0.16	**0.21**	**0.24**	**0.30**	**0.30**
	(0.087)	(0.391)	(0.202)	**(0.084)**	**(0.003)**	**(0.001)**	**(0.001)**
$r_{0,1}$	**-4.40**	**-4.44**	**-4.63**	**-4.68**	**-4.57**	**-4.75**	**-4.76**
	(0.000)	**(0.000)**	**(0.000)**	**(0.008)**	**(0.000)**	**(0.000)**	**(0.000)**

In first specification I test if past performance predicts future returns without controls for R&D intensity and profitability. Average coefficient 0.44 is statistically significant at 7.9 percent level. Other known predictors are significant as well. In next three settings, I test the predictive power of R&D-to-market value. I confirm Novy-Marx's (2013) findings, that gross profitability is not subsuming the effect of R&D-to-market value. However, using twofold decomposition and separating the gross profitability from level of R&D expenditures, R&D-to-gross profits, I find that gross profitability and R&D-to gross profits are subsuming the power of R&D-to-market value to predict monthly returns (specification 4).

As expected, R&D-to-assets variable predicts subsequent returns at a higher significance than R&D-to-market value variable (0.009 vs. 0.012). However, once I disentangle level of R&D

from gross profitability, GPA remains the only significant predictor (specification 7). That is, from three effects, R&D intensity, gross profitability and level of R&D expenditures (RDGP), investors separate and reward firms with highest gross profitability in terms of future returns. Therefore, gross profitability and level of R&D (R&D-to-gross profits) are subsuming the power of R&D intensity to predict future returns (measured with R&D-to-market-value or R&D-to-assets). Additionally, when R&D intensity is measured with R&D-to-assets gross profitability is subsuming level of R&D (R&D-to-gross profits). Cross-sectional regressions control for variables known to predict future returns.

Contrary to Chan et al. (2001) argument I find that gross profitability adds new information to R&D intensity once I condition on the level of R&D expenditures. Gross profitability retains power and subsumes the effect of R&D intensity, past performance and the level of R&D expenditures (scaled by gross profits) in cross-sectional regressions which control for known predictors of future returns. Chan et al. (2001) argument that positive abnormal returns to high R&D-to-market value firms represent instances where management is investing large R&D outlays despite low current profitability and market is slow in recognizing the endeavor is not confirmed. Cross-sectional regressions control for variables known to predict future returns.

Therefore, it is not market participants who are sluggish in revising their expectations and management signaling about future prospects of high R&D-to-market value firms, but improved future profitability which drives positive subsequent returns of high R&D-to-market value firms. I proceed by adding leading indicators for improved future prospects of R&D intensive firms. Namely, I add earnings surprise variables in cross-sectional regression.

Earnings momentum, gross profitability and R&D intensity

Number of firms where I am able to compute earnings momentum is considerably smaller than all firms which report non-zero R&D expenditures. On average there were 920 firms included in cross-sectional regressions in each month in Table 2. Number decreases to 359. Construction of earnings surprise variables, SUE and CAR3, demands quarterly profits and daily price data, in addition to annual COMPUSTAT and monthly CRSP data. That is, for each firm I compute cumulative 3 day excess return around earnings announcements and denote it CAR3. SUE is year-on-year change in quarterly earnings scaled by standard deviation of six to eight most recent earnings announcements in two year window. Table 3 presents cross-sectional regressions.

Table 3: Fama and MacBeth (1973) regressions of monthly stock returns on past performance ($r_{2,12}$), R&D-to-assets, R&D-to-market value, gross profitability (GPA), R&D-to-gross profits, standardized unexpected earnings (SUE) and the cumulative three day abnormal returns around the most recent earnings announcement (CAR3). Regressions include controls for the log of market capitalization (ln(ME)), the log of book-to-market (ln(B/M)) and prior month return ($r_{0,1}$). Independent variables are trimmed at the 1% and 99% levels. The sample covers December 1975 through June 2014, with the dates determined by the year 1975 when FAS No. 2 (1974) came into effect. Slope coefficients are scaled by factor 100. Slope coefficients with p-values bellow 0.10 are in bold. Regressions use Newey-West standard errors (lag 12).

Average R^2	0.071	0.086	0.084	0.098	0.087	0.098	0.106	0.101	0.111	0.119
Average number of firms	359	359	359	359	359	359	359	359	359	359
Number of time periods	451	451	451	451	451	451	451	451	451	451
Independent variable	Estimated coefficient (p-values in parenthesis) (1)	Estimated coefficient (p-values in parenthesis) (2)	Estimated coefficient (p-values in parenthesis) (3)	Estimated coefficient (p-values in parenthesis) (4)	Estimated coefficient (p-values in parenthesis) (5)	Estimated coefficient (p-values in parenthesis) (6)	Estimated coefficient (p-values in parenthesis) (7)	Estimated coefficient (p-values in parenthesis) (8)	Estimated coefficient (p-values in parenthesis) (9)	Estimated coefficient (p-values in parenthesis) (10)
$r_{2,12}$	**0.53**	0.18	**0.51**	0.15	**0.48**	0.44	0.43	0.12	0.08	0.07
	(0.066)	(0.547)	**(0.075)**	(0.617)	**(0.090)**	(0.112)	(0.126)	(0.673)	(0.791)	(0.803)
R&D-to-assets					2.06	2.22	2.33	1.67	1.84	1.86
					(0.323)	(0.299)	(0.437)	(0.431)	(0.397)	(0.517)
R&D-to-market			0.87	0.77						
			(0.393)	(0.464)						
GPA						**0.74**	**0.77**		**0.75**	**0.79**
						(0.020)	**(0.040)**		**(0.018)**	**(0.029)**
RDGP							-0.14			-0.10
							(0.873)			(0.900)
SUE		**0.17**		**0.17**				**0.17**	**0.18**	**0.18**
		(0.000)		**(0.000)**				**(0.000)**	**(0.000)**	**(0.000)**
CAR3		**5.19**		**5.28**				**5.16**	**5.15**	**5.12**
		(0.000)		**(0.000)**				**(0.000)**	**(0.000)**	**(0.000)**
log(ME)	**-0.14**	**-0.15**	**-0.13**	**-0.14**	**-0.11**	**-0.11**	**-0.11**	**-0.12**	**-0.12**	**-0.12**
	(0.005)	**(0.004)**	**(0.008)**	**(0.005)**	**(0.013)**	**(0.020)**	**(0.017)**	**(0.010)**	**(0.016)**	**(0.014)**
log(BM)	0.06	0.07	0.00	0.01	0.10	**0.18**	**0.17**	0.11	**0.19**	**0.19**
	(0.595)	(0.518)	(0.999)	(0.914)	(0.260)	**(0.063)**	**(0.070)**	(0.227)	**(0.047)**	**(0.052)**
$r_{0,1}$	**-4.22**	**-5.18**	**-4.42**	**-5.41**	**-4.42**	**-4.66**	**-4.70**	**-5.40**	**-5.64**	**-5.67**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

R&D intensity, measured either with R&D-to-market value or R&D-to-assets, loses predictive power in sample where I am able to compute earnings surprises. Besides being measured less efficiently, average R&D-to-assets coefficient falls down from 3.72 to 2.06. Similarly, average coefficient estimated on R&D-to-market value variable falls down from

1.19 to 0.87. Both coefficients, 2.06 and 0.87, are not statistically significant at 10% level. Firms in this sample report quarterly earnings and nonzero R&D expenditures.

I confirm findings of Novy-Marx (2015) that in this sample earnings momentum is subsuming the past performance in predicting subsequent returns. When I add controls for earnings momentum (SUE and CAR3 variables) average coefficient estimated on past performance falls from 0.53 to 0.18, and becomes statistically insignificant (specifications 1 and 2). Average coefficients estimated on gross profitability (GPA) and R&D-to-gross profits variable (RDGP) remain of similar magnitude in regressions with and without controls for earnings momentum (specifications 6, 7, 9 and 10). Although not being significant, average coefficient estimated on RDGP variable is negative. That is, contrary to Chan et al. (2001) argument, in this sample, market participants seem to penalize management if it invests large R&D outlays (relative to gross profits) and R&D is not productive (after controlling for current gross profitability). The effect is not driven by earnings momentum.

In sample where I am able to compute earnings momentum variables (firms which report quarterly profits) R&D intensity loses while gross profitability retains power predicting future returns. The effect is not driven by momentum in earnings. Earnings momentum variables lower average coefficient estimated on R&D-to-assets variable from 2.06 to 1.67 while average coefficients estimated on gross profitability (GPA) and R&D-to-gross profits (RDGP) are unchanged. Cross-sectional regressions control for variables known to predict future returns.

Since R&D intensity loses power predicting returns in this sample and since Chan et al. (2001) do not report anywhere that they cut off microcaps with total assets less than or equal to $25 million, or book equity less than or equal to $12.5 million in year t, nor that they exclude stocks with negative book equity, Chan et al. (2001) results could be driven by small stocks and outliers. In annual COMPUSTAT tapes sample size shrinks from 108,347 yearly observations to 70,048 when imposing these restrictions.

5. Small Stocks and R&D Anomaly

In final section I investigate what drives the discrepancy between results in Table 2 and Table 3. I noticed that median market capitalization in sample where I am able to compute earnings surprises is almost twice as big as in the original sample. Both medians are below overall median of NYSE market capitalization in period from 1976 to 2014. Table 4 presents the results.

Table 4: Median market capitalization of firms which report nonzero R&D expenditures and where I am able to compute CAR3 and SUE categories (report quarterly results), which report nonzero R&D expenditures and do or do not report quarterly profits, and of all NYSE stocks (in thousands of dollars)

Time period	Full sample (firms which report nonzero R&D expenditures)	Small sample (with SUE and CAR3)	Median NYSE market capitalization
31.12.1976	73,780	319,526	131,620
31.12.1981	228,862	521,001	232,910
31.12.1986	164,984	354,765	431,420
31.12.1991	139,219	351,532	553,330
31.12.1996	248,193	411,413	792,300
31.12.2001	328,176	534,834	1,163,790
31.12.2006	470,984	602,723	2,235,960
31.12.2011	668,075	745,431	2,014,950
31.12.2013	695,434	734,744	2,923,480
Overall median	232,861	510,614	704,110

Since big firms are included into benchmark indexes, and scrutinized by the investment community, they are more prone to reporting their quarterly results than small firms. I ran cross-sectional regressions in the subsample of big firms to confirm this intuition. Table 5 presents the results.

Table 5: Fama and MacBeth (1973) regressions of monthly stock returns in the subsample of large firms (above median market capitalization in year t) on past performance ($r_{2,12}$), R&D-to-assets, R&D-to-market value, gross profitability (GPA) and R&D-to-gross profits. Regressions include controls for the log of market capitalization (ln(ME)), the log of book-to-market (ln(B/M)) and prior month return ($r_{0,1}$). Independent variables are trimmed at the 1% and 99% levels. The sample covers December 1975 through June 2014 the year when FAS No. 2 (1974) came into effect. Slope coefficients are scaled by factor 100. Slope coefficients with p-values bellow 0.10 are in bold. Regressions use Newey-West standard errors (lag 12).

Average R^2	0.076	0.077	0.084	0.093	0.076	0.084	0.090	0.061
Average number of firms	460	460	460	460	460	460	460	920
Number of time periods	451	451	451	451	451	451	451	451
Independent variable	Estimated coefficient (p-values in parenthesis) (1)	Estimated coefficient (p-values in parenthesis) (2)	Estimated coefficient (p-values in parenthesis) (3)	Estimated coefficient (p-values in parenthesis) (4)	Estimated coefficient (p-values in parenthesis) (5)	Estimated coefficient (p-values in parenthesis) (6)	Estimated coefficient (p-values in parenthesis) (7)	Estimated coefficient (p-values in parenthesis) FULL SAMPLE
$r_{2,12}$	0.22	0.12	0.10	0.09	0.20	0.11	0.10	0.34
	(0.431)	(0.652)	(0.722)	(0.739)	(0.460)	(0.676)	(0.709)	(0.172)
R&D-to-market	0.74	0.47	-0.95	**-1.03**				-0.12
	(0.238)	(0.453)	(0.103)	**(0.056)**				(0.777)
R&D-to-assets				2.33	2.73	2.68	2.39	1.63
				(0.289)	(0.106)	(0.117)	(0.299)	(0.382)
GPA		**0.94**	**1.05**	**1.05**		**0.90**	**0.97**	**1.10**
		(0.011)	**(0.006)**	**(0.014)**		**(0.017)**	**(0.022)**	**(0.001)**
RDGP			**1.18**	0.73			0.11	**0.88**
			(0.095)	(0.369)			(0.885)	**(0.071)**
log(ME)	-0.04	-0.05	-0.05	-0.03	-0.03	-0.03	-0.03	**-0.11**
	(0.455)	(0.371)	(0.319)	(0.528)	(0.607)	(0.503)	(0.519)	**(0.037)**
log(BM)	0.07	0.15	0.22	**0.28**	0.16	**0.22**	**0.22**	**0.31**
	(0.549)	(0.262)	(0.107)	**(0.019)**	(0.109)	**(0.057)**	**(0.047)**	**(0.003)**
$r_{0,1}$	**-4.01**	**-4.26**	-4.29	**-4.39**	**-4.11**	**-4.35**	**-4.34**	-4.79
	(0.085)	**(0.000)**	(0.142)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**

In first specification I test the predictive power of R&D-to-market value variable (RDM). It is essentially gone. The next three specifications test if gross profitability retains power to predict future returns. Not only does gross profitability, in this sample, retains power to predict future returns, but once controlling for the level of R&D (RDGP), the effect of R&D-to-market value variable (RDM) changes direction. Average estimated coefficient falls from 0.74 to -0.95 and becomes marginally significant (at 10.3 percent level). Big firms with higher gross profitability and R&D-to-gross profits earn higher average returns, whereas RDM variable seems to be picking up the effect of past losers (Specification 3).

Negative predictability of RDM variable strengthens with the inclusion of R&D-to-assets variable (specification 4). Average coefficient on gross profitability does not change, whereas average coefficient on RDGP variable decreases from 1.18 to 0.73 and becomes insignificant. That is, gross profitability dominates R&D-to-assets intensity and the level of R&D expenditures (RDGP variable), while negative predictability of R&D-to-market value variable strengthens. Specifications 5 to 7 present similar results for R&D-to-assets variable.

If I compare the results in specification 5 with similar regression ran in a sample of all firms which report nonzero R&D expenditures (Table 2, specification 5) and in the subsample of firms where I am able to compute CAR3 and SUE categories (Table 3, specification 5), estimated coefficients change in magnitude. In full sample, estimated coefficient is the highest, 3.72, and statistically significant at 10 percent level. In sample with CAR3 and SUE variables average coefficient falls to 2.06 and becomes insignificant. Average estimated coefficient on big firms with above median market capitalization in year t which report nonzero R&D expenditures is equal to 2.73 and significant at 10.6 percent level. Gross profitability retains power. Estimated coefficient, 0.90, is of similar magnitude as in full sample, 0.92. Average coefficient estimated on gross profitability increases to 0.97 after controlling for level of R&D expenditures (RDGP variable) in the subsample of big firms (specification 7).

Last specification compares results of a regression ran in a sample of all firms, small and big, which report nonzero R&D expenditures. Again, average coefficient estimated on R&D-to-market value variable changes direction, but not enough to become significant. Interestingly, after controlling for both R&D intensity variables, R&D-to-assets and R&D-to-market value, the level of R&D expenditures becomes significant. That is, once I control for R&D-to-assets intensity, market participants reward firms with high R&D expenditures relative to gross profits which are profitable, whereas high R&D-to-market value intensity seems to be picking up the effect of past losers. In full sample, however, last effect is not strong enough to become significant.

For big firms which report nonzero R&D expenditures predictive power of R&D-to-market value variable (RDM) vanishes. Average coefficient on R&D-to-assets variable falls from 3.72

to 2.73, significant at 10.6 percent level. When I add gross profitability and the level of R&D (RDGP) into regression, average coefficient on RDM variable changes direction from 0.74 to -0.95, and becomes significant at 10.3 percent level. With the inclusion of R&D-to-assets variable negative predictability of R&D-to-market value variable strengthens while gross profitability dominates level of R&D expenditures (RDGP variable) and the R&D-to-assets. Gross profitability is subsuming power of R&D-to-assets and level of R&D expenditures (R&D-to-gross profits) to predict future returns.

6. Conclusions

This paper investigated the relationship between R&D intensity and subsequent returns. Using cross-sectional regressions I find that gross profitability and the level of R&D expenditures (R&D-to-gross profits) subsume the predictability of R&D-to-market value variable (RDM). When I have used R&D-to-assets as a proxy for R&D intensity, gross profitability (gross profits-to-assets) dominated the level of R&D expenditures (R&D-to-assets) as well. I do not find empirical support that positive abnormal returns to high R&D-to-market value firms represent instances where management is investing large R&D outlays despite low current profitability and market is slow in recognizing the endeavor as Chan et al. (2001) argue.

Novy-Marx (2015) finds that earnings momentum is subsuming the power of past performance to predict subsequent returns. Since the power of past performance to predict future returns is driven mainly by its cross-sectional correlation with earnings surprises, and since it is reasonable to assume that earnings momentum is an early signal of improved future profitability, I add earnings momentum variables in the cross-sectional regressions. In the sample where I am able to compute earnings momentum R&D intensity loses while gross profitability retains power to predict subsequent returns. However, this result is not driven by earnings momentum.

Firms which report quarterly earnings and where I am able to compute earnings momentum have almost twice as big median market capitalization than firms which report nonzero R&D expenditures. Median market capitalization in both samples is below overall median NYSE market capitalization. For big firms which report nonzero R&D expenditures predictive power of R&D-to-market value variable (RDM) vanishes. Average coefficient estimated on R&D-to-assets variable decreases substantially as well, from 3.72 to 2.73, and is significant at 10.6 percent level.

When I have added gross profitability and the level effect variable (RDGP) into regression, average coefficient estimated on R&D-to-market value variable became *negative* and marginally significant in the subsample of big firms. With the inclusion of R&D-to-assets variable negative predictability of R&D-to-market value variable strengthened while gross profitability dominated level of R&D expenditures (RDGP variable) and R&D-to-assets variable. Once I control for R&D-to-assets and R&D-to-gross profits big firms with higher gross profitability earn higher average returns, whereas R&D-to-market value variable seems to be picking up the effect of past losers. Therefore, predictive power of both R&D intensity variables, R&D-to-assets and especially R&D-to-market value, could be driven by small stocks.

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