Predictable Research & Development Quality: Testing an Investment Strategy

Samuel Glazer

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Gary Smith

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Abstract

This paper investigates whether one can create an alpha-generating investment strategy based on information about the quality of a firm's R&D expenditures. There is evidence that company's R&D successes are predictable, which under the semi-strong Efficient Market Hypothesis implies that this predictability is considered and priced into stock prices. This paper considers a long-short portfolio of the most research-efficient and least research-efficient firms in every year from 2004 to 2015, compared to traditional equity indices over the same time horizon. We also consider a long-only strategy that is meant to capture the upside of high-quality R&D. The paper concludes with a statistical check of R&D quality persistence and risk-adjusted returns analysis using the Fama-French three-factor model.

Introduction

Today there are three main methods of investment analysis: fundamental analysis, technical analysis, and quantitative analysis. Quantitative analysis can be viewed as a hybrid method where an investor quantifies fundamental or technical factors, or other market factors, in an attempt to create a statistical model to predict returns. Another common name for quantitative investing is factor investing. Fundamental analysts strive to consider and utilize all public information in an attempt to predict the operations of a company into the future. These analysts are given the daunting task of deciphering a firm's financial statements and assessing what future performance should look like. There are many moving pieces in a business but in spite of this complexity some are graspable. For example, most firms require some sort of yearly reinvestment, maintenance capital expenditures, just to continue normal operations. Conversely, there are other unpredictable accounting and business-related events, such as restructuring charges and write-downs, that analysts have more trouble predicting without guidance from management. Predicting these events is key to modeling the free-cash-flow a company will produce in the future, which is discounted appropriately to arrive at an estimate of the fundamental value of a company. The deployment of R&D can have a huge impact on future cash-flows, and therefore the value of a company today.

This paper pursues a further blend of quantitative and fundamental analysis, where we do not include mathematical rigor that a fully-quantitative strategy demands but we do quantify a vital fundamental characteristic: research and development efficiency. The idea is that firms who better deploy R&D expenditures are more likely to create value in the future through continued innovation and breakthroughs. This raises the question of *is good R&D predictable*? As in, *do investors consider a firm's track record in innovation when considering growth prospects?* One may reasonably expect there to be diminishing marginal return to R&D, but we wish to test if return on R&D is considered in share prices. If it is not, we would be able to devise a trading strategy that generates substantial alpha: excess return over the expected return on a stock or portfolio of stocks.

One would think that expert analysts who cover a company over long periods of time would understand the R&D channels that are expected to produce value into the future. Therefore, under the semi-strong form of the Efficient Market Hypothesis, which states that all available public information is reflected in the share price, the expected yield of R&D is incorporated in share prices. But not all R&D is deployed equally. There are many reasons why a company's R&D ventures would fall through: pursuing an extravagant breakthrough, under-funding critical research arms, failing to design clinical trials well, finding a breakthrough and failing to bring it to market, etc. We would like to identify if companies that displayed exceptional quality R&D in the past have predictable value creation that is *not* reflected in their share price. Additionally, we seek to discern if firms with poorly yielding R&D expenditures are predictably value destroying. The flipside of innovative R&D is that the firm burns through cash and awards equity-grants that dilute shareholders in a vain effort to produce sales growth through R&D. This destroys value in the form of taking away capital from projects that may have yielded above the cost of the firm's capital.

If the semi-strong form of the EMH holds empirically there should be no alpha or outperformance generated from the long-short portfolio we create in this paper. Previous literature finds that one can make reasonably accurate predictions about the yield on R&D for a given firm, so analysts should have some sense of revenue growth based on R&D

expenditures. In order to fully reject the semi-strong form of the EMH we need to show that the risk-adjusted alpha generated by our portfolio is statistically significant and not attributed to noise or luck. To this end, we have first investigated summary statistics comparing our portfolio to common market indices over the years 2004 to 2015, and then we have evaluated whether or not the portfolio produced risk-adjusted alpha.

Literature Review

The existing literature finds that investors consistently misprice R&D endeavors. In particular, the literature finds that investors are unable to properly evaluate the chances that R&D will not be profitable. Jensen (1993) finds that the inability to properly evaluate R&D efficiency leads to inflated values for R&D intensive firms. This allows an investor to profit on the short-side from a potential market reversal. Daniel and Titman (2006) show the underperformance of growth stocks is concentrated in stocks that have a lot of "intangible" information. The more recent evidence in the literature points to different measures of R&D being good predictors of future stock performance. For example, Hirshlefier *et al*. (2010) found that using a firm specific measure of R&D efficiency, patents scaled by R&D expense, they are able to forecast future returns. Additionally, Eberhart *et al*. (2004, 2008) showed that large increases in R&D expenditures predict positive future stock returns, which are robust to risk-adjusted measures and show abnormal return rather than anomalous returns. The authors believe the cause for this relationship is investors not properly internalizing the expected future benefits from increases in R&D.

The motivating piece for this paper is Cohen et al. (2012) where the authors find R&D quality is robust and simple to calculate, yet the stock market seems to largely ignore a firm's ability to produce successful R&D ventures. Their analysis is grounded in looking at a firm's past track-record in translating R&D to something of value. They find investors consistently mis-value R&D *ex-ante.* For example, the outcomes for two firms engaging in the same level of R&D can be vastly different, and the authors believe that firms with poor track records will not produce as much value at the same level of R&D. Thus, the market should take into account the quality of R&D at an individual firm, even if the firm is not investing at the optimal level of R&D. If the market was incorrect in valuing every firm's R&D expenditures, given their uncertainty regarding future cash flows, predictability would be compromised because the market will both over- and under-value the R&D. Key to their paper, the authors show that the market consistently under-estimates the value of R&D, evidenced by the strong (9%+) 4-factor alpha generated by their good-R&D portfolio. The authors take their analysis beyond stock returns and show that their measure of good quality R&D is also correlated with tangible results such as more patents, more patent citations and more new products than other firms with the same level of R&D. Finally, their paper shows the consistency in R&D quality for firms that have high quality R&D, which is important and motivating for our paper.

There is also literature that investigates the differences between capitalizing and expensing R&D expenditures. Capitalizing R&D costs (which is okay under certain circumstances, such as acquisitions) reduces the present burden of these expenses on a company's operating performance. Capitalizing R&D costs would increase cash-flow measures such as EBIT and EBITDA,[1] and therefore increase free-cash-flow and the value of the company. Lev and Sougainnis (1996) recast earnings statements for public firms and find the capitalization adjustments are significant for investors. Chan, Lakonishok and Sougainnis (2001) found that firms who exhibit higher levels of R&D intensity, as measured by *R&D/Sales* or *R&D/Market-Cap*, have higher levels of future earnings growth. In the same study, they found that *R&D/Sales* does not predict positive stock performance but *R&D/Market-Cap* does. Perhaps investors are overly pessimistic about the R&D quality of poorly-performing stocks. Or the story behind *R&D/Market-Cap* as a predictor is related to the studies discussed above, where investors are misunderstanding and mis-valuing the yield on present R&D costs relative to the size of the company.

Another interesting facet of the literature is studies that investigate mispricing or risk-discounting (excessive discounting) as the mechanism that causes the positive R&D-related abnormal returns. Chambers et al. (2002) suggest the correlation between R&D scaled investments and the abnormal returns shown in other parts of the literature is due to other risk factors that were not included in the original studies. The same authors admit

[1] Earnings Before Interest and Taxes, and Earnings Before Interest, Taxes, Depreciation and Amortization

the abnormal returns linked to R&D growth do not exhibit the same evidence and so mispricing may be the cause.

Methodology

Research Quotient

Our methodology takes advantage of the Research Quotient (RQ) as provided by Wharton Research Data Services (WRDS). RQ was developed by Anne Marie Knott at Washington University in St. Louis and is used in many of her academic papers. The RQ is defined as the firm specific sales elasticity with respect to R&D expenditures over a previous time period. A firm has high RQ if they consistently generate new products and bring them to market efficiently or generate fewer innovations but exploit them very well in market.[2] Although past performance does not indicate future performance, RQ should be correlated with efficient R&D allocation by management, and capability of R&D units within firms. Another reason we use RQ is because it can be calculated on a rolling basis and so is available for many periods. Note that the methodology employed to calculate RQ does not depend on patents, which alleviates some concerns with how patent data are interpreted.[3] It is also worth noting that RQ is consistent with Endogenous Growth Theory and is an empirical proxy for R&D productivity construct.

The RQ values in the WRDS database are estimated using a random coefficients model that allows for potential omitted variables. The random coefficients model also enables one to capture the firm-specific R&D elasticities that we want to estimate.[4] The estimates from the random coefficients model include a direct effect beta and a firm-specific beta. For the purpose of this paper we use the aggregated RQ estimate which is the

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[2] Knott, RQ User Manual
[3] Lerner and Suru (2015)
[4] For more information about the construction of RQ see: https://wrds-www.wharton.upenn.edu/documents/831/WRDS_RQ_Data_User_Manual.pdf?_ga=2.122497739.1984947321.1552081180-1745350732.1509568233

sum of the direct effect and firm-specific estimate. To construct RQ researchers run rolling regressions over a 10-year window in the Compustat database of:

$$\ln Y_{it} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i}) \ln K_{it} + (\beta_2 + \beta_{2i}) \ln L_{it} + (\beta_3 + \beta_{3i}) \ln R_{i,t-1} + (\beta_4 + \beta_{4i}) \ln S_{i,t-1} + (\beta_5 + \beta_{5i}) \ln D_{it} + \varepsilon_{it} \quad (2)$$

where the RQ measure is $(\beta_3 + \beta_{3i})$, the coefficient of the log of the one-year lagged R&D expenditures on lnY_{it} which is the revenues in year *i.* The rest of the variables are controls that are consistent with the endogenous growth theory. Within each 10-year window each firm has at minimum six years of data. The estimates for the firm-specific β_{3i} are based on a maximum likelihood estimation that gives the best linear unbiased predictions and are calculated post-regression. Lastly, the RQ in a given year is the $(\beta_3 + \beta_{3i})$, from the last year in the rolling window. For example, RQ in 2007 is formed using data from at least the 2001-2007 window.

Portfolio Construction

First, we obtain all of the available RQ data in each year 2004-2015. We sort each year based on the RQ score and take the top quintile and bottom quintile in each year. The actual number of companies each year varies, which is why we chose to use a percentage. The number of firms in each year's portfolio is nearly-monotonically increasing with the year. This trend is likely the result of the dotcom boom that engendered more firms in R&D heavy industries to become public after the turn of the millennium. This should not really affect our results because the portfolio weighting in each year depends on the stocks in the portfolio in that year. We take a long position in the top quintile in each year and a short position in the bottom quintile. For the purpose of this investigation we did not take into account margin requirements for the short positions.

The returns data we use are monthly returns, which give a feel for how the portfolio trades within each year, even though we expect the effects of R&D to have at least a one-year lag. The portfolio return is the equal-weighted return of the long positions less the return of the short positions. As each year rolls over we assume frictionless trading as we take the new long-short positions. We then calculate again the equal-weighted return in the next year. The overall portfolio return is the chained monthly returns of the portfolio each year. The result is a new portfolio each year with a long position in the highest rated RQ stocks and a short position in the lowest value RQ stocks for that particular year.

Data

The RQ data are pulled from WRDS and were constructed as mentioned above. The returns data are from the Center for Research in Security Prices (CRSP)/Compustat merged database provided by WRDS. When pulling RQ data we are able to identify at the firm level through the unique Global Company Key (GVKEY) as assigned in the Capital IQ[5] Compustat database. Tables 1, 2 and 3 in the appendix illustrate a breakdown of the summary statistics for the RQ findings based on the whole portfolio, long only and short only firms, respectively.

The minimum RQ score in the long-portfolio is much greater than the maximum RQ score in the short portfolio. It is worth noting that the mean RQ score for the entire portfolio is positive every year, although can be quite close to zero. In fact, the maximum RQ score in the short portfolio is not too far off from the average in the total portfolio. This is one of the reasons it is worthwhile to investigate a long-only version of this investment strategy.

After getting the RQ score data, we matched the GVKEYs in the merged CRSP/Compustat database to return monthly firm-level data in each year for the companies in our RQ portfolio. There were some missing datapoints in the data aggregated by CRSP, but we did not lose any whole observations. CRSP provides a calculated monthly total return, which includes dividends. The summary statistics for our portfolio returns and for the indices below will be included in the Discussion & Results section.

Tables 4 and 5 show the relative frequencies of the industries represented in our portfolios. We used the broad GICS[6] in order to classify industry.

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[5] Owned and operated by Standard and Poor's Financial Services LLC
[6] Global Industry Classification System, developed by MSCI and Standard & Poor's.

	Energy	Materials	Industrials	Consumer Discr.	Consumer Staples	Healthcare	Financials	Information Tech	Comm. Services	Utilities	Real Estate
2004	1.92%	0.00%	3.85%	4.81%	0.00%	22.12%	0.96%	58.65%	6.73%	0.96%	0.00%
2005	1.30%	2.60%	3.90%	3.90%	0.65%	25.97%	0.65%	53.90%	6.49%	0.65%	0.00%
2006	1.25%	3.75%	4.38%	4.38%	0.62%	28.12%	0.00%	52.50%	3.75%	0.62%	0.62%
2007	1.27%	5.10%	4.46%	4.46%	1.27%	28.03%	0.64%	47.77%	5.73%	0.64%	0.64%
2008	1.89%	4.40%	5.03%	5.03%	1.26%	28.93%	0.63%	45.28%	7.55%	0.00%	0.00%
2009	2.40%	5.39%	4.19%	5.39%	0.60%	30.54%	2.40%	41.32%	7.78%	0.00%	0.00%
2010	1.75%	4.09%	5.26%	7.02%	1.17%	33.92%	1.17%	38.60%	6.43%	0.58%	0.00%
2011	2.65%	4.23%	4.23%	7.94%	2.12%	33.86%	1.06%	37.04%	6.88%	0.00%	0.00%
2012	3.87%	2.21%	4.97%	4.97%	2.76%	35.36%	2.76%	37.02%	6.08%	0.00%	0.00%
2013	2.93%	3.41%	4.39%	6.83%	2.93%	35.12%	2.44%	34.15%	7.80%	0.00%	0.00%
2014	1.42%	4.72%	6.60%	6.60%	4.25%	33.96%	2.83%	33.02%	6.13%	0.00%	0.47%
2015	2.37%	4.74%	5.69%	5.69%	3.79%	35.07%	2.84%	32.70%	6.64%	0.00%	0.47%
Totals	2.13%	3.86%	4.83%	5.70%	1.98%	31.55%	1.64%	41.35%	6.52%	0.24%	0.19%

Table 4: Relative Industry Frequencies for Long-Short Portfolio

	Energy	Materials	Industrials	Consumer Discr.	Consumer Staples	Healthcare	Financials	Information Tech	Comm. Services	Utilities	Real Estate
2004	1.89%	0.00%	3.77%	5.66%	0.00%	15.09%	1.89%	66.04%	5.66%	0.00%	0.00%
2005	1.27%	1.27%	2.53%	5.06%	1.27%	20.25%	1.27%	60.76%	6.33%	0.00%	0.00%
2006	1.23%	3.70%	2.47%	7.41%	1.23%	23.46%	0.00%	54.32%	6.17%	0.00%	0.00%
2007	1.23%	6.17%	2.47%	7.41%	1.23%	24.69%	1.23%	48.15%	7.41%	0.00%	0.00%
2008	2.44%	6.10%	2.44%	6.10%	1.22%	23.17%	0.00%	47.56%	10.98%	0.00%	0.00%
2009	3.57%	7.14%	4.76%	4.76%	1.19%	25.00%	1.19%	41.67%	10.71%	0.00%	0.00%
2010	3.53%	5.88%	4.71%	8.24%	2.35%	32.94%	0.00%	35.29%	7.06%	0.00%	0.00%
2011	3.12%	6.25%	1.04%	8.33%	3.12%	36.46%	0.00%	33.33%	8.33%	0.00%	0.00%
2012	6.32%	2.11%	3.16%	6.32%	3.16%	34.74%	2.11%	34.74%	7.37%	0.00%	0.00%
2013	4.55%	3.64%	2.73%	9.09%	3.64%	33.64%	1.82%	33.64%	7.27%	0.00%	0.00%
2014	2.61%	6.09%	3.48%	7.83%	5.22%	33.04%	2.61%	33.04%	5.22%	0.00%	0.87%
2015	2.70%	5.41%	2.70%	7.21%	5.41%	33.33%	2.70%	32.43%	7.21%	0.00%	0.90%
Totals	2.99%	4.66%	2.99%	7.09%	2.71%	29.01%	1.31%	41.60%	7.46%	0.00%	0.19%

Table 5: Relative Industry Frequencies for Long-Only Portfolio

Healthcare and Information Tech are the most represented industries in both portfolios, which makes sense as they tend to be the most R&D sensitive industries. Utilities are not at all included in the long-only portfolio, but this might be due to the way in which utilities set pricing.[7] The other trend that is worth noting is how Information Tech begins in 2004 as the most represented industry but slowly gives ground to Healthcare. Since IT includes semi-conductor companies, this could be representative of Moore's law post the dot-com boom, with R&D effectiveness slowly declining. Another reason to explain the trend could be related to the dot-com boom and the decreasing marginal return to R&D in the IT space as discoveries were made rapidly. Energy seems a little underrepresented, but there are a lot of industry specific accounting rules that reduce the relevance of R&D.

Return data for the indices: S&P 500, Nasdaq Composite and Russell 1000 were obtained from Yahoo Finance and were adjusted for dividends and stock splits. These indices are generally considered the benchmarks[8] for the general stock market. The S&P 500 is a market-cap weighted index that includes many blue-chip companies. The Nasdaq Composite is a much broader index that tracks the performance of 2,633 stocks that trade on the Nasdaq exchange. The COMP is price-weighted. The Russell-1000 index includes approximately the 1000 largest companies, size based on market-cap, traded in the US. Russell-1000 is a sub-sector of the larger Russell-3000 index and is also capitalization-weighted.

Discussion & Results

After constructing the yearly portfolios described above, one finds that the long-short investment strategy yields a return largely in-line with the market indices, but with significantly less volatility.[9] The Sharpe Ratio[10] is double that of the market portfolio. One dollar invested in the RQ based long-short portfolio would have grown to $1.81 over the 12-year period with a maximum monthly loss of only 3.8%. The very bearable monthly

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[7] Utilities companies have government controls imposed that dictate price (essentially revenue) increases
[8] Some people consider them only large-cap benchmarks
[9] As measured by standard deviation of returns
[10] The excess return, over the risk-free rate, of a portfolio or security divided by its volatility

drawdown is highly significant for this investment strategy because the construction period includes the Global Financial Crisis where equities lost over half of their value. The summary statistics for the long-short portfolio are presented in the following data tables. Although the arithmetic average monthly return for our portfolio is the lowest, the Compound Annual Growth Rate (CAGR) is above that of the S&P 500 and Russell-1000.

Index	Mean Return	Volatility	Sharpe Ratio	CAGR
Portfolio	0.427%	1.75%	0.2445862	5.06%
S&P 500	0.460%	4.09%	0.1125393	4.60%
Nasdaq	0.683%	4.95%	0.1378422	6.92%
Russell 1000	0.556%	5.51%	0.1008781	4.94%

Table 6: Basic Summary Statistics for Monthly Returns of Entire Portfolio and Indices

The key feature of the entire long-short portfolio is the material reduction in volatility. One cannot attribute the reduction in volatility to diversification as many of the stocks in the portfolio will come from similar, R&D-heavy industries with positively correlated returns. The mean return figure is an arithmetic average of the monthly returns over the entire 12-year period, while the CAGR is a geometric average of the value growth over the 12-year period.

Index	Cumulative Return	Max Monthly Drawdown	Largest Monthly Gain
Portfolio	80.8%	-3.8%	7.09%
S&P500	71.5%	-16.9%	10.77%
Nasdaq	123.3%	-17.7%	12.35%
Russell	78.3%	-20.9%	15.33%

Table 7: Further Summary Statistics for Returns of Entire Portfolio and Indices

Cumulative return includes compounding effects and is indicative of the increase in value associated with a $100 investment at the beginning of the period. The portfolio exhibits a cumulative return greater than the S&P 500 and Russell-1000 over this time period, but lags behind the broader Nasdaq index. Below are histograms of the returns of the long-short portfolio and the indices. Consistent with the low volatility metric, the returns of the portfolio are very closely clustered around 0%, and look pretty normal. The Nasdaq, which is the best returning index with the highest Sharpe, has what appears to be a bi-modal distribution with many returns safely above 0%.

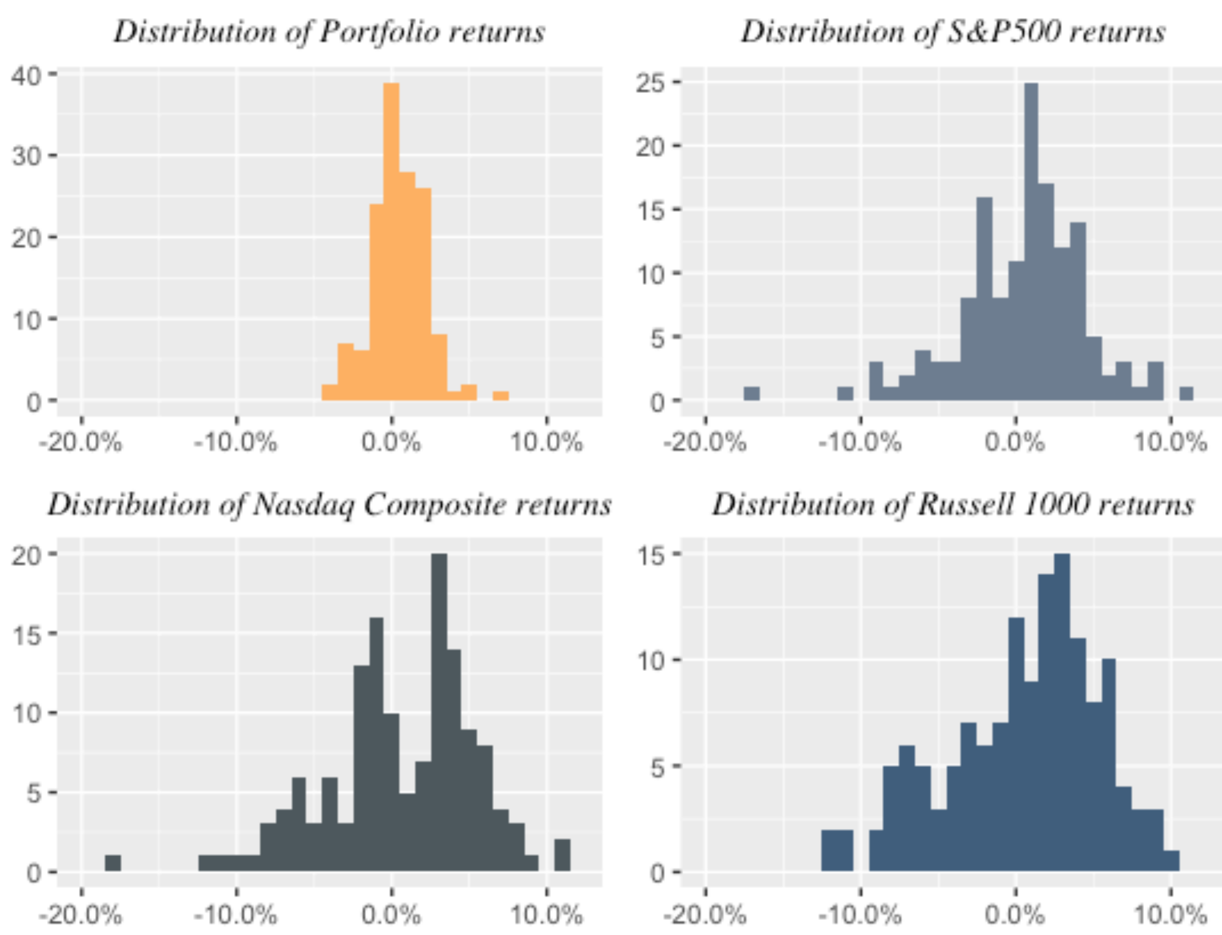

Figure 1: Histograms of the Return Distributions for the Portfolio and Indices

What the long-short strategy is lacking in eye-catching upside returns it makes up for with safe returns protecting against major downside risk. The period where our long-short strategy best outperformed the market was during 2008-2010. The strategy consistently compounds year after year which results in a fantastic upside over a longer period of time. This sort of investment technique is reminiscent of the great value-investors who buy with wide margins-of-safety and are always conscious of downside risk. The compounding speaks for itself. Warren Buffet is often quoted as saying that his favorite holding period is forever. Consider Figure 1 below: our portfolio continues to compound positively while the market indices drop below 0% for their total cumulative return.

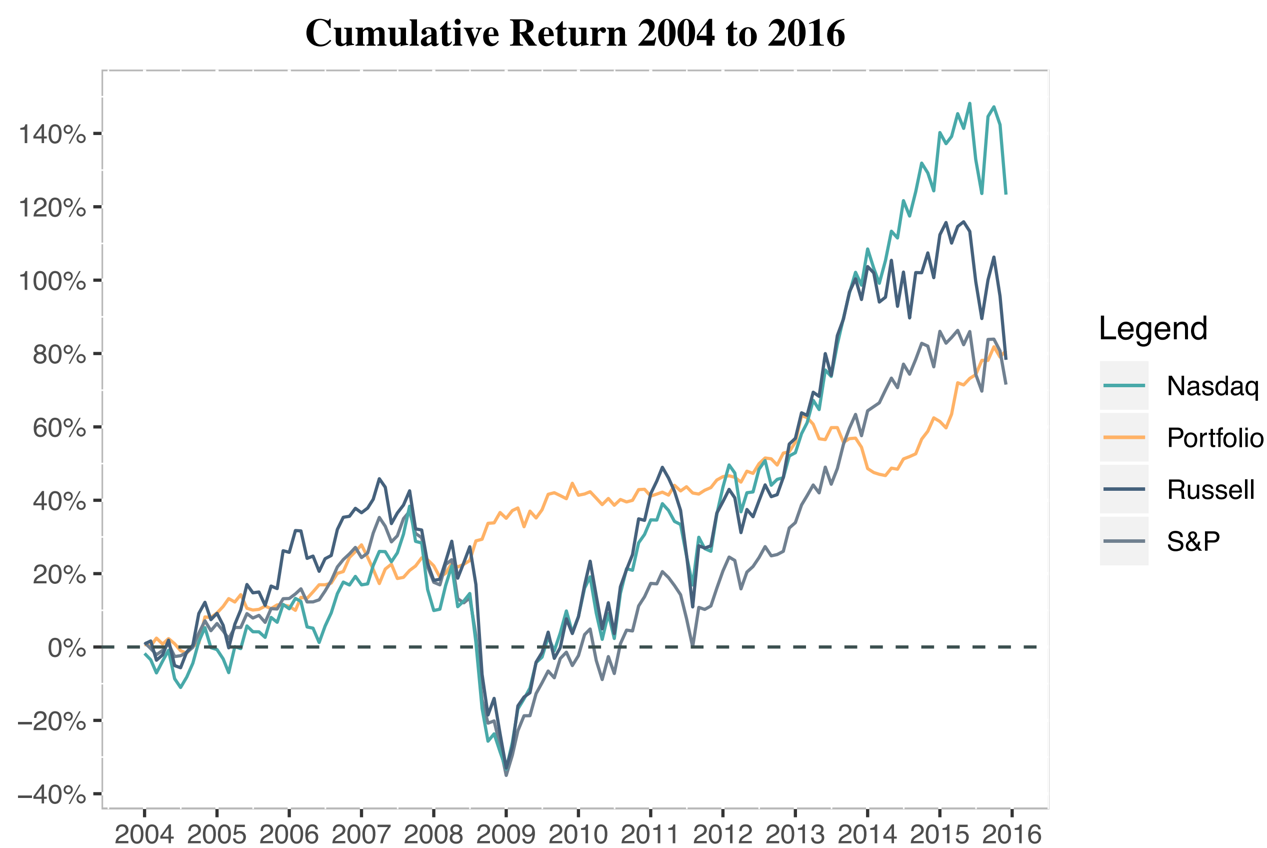

Figure 2: Cumulative Return for the Entire Portfolio and Indices, 2004-2016

In the depth of 2009, the spread between the cumulative return of our long-short portfolio and the market indices widens to around +50%. It is clear during the GFC this strategy fared exceptionally well. To an especially risk-averse investor this aspect of our investment strategy is invaluable. We believe it is reasonable to attribute this performance partially to the short positions in a particularly volatile market, but also to the fact that the long positions are taken in high-quality R&D companies.

Looking at the beta of the portfolio over rolling 3-year periods in Table 8, we find that our portfolio has exceptionally low exposure to S&P 500 returns. The market beta is negative for the period 2007-2009, which is what we expect given the spread during that period. But having such a low market beta in the other time periods indicates that our strategy is similar to a "betting against beta" strategy[11] that generates positive long-term cumulative returns.

	2004-2006	2007-2009	2010-2012	2013-2015
Beta	0.0891026	-0.0845718	0.106724	-0.0464688

Table 8: Rolling Monthly S&P 500 Beta Over 3-Year Periods for Long-Short Portfolio

Long Only

I have two hypotheses as to why the long-only strategy vastly outperforms the long-short portfolio. One is that R&D quality is a good predictor of future growth for a company, but not a good indicator of when a company is engaging in fruitless R&D. Low-quality RQ scores merely indicate that a firm has been relatively unsuccessful in R&D ventures, rather than indicating that a firm is destroying value. The second theory is related to the idea that the firms with high RQ scores will likely be higher quality businesses. Some aspects of a high-quality business include: prudency in capital deployment, growing or unaddressed market, little or no competition in market, etc. These characteristics lead us to expect "better" businesses to outperform in the long run, and explains why the long-only portion of the portfolio materially outperformed the market indices during the GFC. The question remains: *why do investors not appreciate this?*

[11] See: Betting Against Beta by Andrea Frazzini and Lasse Heje Pedersen from NYU Stern, 2014. Also see AQR's post: Betting Against Beta: Equity Factors Data, Monthly; and the fact that AQR employs this strategy in their actual fund

The literature, as well as the results of this paper, indicates that investors consistently misprice returns to R&D. It is difficult to understand why this is the case. One answer is stock-market investors are focused more on short-term returns and performance, which may divert attention from R&D yield that occurs over a longer time period. Or, perhaps investors do not forecast sales based on R&D, and often financial models only treat R&D as an operating expense and not an investment. This implies a fundamental mistreatment of R&D as an accounting line item, rather than investment in a business. It is difficult, if not impossible, to determine the causal mechanism for this phenomenon.

Table 9 includes summary statistics for the long-only portfolio and market indices. Notice the increased volatility, although still below that of the market indices, and the stellar CAGR. There is a jump up of arithmetic mean return, which keeps the Sharpe Ratio well above the market indices. The long-only histogram below also looks quite normally distributed and is clustered around zero. The sizable outperformance is consistent with the idea that RQ can accurately indicate good quality R&D investment and future growth, which may not be understood by many market participants.

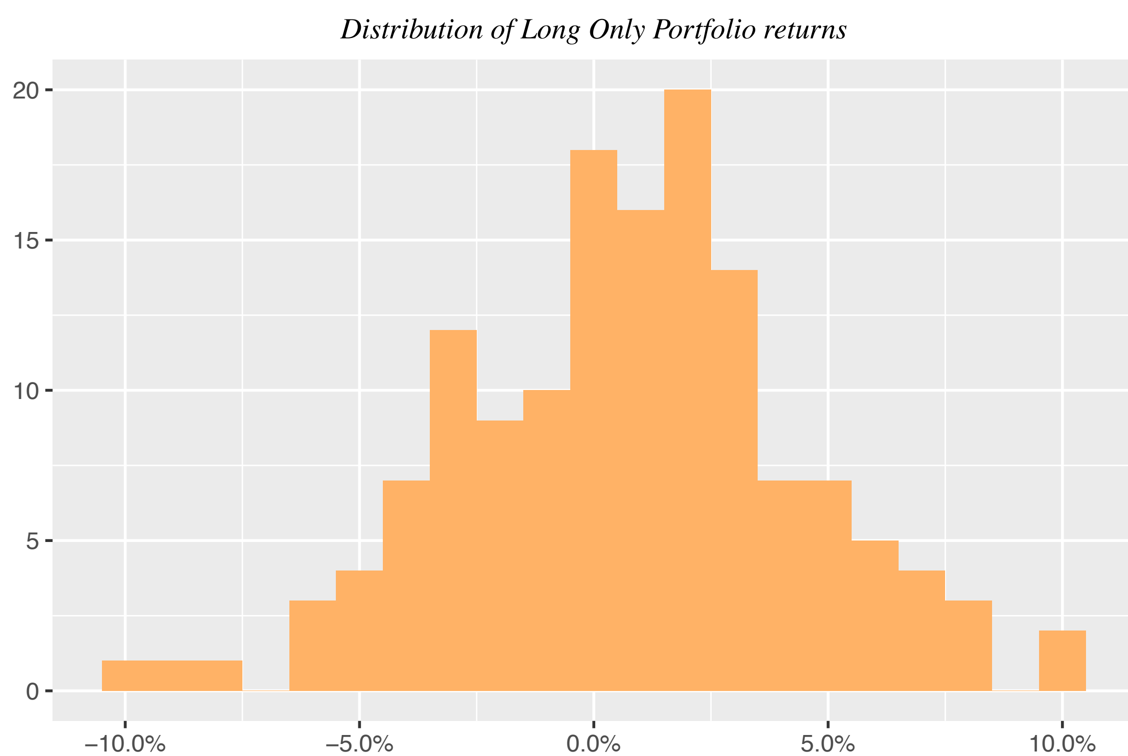

Figure 3: Histogram of Monthly Returns for the Long-Only Portfolio

Index	Mean Return	Volatility	Sharpe Ratio	CAGR
LO Portfolio	0.74%	3.65%	0.2016087	8.34%
S&P 500	0.46%	4.09%	0.1125393	4.60%
Nasdaq	0.68%	4.95%	0.1378422	6.92%
Russell 1000	0.56%	5.51%	0.1008781	4.94%

Table 9: Further Summary Statistics for Returns of Long-Only Portfolio and Indices

This long-only strategy seems vastly superior, with an investment at the beginning of the period more than doubling by the end. Additionally, as one can see on the graph below, the long-only portfolio only dips slightly below a negative cumulative return during the GFC. Post GFC the long-only strategy maintained a remarkable return spread quite above that of the market, although the monthly movements look more correlated than in the long-short portfolio. There is probably more market risk associated with the long-only positions. Risk-adjusting these returns will make clear if the long-only strategy is picking up other risk factors. For example, in the post-GFC period the long-only portfolio could be showing returns similar to a value-based strategy.

These results indicate that while the short side of the constructed portfolio offers a good hedge against market risk, it is a material drag on returns. Again, this is likely because RQ is a better measurement of good quality R&D producing growth, rather than an indication of a company destroying value through R&D. Additionally, given that a firm is engaging in R&D it is reasonable to expect some sort of growth, so outright short sales are not likely to capture any upside due to even poor quality R&D producing some sort of growth.

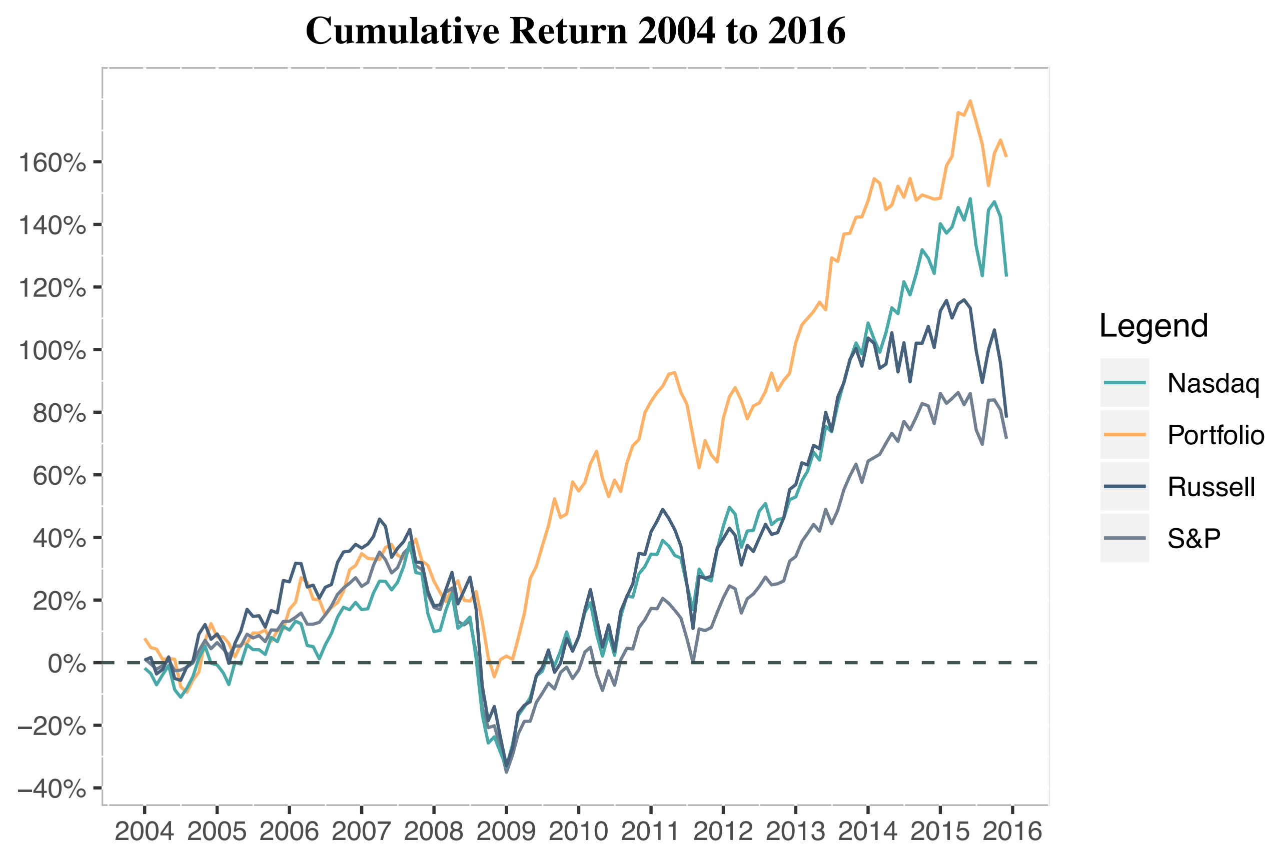

Figure 4: Cumulative Return for the Long-Only Portfolio and Indices, 2004-2016

Table 10 shows that in fact, the S&P 500 market beta for the long-only portfolio is actually very close to 0 in each period. It is not market risk exposure that is driving the excess returns we see for the long-only portfolio. In 2013-2015 the market beta was even negative, which was during a bullish period for the market indices, and the long-only portfolio vastly outperformed.

	2004-2006	2007-2009	2010-2012	2013-2015
Long Only Beta	0.168767	0.172755	0.0308948	-0.100869

Table 10: Rolling S&P 500 Beta for 3-year Monthly Returns for the Long-Only Portfolio

Persistence Check

In order to test the consistency of R&D quality we can look at the turnover in the constructed portfolio. That is, each year we take the top quintile of companies based on their RQ and we want to investigate how often the same company is included in the top quintile of RQ scores. If the same firms are consistently identified as being in the top quintile of RQ score, that may be evidence that R&D quality is likely to persist over time. Table 11 shows summary statistics for the frequency of firms included in the investigational portfolio, it also includes statistics describing how often firms are in the portfolio for sequential years. Of the 2391 total return observations in the portfolio there are only 641 unique companies, for the long-only portfolio only 347 of the 1104 are unique. If R&D quality is not persistent at all, we would expect that firms would not be in any sequential portfolio. If instead R&D quality was random, the probability of a firm in the top quintile in period one to be in the top quintile again in period two would be one-fifth.

	Mean	Standard Deviation	Median	Minimum	Maximum
Long Short Frequency	3.730109	2.574001	3	1	12
Long Short Sequences	3.148206	2.613343	3	0	12
Long Only Frequency	3.432277	2.231642	3	1	12
Long Only Sequences	2.968300	2.373171	3	0	12

Table 11: Summary Statistics of Firm Frequency in Constructed

It is notable that the average long-only sequence is smaller than the average long-short sequence, suggesting that poor R&D quality may be more persistent than good quality R&D. This is important given the greater outperformance of the long-only portfolio.

Although, it is necessary to point out the dispersion in the sample. The range is consistent in both portfolios and the mean does not appear to move a statistically significant amount.

To make the persistence check statistically concrete, we constructed an empirical chi-square test of proportions. Because of dependence in-sample[12] we cannot trust the p-value from a simple chi-square test. Thus, we ran 100,000 simulations with the top and bottom quintiles of 641 unique companies and the top quintile of 347 unique companies recorded, which gives the expected frequency over the portfolio sample period. Using the expected proportions, we ran another 100,000 simulations and recorded the chi-square test statistic from each trial. Then we have an empirical distribution of chi-square statistics that we can compare to the chi-square statistic of our long-short and long-only portfolios. Table 12 shows the 95th percentile and 99th percentile chi-square statistic from the simulations, compared to the actual chi-square statistic from the portfolios.

	95% χ^2 Statistic	**99% χ^2 Statistic**	**Portfolio χ^2 Statistic**
Long-Short	.02248	.03200	8.1024
Long-Only	.04357	.06632	2.3907

Table 12: Empirical and Realized Chi-Square Statistics

Clearly the chi-square statistics from our portfolios are both deep in the tail of the empirical distribution. The p-values are therefore very small and we can reject the null that our portfolio frequencies are the same as if R&D quality was entirely random. The driver of this result is a higher proportion of firms that appear more than 7 times. Similar to the result above of the long-short portfolio having a higher average frequency, the chi-square statistic for the long-short portfolio is stronger than the long-only statistic. This supports the proposition that poor quality R&D persists more than good quality R&D, although is not conclusive. To test that hypothesis, we could perform one-way ANOVA with position direction as the factor.

[12] If one company is in the top quintile, another has a lower chance of being in the top quintile.

Risk-Adjusting Returns

We ran the Fama-French 3-factor model[13] on the returns of both the long-short portfolio and the long-only portfolio over the entire 12-year period by monthly returns. The relevant factor data was pulled from Ken French's data library at Dartmouth. The goal was to give us a sense of whether or not the returns can be said to be "abnormal" or if they are explained by the Fama-French risk factors. This also gives us a sense of whether or not this strategy generates statistically significant alpha, which would be the constant term from the regressions. I expected the long-short portfolio to not be robust to these tests but that the long-only portfolio will show some significant alpha. Interestingly, the results were the opposite. Table 11 has the regression results from running the Fama-French 3-factor model. Running the model means regressing the returns to our portfolio, which are constructed using return data, on the 3 Fama-French risk factors. The result is to identify what factors might be causing the returns. The theory returns to the CAPM model and the idea that investors are rewarded for taking on risk in the form of higher expected return. The regression serves to measure how sensitive our portfolio returns were to the chosen factors and indicate if we are being rewarded for taking on those risks or if our returns were unexplainable. Although, it is still debated if these factors are truly risk factors or just signs of market inefficiency. Regardless, the coefficients from the regression show if our portfolio returns are related to returns of portfolios of factor-specific stocks.

The long-short portfolio generated strong, statistically significant alpha over the whole time period. Given that the outperformance of the long-short portfolio was not that drastic on a total-return basis, we were not expecting to see this result. The alpha was significant at the 95% level and was equivalent to 32 basis-points per month. There was no significance for the loads of any of the risk factors, and the adjusted R^2 and miniscule F-

[13] The Fama-French 3-factor model is a model developed by Eugene Fama and Ken French that is meant to explain stock returns based on risk factors. The factors included in the 3-factor model are: market return, small-minus-big (SMB), and high-minus-low (HML). SMB is commonly referred to as the "size factor" and is constructed by subtracting the performance of large market cap companies from small market cap companies. HML is the "value factor" and is comprised of the returns of high book-to-market multiple companies from low BTM companies. For more information on how exactly these factors are constructed, see: http://mba.tuck.dartmouth.edu/pages/faculty/Ken.French/data_library.html

statistic shows that essentially zero of the long-short portfolio returns can be explained by the Fama-French risk factors. This is compelling that R&D quality does not correlate with the Fama-French factors, although the results for the long-only portfolio lead us to believe that we are actually picking up on these risk factors. The conclusion might be then that the short side of the portfolio is what is allowing us to see uncorrelated returns and therefore significant alpha.

	Dependent variable:	
	Long Short	Long Only
	(1)	(2)
Constant	0.317**	0.205
	(0.149)	(0.161)
Market Return	0.003	0.615***
	(0.040)	(0.043)
SMB	0.036	0.538***
	(0.071)	(0.076)
HML	0.040	-0.173**
	(0.063)	(0.068)
Observations	144	144
R^2	0.006	0.733
Adjusted R^2	-0.015	0.727
Residual Std. Error (df = 140)	1.764	1.913
F Statistic (df = 3; 140)	0.300	127.851***
Note:		*p<0.1**p<0.05***p<0.01

Table 12: Fama-French 3-Factor Regression Results (Std. Error in Parenthesis)

The long-only portfolio returns were strongly explained by the Fama-French factors and did not generate statistically significant alpha. The R^2 and F-statistic indicate that the model as a whole very strongly predicts the in-sample returns. The whole market index used by the Fama-French model picks up on returns that just the S&P 500 does not, which is why the market beta value here is significantly different than before. More interestingly, the positive and significant load on the SMB factor indicates that the long-only portfolio is picking up on excess returns of small companies. The negative load on HML likely indicates that we are also picking up on something of a growth strategy, which is what we would expect as we are investigating the predictability of growth based on R&D expenditures.

Contrasting these results with Cohen *et al.'s* 135 basis points per month of alpha, the key differences lie in the way the authors generate their measure of R&D ability and how they sort the companies in sample. The authors in that paper use the Fama-French methodology of a three-way sort, which likely avoids the issue of picking up on a size or growth strategy when risk-adjusting returns.

Conclusion

This paper shows material outperformance of a portfolio constructed based on a measure of R&D quality, which benefits from investors misunderstanding returns to R&D efforts at the firm level. The approach uses RQ to identify companies that have high returns to R&D, although other methods of measuring R&D quality have been shown to yield similar results. The theory is based on the idea that firms with good R&D practices will continue to have high returns from R&D. Although R&D is itself an uncertain endeavor, the future yield on R&D can be reasonably estimated at the firm level. The portfolio succeeds in reducing realized volatility with returns at or above the market. We believe it is due to the persistence of quality R&D that is estimated by the RQ score. Additionally, we found the yearly persistence and inclusion in the portfolio was statistically significant. The alpha generation was not what we expected. The long-only strategy is likely picking up on market inefficiencies related to the Fama-French factors, while the long-short strategy seems to have no market correlation at all.

In summary, we have found high quality R&D firms tend to outperform the market with reduced volatility. The underlying causal mechanism is unclear, but there are likely qualitative characteristics that can form a story, such as: a talented founder, prudent capital deployment, good R&D culture, industry or product experts in R&D, and more. The outperformance suggests the market is underappreciating R&D yield *ex ante* and reacting to growth, rather than properly forecasting returns to R&D. This could just be a sign of market inefficiency, but it seems to be an exploitable trend in the sample period.

Further research is warranted and can try to pinpoint exactly the underlying mechanisms which cause a firm to have better quality R&D efforts. A cross-sectional look at returns within industry could help to identify some qualitative factors that contribute to long-term growth. Additionally, it would be an interesting study to construct portfolios based on a measure of R&D quality and look at the return over a long horizon – without changing the constituents of the portfolio. The study would reveal if R&D quality *at the firm specific level* is truly predicable and consistently mis-valued by the market. Our study concluded on a broader scale that R&D yield is misunderstood by market participants.

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Appendix

Table 1: RQ Summary Statistics for the Entire Portfolio

Year	Observations	Mean RQ	Std. Dev	Min	Max
2004	114	0.160	0.184	-0.360	0.619
2005	174	0.160	0.246	-0.920	0.826
2006	184	0.170	0.247	-0.415	1.010
2007	180	0.160	0.241	-0.467	0.984
2008	188	0.140	0.231	-0.578	0.922
2009	202	0.120	0.205	-0.560	0.877
2010	214	0.085	0.208	-0.673	0.864
2011	224	0.086	0.208	-0.927	0.738
2012	216	0.098	0.224	-0.694	0.739
2013	234	0.110	0.205	-0.719	0.831
2014	246	0.086	0.195	-0.656	0.745
2015	242	0.070	0.187	-0.806	0.711

Table 2: RQ Summary Statistics for Long Positions

Year	Observations	Mean RQ	Std. Dev	Min	Max
2004	57	0.315	0.1160	0.201	0.619
2005	87	0.359	0.1500	0.215	0.826
2006	92	0.371	0.1770	0.214	1.010
2007	90	0.356	0.1630	0.211	0.984
2008	94	0.323	0.1470	0.206	0.922
2009	101	0.287	0.1250	0.193	0.877
2010	107	0.253	0.1020	0.168	0.864
2011	112	0.250	0.0935	0.174	0.738
2012	108	0.274	0.1180	0.184	0.739
2013	117	0.272	0.1160	0.186	0.831
2014	123	0.240	0.1130	0.159	0.745
2015	121	0.214	0.0957	0.142	0.711

Table 3: RQ Summary Statistics for Short Positions

Year	Observations	Mean RQ	Std. Dev	Min	Max
2004	57	0.00567	0.0771	-0.360	0.0707
2005	87	-0.03940	0.1380	-0.920	0.0606
2006	92	-0.03150	0.0957	-0.415	0.0606
2007	90	-0.03610	0.1130	-0.467	0.0661
2008	94	-0.04830	0.1260	-0.578	0.0671
2009	101	-0.04640	0.1130	-0.560	0.0482
2010	107	-0.08250	0.1390	-0.673	0.0378
2011	112	-0.07850	0.1540	-0.927	0.0487
2012	108	-0.07850	0.1550	-0.694	0.0526
2013	117	-0.05600	0.1300	-0.719	0.0590
2014	123	-0.06790	0.1270	-0.656	0.0522
2015	121	-0.07460	0.1390	-0.806	0.0448