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Summary of WP Student Team

Analysis of Quantitative Investment Strategies

Group constitution:

Student Name	Program	Individual Title
Jan Gregor Ferencz	Finance	Timing of Volatility and Momentum Portfolios
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A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

Analysis of Quantitative Investment Strategies

- Timing of Volatility and Momentum Portfolios
- Research and Development Activity and Stock Returns in the U.S. Market

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Work project carried out under the supervision of:

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Abstract
Low volatility and R&D to market equity based investment strategies can yield abnormal returns on the US equity market. In the first place we are improving the low volatility strategy by using a volatility timing signal, that invests in past winner stocks when the market outlook is bullish. Secondly, the long only R&D portfolio can be improved by making it a zero-investment strategy, that short-sells low R&D past losers. In the last part we show that a combined risk-parity portfolio, that rebalances the two investment strategies on a monthly basis outperforms all common benchmarks between 2001 and 2020.

Keywords
Quantitative Investment Strategies, Low Volatility, Volatility Timing, Momentum, Research and Development, Risk Parity

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Individual Contribution of Jan Ferencz - Timing of Volatility and Momentum Portfolios

Introduction

The well-documented low-volatility anomaly has its origins already shortly after the definition of the CAPM. Black, Jensen, and Scholes (1972) form monthly decile portfolios of US stocks ranked by their five-year rolling beta and observe significant positive alphas for low-beta equities and negative alphas for high-beta stocks. Indicating that the CAPM does not hold, and low risk securities seem to be underpriced, this anomaly has been intensively studied in the US market. Neo and Tee (2021) are trying to improve a static low volatility strategy by suggesting a timing signal that switches from low volatility stocks to high volatility stocks in good market times in the US. As a low-risk investment strategy is outperforming the broad market in the long run, but clearly is missing out on capturing the upside of rather risky investments in bullish market periods, the interesting insights of Neo and Tee’s timing strategy are analyzed and extended with momentum trading strategies for the German and US stock market in this individual part of the field lab. The main goal is to test whether such a volatility-based timing strategy can produce similar results on German equity markets. As the low volatility anomaly has been covered only briefly in Germany compared to US research, important conclusions could be drawn for this market. Additionally, I am trying to improve the results by holding a portfolio that is long past winners during good market conditions instead of switching between purely volatility-based portfolios. The analysis is conducted on the German and US market during 1990 – 2022 for comparison purposes.

Literature Review

After the detection of the low volatility anomaly by Black, Jensen, and Scholes (1972) the phenomenon has been extensively studied on US and international equity markets. Blitz and van Vliet (2007) analyze volatility ranked decile portfolios between 1986 and 2006 in the US, Europe, and Japan. They find significantly higher risk-adjusted returns for the lowest volatility decile portfolio with a Sharpe ratio of 0.72 vs. a 0.05 for the high volatility portfolio of global stocks (incl. all three regions). Furthermore, the study finds a spread of 12% in Alpha between low- and high-volatility stocks. For Europe and Japan, the excess return of a high-volatility portfolio even turns negative (-0.00% and -2.3% for Germany and Japan respectively). Even after correcting for the additional Fama-French value and size risk factors, 8.1% of the global alpha spread remains unexplained and cannot be attributed to an exposure of a low volatility strategy to common risk factors. Dutt and Humphery-Jenner (2013) evaluate the performance of low-risk stocks in developed and emerging markets outside the US and Canada from 1990 – 2010, based on variance quintile portfolios. In-line with US studies, they can find support for the low-volatility anomaly in international equity markets. Additionally, Dutt and Humphrey-Jenner suggest that part of the outperformance of low-volatility stocks can be explained by strong operating performance of the underlying companies. Low volatility firms tend to have high EBIT/Assets, which would increase expected stock returns. Other possible explanations for the outperformance of low-risk equities are leverage constraints of investors and that fund managers tend to stick to a benchmark. In their Betting-against-Beta (BAB) factor, Frazzini and Pedersen (2014) create self-financing portfolios, for US and international asset classes, that are long the half of low-beta securities and short high-beta securities every month. The BAB factor yields positive Sharpe ratios for international equities in 18 of 19 observed countries (time period: from availability – 2012). Interestingly, when funding constraints tighten, the return of the BAB factor is low, suggesting that investors are bidding up higher risk assets under those conditions. Also, their observations of portfolio selection of different types of investors shows, that constrained investors tend to hold higher beta assets, supporting the argument that outperformance of low-risk assets could be caused by leverage constraints of market participants. Looking at the German stock market, Perras, Reberger, and Wagner (2020) are testing volatility quintile portfolios in the US, Europe and Germany. From 2002 – 2018 considering the HDAX, the 110 largest companies listed on the Frankfurt Stock Exchange, their low volatility portfolio yields 3.33% versus -0.82% for the high volatility in annual geometric return. However, their German low-volatility strategy cannot produce statistically significant alpha, whereas their US low-volatility portfolio earns 0.33% of significant abnormal return. In a very recent study Neo and Tee (2021) are trying to enhance the returns of a static low-volatility strategy by introducing a timing signal based on the slope of the volatility decile portfolio's return profile. The authors observe that the high volatility decile portfolio yields significantly higher returns under good market conditions, than the low volatility portfolio. Taking the slope of the volatility decile portfolios ($r_{high\text{-}vol} - r_{low\text{-}vol}$), which tends to be positive in good market regimes, as a predictor, Neo and Tee (2021) manage to enhance to Sharpe ratio of a basic value weighted low volatility strategy in the US market by 30% in the observed period from 1963 – 2016. By holding the mid-volatility portfolio as a default and switching to low-volatility (high-volatility) when the slope is statistically significantly negative (positive), risk-adjusted and absolute return improvements are achieved. The enhanced returns of their timing strategy can be attributed to holding a more diversified portfolio in bear markets and benefiting from a more concentrated portfolio during bull markets.

Interesting insights could be won by combining the volatility timing strategy proposed by Neo and Tee (2021) with momentum portfolios, aiming to enhance the returns in a bull market. A strategy that buys past winners (based on their prior 6-month return) and sells past losers realized a compounded excess return of 12.01% between 1965 and 1989 in the US (see Jegadeesh and Titman 1993). Based on their original momentum paper, trend following strategies have gained popularity internationally and pay a high risk premium. Momentum strategies naturally select high beta stocks during bull markets as they bet on past winners. Hence, holding a robust low volatility portfolio as a default and trying to capture upside by switching to a momentum strategy during good market times could lead to an enhanced performance.

Data and Methodology

The analysis of the volatility-based timing strategy has been carried out on the German and US markets. The methodology of the formation of quantile portfolios and the formation of the timing signal as the slope of the volatility quantile return profile follows the most basic timing strategy of Neo and Tee (2021).

German market

Daily company data from January 1990 until December 2021 has been downloaded from Compustat database. To generate a survivorship bias free dataset, all available German securities in the corresponding timeframe have been downloaded and then filtered for: German ISINs, ordinary shares and currency EUR and DEM only. After applying the filters, a sample of 1,408 companies is left for portfolio formation throughout the sample. Daily returns are computed based on a stock split adjusted total return index including dividends:

$$TRI_{i,t} = \left(PRCCD_{i,t} \div AJEXDI_{i,t}\right) \times TRFD_{i,t} \tag{1}$$

Where, $TRI_{i,t}$ is the total return index for company *i* on day *t*, $PRCCD_{i,t}$ is the closing price for company *i* on day *t*, $AJEXDI_{i,t}$ is the cumulative split adjustment factor for company *i* on day *t* and $TRFD_{i,t}$ is the daily total return factor of company *i* on day *t* to account for cash (equivalent) distributions.

For comparison purposes with the US strategy all returns are converted into US dollars. Daily exchange rate data for DEM/USD has been obtained from Deutsche Bundesbank and EUR/USD rates have been downloaded from FRED, St. Luis Fed. To form the volatility portfolios, I am computing the rolling 30-day standard deviation of stock returns. At the last day of each month only the top 80% based on market capitalization of companies are considered and ranked by their 30-day standard deviation. The lowest quintile is assigned to the low volatility portfolio next month, the 2nd quintile is portfolio number two and so on. For the formation of momentum portfolios at the last day of each month stocks are ranked by their prior 6-month cumulative return. The highest quintile is assigned to the 'winner' portfolio next month, the 2nd strongest quintile is portfolio number four and so on. All portfolios are market capitalization weighted. Appendix 1.1 includes two graphics to show the number of total companies considered and assigned to each quintile portfolio throughout the sample period. For the evaluation of factor exposure and abnormal returns of the strategies I am using Fama/French European 3 Factors and European Momentum Factor from Kenneth French Data Library.

US market

For the US market I am considering all common shares listed on NASDAQ, NYSE and AMEX with a CRSP share code of 10 or 11. Data between January 1990 and December 2021 for all securities (including provided daily returns) are downloaded from CRSP daily database. The formation of volatility and momentum quantile portfolios follows the same logic as on the German market, with the only difference that I am analyzing decile instead of quintile portfolios. At the last day of each month the top 1000 stocks based on market capitalization are ranked by their signals (30-day standard deviation and 6-month cumulative return) and assigned to their volatility and momentum decile portfolios. Descriptive graphs about the number of considered companies and companies per decile portfolio can be found in appendix 1.2.

Timing strategy

In order to improve the performance of a static strategy, that is long the low volatility quantile portfolio the whole time, I am using the slope of the volatility quantile return profile as a predictor of market regimes:

$$Slope_t = r_{high\_vol,t} - r_{low\_vol,t} \quad (2)$$

Where, $r_{high\_vol,t}$ is the return of the high volatility portfolio in month t and $r_{low\_vol,t}$ is the return of the low volatility portfolio in month *t*.

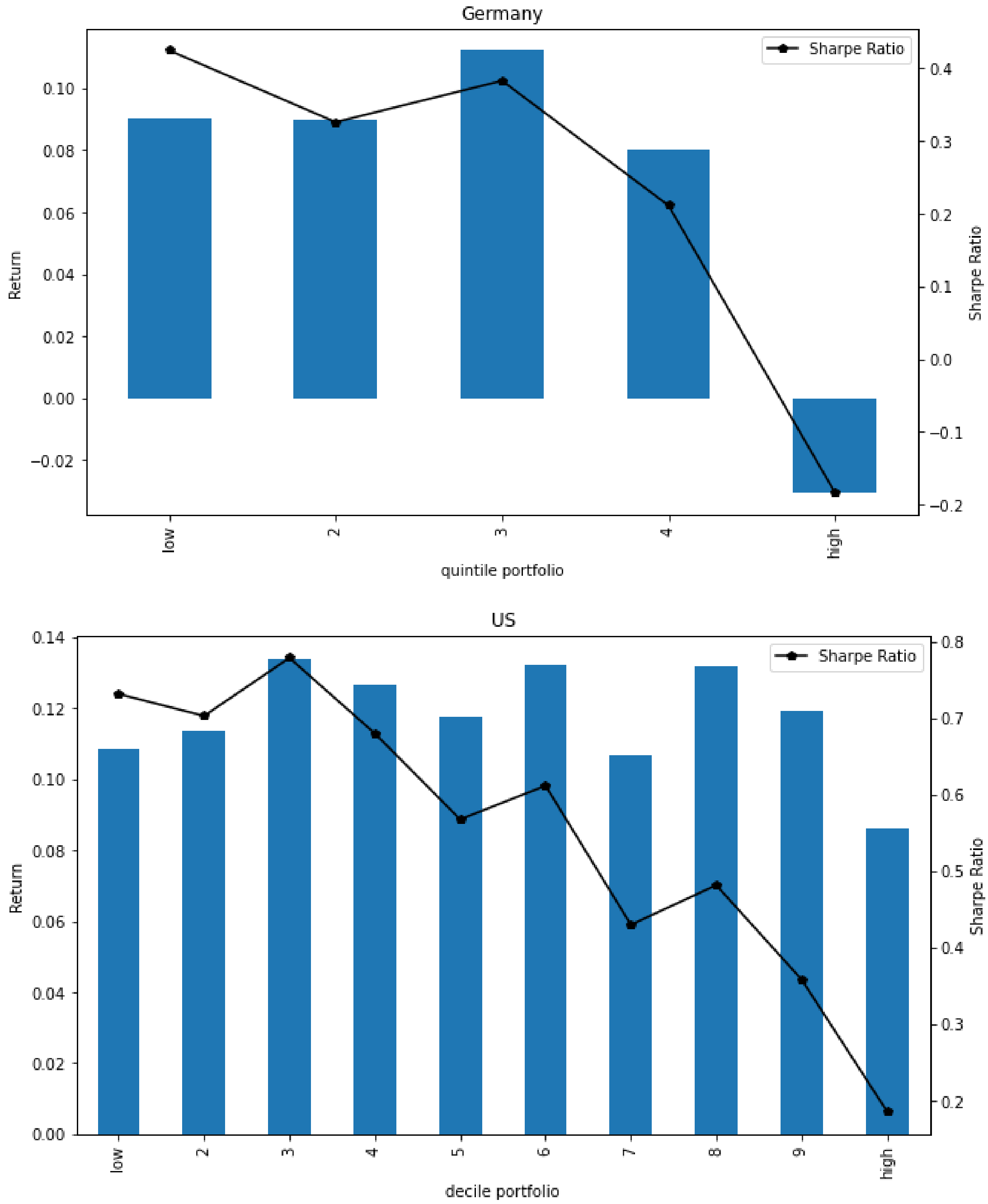
Low volatility strategies tend to underperform in upward-trending market environments as their main benefit stems from diversification. Hence, the economic motivation for the slope parameter, which is expected to be positive in good market environments, is to hold a diversified low volatility portfolio in default and benefit from higher concentration during bull markets, by holding the high volatility portfolio, when diversification is not desired (see Neo and Tee 2021, p.8-9). The investment strategy switches to the high volatility portfolio when the slope parameter is statistically significantly positive for a given month, based on a t-test with 10% significance level on rolling 12-month observations of the slope. Additionally, I am trying to improve this suggested strategy by switching to the past winner portfolio (instead of the high volatility) when the slope parameter becomes positive in a significant way.

Output and Analysis

Isolated strategies and time varying return profiles

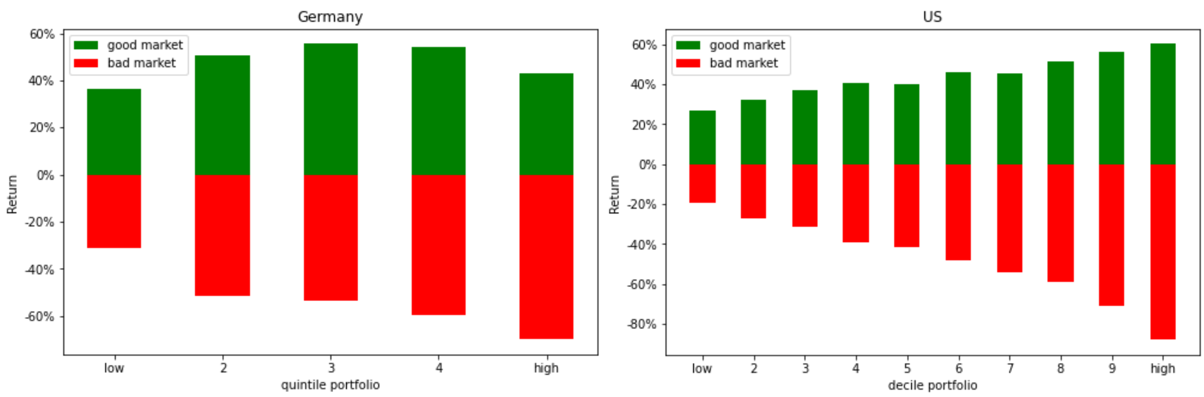
To compare the performance of the different volatility quantile portfolios in US and Germany, their analyzed returns and Sharpe ratios are plotted in exhibit 1.1. Overall, the results are mostly consistent for both markets. On average the Sharpe ratios decrease going from low volatility to high volatility in both countries, with the high volatility portfolio having by far the worst risk-adjusted and absolute return. The low volatility portfolio has a Sharpe ratio of 0.73 in the US and 0.42 in Germany. In Germany the low vol portfolio is clearly the best risk-adjusted performer, where in the US the third decile performs even slightly better than the low vol one. The most significant difference between the two markets is, that in Germany the high volatility portfolio (which was expected to perform worst) even yields a negative annualized return of -3% throughout the 32 observed years. This observation is in-line with the findings of Perras, Reberger, and Wagner (2020, p. 229), who also report negative results for a German high volatility portfolio between 2002 and 2018.

Exhibit 1.1: Returns and Sharpe ratios of volatility quantile portfolios in Germany and the US



The spread in returns between the low and high-risk portfolios is much more aggressive in Germany with 12% and only 2.3% in the US. Especially in Germany it is superior to hold a static low volatility portfolio, to benefit from the highest risk-adjusted performance. To test whether the performance of such a static low vol strategy can be improved through dynamic timing, it is important to look at the time varying return profile of the volatility quantile portfolios. Neo and Tee (2021) find that the highest volatility decile portfolio yields higher returns in good market regimes, so it is beneficial to hold a high volatility portfolio during bull markets. To test if this time varying return observation also holds for Germany, the annualized returns of the volatility quantile portfolios under good markets and bad markets for Germany and US, are compared in exhibit 1.2. A 'good market' is defined when the total stock market portfolio of the given country outperforms the risk-free rate in a given month. As a proxy of the risk-free rate, I am using the one-month Treasury Bill rate.

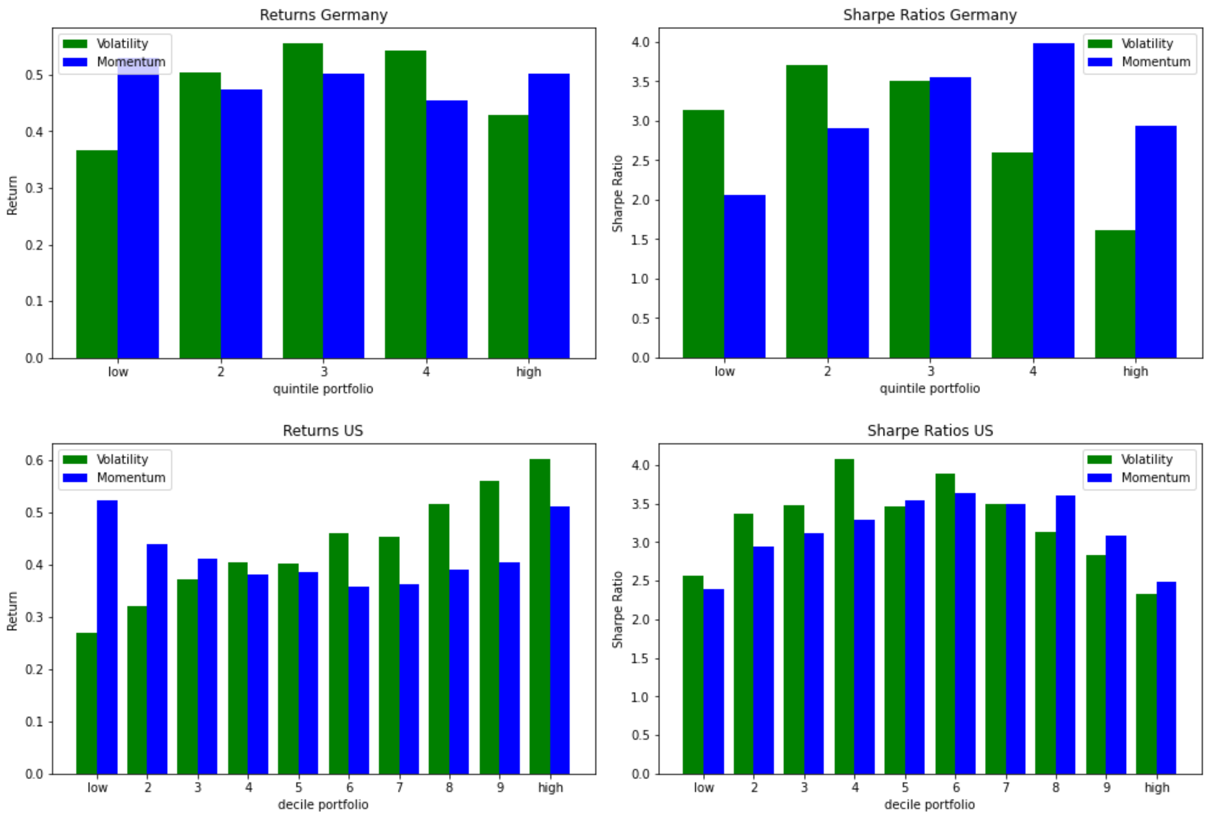
Exhibit 1.2: Volatility quantile portfolio returns during good and bad markets



In Germany the observed sample includes 59% 'good months' and 41% 'bad months'. In the US the total market outperformed the risk-free rate in 65% of the observed months. For both markets we can clearly see that the returns of higher volatility portfolios decrease consistently during bad markets, and therefore it is particularly bad to hold the high vol portfolio in a bad month. The low vol portfolio is the best performer in bad markets and offers the highest downside protection. Looking at the return profile during good months the results between the two countries differ quite a lot. In the US, the performance of higher volatility portfolios increases consistently in good months and the top decile is the best performer. In Germany however the 3rd quintile portfolio has the highest returns in good markets and the high vol portfolio in fact only offers slightly higher returns in strong months, than the low vol portfolio. As a consequence, the conclusions to be drawn for the suggested timing strategy differ for the two markets. In the US it seems feasible to capture the upside of good markets with a high volatility portfolio as it does provide the highest returns under those conditions. In Germany on the other side, the high volatility portfolio only offers slightly better performance in good markets at a much higher downside than the low vol quintile and the return profile of the portfolios in Germany does not seem favorable for this volatility timing strategy.

As the time varying return profile for a timing strategy purely based on volatility quantile portfolios does not seem attractive for the German market, let us analyze if a switch to momentum portfolios in good markets could offer an attractive alternative. Exhibit 1.3 compares the annualized returns and Sharpe ratios of volatility versus momentum portfolios during good markets in Germany and the US.

Exhibit 1.3: Volatility versus momentum portfolios during good months in Germany and the US

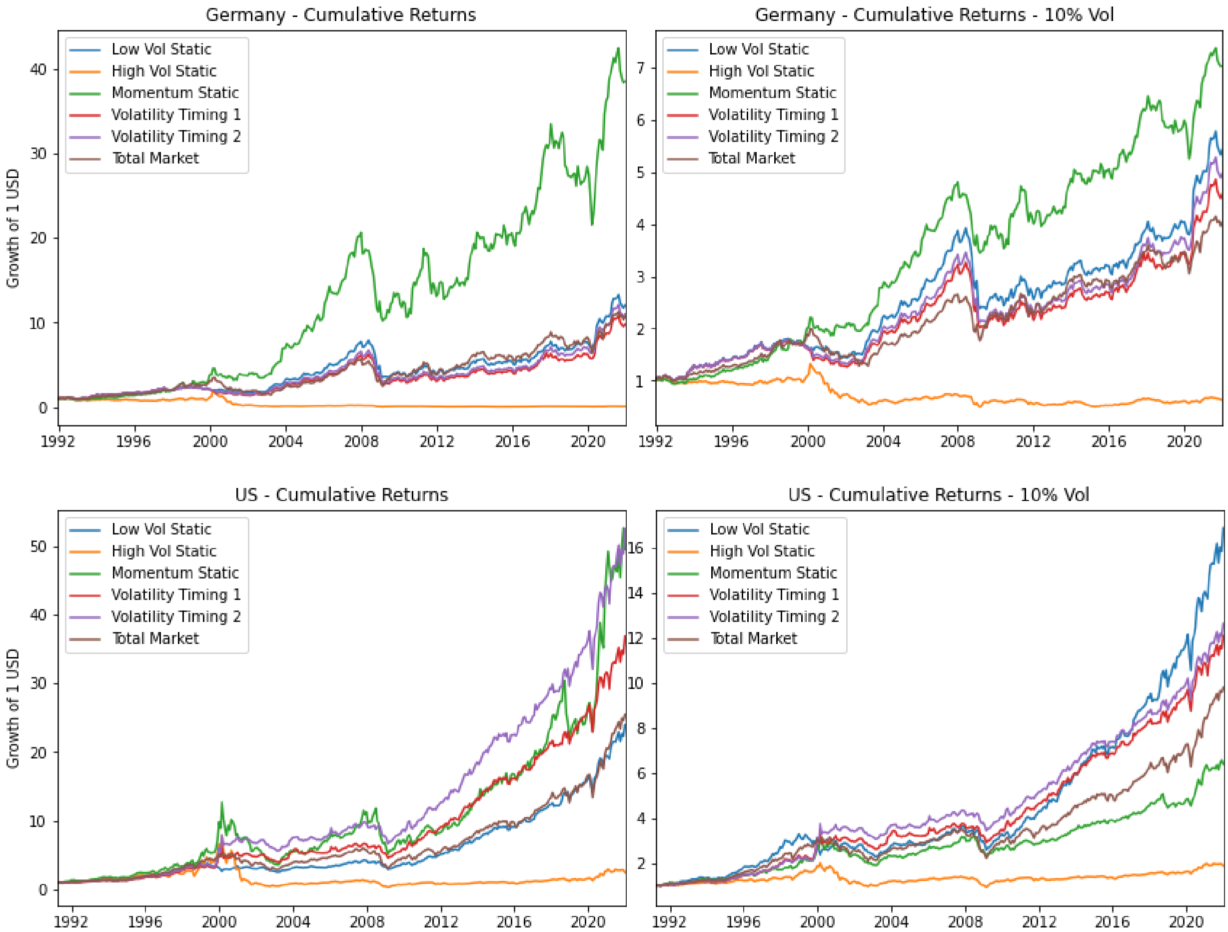


Looking at the German market, the advantages of the past winner portfolio over the high volatility one, are quite clear. In good markets the momentum portfolio yields a higher absolute return than the high volatility portfolio. Also, the past losers perform very strong in the good months. Comparing the risk-adjusted performance, the advantage of the momentum portfolio becomes even more visible. With a Sharpe ratio almost twice as high, as the high volatility portfolio, a momentum strategy is much more attractive during good months in Germany. For the US equity market, the value-add for switching to a momentum portfolio instead of high volatility are not as obvious. The high vol decile earns higher returns than the momentum portfolio and risk-adjusted performance is only marginally better for the past winner decile. The final returns of the static low volatility, momentum and two different volatility timing variants are analyzed in the upcoming section.

Performance of volatility timing strategies

The cumulative performance of the static low volatility, high volatility, momentum, two volatility timing strategies and a total market portfolio are plotted in exhibit 1.4. ‘Volatility Timing 1’ refers to the timing strategy, that holds a low volatility portfolio as default and switches to the high volatility portfolio when the signal is bullish. ‘Volatility Timing 2’ is the modified timing strategy that holds the low volatility portfolio per default and switches to the past winner portfolio when a bullish signal occurs. All strategies are also compared to a total market portfolio. The total market portfolio is a value weighted portfolio of all considered stocks for the quantile portfolio selection (Hence, after filtering for the top market capitalization). Before going in depth into the comparison of the various strategies, it is important to check the efficacy of the slope as a volatility timing signal. In Germany, in a total sample of 362 months, the signal indicates to switch to one of the more aggressive portfolios

Exhibit 1.4: Cumulative strategy returns absolute and normalized to 10% volatility for Germany and the US



Annotation: On the right pane returns have been normalized to a portfolio standard deviation of 10% p.a. in order to compare risk-adjusted performance throughout time. Portfolio returns are recorded from March 1991 for the US, as one year of volatility quantile performance is required to get the first observation of the timing signal (slope with t-test of 12-month rolling window). For Germany return data starts in November 2021 because data for European Fama-French factors (required for the next analysis) is only available from then.

for 10 months. In only 4 out of those 10 months it was superior to switch to the high volatility portfolio and in 3 months only an investor was better off holding the momentum portfolio instead of the default low volatility one. In summary, the slope is quite a poor predictor on the German equity market. On the US market the slope does a much better job in indicating whether it is superior to hold one of the more aggressive portfolios. In a sample of 370 months, the signal predicts to switch to one of the bullish portfolios for 33 months. In 17 out of those 33 months it was superior to either hold the high volatility or momentum portfolio, hence the slope served as a reliable predictor in 51.5% of the cases. Appendix 1.3 contains two tables that analyze during which months the signal indicated to switch portfolios, and whether the decision was optimal. As the slope only indicates to switch from the low volatility portfolio to one of the more aggressive ones in 10 months over the +30 years in Germany, the cumulative returns of the static low volatility and the two timing strategies only differ marginally. As the alternative portfolios were only better in 40% (high volatility) and 30% (momentum) of the indicated cases, the static low volatility outperforms both timing strategies in terms of absolute and risk-adjusted returns. The most remarkable results for the German market are, that the static momentum strategy, that buys past 6-months winners and holds them for one month outperforms all other strategies and the total market portfolio by far, also when comparing with equal risk. All optimal strategies manage to outperform the total market on a risk-adjusted basis in Germany. Looking at US equity markets, where the volatility decile's return slope is a much better predictor of market regimes, the results vary substantially. In terms of absolute returns, the static momentum and volatility timing 2 strategies where the best performers both yielding ~50x return in the +30 years. When accounting for risk, the static momentum strategy does much worse and is the only improved strategy, underperforming the broad market. The most interesting observation in the US is, even if the analysis of performance during good months, carried out in exhibit 1.3, does not clearly indicate that one is better off holding a momentum portfolio instead of a high volatility portfolio during good months, the optimization of the timing strategy works reasonably well and yields higher absolute and risk-adjusted returns over the basic timing strategy. However, like in Germany, the static low volatility strategy still is slightly better than its timing variants in the US, but at a much lower absolute return. Remarkably is too, that the momentum strategy produces the highest risk-adjusted returns in Germany and is the worst performer in the US (apart from the static high volatility portfolio).

Factor analysis and subperiods

To get a better understanding of the source of returns of the individual strategies and test if abnormal returns persist after accounting for exposure to common risk factors, portfolio statistics including a Carhart four-factor model analysis are presented in table 1.1. The model to explain returns of the different investment strategies is defined as:

$$R_{i,t}^{e} = \alpha_i + \beta_{MKT,i}MKT_t + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}MOM_t + \varepsilon_{i,t} \quad (3)$$

Where, $R_{i,t}^{e}$ is strategy's *i* excess return in month *t*, MKT_t is the excess return on the total market portfolio in month *t*, SMB_t, HML_t and MOM_t are the returns on factor mimicking, zero-investment portfolios of size, value and momentum stocks in month *t* (see Fama and French 1996; Carhart 1997; Jegadeesh and Titman 1993).

Table 1.1: Strategy performance metrics and risk-factor exposure in Germany and the US

Germany

	Low Vol Static	Momentum Static	Volatility Timing 1	Volatility Timing 2	Total Market
Ann. return %	9.50	14.17	8.90	9.24	9.68
Std %	15.53	20.32	16.04	15.86	18.87
Sharpe	0.47	0.59	0.41	0.44	0.39
Cum. return %	1104.51	3746.78	880.93	996.21	966.50
Alpha %	(-0.3, 0.88)	(-0.5, 0.84)	(-1.6, 0.46)	(-1.0, 0.64)	(0.03, 0.98)
Beta_mkt	(0.67, 0.0)	(1.0, 0.0)	(0.69, 0.0)	(0.69, 0.0)	(1.05, 0.0)
Beta_smb	(-0.05, 0.5)	(0.08, 0.38)	(0.01, 0.87)	(-0.01, 0.92)	(-0.05, 0.38)
Beta_hml	(0.22, 0.0)	(0.09, 0.25)	(0.22, 0.0)	(0.21, 0.0)	(-0.15, 0.0)
Beta_mom	(0.2, 0.0)	(0.47, 0.0)	(0.25, 0.0)	(0.23, 0.0)	(0.03, 0.34)
Adj. R_squared	0.52	0.61	0.51	0.52	0.85
F-test	97.99	141.46	93.54	97.28	502.65

US

	Low Vol Static	Momentum Static	Volatility Timing 1	Volatility Timing 2	Total Market
Ann. return %	10.99	15.4	12.85	14.11	11.63
Std %	11.34	23.6	14.93	16.18	14.67
Sharpe	0.76	0.55	0.7	0.73	0.63
Cum. return %	2298.95	4843.05	3581.92	5145.72	2443.39
Alpha %	(2.63, 0.05)	(-1.61, 0.47)	(2.52, 0.24)	(3.47, 0.14)	(0.1, 0.22)
Beta_mkt	(0.61, 0.0)	(1.21, 0.0)	(0.64, 0.0)	(0.65, 0.0)	(1.0, 0.0)
Beta_smb	(-0.33, 0.0)	(0.45, 0.0)	(0.16, 0.01)	(0.2, 0.0)	(-0.08, 0.0)
Beta_hml	(0.23, 0.0)	(-0.22, 0.0)	(0.13, 0.03)	(0.09, 0.15)	(-0.01, 0.0)
Beta_mom	(0.09, 0.0)	(0.55, 0.0)	(0.28, 0.0)	(0.31, 0.0)	(0.01, 0.0)
Adj. R_squared	0.62	0.74	0.42	0.39	1
F-test	148.63	267.23	66.46	60.56	111723.22

Annotation: Returns, standard deviations, Sharpe ratios and alphas have been annualized. P-values of factors and alpha are indicated in 2nd place in brackets.

As already visible in exhibit 1.4, in Germany the best absolute and risk-adjusted investment strategy is the momentum portfolio with a Sharpe ratio of 0.59 and annualized return of 14.17% over the whole observed period. The extensively researched low volatility anomaly cannot be observed on the German market in the period from 1991 – 2021. A static low volatility portfolio has even slightly negative alpha of -0.3%, which is not statistically significant. As expected, the static low risk strategy has a much lower exposure to the market factor, with a beta of 0.67 and loads positively on value and large cap stocks. Interestingly the low volatility portfolio also loads positively to the momentum risk factor, with a beta of 0.22, which might explain the absence of alpha after accounting for Carhart four factors in Germany. Since the volatility quintile's return slope is not a very reliable predictor of market regimes in Germany, the two timing strategies yield slightly lower Sharpe ratios than the static volatility strategy with 0.41 and 0.42 respectively. The signal only indicates switches to the high volatility or momentum portfolio in 10 months, therefore the risk-return profiles and factor exposures of the static low volatility and timing strategies are mostly similar.

On the US market, the low volatility anomaly persists and produces an abnormal return of 2.63% at the 5% significance level. Compared to Germany the static low volatility portfolio does not have such a high exposure to the momentum factor, with a beta of only 0.09. When looking at the two timing strategies, the alphas persist but are only significant at the 14% level for the optimized timing strategy. The higher absolute returns of the timing strategies over the static low volatility portfolio seem to come from a stronger exposure to the momentum factor. This was expected for the 2nd timing strategy, as it switches to the momentum portfolio in good months. Interestingly, the original timing strategy, that holds the high volatility portfolio when the signal is bullish, has a similar significant exposure to the momentum factor. Both timing strategies have slightly lower Sharpe ratios (0.70 and 0.73) than the low volatility strategy (0.76) but especially the improved timing strategy can yield a much higher absolute return.

To check how the strategies performed throughout different market times since 1990 the same analysis as in table 1.1 has been carried out for six subperiods for the low volatility strategy and its timing variants. Results are presented in appendix 1.4. The strategies are analyzed during bull and bear markets, where the whole sample has been split into the following periods: 1990s (bull, until March 2000), dotcom bubble (bear, until September 2002), 2000s (bull, until December 2007), subprime crisis (bear, until February 2009), 2010s (bull, until December 2019) and an overall bullish but highly volatile covid period until December 2021. In Germany the static low volatility strategy outperformed its timing variants in almost all subperiods. Only during the subprime crisis and covid the signal did not indicate a switch and the three strategies had the same returns. Until the end of the subprime crisis the volatility strategies tend to have a lower market beta in the bullish periods and a higher beta, when markets crashed. This might explain the relatively poor performance of the static low volatility strategy and also its timing variants in Germany, as the risk exposure to the market tends to be higher during crashes and lower during upswings, when a stronger covariance with the market is desired. Also, the timing strategies do not achieve to get a significantly higher market risk exposure, than the static strategy, during bull markets.

In the US the low volatility strategy has a much more favorable risk exposure profile. Contrary to Germany, the static low volatility strategy tends to have a higher market beta in bull markets and a lower one during crashes. The timing signal does not indicate a single switch to one of the riskier portfolios during the two market crashes, another evidence that the slope is a safer predictor in the US than in Germany. When looking at the subperiods in the US, we can also see that the significant abnormal returns of the static low volatility strategy are coming from the 2nd half of the whole period. Only since 2010 the alpha of a low volatility portfolio is existent and significant.

Conclusion

In this individual part of the field lab a static low volatility strategy has been analyzed on the German and US equity markets. Additionally, a volatility timing strategy, suggested by Neo and Tee (2021) has been tested and tried to be improved. The time varying return profile of momentum strategies looked favorable on the German market to enhance a purely volatility quintile portfolio based timing strategy by going long a momentum portfolio, instead of a high volatility portfolio during bullish market times. The first main observation is that the low volatility strategy performs worse in Germany than in the US. Even though it still outperforms the total equity market, the strategy cannot produce significant alpha after accounting for common risk factors. The next important take-away is that the slope of the volatility quantile return profile is not a reliable predictor of market regimes in Germany and works much better in the US, hence there is no value-add of such a timing strategy on the German market. On the US market, the static low volatility strategy still has a slightly higher risk-adjusted performance than the timing variants. However, especially for the improved timing strategy the Sharpe ratio is only three basis points lower, but cumulative return is more than twice as high in the observed period. Considering that leverage is not free, investors might be willing to give up a marginal amount of risk-adjusted performance for considerably higher returns.

Individual Contribution of Frederico C. Jorge -
Research and Development Activity and Stock Returns in the U.S. Market

Introduction

When firms invest in research and development (R&D), the primary output is an ambiguous, hard to value, intangible asset that comes in the form of employee "tacit" knowledge, used to generate future cash flows. When looking at countries, the returns of R&D investments are generally positive and usually higher than other sorts of capital in general, with substantial social benefits that are not present on financial statements. (Hall, Mairesse, and Mohnen 2009). The increasing productivity that individuals achieve with the help of information technology in the 21st century begs the question - Do high R&D firms know more than the U.S. markets about their own prospects?

This work project confirms the presence of abnormal returns found by previous researchers in firms with high R&D intensity in the period of 2000-2021 and builds an investable Long-Short strategy with significant alpha of 10.0% constructed with the help of momentum.

Literature Review

Early literature suggests that firms hesitate to increase spending in knowledge given its uncertainty. It is only profitable if competitors do not discover and take advantage of it (Arrow 1962). Jensen (1993) hints that firms do overinvest in R&D, some of these investments not being profitable which leads to excessive valuations. The criticism for investors' short-term horizons is brought up as Porter (1992) denotes that myopic profitability forgoes positive long-term investment opportunities and is at core for the underinvestment in assets that develop the employee's skills and potential, which contrast Bublitz and Ettredge (1989) findings assessing that R&D is treated as a long-term investment by U.S. markets. Hall (1992) shows that firms with high R&D activity do not adopt debt as their preferred method of obtaining financing and that tilting a firms capital structure by levering up on debt usually results in R&D spending cuts.

The same research piece also points out that even with external incentives the cost of R&D financing is very high, forcing firms to abandon innovative projects and possibly missing out on profits. Nonetheless, Chan, Martin, and Kensinger (1990) propose that markets react positively to increases in R&D spending for technologically advanced firms, and negatively for low tech firms. On a similar level, Penman and Zhang (2002) address the existence of a positive relationship between sudden changes in R&D spending and stock returns.

Chan, Lakonishok, and Sougiannis (2001) lay out the foundation for this work project by forming portfolios ranked on R&D expenditures relative to sales and equity market capitalization and observing significant abnormal returns that high R&D to market capitalization firms produce against their low R&D peers. The origin of the positive relation with returns presumably stems from two sources – either due to investor mispricing of R&D investments and/or a failure to appropriately control for higher risks that these firms entail. Mispricing may occur as R&D is expensed rather than capitalized, making firms appear to be more indebted than they are in reality. If there is R&D misinformation and analysts value these firms with multiples such as book-to-market, that ignore intangibles, underpricing may occur. However, they also show that on average R&D is correctly priced as firms doing R&D don't perform differently than firms not doing R&D. In addition, the authors argue that mispricing may also occur as a failure to react to management signals (Ikenberry, Lakonishok, and Vermaelen 1995). Lower market valuations place substantial pressure on firms' management to downsize their R&D spending as their positions are at risk. A reluctance to cut costs can be perceived as a vote of confidence in the firm's future performance.

Furthermore, R&D activity is linked to uncertainty as the outcome of these investments is everything but guaranteed and only materializes late if at all, making the point for unaccounted risk when evaluating excessive returns. The authors also find that firms ranking the highest in R&D activity scaled by its market equity tend to consist mostly of stocks with poor past performance and its returns are eventually explained by long-term reversals (DeBondt, Thaler 1985), though previous literature shows that long-term losers do not earn alpha after controlling for size and value (Fama and French 1996). However, Jegadeesh and Titman (1993) show in their original momentum paper that previous short-term winners perform significantly better than previous short-term losers, howbeit being more exposed to market downturns. A combination of momentum and high R&D firms will be further analyzed in this work project. Moreover, the investor base for R&D intense and poor performing stocks is narrow, as value investors do not identify with these kinds of stocks and growth investors tend to sell of poor performers leading to harsh mispricing. The unexplained riskiness of the excessive returns has been further investigated, with Chambers, Jennings, and Thompson (2002), concluding that higher unmeasured risk is inherent, while not ruling out the possible presence of mispricing as well.

More recently, Li (2011) shines a light on the subject by confirming that differences in forecasts and actual results are higher for R&D intensive firms compared to low R&D firms. On a further note, he finds that forecasts are more positive for firms with more current and historical R&D expenditures in comparison to their less spending peers after controlling for recent changes in R&D spending. He concludes by denoting that excess returns produced by R&D intensive firms are not correlated to coverage, aiming to prove that analyst mispricing is likely not the source of the positive performance high R&D spenders have.

Strategy Description

To build the investment strategy, monthly portfolios will be formed based on U.S. firms' last known yearly R&D expenditures figure divided by its market equity. Firms with the highest (lowest) signal will be allocated to the top (bottom) portfolio. The goal is to analyze and understand whether markets correctly price firms highly involved in R&D, particularly the ones that have gloomy valuations and tend to bear the highest signals.

The underlying economic motivation is that markets do not place enough focus on the confidence poor performing firms have to keep investing in the acquisition of intangible knowledge. A second aspect is that the investor base for this kind of firms is not well developed with value investors opting to invest in companies that have low prices relative to its fundamentals while growth investors tend to focus their attention on indicators that pick already growing firms. A possible lack of attention for firms ranking the highest in this strategy would mean that markets take more time to realize a positive outcome of its R&D investments. Once they do, the share price of firms in the top portfolio grows until profits are shaved off, their signal ratio is lowered, and other higher-ranking firms are included. Scaling R&D by its market equity means that the top portfolio will not be tilted to excessively valued companies and rather by past poor performers. In contrast, firms with a low signal show lack of confidence in their own ability to generate future profits from investing in knowledge and would be better off by avoiding these costs at the outset. Exploiting the spread in performance that both groups display is one of the main targets of the strategy. Furthermore, the highest and lowest quantiles are then split into groups of previous 6-month winners and losers to understand their past behavior and optimize a long-short investment strategy.

Data and Methodology

The dataset for the following analysis stems from CRSP and Compustat consisting of publicly traded U.S. stocks with monthly data, starting January 2000 until December 2020 and was constructed by Jensen, Kelly, Pedersen (2021). Further filters are set in place to include only one primary observation per security each month for common stocks. Only USD listed stocks in the AMEX, NYSE and Nasdaq of share code 10 or 11 with valid market equity capitalizations are examined. The signal on which the strategy is based is constructed with the last available yearly figure of R&D, with the assumption that accounting information is publicly available 4 months after the end of the accounting period. This figure is then divided by the corresponding firms' market equity at the time of the monthly observation.

Subsequently, the largest 1000 stocks measured by market equity are sorted into quantile portfolios based purely in their R&D signal at the last day of each month. Firms that do not report R&D do not possess a valid signal and are not sorted. Hence, the analysis focuses on the difference between low and high R&D intensity firms, considering previous findings show that on average markets correctly price R&D activity. With this in mind, and only 42.88% of the sample reporting R&D, the smallest firm in this subset of 1000 stocks ranks on average about 2300th in terms of market size in the U.S. stock market. In addition, a further sorting by the stocks' previous 6 months holding period returns, is made in two groups of namely winners and losers every month. A second group of portfolios that considers both, R&D and previous 6-month returns, lagged by one month, is then formed to assess the behavior of previous winners and losers within each R&D group.

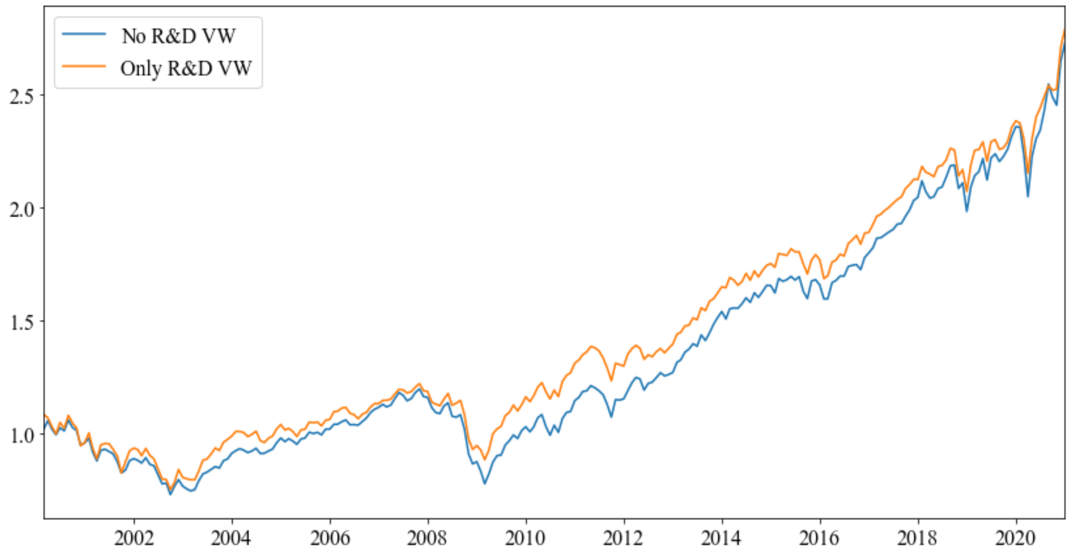
Each firm is weighted by its market equity relative to the portfolio's group total market equity. To perform this weighting, market equity values are winsorized at the 80th percentile of the 1000 firms each month to ensure large stocks do not dictate the portfolios' performance, while improving the diversification effect. Weights and signal rankings are calculated at the end of each month and furtherly shifted one month to ensure portfolios are formed and evaluated free of forward-looking biases. For the evaluation of factor exposure and abnormal returns of the strategies, factor portfolio returns for market premium, small-minus-big, high-minus-low and winners-minus-losers (momentum) are downloaded from the Kenneth French data library. Subperiods for the full sample are created to assist with the analysis, their specific date intervals can be found in Appendix 2.1.

Appendix 1.2 shows the distribution of unique firms listed in the AMEX, NYSE and Nasdaq exchanges and Appendix 2.2 its allocation to decile portfolios based on the described R&D signal.

Signal Performance

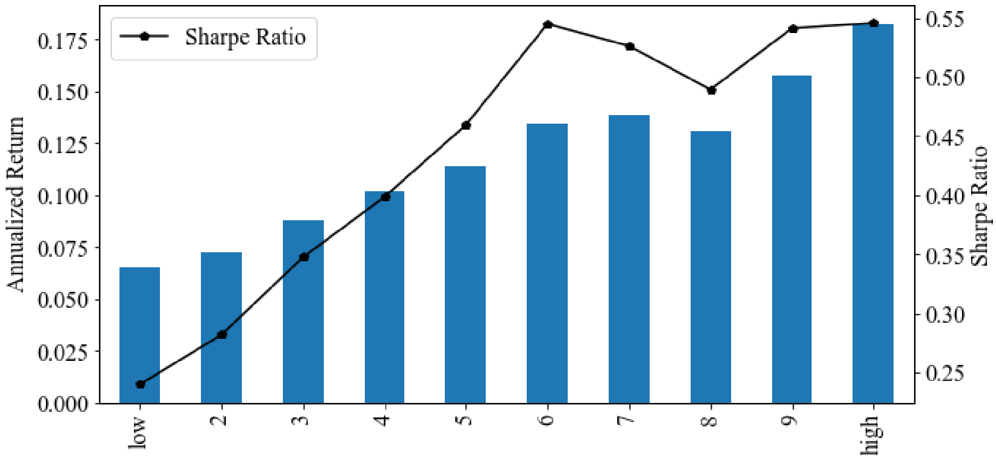
At the outset, it should be clear that the strategy at hand does not aim to bet on the belief that firms invested in R&D just perform better than the market. By comparing the returns of all top 1000 firms engaged in R&D against their non-reporting counterparts of the same size, the differences in performance in the sample are minimal. After normalizing the returns to 10% volatility, a dollar invested in January 2000 would be worth 2.72$ and 2.79$ in the end of 2020 for non-R&D firms and R&D firms respectively.

Exhibit 2.1: Firms investing in R&D vs. Firms not investing in R&D



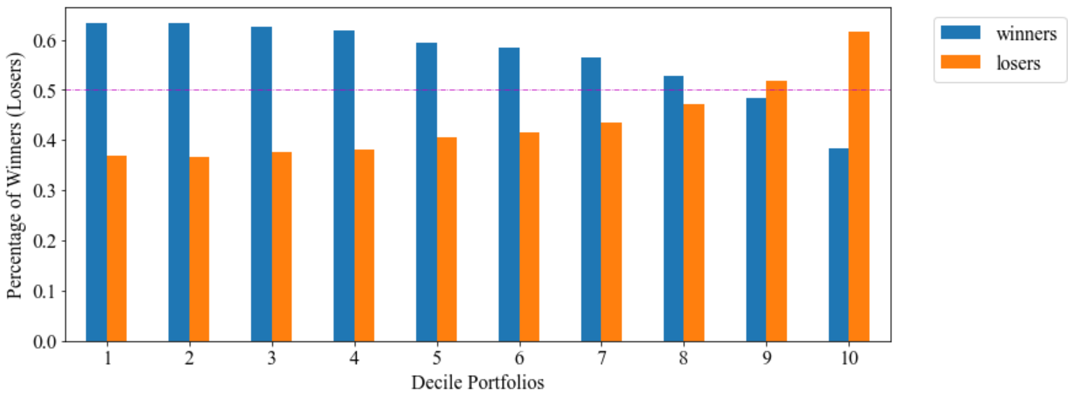
Running a two-sided t-test outputs a p-value of 0.92, failing to reject the null that the mean in returns is different for any conventional confidence level. Appendix 2.3 displays average annual returns, standard deviation, and Sharpe ratios of both groups for the total sample and each half. By sorting stocks into decile portfolios (Exhibit 2.2), it becomes evident that the upper deciles perform better in both, absolute and risk adjusted returns. The highest decile portfolio has a Sharpe ratio of 0.54 and annual returns of 17.5% whereas the low decile portfolio shows clearly lower annual returns of 1.1% and Sharpe ratio of 0.24. A positively sloped trend emerges and,

Exhibit 2.2: Returns and Sharpe ratios across Decile Portfolios



not necessarily has the highest decile the best performance, but at an investor would be preferably exposed to the higher rather than lower deciles. Sorting firms monthly into winners and losers by their previous 6-month returns independently, it is insightful to observe that the majority of firms within lower R&D deciles are previous winners and firms in higher R&D deciles tend to be previous losers. (Exhibit 2.3). Chan, Lakonishok, and Sougiannis (2001)

Exhibit 2.3: Distribution of Winners and Losers among Decile Portfolios



present similar findings. However, they construct the sorting on 3-year, rather than 6-month previous returns, as they look to analyze reversals within high R&D intensity stocks.

Jegadeesh and Titman (1993) show that a in 1965-1989 a trading strategy that buys previous winners and sells previous losers based on the 6-month realized an average compounded excess returns of 12.01% per year, in part attributed to delayed price reaction to firm specific information, though positive returns tend to perish on the long-run after portfolio formation. With the aim of developing an investment strategy, the question arises whether previous losers are dragging down the performance of high R&D signal firms. Appendix 2.4 shows that difference in returns between winners and losers are also present in this full sample.

Strategy and Optimization

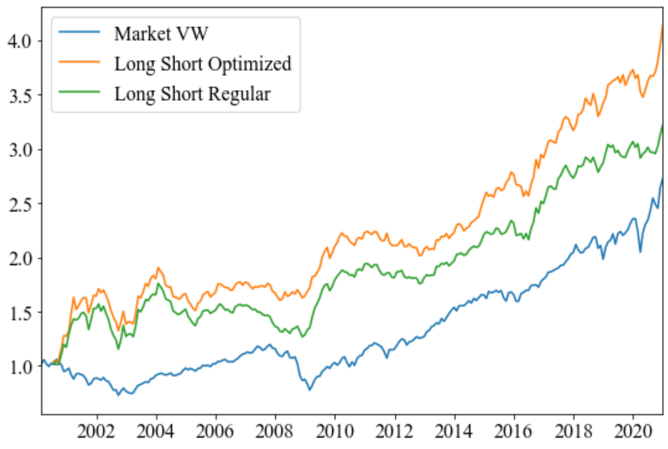
Triggered by the findings above, the 1000 stocks universe are now allocated to 5 quintiles based on the R&D signal and then each quintile is split between winners and losers, forming 10 portfolios in total. The reason R&D quantiles are halved is to ensure portfolios still carry about 100 stocks each month to benefit from diversification, without having to consider smaller companies. Appendix 2.5 shows the 1st and 2nd half returns, Sharpe ratios, regression outputs and Information ratios for the top and bottom portfolios formed above as well as the high-low.

Table 2.1: Performance of Long-Only and Long-Short Strategies – Full Sample

	Total					
	Low R&D		**High R&D**		**High-Low**	
	losers	**winners**	**losers**	**winners**	**Regular**	**Optimized**
ann_return	4.7%	9.0%	16.5%	15.6%	9.2%	11.3%
std	23.7%	17.3%	31.2%	24.8%	14.8%	15.2%
sharpe	0.14	0.43	0.48	0.57	0.62	0.74
cum_return	0.46	3.58	9.88	11.89	4.26	7.00
ann_alpha	(-0.05, 0.03)	(-0.01, 0.56)	(0.06, 0.02)	(0.05, 0.06)	(0.08, 0.0)	(0.1, 0.0)
market_beta	(1.13, 0.0)	(1.04, 0.0)	(1.26, 0.0)	(1.17, 0.0)	(0.13, 0.02)	(0.08, 0.21)
smb	(0.33, 0.0)	(0.34, 0.0)	(0.79, 0.0)	(0.67, 0.0)	(0.39, 0.0)	(0.4, 0.0)
hml	(-0.43, 0.0)	(-0.12, 0.0)	(-0.35, 0.0)	(0.0, 0.98)	(0.1, 0.15)	(0.25, 0.0)
mom	(-0.28, 0.0)	(0.24, 0.0)	(-0.6, 0.0)	(-0.13, 0.0)	(-0.34, 0.0)	(-0.08, 0.15)
R2_adj	0.85	0.88	0.88	0.81	0.36	0.13
te	2.62%	1.73%	3.04%	3.10%	3.39%	4.06%
IR	-0.15	-0.04	0.15	0.12	0.19	0.20

A Long-Short portfolio, that goes long (short) the top (bottom) R&D signal portfolio is built to exploit the spread of returns that both groups of stocks display. Average annual returns for winners vs. losers within low R&D are 4.3 percentage points higher and the Sharpe ratio 0.29 basis points higher for the full sample. Similar conclusions are drawn for the first and last 10 years of the sample, confirming the suspicion that low R&D 6-month losers perform substantially poor. Withal, when looking at the top R&D portfolio, the disparity of performance between winners and losers is not picture clear. In fact, high R&D losers produce annual returns higher than winners for the full sample, 16.5% vs 15.6% with a remarkably high annual volatility of 31.2%, resulting in slightly lower risk-adjusted returns. High R&D winners take the edge with a Sharpe ratio of 0.57 vs. the losers' 0.48, driven by the unstoppable bull-run markets experienced after the 2008 financial crisis extending to the end of the sample. Notably, Chan, Lakonishok, and Sougiannis (2001) also show that in their 1975-1995 sample that previous 3-year losers within the highest firms sorted by R&D over sales outperform the winners by 4.3 percentage points. In the light of the above, tough conscious that the authors' findings occur with a slightly different signal and different 3-year instead of a 6-month window, the possibility that losers within the long portfolio perform better than winners in a different time-period is not discarded. Hence, an optimized long-short portfolio with the same long component is built, with the twist that only losers within low R&D to market equity will be short sold. A further attempt to develop and optimize the investment strategy was carried out, by sorting the 1000 stocks into 3x3 groups of different R&D signals and momentum rankings resulting in 9 different portfolios with a similar number of firms. The underlying idea was levered by the findings in Exhibit 2.2 that suggest that the highest risk-adjusted performance do not necessarily origin from the highest decile, but in general from high R&D to market equity ranking firms. The narrowing down would be made in the momentum groups by sorting firms into terciles instead of only winners and losers. The lowest ranking losers tercile within R&D would be short sold. Appendix 2.6 lays out the results in terms of performance this third

Exhibit 2.4: Zero Investment Strategies and Market Returns – 10% Volatility



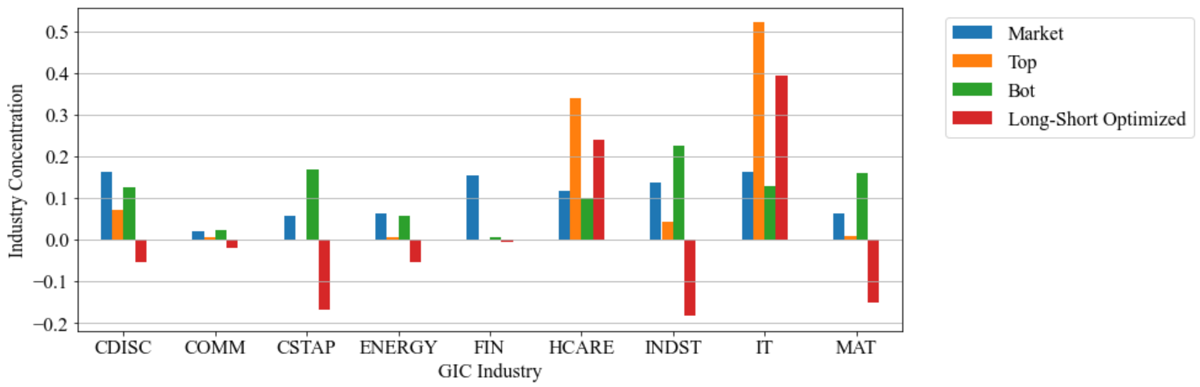
strategy yields. As the results are very similar, and this projects' focus being R&D scaled by market equity rather than momentum, the original strategy will be utilized for the remaining analysis.

Table 2.2: Optimized Zero-Investment R&D Strategy - Full Sample

	Full Sample	2000-2010	2010-2020	dotcom	2000s	subprime	2010s	covid
ann_return	11.3%	13.2%	9.4%	21.5%	9.1%	-1.2%	10.9%	21.6%
std	15.2%	19.0%	10.4%	28.5%	16.5%	11.6%	10.7%	13.1%
sharpe	0.74	0.7	0.91	0.75	0.55	-0.1	1.02	1.65
cum_return	7.00	2.10	1.57	0.48	0.49	-0.02	2.07	0.21
ann_alpha	(0.1, 0.0)	(0.07, 0.21)	(0.08, 0.01)	(-0.15, 0.37)	(-0.05, 0.35)	(0.0, 0.99)	(0.09, 0.01)	(0.07, 0.71)
market_beta	(0.08, 0.21)	(0.13, 0.26)	(0.04, 0.51)	(-0.1, 0.71)	(0.86, 0.0)	(0.03, 0.91)	(0.11, 0.15)	(0.01, 0.93)
smb	(0.4, 0.0)	(0.38, 0.03)	(0.53, 0.0)	(0.48, 0.17)	(0.59, 0.0)	(0.26, 0.64)	(0.39, 0.0)	(1.37, 0.05)
hml	(0.25, 0.0)	(0.52, 0.0)	(-0.07, 0.53)	(1.41, 0.0)	(-0.0, 0.99)	(-0.14, 0.58)	(-0.08, 0.5)	(0.25, 0.37)
mom	(-0.08, 0.15)	(-0.15, 0.08)	(0.05, 0.57)	(-0.58, 0.01)	(-0.3, 0.01)	(-0.1, 0.61)	(-0.0, 0.99)	(0.45, 0.15)
R2_adj	0.13	0.18	0.16	0.48	0.60	0.08	0.10	0.66
te	0.04	0.05	0.03	0.05	0.03	0.03	0.03	0.02
IR	0.20	0.12	0.25	-0.24	-0.14	0.00	0.26	0.35

The earlier defined optimized R&D strategy, displayed in Table 2.2 and Exhibit 2.4 seven-folds within the sample's 21 years, yielding an average return of 11.3% vs the regular long-short's 9.2%. A valid criticism for this strategy is that short selling a subset of firms that exhibit an average volatility of 23.7% for the full sample, 27.9% for the first half, does not come for free. The investor would have to bear the margin interest cost for the entirety of the investment horizon which could lower the performance of the strategy substantially. Retail investors are also impotent as there is not an affordable, liquid ETF today than can help and investor simulate at least the long part of this strategy. A further key characteristic of the strategy is, that despite its slight loading on value companies, further analyzed in more detail, it is rather highly exposed to the information technology (IT) and healthcare GIC sectors.

Exhibit 2.5: Strategy - Average GIC sector exposure – Full Sample



Being a zero-investment strategy helps attenuate the effect of the 52% IT and 34% healthcare industry concentration that the long portfolio reveals, netting a total exposure of 39% to IT and 24% to healthcare. A further note - the S&P500 and Nasdaq-100 indexes have currently an IT exposure of about 28% and 50% respectively. As a standalone investment, the exposures for the proposed strategy are not ludicrous, though they pose a barrier for investors looking to diversify away from IT stocks without selling some of their holdings. Appendix 2.7 presents the top 5 holdings in the long and short tail of the portfolio and their respective industries by December 2020 to give investors a more practical example of what his holdings could look like. Another implementation challenge is the weighting. Attributing either market/value weights or equal weights to the stocks within the portfolios would also interfere with its diversification. Pure value weights would cause mega-caps to dominate the portfolio, dictating its returns while simple equal weights would make the strategy not fitting for a large fund. 80th percentile winsorized market weights are given to each stock, resulting in smaller weightings for large firms and somewhat larger weightings in smaller stocks. The average maximum weight for long and short tail of the optimized long-short portfolios is 3.2% and 2.8% respectively. Appendix 2.8 shows its highest single stock weighting over time.

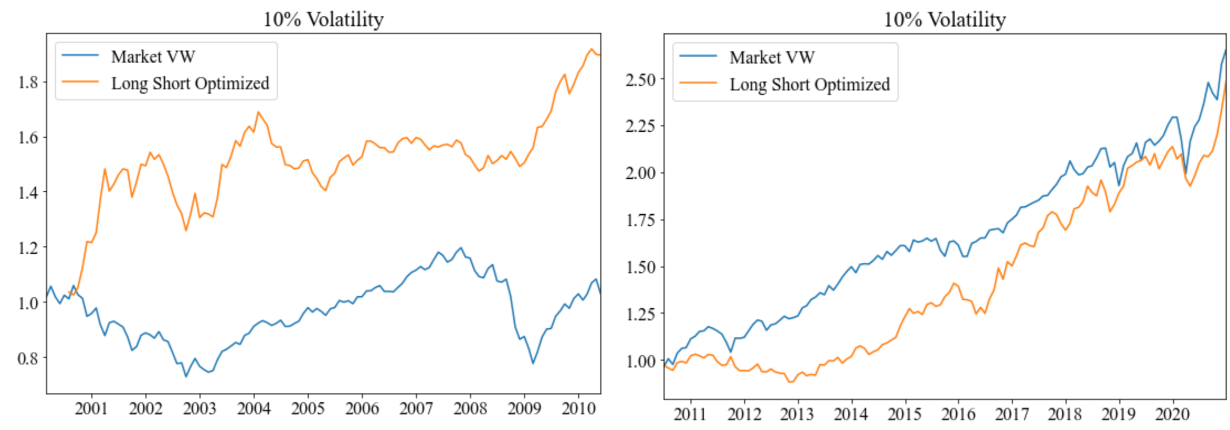
Regression Analysis

To quantitatively assess the returns of the strategy, the Carhart 4-factor model (3) will be deployed.

Table 2.3: Market Metrics for comparison

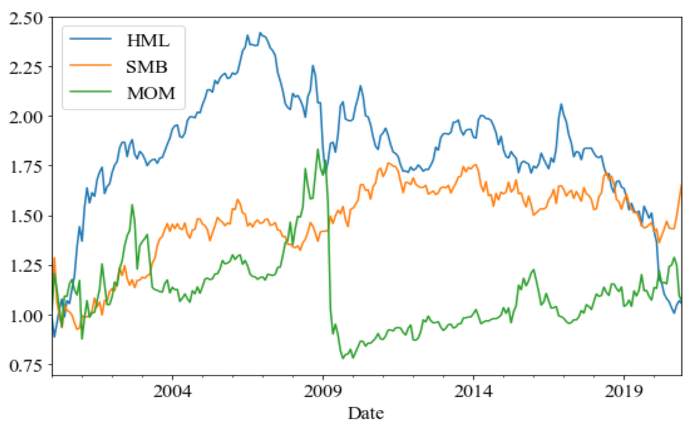
	Full Sample	**2000-2010**	**2010-2020**	**dotcom**	**2000s**	**subprime**	**2010s**	**covid**
ann_return	8.3%	9.0%	16.5%	-17.5%	15.7%	-49.0%	16.6%	27.6%
std	15.7%	17.3%	31.2%	18.9%	9.8%	20.0%	13.3%	28.8%
sharpe	0.43	0.43	0.48	-1.13	1.32	-2.53	1.21	0.95
cum_return	3.38	3.58	9.88	-0.40	1.16	-0.50	4.50	0.24

Exhibit 2.6: Performance of Optimized R&D Strategy and the Market – 1st and 2nd half



The proposed strategy yields a Sharpe ratio of 0.74 for the full sample vs the market's 0.43, suggesting strong risk-adjusted performance. The same trend is present in each half of the sample, though the stock market presents better results in terms of absolute performance in the second half by 7.1 percentage points. Going a step deeper, it is striking to observe the negative, however insignificant alpha in the "dotcom" bear market, with average returns and the Sharpe ratio being 39.0 percentage and 188 basis points higher than the market respectively. In this crash, the strategy reaped benefits from being market neutral, while disappointing in the period of expansion of the remaining 2000's in terms of alpha, nevertheless not significant at standard confidence levels. Other conclusions are drawn from the subprime crisis and the 2010's expansion period, with the strategy performing somewhat neutrally in the crash while the market dips and lagging by a few points when it rebounds in the 2010's, howbeit with strong significant annual alpha of 9%. Lagging bull-markets is one of the pain points of the strategy, evident in the second half of the sample (Exhibit 2.6). From the peak before the coronavirus pandemic crash in 2020 to the end of the sample the strategy's Sharpe ratio is 1.65 vs. the market's 0.95, by yielding smaller returns with less than half of the market's volatility. Only considering the Sharpe ratio, it seems the strategy naturally performs better in periods of recession and slightly worse in periods of expansion relative to the market, based on data from the dotcom and subprime crisis. It does not go without saying that the model (adjusted R^2) only explains 13% of the optimized strategy's returns for the full sample, which is rather low even for financial analysis. This can invalidate some of the analysis. A clearer picture emerges as further regression outputs are considered. One first benefit of a zero-investment strategy is that it aims to be market neutral by cancelling out the market exposures with bought and short sold portfolios, lowering the chances of a liquidity shock for investors in crashes. Subsequentially, the strategy has a not significant market beta of 0.08 for the full sample. These results do not surprise as the long leg has betas of 1.26 (losers) and 1.17 (winners) and the short (losers) portfolio a beta of 1.13. What should surprise, is that a strategy built using R&D has a positive and significant loading of 0.25 on the hml (value) factor, which reaches 1.41 during the dotcom bear market and dissipates throughout the remainder of the sample. This is a period where value investments performed particularly well, depicted by hml's performance in Exhibit 2.7. The temporary value exposure mainly results from the strategy's short leg -0.62 loading on value stocks of during the first half of the sample. In this period the momentum factor performed decently and the strategy's exposure to it is negative 0.58. As a result the strategy's annual return of 21.5% mainly levers on the strong results posted by the high value factor exposure during this period. As a result of the market showing signs of overheating in the early 2000's, the strategy was not allocating firms with preposterous valuations to the long leg of the strategy. It was rather picking up beaten down, highly R&D intense stocks that could be considered value investments with growth characteristics. The smb factor loading of the strategy is positive and mostly significant throughout the sample, suggesting the strategy levers on the returns of smaller companies. Winsorizing market

Exhibit 2.7: Factor portfolios – Kenneth French library



weights also contributes to this loading by limiting the return contribution of larger firms. Another revealing finding is the strategy's negative, still, only significant at an 85% confidence level, loading on the momentum factor for the full sample even though only low R&D losers are being considered for the short leg. This is due to the fact that even winners within high R&D to market equity firms show negative momentum characteristics, which might be confusing at first. Firms in the long tail of the strategy are only present because they were either, 1. - lagging the general market to produce returns observed by a relatively low market equity which increases the ratio and/or 2.- they have massive R&D spendings. The first case can be directly linked to negative momentum. The second case might come to existence because markets miss evaluate this specific subset of firms' abilities to come up with positive results from the R&D investments either due to pessimistic R&D returns forecasts or extreme risk discounting.

Further analysis shows that the strategy presents significant positive alpha of 10.0% after controlling for the market, smb, hml and momentum factors which confirms our previous suspicion of abnormality in returns. Perhaps more revealing are the high annual tracking error figures presented by the strategy, 14.05% for the full sample, reaching 16.85% in the first half. These high tracking errors lower the values for the Information ratio of 0.20 (full sample), but most importantly, deliver an insight regarding the source of the mispricing. There is no doubt that the strategy performs well, but if the abnormal returns are being generated over a benchmark that does not tightly fit, possibly the benchmark does not appropriately capture all the risk the entailed. And if this is the case, then the eventual extreme risk discounting given to firms on the long tail is justified, explaining part of the performance laid out by firms with high R&D over market capitalization.

Conclusion

To conclude, this project acknowledges that companies invested in R&D do not display superior returns performance compared to ones not invested in R&D. Howbeit, the spread in performance that the high R&D scaled by market equity quantile firms produce over its low R&D peers is evident, as previous researchers also find in their samples. When independently ranking U.S. stocks' previous 6-months returns, the highest R&D signal quantile contains more losers than winners and vice-versa for low R&D. An insightful finding because winners tend to outperform losers. However, both winners and losers in the high R&D portfolio do not seem to perform differently. An optimized long-short strategy is built to exploit the differential in performance within R&D signal extremities, with the twist that only low R&D losers are short sold. The strategy shows a high, positive and significant annualized alpha of 10.0% for the full sample. It loads positively on smaller and curiously on value firms; surprising given R&D being usually linked with growth. Remarkably, it also loads negatively on momentum despite only short selling previous losers. This is driven by high R&D signal stocks carrying a negative momentum exposure. The strategy has an average sector exposure of 39% to IT, 24% to healthcare despite being market neutral, which may pose a barrier for investors looking to diversify without having to sell holdings.

As a final remark the proposed strategy generates significant annual alpha of 10.0%. Using the Carhart 4-factor model as a benchmark, the strategy produces a high tracking error of 14.1% for the full sample which hints that the benchmark and the strategy do not tightly fit. This suggests that risk is being inadequately measured and that the abnormal returns displayed by the strategy are partially a result of additional risk exposure that current models don't capture.

Group Contribution – Combing Investment Strategies

Volatility Timing – Strategy Description

The first individual strategy to be part of a combined portfolio is the optimized volatility timing strategy analyzed in part 1 of this report. Extensive academic research on the low volatility anomaly has shown, that an investment strategy, that ranks stocks based on their past realized standard deviation of returns and systematically buys the least risky ones can achieve abnormal returns on the US stock market. Low volatility strategies tend to outperform the broad equity market in the long run but also naturally underperform during good market times. As the stock selection by low standard deviation of returns naturally selects securities, that have low co-movement with the broad market portfolio (low beta stocks), investors do not benefit from higher concentration, when desired. In an attempt to improve the static low volatility strategy Neo and Tee (2021) present a volatility timing signal, that holds the low volatility portfolio per default and switches to the high volatility decile portfolio, when the signal is bullish (in their most basic variation). The slope of the volatility decile return profile as described in formula (2), serves as the predictor of market regimes and is expected to be positive during bull markets. When the slope is significantly positive, the investment strategy switches from the low volatility to the high volatility decile portfolio for the next month. As this basic variation of the volatility timing strategy only yields slightly higher returns at a higher risk (see Neo and Tee 2021 and table 1.1), the strategy has been improved by holding a portfolio that buys past winners, instead of simply holding the high volatility decile. It is to note, that this improvement of the strategy only achieved reasonable results for the US and not for the German equity market. In Germany, where all analyzed volatility-based strategies performed worse than in the US, the slope of the volatility quantile portfolio’s return profile is not a reliable predictor. For this reason and to keep the focus on the US market, the combination with a R&D based strategy will be done with the improved volatility timing strategy on the US market. As indicated in table 1.1 in the analyzed period from 1991 – 2021 the improved strategy (volatility timing 2) yields an annualized return of 14.11% at a standard deviation of 16.18%, and an annualized alpha of 3.47% after accounting for size, value and momentum risk factors (only significant at the 14% level). This performance means a slight deterioration in Sharpe ratio of 0.03 over the static low volatility portfolio, however at a significantly higher return. Hence, the trade-off should be reasonable. When comparing the timing strategy against the momentum strategy, that buys past winners and holds them for a month, the improvements are much more noteworthy as the timing strategy can avoid severe momentum crashes. Note that for data compatibility reasons the observation period of the volatility timing strategy is aligned with the R&D strategy from 2000 – 2020.

Optimized R&D over Market Equity – Strategy Description

The second component of the combined portfolio is the optimized R&D over market equity strategy analyzed in part two of this report. The origin of this strategy came after brainstorming about what kind of signal would need to be constructed, that would pick up high potential stocks that would fly under the radar according to most common investment strategies. To achieve this, two ingredients would be necessary. A numerator that is linked to potential future returns though not relying on common growth indicators. The second ingredient would need to screen overvalued companies out of the strategy. The found solution was to invest in companies according to their R&D to market equity ratio.

High signal bearers show confidence by maintaining high levels of R&D spending even when the firms are being poorly valued or have had poor past returns, which Chan, Lakonishok, and Sougiannis (2001) mention. As referenced in the individual part, previous studies show that stock markets take time to react to management signals (Ikenberry, Lakonishok, and Vermaelen 1995), and if they do in this particular case, the strategy will benefit from it. A secondary goal is to quantitatively find value firms with growth characteristics, which might be possible with this ratio. The strategy consists of portfolios formed based on firms' last known yearly R&D expenditures figure divided by its market equity. High signal ranking firms are allocated to the top quantile portfolios. Secondly, a sorting on previous 6-month winners and losers is performed. Then, a zero-investment strategy that goes long (short) high (low) R&D signal firms is built. There is a slight twist in the short tail of the strategy, as only low R&D signal and previous 6-month losers are considered. Winsorized, market cap weights are given to stocks such that mega-caps do not dominate. Smaller companies carry more weight to balance the distribution but are not extremely weighted as they would be with equal weights.

The difference in returns between high and low signal firms is evident. Only short selling losers withing low R&D signal improves the strategy in terms of alpha and Sharpe ratio while decreasing the negative on momentum. The strategy generates annualized alpha of 10.0% and has a Sharpe ratio of 0.74 compared to the market's 0.43. Still notably, its returns are mainly driven by the strong performance in the first half as it seems to slightly lag the market on the second half. It loads positively on the smb and value firms, though being constructed with a signal that investors associate with tech and growth. Taking a more critical approach, the strategy is highly exposed to the IT and healthcare sectors and the alphas generated come from a model that only has an adjusted R^2 of 0.13.

Strategy Comparison

This section will focus on the benefits of combining the optimized R&D with the volatility timing strategy. The volatility of a two-asset portfolio, A and B, can be described the following formula:

$$\sigma_p = \sqrt{(w_a^2 \cdot \sigma_a^2) + (w_b^2 \cdot \sigma_b^2) + 2 \cdot w_a \cdot w_b \cdot \sigma_a \cdot \sigma_b \cdot \rho_{a,b}} \tag{4}$$

Where w_a, w_b are the weights in both assets and σ_a, σ_b their respective volatilities. The crucial element of the benefits of combining two assets comes from the way they correlate, measured by $\rho_{a,b}$. Perfect correlation boils down to a $\rho_{a,b}$ of 1, when assets behave meticulously the same. Perfect negative correlation, $\rho_{a,b} = -1$ happens if asset A and B's returns exactly offset each other, reaching maximum diversification benefits. The optimized R&D strategy consists of a zero-investment, market neutral strategy built by a long and a short leg, whereas volatility timing follows a more traditional long-only approach. They are therefore presumed to display different patterns of returns.

Table 3.1: Correlation Matrix

	volatility timing	optimized R&D
volatility timing	1.0000	0.1824
optimized R&D	0.1824	1.0000

Exhibit 3.1: Comparison of Strategies – 1st and 2nd half of 2000-2020

The optimized R&D and the volatility timing strategy exhibit a correlation of only 18.24%, meaning that the combination of both shows evidence of strong diversification benefits. Both strategies also exhibit different performance when assessing different time periods. As indicated in the performance graphs of exhibit 3.1, during the first half of the sample the R&D strategy dominates volatility timing, by strongly benefiting from a neutral market beta. It not only absorbs the losses from the dotcom and subprime crash but posts strong results. A role-swap happens in the second half of the strategy as the volatility timing strategy performed much better during the 2010's by picking firms with stable returns, in a period where the U.S. market performed extremely well.

Table 3.2: Individual strategy performance metrics and factor exposure comparison

	Full Sample		2000-2010		2010-2020	
	Volatility Timing	**Optimized R&D**	**Volatility Timing**	**Optimized R&D**	**Volatility Timing**	**Optimized R&D**
Ann. return %	10.01	11.31	3.98	13.23	15.65	9.52
Std %	11.89	15.19	12.88	19.04	10.67	10.44
Sharpe	0.72	0.74	0.12	0.69	1.42	0.91
Cum. return %	568.64	699.84	36.67	210.33	389.23	157.74
Alpha %	(3.83, 0.02)	(9.6, 0.0)	(-0.17, 0.95)	(7.19, 0.21)	(4.83, 0.02)	(8.23, 0.01)
Beta_mkt	(0.68, 0.0)	(0.08, 0.21)	(0.67, 0.0)	(0.13, 0.26)	(0.68, 0.0)	(0.04, 0.57)
Beta_smb	(-0.19, 0.0)	(0.4, 0.0)	(-0.06, 0.44)	(0.38, 0.03)	(-0.3, 0.0)	(0.53, 0.0)
Beta_hml	(0.21, 0.0)	(0.25, 0.0)	(0.34, 0.0)	(0.52, 0.0)	(-0.01, 0.88)	(-0.07, 0.52)
Beta_mom	(0.21, 0.0)	(-0.08, 0.15)	(0.22, 0.0)	(-0.15, 0.08)	(0.11, 0.05)	(0.05, 0.59)
Adj. R_squared	0.63	0.13	0.62	0.18	0.68	0.16
F-test	105.01	9.89	48.14	7.55	68.45	6.94

Annotation: Measured in the common timeframe of the Risk-Parity strategy built in the future section

This is reflected in the numbers displayed by table 3.2. Volatility timing has a higher, yet still low market beta of 0.68 vs 0.08 for the R&D strategy for the full sample. Another inequality is that volatility timing is slightly tilted to larger companies and optimized R&D more to smaller firms as observed by their smb betas of -0.19 and 0.4 respectively, though very similarly matched in exposure to high book-to-market firms. Both strategies display a similar strong risk adjusted performance for the full sample, with different behavior in each subperiod as described above. As expected, volatility timing loads stronger on the momentum factor with a full sample beta of 0.21 vs -0.08 of the optimized R&D strategy. Furthermore, the strategies outperform their respective factor benchmarks for the full sample measured by the alpha: 3.83% and 9.6% for volatility and R&D respectively, however only 13% of the variations in the returns is explained by the latter model, measured by the adjusted R^2. Adding to the mean-variance benefits found in the sample, the combination of both strategies could lead to an investment that is stable under down turns while reaping most benefits from bull markets. The optimal combination method will be put to test in the following sections.

Tangency Portfolio

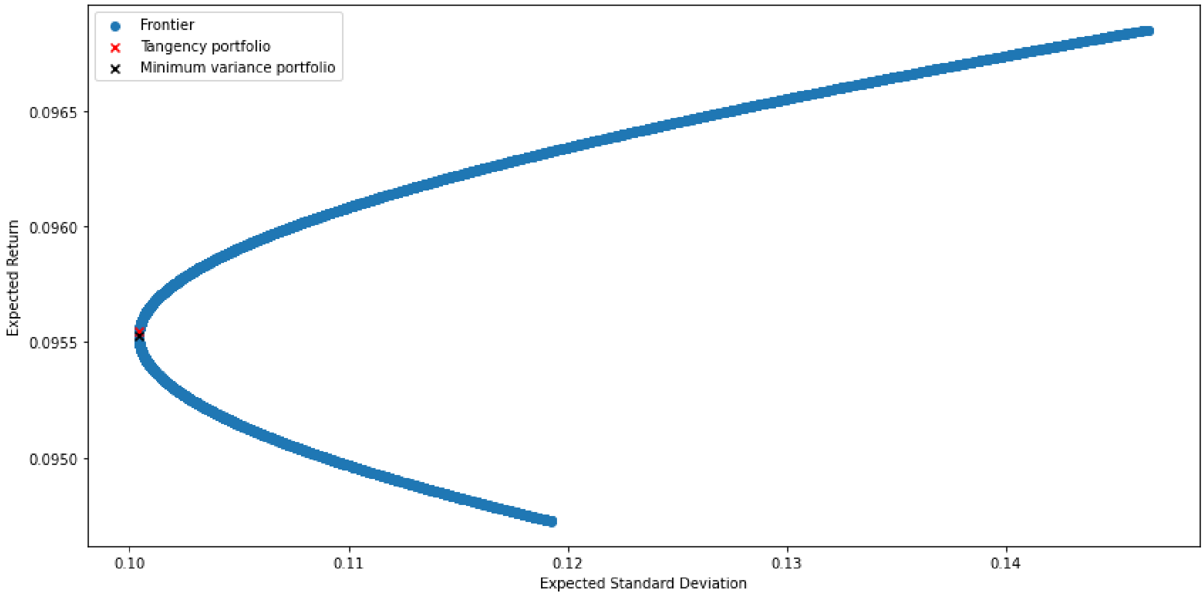
The first analysis to be made to find the optimal combination of a portfolio consisting of a volatility timing and a R&D over market equity strategy, is to find the tangency portfolio out of those two strategies. By modern portfolio theory investors should be trying to hold a portfolio, that maximizes the expected return and minimizes portfolio variance (risk). To hold such a portfolio, one has to find the optimal combination of available assets, that satisfies above mentioned conditions (see Markowitz 1952). Considering, that an investor wants to hold two assets: 1) An investment strategy, that holds a low volatility portfolio and switches to a past winner portfolio during bullish market times and 2) An investment strategy that goes long in stocks with a high R&D over market cap ratio and shorts stock with low R&D ratio, that were past losers based on their 6-month cumulative return. To find the optimal portfolio out of these two assets, we are calculating the weights in each strategy that maximize the portfolio Sharpe ratio, defined as:

$$SR_P = \frac{\overline{R_P} - \overline{RF}}{\overline{\sigma_P}} \tag{5}$$

Where, $\overline{R_P}$ is the expected annualized portfolio return, $\overline{RF}$ is the expected annualized risk-free rate and $\overline{\sigma_P}$ is the expected annualized portfolio volatility (see Sharpe 1966). By maximizing the Sharpe ratio, the weight combination is found, that yielded the maximum excess return per unit of risk.

To achieve this goal, we are simulating 10,000 possible weight combinations of the two strategies and compute the combined portfolio with the weight combinations of the maximum Sharpe ratio portfolio. The risk / return relationship of all simulated weighting combinations is presented in exhibit 3.2. The computed tangency portfolio holds 38.5% of the R&D strategy

Exhibit 3.2: Efficient frontier and tangency portfolio



and 61.5% of the volatility timing strategy. Through this weight combination the Sharpe ratio can be maximized and has a value of 0.82 over the observed period. The exhibit also indicates the minimum variance portfolio. The minimum variance portfolio is the weight combination that minimizes the portfolio risk and assigns 37.6% to the R&D strategy and 62.4% to the volatility timing portfolio. All portfolios that are above the minimum variance portfolio on the frontier are mean-variance efficient. Hence, they reflect optimal risk / return relationships.

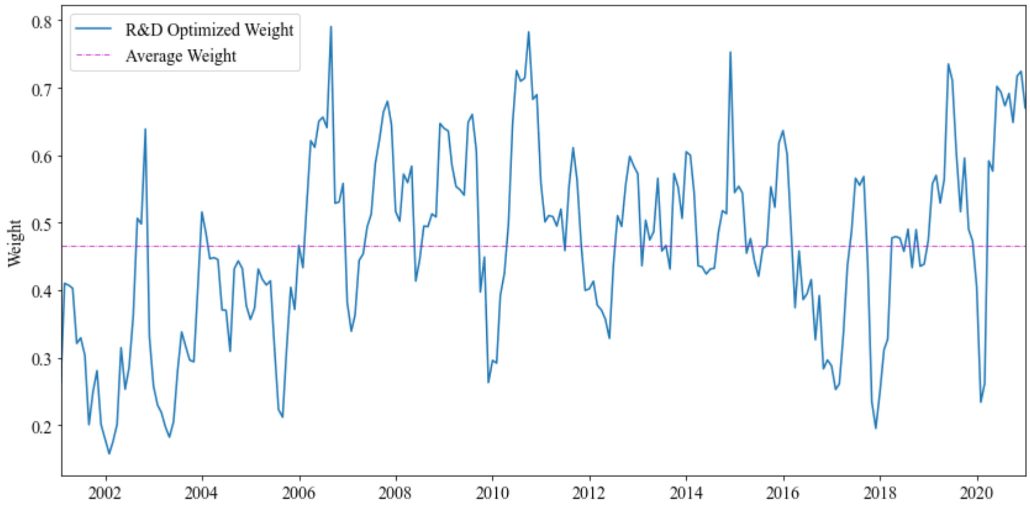
It is to mention, that this way of optimizing the portfolio relies on the assumption that historical covariances between the two strategies will persist in the future. The tangency portfolio reflects the weight combination that maximize the Sharpe ratio based on past returns. These results were not implementable during the observed period and just present the ex-post theoretical optimal asset combination. To receive some investible results, we will be computing a rolling risk-parity portfolio of the two strategies, that rebalances every month. The tangency portfolio can be used for benchmarking purposes to see how an actually implementable strategy compares to the theoretical optimal fixed weights. All risk and performance results of the combined strategies will be presented in the last part of this analysis.

Risk-Parity Portfolio

Throughout time, finance practitioners have tried to develop more sophisticated methods of weighting assets to achieve stronger performance, some of these methods relying extensively on mean-variance estimations. DeMiguel, Garlappi, and Uppal (2009) find that none of the 14 sample-based models they analyze consistently performs better out-of-sample than the simple equal-weight portfolio, mainly due to estimation error. Similarly, observing portfolio weighting performance comparisons, it stands out that the risk-parity portfolio tends to outperform its peers that rely on additional estimations. This method only needs each individual asset's volatility as an input, reducing the necessary number of estimations and therefore estimation error. In addition, one of the pitfalls in mean-variance estimations is that returns show a low degree of predictability. However, volatility shows to be persistent and autocorrelated, with low (high) volatility periods generally following low (high) volatility periods and vice-versa. This effect is decently captured by GARCH models (see Engle 1982; Bollerslev, Chou, and Kroner 1992). As a result, dynamic monthly weights attributed to assets based on historical short-term volatility, are likely to reflect present volatility. Chaves et al. (2011) find in their sample that the traditional risk-parity does not consistently outperform the standard 60/40 or the simple equal-weight method, but it shows to be more robust than minimum and mean-variance efficient portfolios.

Motivated to weight each strategy such that each asset has the same risk contribution without forgoing performance, we built the risk-parity portfolio. We start by calculating 6-month rolling standard deviations and weight each strategy dynamically each month to meet a target volatility of 15.0%. By observing that the optimized R&D strategy tends to have a higher standard deviation than the volatility strategy, especially in the first half (table 3.2), it is expected to carry a lower weight on average throughout the whole sample. The resulting average weight for the optimized R&D strategy is 46.5% and 53.5% for the volatility timing strategy confirming

Exhibit 3.3: Optimized R&D over Market Equity weights in the Risk-Parity Strategy



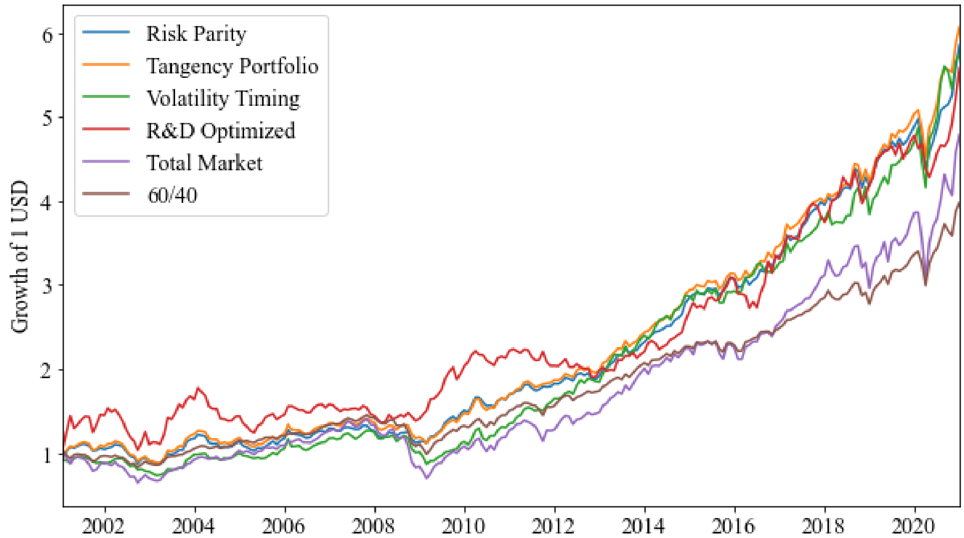
previous expectations. The optimized R&D strategy weights as low as 15.8% in the start of 2002, averaging a weight of 34.0% until January 2006. As indicated by exhibit 3.3, one disadvantage of the rolling risk parity strategy is that weights between both strategies shift considerably throughout time, likely to result in slightly higher transaction costs compared to a simple 1/N weighting method. Despite the weights changes this strategy encompasses, it is surprising how it performs against the statically weighted tangency portfolio, which will be analyzed in the following section.

Performance Comparison

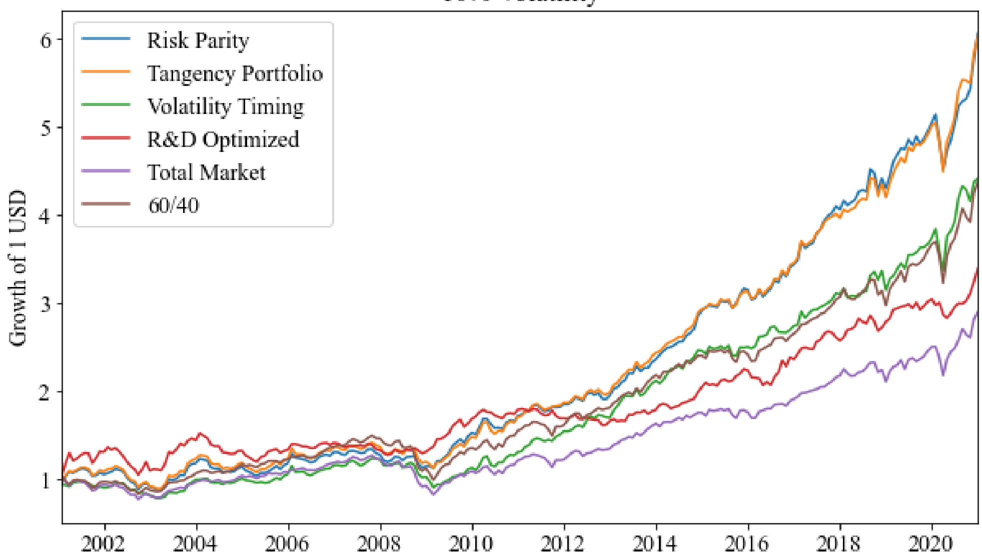
Cumulative Returns

To assess the strategies' performance, we are using standard benchmarks such as the total U.S. market. The data for the U.S. market stems from the Mkt-Rf factor, downloaded from the Kenneth French library to which we add back the risk-free rate. This would be the opportunity cost for an equity long-only investor. We are not only comparing the combined portfolio to the total market portfolio but also to a classic 60/40 weighted equity bond investment strategy. To construct the 60/40 portfolio the Fama-French market factor serves as proxy for equities. Bond investments are represented by the Bloomberg US Aggregate Bond Index, an index that measures investment grade, US dollar-denominated, fixed-rate bonds including Treasuries, corporate bonds, and mortgage and asset backed securities, to get a broad exposure to the US bond market. Data for the bond index has been obtained from Bloomberg. Indexes and not ETFs have been used to keep a fair comparison as the investment strategies do not reflect trading costs. A portfolio that is invested 60% in equities and 40% in bonds serves as the base-case, as it is a widely spread asset allocation strategy among institutional and retail investors to benefit from diversification coming from the low correlation of equities and bonds. Even though this standard asset allocation approach seems to be outdated in the current market environment, after a decade of rate cuts, low inflation and bull run for equities, it has been the state-of-art benchmark in the portfolio management industry.

Exhibit 3.4: Cumulative Returns of Combined Strategies and Common Benchmarks



10% Volatility



Combining the strategies in a tangency and risk-parity (RP) portfolio described above we draw a positive initial impression displayed in exhibit 3.4. This combination and analysis are performed on a reduced observation period from January 2001 until December 2020, to have aligned timeframes with the combined strategies.[1] The RP portfolio clearly outperforms the individual strategies, but also the total market and popular 60/40 portfolio looking at normalized returns. The next important observation is, that it is very hard to tell the difference between RP and the mean-variance efficient portfolio during our sample, which shows the strength of the dynamically weighted RP against the non-investible, optimal tangency portfolio. As referenced before, the optimized R&D strategy performs better in the first half of the sample where in the second half volatility timing is clearly the top performer. Overall, the diversification benefits of the RP strategy are evident as the combined strategy displays better risk adjusted returns than any of the strategies individually. An example can be obtained by looking at the normalized chart slope after 2013. The combined strategies' slope is even higher than the best performing individual strategy.

Factor Analysis and Subperiods

To get some in-depth insights about combined portfolio metrics and benchmarking over the entire and sub periods, performance- and risk metrics as well as regression results of a Carhart four-factor model are presented in table 3.3. The first important observation, already visible in the graphs of exhibit 3.4 is the similarity in (risk- adjusted) performance between the mean-variance efficient portfolio and the monthly adjusting risk-parity. Over the full period the RP can even achieve a slightly higher alpha of 4.24% versus 4.07% of the tangency portfolio. In the 2nd half of the period the tangency portfolio had a slightly higher Sharpe ratio. Next, even though the 60/40 portfolio can significantly reduce its market beta (0.59) due to the addition of

[1] Six months of data are lost as we will introduce a risk-parity portfolio based on prior 6 months standard deviations

Table 3.3: Combined Strategy Performance Metrics and Risk Factor Exposure

	Risk Parity	Tangency	Total Market	60/40
Total				
Ann. return %	9.35	9.55	9.08	7.36
Std %	9.79	10.04	15.59	9.32
Sharpe	0.82	0.82	0.5	0.65
Cum. return %	485.79	507.44	379.06	298.3
Alpha %	(4.24, 0.01)	(4.07, 0.01)	(0.0, 0.0)	(1.46, 0.0)
Beta_mkt	(0.45, 0.0)	(0.5, 0.0)	(1.0, 0.0)	(0.59, 0.0)
Beta_smb	(0.08, 0.14)	(0.07, 0.19)	(0.0, 0.76)	(-0.02, 0.13)
Beta_hml	(0.12, 0.01)	(0.12, 0.01)	(-0.0, 0.74)	(-0.01, 0.15)
Beta_mom	(0.13, 0.0)	(0.13, 0.0)	(0.0, 0.4)	(-0.0, 0.47)
Adj. R_squared	0.45	0.55	1	0.98
F-test	50.35	72.78	7.2083E+29	2797.18
1st Half	**Risk Parity**	**Tangency**	**Total Market**	**60/40**
Ann. return %	5.7	5.35	2.2	3.65
Std %	11.66	12.04	16.46	9.89
Sharpe	0.29	0.26	0	0.14
Cum. return %	60.38	54.66	8.11	34.61
Alpha %	(1.62, 0.57)	(0.92, 0.73)	(0.0, 0.0)	(1.43, 0.01)
Beta_mkt	(0.52, 0.0)	(0.56, 0.0)	(1.0, 0.0)	(0.59, 0.0)
Beta_smb	(0.11, 0.2)	(0.15, 0.07)	(-0.0, 0.96)	(-0.01, 0.41)
Beta_hml	(0.25, 0.0)	(0.27, 0.0)	(0.0, 0.99)	(0.02, 0.26)
Beta_mom	(0.14, 0.0)	(0.13, 0.0)	(-0.0, 0.79)	(-0.01, 0.18)
Adj. R_squared	0.48	0.55	1	0.98
F-test	26.52	35.92	1.0399E+29	1113.26
2nd Half	**Risk Parity**	**Tangency**	**Total Market**	**60/40**
Ann. return %	12.6	13.29	15.2	10.67
Std %	7.69	7.74	14.6	8.7
Sharpe	1.57	1.65	1.01	1.17
Cum. return %	265.26	292.76	343.11	195.89
Alpha %	(6.38, 0.0)	(5.94, 0.0)	(0.0, 0.0)	(1.05, 0.0)
Beta_mkt	(0.36, 0.0)	(0.44, 0.0)	(1.0, 0.0)	(0.6, 0.0)
Beta_smb	(0.1, 0.13)	(0.02, 0.74)	(-0.0, 0.78)	(-0.02, 0.21)
Beta_hml	(-0.02, 0.75)	(-0.03, 0.57)	(-0.0, 0.55)	(-0.05, 0.0)
Beta_mom	(0.09, 0.07)	(0.09, 0.05)	(-0.0, 0.93)	(-0.0, 0.71)
Adj. R_squared	0.46	0.61	1	0.98
F-test	27.76	49.29	2.6573E+30	1960.66

Annotation: Returns, standard deviations, Sharpe ratios and alphas have been annualized. P-values of factors and alpha are indicated in 2^{nd} place in brackets.

bonds and yield an alpha of 1.43%, the combined RP outperforms not only as expected with a higher cumulative return (as it is equity only) but also with an improved Sharpe ratio, that is 17 bps higher, and almost similar standard deviation. Especially in the 2^{nd} period, that experienced a very strong run for equities and bonds, the outperformance of the RP strategy over a passively managed market or 60/40 strategy is noteworthy. Even throughout a decade where the broad equity market already had a Sharpe ratio of +1, the actively managed risk-parity strategy, dynamically weighting the volatility timing and R&D strategy, outperforms. Looking at the risk factor exposure over sub-periods we can see that the high alpha of 6.38% for the RP portfolio is supported by a decline in risk factor exposure. The market beta drops from 0.52 from the first to 0.36 in the second half. The positive value factor exposure completely disappears in the 2^{nd} period for both individual strategies and consequently for their combined RP portfolio, which has been particularly beneficial as that decade has been dominated by growth stocks and the strategy's co-movement with weaker performing value stocks diminished.

Conclusion

In this group part of the field lab, we are combining two individual trading strategies to optimize the risk return profile. The considered trading strategies are: 1) A volatility timing strategy that holds the low volatility decile portfolio per default and switches to the past winner portfolio in case of a bullish timing signal and 2) A zero investment R&D over market capitalization based strategy, that goes long the high R&D quintile portfolio and shorts past losers of the low R&D quintile. Both strategies outperform the broad market as a benchmark and after accounting for value, size and momentum risk factors they also generate significant alpha. In the observed period from January 2001 – December 2020 the strategies exhibit a relatively low correlation of 18.24%, while the R&D based strategy performs better in the first 10 years and the volatility timing strategy does better in the second half. To receive a first benchmark, we are computing the mean-variance optimized portfolio of the two strategies over the entire period. Subsequently we are considering a monthly rebalancing risk-parity portfolio between the two strategies and observe a very similar performance compared to the ex-post information based optimal tangency portfolio. Hence, by dynamically weighting each strategy in a way that they contribute with equal risk, we form an investible strategy yielding a similar risk-adjusted return as the optimal fixed-weight portfolio. In comparison to the broad market and the popular 60/40 equity bond portfolio, the combined risk-parity strategy clearly outperforms in absolute and risk-adjusted terms. Our combined strategy produces an average annual standard deviation of 9.72% versus the 9.31% for the 60/40. Producing higher returns at a similar standard deviation of a portfolio partially investing in bonds is a remarkable achievement for an equity only strategy. Key aspects of the strategy are its low market beta of 0.52, small loadings of 0.08 and 0.13 on the size and momentum factors and an exposure to value companies that disappears in the second half of the sample.

Being strategically positioned with the proposed investment strategy will serve a risk averse investor with an asset allocation, that shows to historically perform during bull markets while smoothing out market crashes and keeping standard deviation of returns at a low level of less than 10%.

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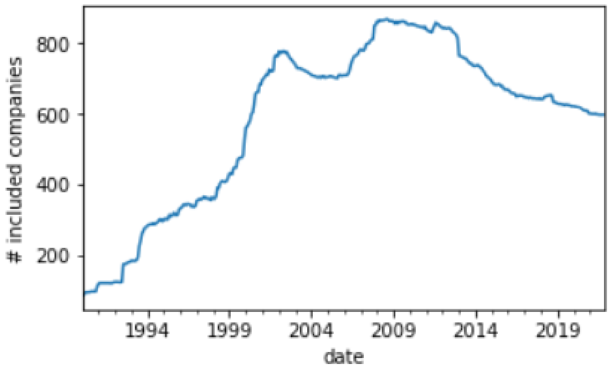
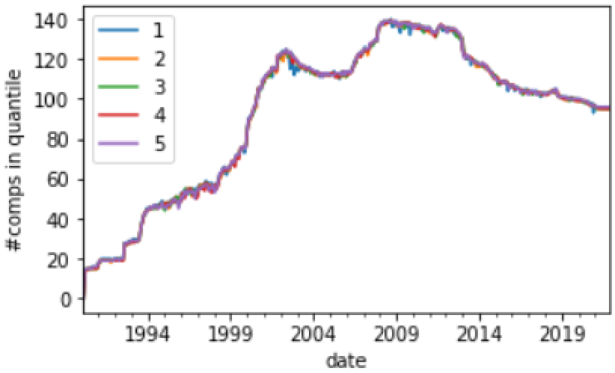
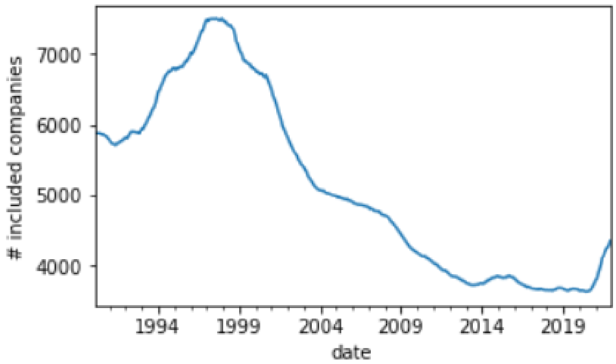
Appendix

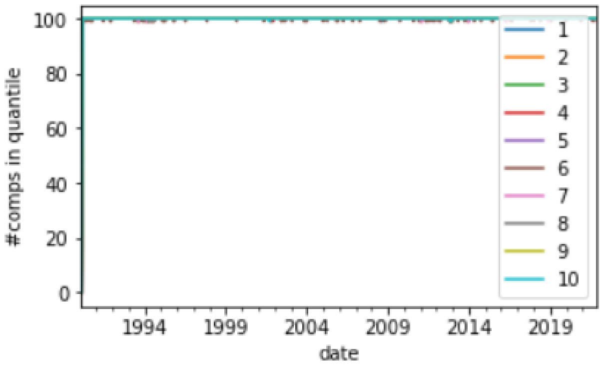
Appendix 1.1: Number of considered companies for portfolio formation each month and companies per quintile portfolio on the German market





Appendix 1.2*:* Number of considered companies for portfolio formation each month and companies per decile portfolio on the US market





Appendix 1.3: Months with bullish signal in the US and Germany

	Germany		
Date	**Low Vol Static**	**Vol Timing 1**	**Vol Timing 2**
31.03.2000	0.61%	-11.09%	-0.51%
30.04.2000	-4.07%	-10.37%	-14.86%
31.10.2005	-2.56%	-6.53%	-5.72%
30.04.2016	-0.91%	2.19%	-0.03%
31.12.2016	6.90%	4.21%	5.04%
30.06.2017	-0.62%	4.97%	-0.77%
31.07.2017	1.86%	8.33%	7.62%
31.08.2017	0.44%	-5.00%	6.16%
31.10.2017	2.21%	8.11%	1.77%
30.11.2017	1.42%	-7.71%	-1.25%

US

Date	Low Vol Static	Vol Timing 1	Vol Timing 2
30.11.1991	-1.78%	-7.88%	-3.61%
31.08.1995	1.39%	-1.14%	0.47%
30.09.1999	-5.22%	-1.42%	-1.12%
31.10.1999	5.15%	10.80%	9.97%
30.11.1999	-3.96%	16.87%	20.72%
31.12.1999	-4.73%	26.53%	37.64%
31.01.2000	-8.23%	-5.90%	-8.85%
29.02.2000	-8.91%	28.26%	42.39%
31.03.2000	9.77%	-26.24%	-18.26%
31.10.2003	3.48%	15.00%	10.73%
30.11.2003	2.42%	3.17%	2.53%
31.01.2004	1.21%	5.55%	0.04%
29.02.2004	3.01%	1.15%	1.00%
31.03.2004	-0.90%	-2.88%	0.36%
30.04.2004	-0.94%	-7.35%	-5.50%
31.08.2005	-1.79%	-1.28%	3.05%
30.09.2005	0.81%	2.08%	3.58%
31.10.2005	0.16%	-1.53%	-2.24%
30.11.2005	4.70%	3.24%	4.87%
31.12.2005	-0.43%	1.65%	2.63%
31.01.2006	0.48%	12.07%	10.34%
28.02.2006	1.92%	-4.97%	-7.43%
30.04.2006	2.74%	3.31%	0.82%
31.05.2006	-0.45%	-7.75%	-3.79%
31.08.2007	2.69%	-0.44%	2.27%
28.02.2010	1.92%	4.29%	5.58%
31.03.2010	3.60%	10.02%	9.41%
30.04.2010	0.54%	5.30%	1.91%
31.05.2010	-7.03%	-7.51%	-9.54%
31.03.2017	1.27%	-1.59%	-2.98%
30.06.2018	1.70%	1.18%	2.29%
31.07.2018	5.13%	-0.45%	0.10%
28.02.2021	-1.30%	-6.47%	-4.66%

Annotation: Months during which the timing signal led to a better performance than the default low volatility portfolio are indicated in green. Months during which the performance was worse, and the

Appendix 1.4: Strategy performance metrics and risk-factor exposure in Germany and the US over subperiods

Germany

	90s			Dotcom			2000s			Subprime			2010s			Covid		
	Low Vol Static	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**
Ann. return %	9.52	8.12	9.38	-3.63	-6.15	-7.95	28.35	27.6	27.75	-60.13	-60.13	-60.13	8.2	8.55	8.87	24.08	24.08	24.08
Std %	13.16	13.78	13.16	12.42	13.78	15.31	12.05	12.49	12.38	32.64	32.64	32.64	13.83	14.49	14.02	20.19	20.19	20.19
Sharpe	0.39	0.27	0.38	-0.6	-0.72	-0.77	2.12	1.98	2.01	-1.88	-1.88	-1.88	0.56	0.56	0.6	1.18	1.18	1.18
Cum. return %	106.84	82.77	104.53	-10.42	-16.3	-20.49	320.21	303.08	306.58	-54.51	-54.51	-54.51	118.82	125	134.53	55.41	55.41	55.41
Alpha %	(1.19, 0.76)	(-2.26, 0.61)	(0.86, 0.83)	(-6.27, 0.41)	(-7.84, 0.33)	(-8.95, 0.32)	(6.13, 0.26)	(4.59, 0.41)	(4.91, 0.37)	(4.78, 0.81)	(4.78, 0.81)	(4.78, 0.81)	(-1.29, 0.61)	(-1.06, 0.71)	(-0.76, 0.77)	(11.23, 0.41)	(11.23, 0.41)	(11.23, 0.41)
Beta_mkt	(0.57, 0.0)	(0.56, 0.0)	(0.57, 0.0)	(0.67, 0.0)	(0.75, 0.0)	(0.81, 0.0)	(0.58, 0.0)	(0.62, 0.0)	(0.61, 0.0)	(1.05, 0.0)	(1.05, 0.0)	(1.05, 0.0)	(0.69, 0.0)	(0.69, 0.0)	(0.7, 0.0)	(0.8, 0.0)	(0.8, 0.0)	(0.8, 0.0)
Beta_smb	(-0.16, 0.22)	(-0.07, 0.62)	(-0.15, 0.25)	(0.23, 0.21)	(0.34, 0.08)	(0.42, 0.06)	(-0.23, 0.26)	(-0.21, 0.32)	(-0.21, 0.31)	(-0.43, 0.47)	(-0.43, 0.47)	(-0.43, 0.47)	(-0.04, 0.76)	(0.0, 0.99)	(-0.02, 0.88)	(-0.6, 0.31)	(-0.6, 0.31)	(-0.6, 0.31)
Beta_hml	(0.17, 0.32)	(0.23, 0.22)	(0.18, 0.31)	(0.33, 0.04)	(0.32, 0.05)	(0.32, 0.08)	(0.5, 0.16)	(0.48, 0.19)	(0.48, 0.18)	(0.84, 0.38)	(0.84, 0.38)	(0.84, 0.38)	(0.19, 0.08)	(0.24, 0.04)	(0.2, 0.06)	(-0.28, 0.55)	(-0.28, 0.55)	(-0.28, 0.55)
Beta_mom	(-0.19, 0.13)	(-0.01, 0.94)	(-0.17, 0.17)	(0.22, 0.02)	(0.3, 0.0)	(0.36, 0.0)	(0.45, 0.0)	(0.47, 0.0)	(0.46, 0.0)	(0.45, 0.32)	(0.45, 0.32)	(0.45, 0.32)	(0.25, 0.0)	(0.27, 0.0)	(0.26, 0.0)	(0.29, 0.49)	(0.29, 0.49)	(0.29, 0.49)
Adj. R_squared	0.36	0.29	0.36	0.53	0.59	0.58	0.39	0.4	0.4	0.73	0.73	0.73	0.67	0.63	0.66	0.27	0.27	0.27
F-test	15.19	11.22	14.82	9.34	11.37	10.99	10.95	11.42	11.38	9.74	9.74	9.74	67.72	54.97	64.94	3.08	3.08	3.08

US

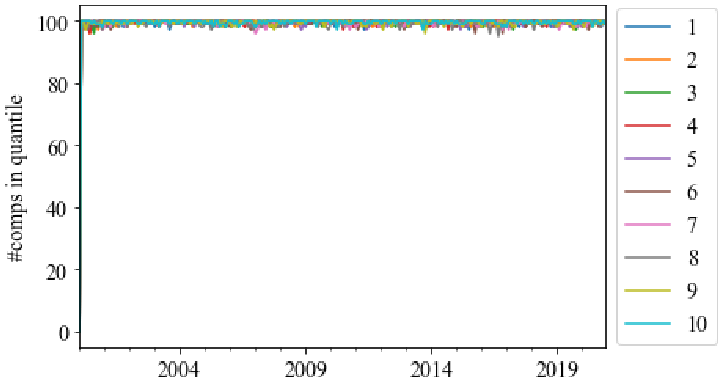
	90s			Dotcom			2000s			Subprime			2010s			Covid		
	Low Vol Static	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**	**Low Vol Static**	**Volatility Timing 1**	**Volatility Timing 2**
Ann. return %	12.5	18.71	23.06	-1.2	-1.2	-1.2	8.29	8.65	9.08	-29.61	-29.61	-29.61	16.23	16.6	16.19	21.76	19.18	20.08
Std %	12.01	19.73	23.2	11.32	11.32	11.32	7.66	12.58	10.91	15.8	15.8	15.8	9.18	9.67	9.83	18.07	18.88	18.52
Sharpe	0.67	0.72	0.8	-0.44	-0.44	-0.44	0.71	0.46	0.57	-1.96	-1.96	-1.96	1.72	1.67	1.6	1.19	1	1.07
Cum. return %	190.38	356.38	547.08	-4.47	-4.47	-4.47	52.02	51.15	56.03	-30.52	-30.52	-30.52	448.2	468.19	442.58	49.36	41.53	44.27
Alpha %	(-0.82, 0.76)	(-3.81, 0.49)	(-3.04, 0.62)	(-4.87, 0.46)	(-4.87, 0.46)	(-4.87, 0.46)	(-0.9, 0.75)	(-6.19, 0.14)	(-3.47, 0.37)	(-0.25, 0.98)	(-0.25, 0.98)	(-0.25, 0.98)	(5.85, 0.0)	(6.17, 0.0)	(5.49, 0.01)	(5.01, 0.43)	(1.33, 0.86)	(2.62, 0.71)
Beta_mkt	(0.67, 0.0)	(0.56, 0.0)	(0.61, 0.0)	(0.48, 0.0)	(0.48, 0.0)	(0.48, 0.0)	(0.58, 0.0)	(0.97, 0.0)	(0.8, 0.0)	(0.56, 0.0)	(0.56, 0.0)	(0.56, 0.0)	(0.64, 0.0)	(0.65, 0.0)	(0.67, 0.0)	(0.85, 0.0)	(0.88, 0.0)	(0.87, 0.0)
Beta_smb	(-0.25, 0.0)	(0.45, 0.0)	(0.53, 0.0)	(-0.12, 0.31)	(-0.12, 0.31)	(-0.12, 0.31)	(-0.23, 0.05)	(-0.02, 0.9)	(-0.06, 0.68)	(0.33, 0.32)	(0.33, 0.32)	(0.33, 0.32)	(-0.3, 0.0)	(-0.24, 0.0)	(-0.28, 0.0)	(-0.59, 0.0)	(-0.58, 0.01)	(-0.58, 0.01)
Beta_hml	(0.4, 0.0)	(0.06, 0.74)	(0.05, 0.82)	(0.39, 0.0)	(0.39, 0.0)	(0.39, 0.0)	(0.22, 0.11)	(0.59, 0.0)	(0.42, 0.03)	(0.28, 0.06)	(0.28, 0.06)	(0.28, 0.06)	(-0.05, 0.4)	(0.04, 0.57)	(0.04, 0.61)	(0.07, 0.57)	(0.02, 0.87)	(0.04, 0.77)
Beta_mom	(-0.07, 0.25)	(0.63, 0.0)	(0.82, 0.0)	(0.1, 0.11)	(0.1, 0.11)	(0.1, 0.11)	(0.06, 0.35)	(0.33, 0.0)	(0.25, 0.01)	(0.09, 0.44)	(0.09, 0.44)	(0.09, 0.44)	(0.12, 0.0)	(0.17, 0.0)	(0.17, 0.0)	(0.05, 0.73)	(0.13, 0.47)	(0.1, 0.54)
Adj. R_squared	0.64	0.47	0.51	0.44	0.44	0.44	0.39	0.51	0.42	0.81	0.81	0.81	0.65	0.63	0.63	0.8	0.73	0.76
F-test	49.48	25.05	29.04	6.75	6.75	6.75	11.07	16.95	12.36	15.05	15.05	15.05	61.14	54.77	56.72	24.03	16.24	18.93

Annotation: Returns, standard deviations, Sharpe ratios and alphas have been annualized. P-values of factors and alpha are indicated in 2nd place in brackets.

Appendix 2.1: Dates used for subperiods

Periods	Dates (end of month)	
Full Sample	1/2000	12/2020
First half	1/2000	5/2010
Second Half	6/2010	12/2020
Dotcom	1/2000	3/2003
2000's	3/2003	9/2008
Subprime	10/2008	9/2009
2010's	10/2009	3/2020
Covid	4/2020	12/2020

Appendix 2.2: Number of unique firms listed in the Amex, NYSE and Nasdaq exchanges across the 2000-2021 period allocated to decile portfolios based on the R&D over market equity signal



Appendix 2.3: Performance figures for firms with R&D activity compared to firms without R&D activity

	Total		*2000-2010*		*2010-2020*	
	No R&D	**Only R&D**	**No R&D**	**Only R&D**	**No R&D**	**Only R&D**
ann_return	8.20%	11.90%	1.20%	5.00%	14.10%	17.70%
std	15.50%	21.90%	16.30%	25.40%	14.60%	17.90%
sharpe	0.43	0.47	-0.09	0.1	0.93	0.96

Appendix 2.4: Winners and losers by 6-month previous returns – Full Sample

	losers	**winners**
ann_return	9.9%	11.0%
std	25.0%	17.3%
sharpe	0.338	0.55

Appendix 2.5: Performance of long-only and long-short strategies – 1st and second half

2000-2010

	Low R&D		High R&D		High-Low	
	losers	**winners**	**losers**	**winners**	**Regular**	**Optimized**
ann_return	-3.0%	2.5%	11.3%	9.1%	10.5%	13.2%
std	27.9%	19.8%	38.0%	28.9%	18.9%	19.0%
sharpe	-0.2	0	0.23	0.23	0.55	0.7
cum_return	-0.51	0.05	0.53	0.64	1.37	2.10
ann_alpha	(-0.0, 0.88)	(0.01, 0.68)	(0.09, 0.03)	(0.05, 0.26)	(0.06, 0.18)	(0.07, 0.21)
market_beta	(1.22, 0.0)	(1.17, 0.0)	(1.36, 0.0)	(1.34, 0.0)	(0.16, 0.11)	(0.13, 0.26)
smb	(0.4, 0.0)	(0.35, 0.0)	(0.91, 0.0)	(0.65, 0.0)	(0.41, 0.01)	(0.38, 0.03)
hml	(-0.62, 0.0)	(-0.14, 0.02)	(-0.28, 0.0)	(0.08, 0.45)	(0.28, 0.02)	(0.52, 0.0)
mom	(-0.21, 0.0)	(0.3, 0.0)	(-0.62, 0.0)	(-0.09, 0.15)	(-0.4, 0.0)	(-0.15, 0.08)
R2_adj	0.87	0.87	0.9	0.81	0.4	0.18
te	2.85%	2.02%	3.38%	3.57%	4.15%	4.87%
IR	-0.01	0.04	0.21	0.11	0.13	0.12

2010-2020

	Low R&D		High R&D		High-Low	
	losers	**winners**	**losers**	**winners**	**Regular**	**Optimized**
ann_return	11.2%	14.3%	20.4%	20.9%	7.9%	9.4%
std	18.8%	14.6%	23.4%	20.1%	9.5%	10.4%
sharpe	0.57	0.94	0.85	1.02	0.83	0.91
cum_return	1.74	3.06	5.48	6.41	1.21	1.57
ann_alpha	(-0.04, 0.11)	(-0.0, 0.95)	(0.02, 0.42)	(0.07, 0.02)	(0.06, 0.02)	(0.08, 0.01)
market_beta	(1.05, 0.0)	(0.91, 0.0)	(1.2, 0.0)	(0.98, 0.0)	(0.11, 0.04)	(0.04, 0.51)
smb	(0.17, 0.05)	(0.32, 0.0)	(0.65, 0.0)	(0.75, 0.0)	(0.46, 0.0)	(0.53, 0.0)
hml	(-0.11, 0.16)	(-0.12, 0.01)	(-0.3, 0.0)	(-0.05, 0.56)	(-0.06, 0.49)	(-0.07, 0.53)
mom	(-0.31, 0.0)	(0.15, 0.0)	(-0.39, 0.0)	(-0.13, 0.1)	(-0.18, 0.01)	(0.05, 0.57)
R2_adj	0.86	0.92	0.87	0.83	0.32	0.16
te	2.00%	1.18%	2.35%	2.35%	2.22%	2.70%
IR	-0.15	-0.01	0.08	0.23	0.24	0.25

Appendix 2.6: Furter attempt to optimize strategy with 3x3 groups – Subperiods

	Full Sample	**2000-2010**	**2010-2020**	**dotcom**	**2000s**	**subprime**	**2010s**	**covid**
ann_return	11.2%	13.6%	8.8%	35.2%	5.1%	21.6%	6.8%	23.5%
std	14.6%	17.7%	10.9%	26.8%	10.6%	17.8%	12.2%	8.9%
sharpe	0.77	0.77	0.81	1.31	0.48	1.21	0.56	2.64
cum_return	6.97	2.30	1.39	1.03	0.26	0.31	0.93	0.23
ann_alpha	(0.11, 0.0)	(0.07, 0.21)	(0.08, 0.02)	(-0.11, 0.47)	(-0.01, 0.78)	(0.12, 0.59)	(0.06, 0.09)	(0.18, 0.43)
market_beta	(-0.13, 0.05)	(-0.22, 0.04)	(-0.03, 0.72)	(-0.5, 0.05)	(0.27, 0.04)	(-0.31, 0.32)	(0.07, 0.39)	(-0.13, 0.37)
smb	(0.24, 0.02)	(0.29, 0.08)	(0.3, 0.02)	(0.48, 0.13)	(0.56, 0.0)	(-0.07, 0.93)	(0.08, 0.57)	(0.69, 0.34)
hml	(0.33, 0.0)	(0.64, 0.0)	(-0.09, 0.45)	(1.18, 0.0)	(0.15, 0.45)	(0.51, 0.16)	(0.04, 0.76)	(0.06, 0.85)
mom	(0.15, 0.01)	(0.05, 0.52)	(0.26, 0.01)	(-0.27, 0.12)	(-0.2, 0.03)	(0.01, 0.96)	(0.3, 0.0)	(0.35, 0.32)
R2_adj	0.11	0.21	0.09	0.38	0.42	0.20	0.11	0.30
te	0.04	0.04	0.03	0.05	0.02	0.04	0.03	0.02
IR	0.23	0.12	0.22	-0.19	-0.04	0.23	0.16	0.78

Appendix 2.7: Strategy holdings December 2020

	Company	Industry
Long	FORD MOTOR CO DEL	CDISC
	GENERAL MOTORS CO	CDISC
	DELL TECHNOLOGIES INC	IT
	NETWORK APPLIANCE INC	IT
	ON SEMICONDUCTOR	IT
Short	CONAGRA INC	CSTAP
	CHURCH & DWIGHT INC	CSTAP
	KIMBERLY CLARK CORP	CSTAP
	KEURIG DR PEPPER INC	CSTAP
	TYLER TECHNOLOGIES INC	IT

Appendix 2.8: Maximum weights of long and short leg – Optimized R&D strategy