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Combining Momentum and Low Risk

Investing in boring trends?

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TIIVISTELMÄ:

Monet tutkimukset osoittavat kuinka alhaisen riskin osakkeilla on tapana tuottaa enemmän, kuin niiden riskisyyden perustella voitaisiin odottaa. Tämän lisäksi on havaittu, että osakkeilla on tapana jatkaa aiempaa hintakehitystään lyhyellä ja keskipitkällä aikavälillä. Ensimmäistä näistä havainnoista kutsutaan usein alhaisen riskin -ilmiöksi ja jälkimmäistä puolestaan momentum-ilmiöksi. Vahvan tutkimusnäytön lisäksi näitä molempia ilmiöitä tukevat vahvat teoreettiset selitykset. Tämä tutkielma tutkii näiden kahden ilmiön vuorovaikutusta, ja sitä mahdollistaako näiden kahden ilmiön yhdistäminen suoraviivaiseksi sijoitusstrategiaksi ylituottojen ja lisäarvon luomisen. Tämän työn tutkimustulokset osoittavat, että riskikorjatut tuotot ja ylituotot ovat korkeampia vahvan momentumin sekä alhaisen riskin osakkeilla, mikä antaa olettaa, että molemmat ilmiöt ovat vaikuttaneet Nasdaq osakepörssissä vuosina 1995 – 2020. On kuitenkin huomioitava, että momentum- ja alhaisen riskin -strategioiden ylituotot katoavat, kun otetaan huomioon osakkeiden tuottojen kuvaamisessa käytettyjen riskifaktorien selitysvoima.

Vastaavasti osakkeiden kaksinkertainen lajittelu menneiden tuottojen ja riskimittareiden perusteella, osoittaa että yli- ja alituotot kasvavat monotonisesti, kun osakkeiden menneet tuotot kasvavat, ja kun osakkeiden riski pienenee. Toisin sanoen osakkeet, joilla on sekä vahva momentum että alhainen riski tuottavat paremmin, kuin osakkeet, joilla on vain vahva momentum tai alhainen riski. Tulokset osoittavat, että yhdistämällä momentum alhaisen riskin faktoreiden kanssa, sijoittajat voivat ansaita ylituottoa ja parantaa riskikorjattua suoriutumistaan. Sisällyttämällä alhaisen volatiliteetin tai alhaisen betan faktori momentum-sijoitusstrategiaan portfolion volatiliteetti ja arvon tuhoutumiset pienenevät huomattavasti ilman, että tuotot laskisivat momentum-strategiaan verrattuna. Tulokset vihjaavat, että etenkin momentumin ja alhaisen volatiliteetin kombinaatio voi auttaa sijoittajia generoimaan momentum-strategian kaltaisia korkeita tuottoja, mutta huomattavasti pienemmällä riskiprofiililla. *Momentum-alhainen volatiliteetti* faktorikombinaation hajautushyötyjä kuvaa muun muassa näiden kahden faktorin korrelaatiodynamiikka, joka on yleensä korkea ja kasvaa nousukausien aikana ja puolestaan laskee jopa negatiiviseksi laskukausien aikana. Kokonaisuudessaan tämä tutkielma esittää, kuinka sijoittajat voivat hyötyä momentumin ja alhaisen riskin faktoreiden yhdistämisestä ja huomioonottamisesta sekä sitä kuinka nämä faktorit vuorovaikuttavat toistensa kanssa.

AVAINSANAT: Momentum, low-risk factors, multi-factor portfolios

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ABSTRACT:
Various studies have documented the anomalous overperformance of low-risk stocks and the tendency of recent winner stocks to provide abnormal returns in near future, i.e., momentum. In addition to the robust empirical evidence, both anomalies are supported by strong theoretical explanations. This paper studies the interaction of these effects and whether combining momentum and low-risk factors can provide added value for investors. The findings show that risk-adjusted and abnormal returns are greater for stocks with higher price momentum or with lower ex-ante risk metrics, suggesting that both effects were prevalent in the Nasdaq stock exchange during 1995-2020. However, controls for the common risk factors tend to diminish the abnormal returns of the pure-play strategies.

In turn, the abnormal returns for the double-sorted portfolios increase monotonically moving from high risk to low risk and from low momentum to high momentum. Stocks with high momentum and low risk tend to outperform stocks that exhibit *just* high momentum or low risk. By combining momentum and low-risk factors investors can obtain abnormal returns and increase the risk-adjusted performance of the pure momentum or low-risk strategies. Furthermore, via the incorporation of low volatility or low beta signals, portfolio volatility and drawdowns are greatly reduced without a simultaneous decrease in returns in comparison to the pure momentum strategy. It seems that especially the *momentum-low volatility* combination can help investors to capture the high returns affiliated with momentum, but with much less risk. For instance, the low-volatility factor tends to exhibit negative correlation with momentum during recessions but moves higher during expansions. Overall, the study exhibits possible diversification benefits for momentum investors from low-risk factors and provides insights into how investors can benefit from betting on low-risk winner stocks.

KEYWORDS: Momentum, low-risk factors, multi-factor portfolios

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1 Introduction

One of the first and most well-known anomalies in empirical asset pricing is the low-risk effect, that is, the observation that low-risk securities overperform high-risk securities in absolute and risk-adjusted terms. The low-risk anomaly was first documented by Black, Jensen and Sholes (1972) who show that the relation between stock's beta and return is flatter than the Capital Asset Pricing Model (CAPM) predicts. Following the low-beta anomaly there have been multiple studies that exhibit the same dynamic with different risk factors, such as, volatility and short-term idiosyncratic volatility.

Another strong, widely documented, and rigorously studied anomaly is the momentum anomaly, namely, the empirical observation that a trading strategy that takes a long position in previous winner stocks and a short position in previous loser stocks earns statistically and economically significant positive risk-adjusted returns. After Jegadeesh and Titman (1993) provided the first documentation of the momentum anomaly, it has been studied across asset classes, markets, and time periods. The tendency of recent winners to keep winning and recent losers to keep losing has proven to be one of the most robust and significant anomalies in finance literature.

Both low-risk and momentum effects have remained in the center of the market efficiency debate for decades. They are one of the most persistent, significant, pervasive, robust to various definitions, and implementable factors in the finance literature. Furthermore, they are supported by strong risk-based or behavioral-based explanations for why they should persist. However, despite the good track record of low-risk and momentum factors, no factor has generated consistent excess returns across every time period and region. Diversifying factor exposure may provide investors with more attractive and consistent returns.

Given the thorough empirical research on these anomalies and popularity among practitioners, it is surprising that the combination of low-risk and momentum has been left with such little notice. Especially, since previous literature on these subjects indicates potential diversification benefits which might provide an opportunity to earn high returns with lower portfolio risk. A portfolio of recent winners with low risk should sound compelling to most investors.

Inspiration for this study is predominantly drawn from a research note "*LOVM: LOW VOLATILITY-MOMENTUM PORTFOLIOS: The Factor Combination Creating the Least Amount of Emotional Pain?*" by Nicolas Rabener (2020). Rabener provides an empirical survey into the returns and portfolio characteristics of long-only Low Volatility-Momentum strategies between 1989 – 2018. In addition, further motivation and justification for the study is gained from Garcia-Feijóo, Kochard, Sullivan, and Wang (2015) who present evidence of possible diversification benefits amongst low volatility and momentum factors. Altogether, this study aims to extend these studies and offer a more comprehensive view into the returns of *momentum-low risk* portfolios and into the interplay of momentum and low-risk factors.

1.1 Purpose of the study

The literature focuses mainly on examining momentum and low-risk anomalies separately. The purpose of this study is to analyze the added value of combining momentum and low-risk factors in the Nasdaq stock exchange, that is, whether they can add value to simple market exposure or single-factor strategies. For instance, the study examines if *momentum-low risk* portfolios provide significant positive abnormal returns, and how the portfolios perform relative to the pure momentum and low-risk strategies and to broad market index returns in risk-adjusted and absolute terms.

Although this study has some confluences with previous literature examining risk-managed momentum strategies which try to increase momentum's profitability and decrease crash risk, the methodologies and multi-factor portfolios investigated in this study are fundamentally and qualitatively different. Furthermore, the study will also review previous literature regarding the empirical results and different explanations of the low-risk and momentum anomalies.

The momentum and low-risk factors applied in this study are acknowledged and documented in previous literature. The low-risk factors bet against volatility, beta, and investors' lottery demand (idiosyncratic skewness). Both, long-short and long-only portfolios are analyzed. Furthermore, the study utilizes two different portfolio construction methodologies – intersectional and sequential (conditional) model which are presented in Rabener (2018) and are explained later in this study in section 5.2.1.

1.2 Research hypotheses

The study aims to find out if combining momentum and low-risk factors can provide diversification benefits and an overall attractive multi-factor strategy. In more detail, the empirical tests provide insights into whether the well-known and empirically proved risk factors can explain the momentum-low risk strategies' returns, and how do the different strategies perform in relation to each other in risk-adjusted and absolute terms? Furthermore, can the incorporation of low-risk factors prevent large drawdowns and diminish the risk of pure momentum strategies? Based on the previous studies on momentum and low risk anomalies as well as on the performance of low volatility-momentum portfolios (Rabener, 2020) and the possible diversification benefits (Garcia-Feijóo et al., 2015; Rabener, 2020), the *momentum-low risk* portfolios are expected to generate attractive and consistent returns. Furthermore, the portfolios are expected to yield positive regression intercepts in the traditional asset pricing models. Research hypotheses are expressed as follows:

H1: Combination strategies outperform the market index on an absolute and risk-adjusted basis.

H2: Combination strategies outperform the pure momentum and low-risk strategies on an absolute and risk-adjusted basis.

H3: Combination strategies generate abnormal returns.

1.3 Intended contribution

There is a vast amount of literature on the low-risk effect and momentum separately, but multi-factor portfolios that combine these factors have not received as much attention. This paper aims to contribute to that gap in the literature, and to consider whether combining low risk and momentum can offer significant abnormal returns as well as attractive risk-adjusted and absolute returns. In its motivation and goals, this study is similar to many multi-factor and style investing papers that seek to diversify factor exposure and increase risk-adjusted returns. Overall, combining different factors, including momentum and low risk, has proven to be a highly profitable and attractive investing strategy (see Asness, Ilmanen, Israel & Moskowitz, 2015; Clarke & De Silva, 2016; Bender & Wang, 2016; Brightman, Kalesnik, Li & Shim, 2017; Ghayur, Heaney & Platt, 2018; Li & Shim, 2019; Grobys, Silvasti & Äijö, 2021). Many of the existing multi-factor papers often examine multi-factor or style investing at a high level and focus on methodologies and factor combinations of three or more factors.

However, in addition to Rabener (2020) and Garcia-Feijóo et al. (2015), there are some studies that have exhibited interest in the momentum-low risk factor pair in passing, for example, Bender and Wang (2016) (momentum-low volatility) and Grobys et al. (2021) (momentum-low beta). Altogether, this study aims to contribute to the literature by concentrating solely on the *momentum-low risk* combination, rather than simulating the optimal combinations of all factor portfolios or studying the factor pair only briefly in passing. Through this focus, the study tries to provide a nuanced and deep look into the portfolio characteristics of *momentum-low risk* portfolios and into the interaction effects between these factors.

2 Theoretical background

This section reviews the standard asset pricing models and the classical theoretical framework of financial markets. In order to understand the implications, relevance, and possible explanations of the low-risk and momentum anomalies, as well as, the empirical findings of this study, it is essential to review the theoretical framework in which these anomalies and results are being evaluated. Section 2.1 reviews the efficient market hypothesis stating that the information set (historical prices) used in this study should not give any information advantage to investors. Section 2.2 introduces the most well-known asset pricing models explaining variation in the cross-section of expected returns via common risk factors.

2.1 Efficient market hypothesis

The efficient market hypothesis (EMH) states that stock prices already reflect all available information, and that prices follow a "random walk with a drift" (Fama, 1970). Fama (1970) notes that the random walk notion of the stock prices' stochastic process used in the early statements of EMH often implies that the expected price change may be a non-zero and successive price changes are independent and identically distributed. In his paper, Fama suggests that it is best to regard the random walk model more as a "fair game" efficient market model that states the conditions of the market equilibrium in terms of expected returns, rather than focusing on the assumption of independence. In general terms, based on some relevant information set, investors compute the equilibrium expected return as a function of its risk by fully utilizing the available information (Fama, 1970). This fair game notion of the markets rules out the possibility of trading strategies that exhibit greater expected returns than the equilibrium expected returns based on the available information set. Furthermore, Fama (1970) states sufficient conditions for capital market efficiency as:

1. "There are no transactions costs in trading securities"

2. “All available information is costless available to all market participants”
3. “All agree on the implications of current information for the current price and distributions of future prices of each security”

If these assumptions are fulfilled, current prices will always reflect all available information. These conditions are not necessary for capital market efficiency, but deviations from these, such as transactions costs, asymmetric information, and disagreement among investor, can be potential sources for market inefficiency (Fama, 1970).

Fama (1970) separates the tests of EMH into three categories based on the available information set in each case: weak-form tests, semi-strong form tests, and strong-form tests. According to the weak-form hypothesis markets should fully reflect all historical price information. This implies that past returns cannot be used to predict future returns. The semi-strong-form hypothesis claims that prices fully reflect all public information, meaning that in addition to past prices asset prices reflect all available fundamental information, such as annual reports and announcements of security issues and stock splits. The strong-form version addresses the problem of monopolistic information access. In the strong-form asset prices reflect all information relevant for price formation of the firm, even insider information. This categorization helps to form useful benchmarks for testing market efficiency and to find the level of information at which the hypothesis fails (Fama, 1970). Moreover, the weak form of EMH is especially important for the purposes of this paper since the low risk-momentum strategies investigated in this paper use only historical price information in the construction of the portfolios. Hence, the low risk-momentum strategies examined later in this paper will test the validity of the market efficiency hypothesis.

2.2 Asset pricing models

Capital asset pricing model (CAPM)

The CAPM is independently introduced and derived in Sharpe (1964) and Lintner (1965). The classical financial doctrine states that in market equilibrium there will exist a linear relationship between the expected return and standard deviation for efficient combinations of assets, but as Sharpe (1964) notes this does not provide a consistent model for explaining the relationship of expected return and total risk for individual assets. Hence, Sharpe suggests that total risk is not relevant for price formation of an individual asset since some of the risk can be exterminated by diversification. The CAPM provides a consistent relation between an individual asset's expected return and its systematic (non-diversifiable) risk (Sharpe, 1964). Sharpe notes that the systematic risk (dependence on the overall economic activity) remains even in the efficient combinations of capital assets, and thus, only the sensitivity to the overall economic activity is relevant for the price formation of an individual asset. This suggests that in market equilibrium there is a linear relationship between the sensitivity to overall (undiversifiable) economic activity and expected return, meaning that assets with low sensitivity (beta) to overall economic activity have lower expected returns than high sensitivity assets. Consequently, assets that are unaffected by changes in economic activity return the risk-free rate (Sharpe, 1964). The model is commonly expressed as:

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \tag{1}$$

where $E(R_i)$ is the expected return of asset i, R_f is the risk-free rate, β_i is the beta coefficient or market sensitivity of asset i, and $E(R_m)$ is the expected return of the market portfolio. The systematic risk β_i is the slope parameter of asset i's return regressed on the market return in excess of the risk-free rate R_f.

For the equation 1 to hold, the CAPM requires a certain set of assumptions. These assumptions are presented in Black (1972) as follows:

1) "All investors have a common joint probability distribution for the returns of all available assets. Thus, they have the same opinion or view about the possibilities

of various prices for the assets at the end of the period."

2) "The expected returns for the assets are normally distributed."

3) "All investors choose a portfolio that maximizes their utility of wealth at the end of the period: the utility function increases at a decreasing rate as the end-of-period wealth increases. Also, all investors are expected to be risk-averse."

4) "All investors may take a long of short position without any limitations in size or in the choice of asset, including the risk-free asset. All investors may borrow or lend without limitations at the risk-free rate of interest."

Sharpe (1964) concedes that these assumptions can be highly unrealistic and restrictive, but it is the acceptability and compatibility of the implications of the model with regards to the classical financial doctrine that favour its relevance. The model provides capital asset price equilibrium conditions that are consistent with the equilibrium conditions in the capital market as whole (Sharpe, 1964).

Fama and French three-factor model

Although the CAPM has been widely accepted and used among academics and practitioners, there is an overwhelming body of evidence of how asset prices do not behave as the CAPM predicts. For instance, Banz (1981) shows that, on average, small NYSE firms exhibit significantly larger risk-adjusted returns than large NYSE firms over the 1936 – 1975 period. Given the betas (market sensitivities), average returns on low market equity firms are too high, and average returns on high market equity firms are too low. Further, his empirical analysis shows how firm size (market equity) significantly improves the explanation of the cross-section of average stock returns. Additionally, there is evidence that the ratio of a firm's book equity to its market equity (B/M) has a strong positive relationship with average stock returns (Stattman, 1980; Rosenberg, Reid & Lanstein, 1985; Chan, Hamao & Lakonishok, 1991; Fama & French, 1992).

These findings are investigated further by Fama and French (1992) who find that returns increase within B/M deciles when a firm's size decreases, and within size deciles when a firm's B/M value increases. Furthermore, they observe that, on average, the excess monthly return on the highest B/M-decile portfolio over the lowest B/M-decile portfolio in a size decile is 0.99%. Similarly, the excess monthly return on the lowest size portfolio over the highest size portfolio within B/M deciles is on average 0.58%.

Fama and French (1992) also find that market betas offer little information about average returns, while size, book-to-market equity (B/M), leverage, and earnings-to-price have clear explanatory power in the cross-section of average returns. But since all these four variables can be regarded as versions of stock price information, Fama and French (1992) examine the joint effects of these variables in multivariate tests. They show that B/M and size are the most robust variables, as they absorb earnings-to-price's and leverage's explanatory power in the cross-section of average returns. They conclude that the results imply that stock risks are multidimensional, and that the combination of size and B/M seem to capture the cross-sectional variation in average returns related to market betas, leverage, B/M, earnings-to-price, and size.

The literature regarding the cross-section of expected returns and common risk factors is extended in Fama and French (1993) where they introduce a three-factor model that does a good job in producing a common variation in stock returns and explaining the cross-section of average returns. The first risk factor in their model is the excess market return ($R_m - R_f$), which, despite its lacking predictive power, captures the difference between the average stock returns and the risk-free rate which is not picked up by other factors. Motivated by the empirical evidence, Fama and French (1993) augment the CAPM with size (SMB, small minus big) and book-to-market factors (HML, high minus low) to explain much of the unexplained variation left out by the market factor. SMB and

HML mimic risk factors related to size and book-to-market values, respectively. SMB represents the excess returns of small market capitalization stocks over big market capitalization stocks. While HML, also known as the "value" factor, represents the excess returns of high book-to-market stocks over low book-to-market stocks. The model can be expressed as in Fama and French (1993):

$$E(R_i) - R_f = \beta_i\left[E(R_m) - R_f\right] + s_i E(SMB) + h_i E(HML) \qquad (2)$$

where $E(R_i) - R_f$ is the expected excess return on portfolio i, $E(R_m) - R_f$, $E(SMB)$, and $E(HML)$ are the expected market, size, and value premiums, and β_i, s_i, and h_i, are the slopes in the time-series regression, i.e. factor loadings or sensitivities. If the model captures the variation in returns, the regression intercept is zero.

For the 25 sub-decile stock portfolios formed on size B/M in Fama and French (1993), the three-factor regression in equation 2 produces intercepts close to zero and exhibits great explanatory power. The market factor alone produces only two R2 values greater than 0.9, while the three-factor regression produces 21/25 R2 values over 0.9 (Fama & French, 1993). In conclusion, Fama and French (1996) note that the empirical success of the three-factor model in capturing much of the variation in the cross-section of average returns and absorbing the CAPM anomalies, suggests that it is an equilibrium pricing model with the new SMB and HML factors mimicking combinations of two underlying risk factors.

Five-factor model

Fama and French (2006) show that the dividend discount model establishes expected profitability, B/M, and expected investment as predictors of expected returns. Later studies have since shown that the three-factor model fails to explain much of the profitability- and investment-related variation in average stock returns. For example, Novy-Marx (2013) finds that profitability proxied by gross profits-to-assets is strongly related to average stock returns. He observes that the excess returns of portfolios sorted on gross profitability generally increase with profitability. The decile-portfolio spreads are especially large when stocks are double-sorted on B/M and gross profitability. Moreover, the inclusion of the gross-profitability factor significantly improves the prediction of the cross-section of average returns (Novy-Marx, 2013). As for the third relation implied by the dividend discount model, Aharoni, Grundy, and Zeng (2013) find a reliable negative relation between expected investment and returns. Unsurprisingly, they also find that expected profitability and B/M are positively related to expected returns.

Motivated by the empirical findings and theory, Fama and French (2015) examine a model that adds investment (CMA, conservative minus aggressive) and profitability (RMW, robust minus weak) factors to the previous three-factor model. CMA reflects the difference between the returns on portfolios of low (conservative) and high (aggressive) investment firms, and RMW reflects the difference between the returns on portfolios with robust and weak profitability firms. The model can be expressed as:

$$E(R_i) - R_f = \beta_i\left[E(R_m) - R_f\right] + s_i E(SMB) + h_i E(HML) + r_i E(RMW) + c_i E(CMA) \quad (3)$$

where $E(R_i) - R_f$ is the expected excess return on portfolio i, $E(R_m) - R_f$, $E(SMB)$, $E(HML)$, $E(RMW)$, and $E(CMA)$ are the expected market, size, value, profitability, and investment premiums, and β_i, s_i, h_i, r_i, and c_i are the slopes in the time-series regression, i.e. factor loadings or sensitivities. If the model captures the variation in returns, the regression intercept is zero.

Fama and French's (2015) results imply that the three-factor model performs relatively poorly when applied to portfolios with strong tilts to investment and profitability, and that the five-factor provides improvements in the explanatory power and average absolute regression intercepts in their tests. The five-factor model explains 71% – 94% of the variation in cross-section of expected returns for the portfolios sorted on investment, profitability, size, and B/M. Furthermore, Fama and French (2016) show that the five-factor model helps to dissect some of the anomalies that the three-factor model cannot explain. The five-factor model helps to explain the high (low) average returns related to low (high) beta, low (high) return volatility, and share repurchases (large share issues) via the positive (negative) loadings to CMA and RMW factors (Fama & French, 2016).

Six-factor model

Fama and French (2018) introduce a six-factor model that augments their previous five-factor model with momentum (UMD, up minus down) factor. Despite the wide documentation of momentum and the fact that the six-factor model proves itself in Fama and French's tests by enhancing model performance, the authors highlight their concerns with the factor. They note that the UMD factor is added due to "popular demand" and they themselves are concerned with momentum's lack of theoretical grounding. The six-factor model can be expressed as:

$$E(R_i) - R_f = \beta_i\left[E(R_m) - R_f\right] + s_i E(SMB) + h_i E(HML) + r_i E(RMW) + c_i E(CMA) + m_i E(UMD) \quad (4)$$

where the notations are identical to the five-factor model except the model is augmented with the momentum (UMD) factor. $E(UMD)$ is the expected momentum premium, i.e., it reflects the difference between the returns on portfolios of strong (up) and weak (down) momentum firms.

3 Low-risk effect

One of the fundamental assumptions in finance theory is that risk and return should move in conjunction. Higher risks should be accompanied by higher expected returns. However, many studies show that this is not often the case. This section reviews some of the empirical tests, evidence, and explanations regarding the low-risk effect. Many of the existing low-risk factors are naturally highly correlated and differentiating the underlying economic drivers behind the low-risk anomaly is not often straightforward.

3.1 Beta anomaly

Black et al. (1972) find that the capital asset pricing model fails to predict asset returns. Their observations conflict with CAPM's prediction that the expected excess return on an asset is equal to its systematic risk, β, times the expected excess return on the market portfolio (Black et al., 1972). Their study shows that low-beta assets exhibit significant positive intercepts (alpha) and high-beta assets exhibit significant negative intercepts. Black et al. present an economic rationale for this low-risk effect by introducing the theory of leverage constraints. They suggest that due to margin requirements and constraints on leverage, investors overweight risky (high beta) assets instead of levering up less risky investments. This influences the security market line and implies lower risk premiums and expected returns for high-risk assets, and higher risk premiums and expected returns for low-risk assets than the CAPM predicts. Fama and French (1992) also show that market beta does not help to explain the cross-section of average stock returns, especially after controlling for size.

The theory of leverage constraints and the low-risk effect is extended by Frazzini and Pedersen (2014), who study a broad set of global asset returns based on their betting against beta (BAB) factor. Frazzini and Pedersen test the theory of leverage constraints by constructing a BAB factor portfolio that shorts assets with high beta, deleveraged to beta of one, and holds assets with low beta, leveraged to beta of one. Their findings provide evidence that the relative flatness of the security market line is a global phenomenon, providing strong evidence for the existence of systematic low-risk effect. After accounting for the exposure to market, value, size, momentum, and liquidity factors, the BAB factor has highly significant returns. Furthermore, the U.S. BAB factor yields a Sharpe ratio of 0.78 between 1926 and 2012, which is approximately double of the value factor and 40% greater than that of the momentum factor over the same time period (Frazzini & Pedersen 2014).

Frazzini and Pedersen (2014) also observe that their data matches the theory of leverage constraints. They find that investors facing leverage constraints are more likely to hold riskier assets. The underlying mechanism of the theory of leverage constraints is investigated rigorously by other papers, which exhibit compelling evidence that margin requirements, funding constraints, financial intermediary leverage, and international illiquidity impact the slope of the security market line. For example, Jylhä (2018) finds that changes in initial margin requirements (leverage constraints) affect the security market line. He shows that higher initial margin requirements flatten the relation between market betas and expected returns, thus supporting the theory that leverage constraints explain the empirical failure of the CAPM.

Adrian, Etula, and Muir (2014) argue that financial intermediaries' funding constraints are an important factor in asset pricing. They proxy funding constraints via financial intermediaries' leverage and find that their leverage factor correlates well with other funding constraint proxies, such as volatility, Baa-Aaa spread, and asset growth. Related to the BAB anomaly, they argue that high-beta stocks underperform low-beta stocks when funding constraints tighten and leverage decreases. Vice versa, low-beta stocks should overperform when leverage increases. Consistent with this hypothesis, they observe that financial intermediary leverage has a strong relation with the BAB factor, and it explains the cross-section of BAB returns.

Boguth and Simutin (2018) end up in similar conclusions as Jylhä (2018), but they measure leverage constraint tightness as the market beta of aggregate mutual funds' stock holdings. They argue that since mutual funds face leverage restrictions, they tilt their stock holdings to high-beta stocks to capture their implicit leverage. Consistent with Frazzini and Pedersen (2014), the authors observe that when leverage constraints tighten, i.e. the market beta of aggregate mutual funds' stock holdings increases, the BAB profits increase, and vice versa. Furthermore, they find that the aggregate mutual fund's beta is a relevant predictor of BAB-, mutual fund-, and stock returns. Overall, these findings further strengthen the claim that leverage constraints drive the beta anomaly.

Malkhozov, Mueller, Vedolin and Venter (2017) argue that international illiquidity contributes to the low-risk effect. They measure illiquidity as pricing deviations on government bonds, where larger deviations from the fitted yield curve signal illiquidity. Their results show that global illiquidity flattens the slope and increases the intercept of the global security market line, and that local differences in liquidity are correlated with significant differences in alphas. As for what causes illiquidity, the study points out that the financial frictions and illiquidity can be caused by many systematic reasons, such as capital requirements, margins, investment taxes, restricted borrowing, or endowment shocks.

Although the BAB anomaly is strongly documented and theorized, it has also received criticism. For example, Novy-Marx and Velikov (2018) argue that Frazzini and Pedersen's (2014) BAB strategy gains its profitability from non-standard procedures, such as rank-weighted portfolio construction, hedging by leverage, and novel beta estimation technique. Novy-Marx and Velikov suggest that the rank weighting non-transparently generates equal-weighted portfolios which are then leveraged/deleveraged to achieve market-neutrality. They argue that this method leads to overweighting micro- and nano-cap stocks which makes the strategy hard to realize in practice. Also, accounting for the tilts toward profitability and investment as well as transaction costs, the BAB strategy loses most of its unexplained returns. In total, Frazzini and Pedersen's BAB methodology is far from transparent and straightforward beta arbitrage. It cannot be actualized and even the remarkable paper performance is achieved via non-standard methodology choices. Lastly, Novy-Marx and Velikov criticize the use of such "sophisticated" methods in empirical research since they can be used to yield stronger results without further insights or motivation.

3.2 Volatility anomaly

Since this study seeks to examine profitability of the momentum-low risk combination rather than finding what drives the low-risk effect, the low-volatility effect is particularly interesting. Many studies have shown that volatility-based strategies tend to outperform BAB-type strategies (Blitz & Vliet, 2007; Novy-Marx, 2014; Blitz & Vidojevic, 2017).

Blitz and Vliet (2007) construct decile portfolios by ranking stocks in respect to their past-three-year volatilities. In their sample, they find that the top-decile portfolios earn significantly higher risk-adjusted returns compared to the market portfolio, while the high-volatility portfolios underperform the market. Their results show that the Sharpe ratio declines steadily from low-volatility portfolios to high-volatility portfolios. Blitz and Vliet find that the difference of Sharpe ratios between the top-decile portfolio of low-risk stocks and market portfolio is statistically significant at a 5% significance level, while the bottom-decile portfolio has a significantly lower Sharpe ratio compared to the market portfolio. They also find that the three-factor model could not explain the volatility effect, as the global three-factor alpha spread between the top-decile and bottom-decile portfolios is 8.1%.

Novy-Marx (2014) studies and compares extensively the performance and characteristics of defensive equity strategies. Contributing to the volatility and beta battle, he finds that the volatility anomaly is stronger than the beta anomaly. His results show that the strategy based on the beta anomaly does not exhibit significant alpha in the Fama and French (1993) three-factor regression, while the long-short volatility portfolio yields three-factor abnormal returns of 0.68% per month and a t-statistic of 4.29. Novy-Marx also exhibits that accounting for profitability is essential for understanding the performance of low-risk strategies. The results show that defensive equities have negative relation with profitability, valuation, and size. Furthermore, Novy-Marx (2014) and Fama and French (2016) argue that the volatility anomaly and the abnormal returns of defensive equity strategies are driven by highly volatile stocks that tend to be unprofitable, small, and highly valued, and that the Fama and French (2015) five-factor model of the market, size, value, profitability, and investment explains the low-risk effect.

Likewise, Blitz and Vidojevic (2017) find mispricing for market beta exposure but they also observe that mispricing for volatility is greater than the mispricing for beta, suggesting that the low-volatility anomaly dominates the low-beta anomaly. Furthermore, their study reports the results of modified Fama-MacBeth (1973) regressions which uses beta-adjusted returns as the dependent variable. The study tests the explanatory power of volatility and beta by using them as explanatory variables in the regressions. The regressions exhibit that when controlling for only beta and volatility, beta is dominant, but when added the Fama and French (2015) five-factor model plus momentum, the negative alpha shifts completely from beta to volatility, and that the t-statistic for the negative alpha of volatility is more prominent than for the previous negative alpha measured for beta. In total, all three studies, Blitz and Vliet (2007), Novy-Marx (2014), and Blitz and Vidojevic (2017) find that, the volatility anomaly is considerably stronger than the beta anomaly.

Jordan and Riley (2015) study the explanatory power of mutual fund volatility as a predictor of future abnormal results. Their results show that past returns' volatility is a significant predictor of mutual funds' future returns, and that a pricing factor that contrasts the returns on low and high volatility stocks eliminates the abnormal performance of both low and high volatility funds. They find that a portfolio that holds low volatility mutual funds based on the past year's standard deviation of daily returns generates an arithmetic average annual return of 8.5% while the high volatility portfolio gives only a return of 4.4% per year, and the difference in risk-adjusted terms is even more significant. Furthermore, Jordan and Riley show that it is total volatility that contributes to the difference in returns, not idiosyncratic volatility. Unlike the previously accounted studies, Jordan and Riley's study extends the volatility anomaly into realized and actual returns instead of focusing on hypothetical factor portfolios by showing that the low volatility anomaly is a significant contributor to actual mutual fund performance.

For further confirmation of the low-volatility effect, Blitz, Pang and Vliet (2013) extend the low-risk literature by investigating the low-risk effect in emerging markets. They confirm that a similar negative empirical relation between risk and return exists in emerging markets as in developed markets, and that the volatility anomaly is stronger than the beta anomaly. They also find low correlations between the volatility anomaly in emerging and developed markets, thus diminishing the power of the argument that the low-risk effect is driven by a global systematic risk factor.

Blitz et al. (2013) argue that the results provide evidence for the hypothesis that agency issues involved with delegated portfolio management contribute to the low-risk anomaly. Their study shows that the volatility effect in emerging markets has strengthened over time, as emerging markets have evolved to a mainstream asset class and the participation of delegated portfolio managers has grown. The agency issues that are argued to be involved with the low-risk and low-volatility anomalies, are related to, for example, beating the benchmark index, portfolio managers' incentive contracts, and return-chasing investors.

For instance, Brennan (1994) predicts that delegated portfolio managers whose performance is evaluated in relation to some fixed benchmark index will bid-up high-risk stocks and overlook low-risk stocks. He suggests that managers who try to maximize the information ratio (alpha divided by tracking error) may not build a portfolio that optimizes Sharpe ratio and alpha. Instead, they might cause the relation between risk and return to invert (Brennan, 1994).

In a similar vein, Baker and Haugen (2012) question why institutions do not capitalize on the well-documented low-risk effect? They argue that the limit to arbitrage is caused by fund managers' option-like pay structures. Compensation structures with a fixed salary and a bonus if performance is sufficiently high may steer portfolio managers to construct more volatile portfolios. With these kinds of structures, institutional fund managers have an incentive to prefer high-risk stocks to maximize the expected value of their compensation (Baker & Haugen, 2012). In addition to the fund managers' incentive problems, Baker, Bradley, and Wurgler (2011) observe that the highest volatility stocks are small and illiquid, which might make it hard for sophisticated investors to arbitrage the low-high volatility spread.

A third agency issue explanation of the low-risk anomaly is that mutual fund investors' return-chasing behaviour creates pressure for fund managers to adopt more aggressive investment portfolios than they otherwise would (Karceski, 2002). Karceski (2002) finds that mutual funds cash inflows are largely affected by overall market performance and funds' performance in relation to other funds. He suggests that this dynamic of mutual fund cash inflows causes portfolio managers to over-allocate in high-risk stocks to outperform their peers, especially in market runups. Data on mutual fund holdings supports this hypothesis by exhibiting over-allocation among mutual funds to high-risk stocks relative to the overall market (Karceski, 2002).

Qian and Qian (2017) introduce an interest-based explanation of the low-volatility anomaly. The authors argue that it is traditionally assumed that bond markets anticipate market movements before equity markets, thus changes in interest rates would lead market movements. They study if low-volatility stocks benefit from a decline in interest rates and offer interesting insight and empirical evidence on the relationship between interest rates and the volatility anomaly. They find that changes in interest rates and volatility-strategy profits are contemporaneously and serially related. But surprisingly, Qian and Qian find that the volatility anomaly is prescient to interest rate changes. That is, when the low-volatility strategy overperforms (underperforms) yields are predicted to decline (rise). They conclude that some of the volatility anomaly can be attributed to interest rate changes, and that volatility-strategy returns seem to predict changes in interest rates and macroeconomic shocks.

Overall, to understand the low-volatility or any other anomaly, it is important to understand who is going to pay for the systematic overperformance by suffering long-run underperformance and why? There seems to be many explanations relating to limits to arbitrage and incentives that can help to explain the structural appearance of the low-volatility or low-beta anomalies throughout the years and why the low-risk anomaly might persist in the future. For example, in line with the model of Baker and Haugen (2012), Blitz (2018) finds that portfolio managers do in fact overpay for high-volatility stocks. The paper reduces concerns regarding the “overcrowding” of the low-volatility trade via the finding that the multi-trillion hedge fund industry has structurally betted against the low-volatility trade. Whatever the root causes are, institutional investors seem to be driving the low-risk effect rather than capitalizing on it.

3.3 Idiosyncratic volatility and lottery demand puzzles

The alternative explanations of the low-risk effect focus on investor behaviour. One underlying theory in explaining the low-risk effect is that investors prefer lottery-like returns, i.e., positively skewed securities are overpriced and earn negative excess returns (Barberis & Huang, 2008; Brunnermeier, Gollier & Parker, 2007). A tendency to prefer or overpay for assets that have a relatively small probability of a large payoff is consistent with Tversky and Kahneman’s (1992) cumulative prospect theory (Bali, Cakici & Whitelaw, 2011). Considering the low-risk effect from this viewpoint, the focus shifts to idiosyncratic risk and individuals’ behavioural biases.

Ang, Hodrick, Xing and Zhang (2009) find that idiosyncratic stock return volatility is a priced cross-sectional risk factor across the U.S. and international markets. After sorting stocks across 23 countries on past idiosyncratic risk and controlling for value, market and size factors, the difference in alpha between the highest and lowest quintile portfolios is -1.31% with high statistical significance (Ang et al., 2009). Further, Liu, Stambaugh and Yuan (2018) show that the positive correlation between idiosyncratic volatility and beta, creates the beta anomaly. Their findings challenge the beta-driven explanations of the beta anomaly since after controlling for idiosyncratic volatility the anomaly becomes insignificant.

On the other hand, many studies provide convincing explanations for the idiosyncratic volatility puzzle, such as lottery-seeking retail investors (Bali et. al., 2011; Han & Kumar, 2013), coskewness with the market (Chabi-Yo & Yang, 2009), one-month return reversal (Fu, 2009; Huang, Liu, Rhee, & Zhang, 2010), and illiquidity (Han & Lesmond, 2011). Hou and Logh (2017) examine many of these explanations and variables. They find that investors' lottery demand and market frictions can explain a sizeable amount of the negative relation between idiosyncratic volatility and subsequent stock returns. Together the existing variables that include different lottery preference, market friction, and other variables, explain 78–84% of the returns of idiosyncratic volatility-sorted portfolios (Hou & Logh, 2017).

Bali et al. (2011) investigate the behavioural preference for lottery-like returns in the cross-sectional pricing of stocks by examining the relation between the maximum daily return over the past one month (MAX) and expected returns. Consistent with Tversky and Kahneman's (1992) cumulative prospect theory, the authors suggest that investors cause mispricing due to errors in their probability weighting. They claim that investors overvalue stocks that have a small probability of a large gain. The results support this theory by displaying that investors tend to overpay for stocks that experience extreme positive returns in the previous month, and thus, extreme positive returns predict lower future returns.

In a similar vein, Bali, Brown, Murray and Tang (2017) explain the betting against beta anomaly with investors' preference for lottery-like returns and idiosyncratic risk. The authors define stocks' lottery demand as the average of the 5 highest daily returns over the past month. After controlling for the lottery demand, they find that the beta anomaly disappears, suggesting that the demand for lottery-like returns is a significant driver of the beta anomaly and the low-risk effect. In other words, investors' preference for lottery-like returns puts disproportionate price pressure on high-beta stocks which flattens the security market line, explaining the beta anomaly. While, vice versa, the lottery-demand anomaly is statistically significant even after controlling for the beta anomaly, supporting the robustness of the lottery-demand hypothesis. (Bali et al. 2017). Overall, in addition to limits to arbitrage and portfolio managers' incentives, the literature seems to suggest that some of the low-risk anomaly is attributable to idiosyncratic and behavioural factors.

3.4 Low-risk factor horse race

How do the different low-risk factors interact with each other and which theory and factor are the ultimate drivers of the low-risk effect? Asness, Frazzini, Gormsen, and Pedersen (2020) note that the existing literature on the low-risk effect is a competition between naturally highly correlated factors since risky assets are often risky in many ways, in systematic and idiosyncratic ways. Their study strives to distinguish the low-risk theories by creating a factor that is relatively unrelated to the other low-risk factors or theories. This is done by essentially decomposing the BAB factor into betting against correlation factor (BAC) and betting against volatility (BAV). The BAC factor is a pure bet against systematic risk and BAV is a pure bet on volatility that is more closely related to the behavioral factors (Asness et al., 2020).

They also decompose the MAX return factor into a new scaled MAX factor (SMAX) and a short-term total-volatility factor. The SMAX factor is a long-short portfolio betting against stocks with lottery-like return distributions. It goes long (shorts) stocks with low (high)

MAX return divided by ex-ante volatility. This way the lottery-demand effect is isolated from the overall volatility of a stock, making it a more purely a bet on the idiosyncratic skewness of the stock's return distribution. With the new uncorrelated BAC and SMAX factors, Asness et al. (2020) are better equipped to distinguish between the two theories – the theory of leverage constraints and behavioural explanations. Similar to earlier studies, their results suggest that both theories play a part in explaining the low-risk effect, although, in the end, the systematic factors create stronger and more robust effects.

Overall, all the previous literature shows that after rigorous testing, the low-risk effect has a strong place in the finance literature. Blitz and Baltussen (2020) provide a comprehensive review of previous studies and explanations regarding the low-risk effect. They argue that the low-risk effect is not explained by existing risk factors. For example, value and profitability effects do subsume the abnormal returns of the low-risk factors, and the low-risk effect is not robust for every sub-period. However, overall, the existing risk factors explain only a part of the effect, or the performance over some specific sub-period. Furthermore, despite the rising interest of practitioners towards the low-risk anomaly, the empirical evidence suggests that investors continue to be on the losing side of the low-risk trade (Blitz & Baltussen, 2020).

The low-risk anomaly is also supported by strong theoretical explanations in the forms of the theory of leverage constraints, agency issues, and behavioral biases. Most of these theories are backed by strong empirical results, but since the theories and results are highly correlated there is no clear distinction between the theories or factors. Although, Blitz and Baltussen (2020) argue that this distinction is not relevant, at least in the highest level of emergence. They note that the choice between low-volatility or beta is effectively a choice on the added value of correlation. As Asness et al. (2020) exhibit, correlations matter when keeping volatility constant which implies that the added value of correlations is a second-order effect (Blitz and Vliet, 2020). Thus, from a trading strategy perspective, the volatility anomaly seems to be the most attractive. In accordance with the previous empirical results, this study will focus especially on the combination of momentum and volatility, but it will also review momentum-beta and momentum-SMAX combinations.

4 Momentum

The EMH and random walk model imply that past returns should not offer information about future returns. The philosophy behind momentum strategies directly challenges this assumption of the efficient market hypothesis. Can trading strategies based on past returns generate abnormal returns, or can we accept that markets are a fair game at least in their weak form?

4.1 Momentum strategies

Jegadeesh and Titman (1993) were first to document the profitability of momentum strategies by analyzing NYSE and AMEX stocks. They investigate strategies that buy stocks that have performed well in the past and sell stocks that have performed poorly in the past over the 1965 – 1989 period. Their findings show that these kinds of systematic strategies can yield significant positive returns which cannot be explained by systematic risk.

Jegadeesh and Titman (1993) form their winner and loser portfolios based on the past J months returns and hold them for K months. They name this strategy as J-month/K-month strategy. They observe returns over the past 3, 6, 9, and 12 months and then divide the stocks into ten decile portfolios where the top portfolio withholds the "losers" and the bottom portfolio the "winners". Then, in each month t, the strategy buys the winner portfolio and sells the loser portfolio and holds them for K months. In addition to strategies that are formed right after the formation period, they also examine strategies that include a one-week skipping period to avoid shorter-term reversals found in Jegadeesh (1990) and Lehmann (1990).

Jegadeesh and Titman (1993) find that all strategies generate positive returns, and only the 3-month/3-month strategy with no skipping period does not create statistically significant returns. The most successful strategy in their study is the 12-month/3-month strategy with one week skipping period, generating an average monthly return of 1.49% with a t-statistic of 4.28. Moreover, on average, the strategies that include skipping period are found to generate better returns than strategies formed right after the formation period (Jegadeesh & Titman 1993). In conclusion, Jegadeesh and Titman note that common interpretations of return reversals and return persistence are not enough to explain the momentum phenomenon, and more sophisticated models are needed to explain systematically biased investor expectations. Furthermore, Jegadeesh and Titman (2001) revisit their 1993 research to confirm the results and to indicate that their previous results were not just data mining. They investigate momentum strategies over the 1965 – 1998 period and show that the momentum effect continued also in the 1990s.

Rouwenhorst (1998) extends the study of the momentum effect to outside of the United States. He finds statistically significant positive momentum premia in 12 European countries over the 1980 – 1995 period. The results are similar to Jegadeesh and Titman's (1993) results and increase the robustness of the momentum anomaly. Doukas and Mcknigth (2005) confirm the findings of Rouwenhorst (1998) by exhibiting that the momentum effect was present in 13 European markets during 1988 – 2001, and significant in 8 out of the 13 countries. Asness, Moskowitz and Pedersen (2013) also provide evidence that positive momentum premium is an international phenomenon, and especially strong in Europe. They found significant positive momentum premia in individual stocks in Europe, US, and UK, but insignificant premia in Japan.

Furthermore, Rouwenhorst (1999) extends the momentum literature by studying 20 emerging markets using 1750 individual stocks and finds momentum premia in emerging markets as well, favoring the hypothesis that momentum is a global phenomenon. In a similar vein, Griffin, Ji and Martin (2003) find that the zero-cost 6-month/6-month (with a one month skipping period) momentum strategy is, on average, profitable around the world. They find average regional monthly momentum profits of 0.77%, 0.78%, 0,32%, and 1.63% in Europe, America (excluding the United States), Asia, and Africa, respectively.

Asness, Liew and Stevens (1997) take the investigation of momentum from individual stocks also to the country-level by investigating the cross-section of country returns and parallels of momentum's explanatory power for countries and individual stocks. They find that the country version (1-year past country returns) of the momentum helps to explain the cross-section of expected country returns. Furthermore, the evidence for the country-level portfolios is similar to portfolios formed from individual stocks (Asness et al. 1997). For example, the study shows that the winner portfolio constructed from countries generates an average return of 1.71% per month, while the winner portfolio of U.S. stocks yields a monthly return of 1.65%. The difference between winner and loser country portfolios is 1.03% per month and statistically significant with a t-statistic of 4.15. Similarly, Chan, Hameed and Tong (2000) report significant profits of country-level momentum strategies based on past returns of country indices.

Moskowitz and Grinblatt (1999) study the industry component of the individual stock momentum returns and profitability of industry momentum strategies. They form 20 value-weighted industry portfolios for every month over the 1963 – 1995 period. The portfolios are then ranked based on the past 1- to 6-month industry returns to form long-short strategies that sell three of the most poorly performed industries and buys the three best-performed industries. Their results exhibit strong and robust evidence that the industry momentum effect is not explained by the individual stock momentum. Moreover, they find that profits from individual stock momentum are substantially explained by the industry effects, and, after industry adjustments, the individual equity momentum profits are predominantly insignificant. The results show that industry momentum consistently overperforms individual equity momentum and is also more balanced. Individual stock momentum strategies usually generate most of the profits on the sell side, while industry momentum is more balanced between the profitability of the buy and sell side, or even tilts to the buy side (Moskowitz & Grinblatt, 1999). In conclusion, Moskowitz and Grinblatt expose the existence of a significant and robust industry momentum phenomenon that might account for much of the individual momentum effect, but they do not explicitly state *why* this phenomenon exists.

In addition to country-, industry-, and individual stock level momentum, there is evidence that momentum premium exists across asset classes too. Asness et al. (2013) provide a comprehensive study of momentum across countries and asset classes. They examine individual stocks, country equity index futures, government bonds, currencies, and commodity futures. They find consistent momentum returns among all asset classes, but most importantly, they capture significant comovement among momentum strategies across asset classes. Thus, not only are the momentum returns correlated inside asset classes locally, but also across asset classes globally (Asness et al., 2013). Asness et al. (2013) suggest that the strong correlations amongst the momentum portfolios in unrelated asset classes indicate that there exists a common global risk factor related to momentum.

Grinblatt, Titman and Wermers (1995) extend momentum studies to mutual funds and realized returns. They analyze mutual fund behaviour and to what extent the funds exhibit momentum-type investing and how does this affect mutual fund returns. They find that 77% of the funds in their study were “momentum investors”. On average, funds that followed momentum strategies reported significant excess returns (Grinblatt, Titman and Wermers, 1995). Carhart (1997) finds that mutual funds also exhibit short-term persistency themselves. The results of mutual fund decile portfolios sorted on one-year past returns show that post-formation monthly excess returns regularly drop from top-decile to bottom-decile portfolios, with approximately an 8% annualized spread between top- and bottom-deciles (Carhart, 1997).

Moskowitz, Ooi and Pedersen (2012) introduce an alternative momentum-type strategy which they call “time-series momentum”. Traditional momentum strategies, like the ones presented above in this section, focus on the relative performance of assets in the cross-section, while the time-series momentum focuses only on asset’s own return (Moskowitz et al., 2012). Cross-sectional momentum strategies rank assets and form long-short portfolios based on the relative returns of securities, whereas the time-series momentum portfolio formation is based on securities' absolute returns, or, in other words, securities own trend (Moskowitz et al., 2012).

Moskowitz et al. (2012) investigate the time-series momentum in equity indices and in currency, commodity, and bond futures. They measure the time-series momentum by a portfolio which is long instruments which have had positive excess return over the past 12 months and short instruments that have had negative returns and size the positions so that ex-ante 40% annualized volatility (similar to an average stock) is reached. The 12-month/1-month time-series momentum exhibits positive profits for each of the 58 contracts they examine. The authors find that time-series momentum has low risk-factor loadings and it cannot be explained by the standard asset pricing models or by cross-sectional momentum. Furthermore, the significance of the time-series momentum is robust with different look-back and holding periods as well as across asset classes (Moskowitz et al., 2012).

Ehsani and Linnainmaa (2019) show that in addition to individual stocks, countries, currencies, commodities, and industries, also, asset pricing factors exhibit strong and significant momentum, and how this can be used to create a profitable momentum strategy. They use 20 factors to create a time-series factor momentum strategy that bets purely on the positive autocorrelations in factor returns. This strategy earns an annualized return of 4.2% with a t-statistic of 7.04. Furthermore, in their sample, the average factor with a positive past one-year return generates a return of 0.52% per month, while the average factor with a negative past one-year return yields a monthly return of 0.02%. This spread between average returns is statistically significant with a t-statistic of 4.67.

4.2 Explanations

In total, the wide-ranging studies show that momentum has proven to be one of the most robust anomalies across asset classes and geographies in finance literature. After a couple of decades, momentum is still central to market efficiency and asset pricing debate, and it continues to inspire the creation and testing of competing explanations and theories for its existence. The explanations for the momentum premia can be roughly divided into two: behavioural and risk-based explanations. Risk-based explanations argue that momentum premium is compensation for some source of risk, while the behavioural explanations are often based on behavioural patterns, such as underreaction or delayed overreaction to information (Moskowitz, 2010).

Asness, Frazzini, Israel and Moskowitz (2014) note that there are several reasonable theories for the existence of the momentum premia, but it is not clear which theory is the dominant one. Most probably momentum premium is affected by several of these explanations (Moskowitz, 2010). From a practical viewpoint, the distinction between the driving forces of momentum is not relevant, since, as long as the risks, tastes for risks, behavioral biases, and limits to arbitrage will exist, momentum premia will also exist (Asness et al., 2014).

Initially, Jegadeesh and Titman (1993) show that momentum returns are not driven by systematic risk. They suggest that the momentum anomaly is driven by investor behaviour and systematically biased expectations. They propose that the anomaly is caused by positive feedback trading, or, alternatively, by underreaction to short-term prospects and overreaction to long-term prospects. These hypotheses are investigated, for example, by Chan, Jegadeesh and Lakonishok (1996) who try to rationalize and solve the puzzle of momentum by investigating markets' underreaction to information.

Chan et al. (1996) conclude that evidence does not, at least entirely, support the positive-feedback-trading hypothesis since subsequently the trend of future returns does not reverse. They also note that risk-based explanations are challenged by the empirical observation that past winners earn average-like returns in the second and third years. Furthermore, they find that momentum returns cannot be explained by market, size and value factors.

Alternatively, Chan et al. (1996) investigate markets' reaction and adjustments to information. They find that momentum can be partly explained by underreaction to earnings information, as a substantial part of the momentum profits is generated around subsequent earnings announcements. Though, Chan et al. note that price momentum is not subsumed by earnings momentum, and that the large drifts in future returns are probably affected by many other sources of information, such as buybacks, insider trading and equity issues. They find that the gradual adjustment to information does not concern just investors but analysts as well. Analysts are slow to update their forecasts which might also partly explain markets' underreaction to new information (Chan. et al., 1996).

Attempting to explain investors' under- and overreaction to information, Barberis, Shleifer and Vishny (1998) build a model of measuring investor sentiment to explain both long-term return reversals and short-term return continuation. They account for two well-documented phenomena in psychology – representativeness and conservatism. Representativeness refers to the tendency of people to view events as representative of future events and misjudge probabilities (Kahneman & Tversky, 1974). Conservatism, on the other hand, relates to the observation that humans are slow to update their beliefs or models (Edwards, 1968). By accounting for these cognitive biases, their model predicts that markets underreact to earning announcements and similar events but overreact to consistent patterns of information due to extrapolation.

Hong and Stein (1999) pursue a similar goal as Barberis et al. (1998) of building a behavioral model explaining the markets' gradual reaction to new information. They introduce a model that focuses on the gradual spreading of firm-specific private information in a population that causes the initial underreaction of markets. In their model, so-called "newswatchers" initially act on a fraction of the new information. This causes the gradual diffusion of the fundamental information and an upward price trend in the direction of fundamentals. The newswathers are then followed by "momentum traders" who trade based on price signals and accelerate the existing trends and push prices past the fundamentals and long-term equilibrium prices. The central prediction of this model is that those stocks where new information diffuses slowly exhibit stronger momentum.

Hong, Lim and Stein (2000) test the model predictions of Hong and Stein (1999) and obtain three main results that are in line with the above-presented hypothesis. First, they show that momentum is more profitable amongst small firms where the information is intuitively assumed to be diffusing more slowly. Second, as Hong and Stein (1999) hypothesize, ceteris paribus, the momentum effect is stronger for stocks with low analyst coverage. Third, the low-analyst-coverage effect is greater for small firms and past losers, than for bigger past-winner firms.

In a similar vein, Chan (2003) compares returns of firms that exhibit headline news with returns of firms that exhibit no news. His setting has a theoretical link to the Hong-Stein model's newswathers and momentum-traders with the distinction that Chan focuses on public information. In line with the Hong-Stein model, Chan (2003) finds that investors tend to underreact to news (newswathcers) while the no-news stocks (momentum-traders) tend to exhibit reversals, consistent with the hypothesis that investors overreact to non-informative signals. Moreover, most of the momentum premium is caused by negative drift among small illiquid stocks which could explain why sophisticated investors do not arbitrage this premium away (Chan 2003).

Alternatively, Daniel, Hirshleifer, and Subrahmanyam (1998) suggest that investor overconfidence, biased self-attribution, and delayed overreaction contribute to the momentum anomaly. They theorize that investors are overconfident regards to their private information, especially with self-produced signals. Thus, creating an overreaction to private signals, whereas public information signals are adopted only gradually. Daniel et al. (1998) suggest that if investors' confidence acts as a function of investing outcomes, positive autocorrelation and overreaction will appear. Subsequently, the slow diffusion of public information will finally cause the reversal towards the fundamentals (Daniel et al., 1998).

Another behavioural explanation of the momentum premium is the disposition effect. It implies that investors tend to hold onto assets that have dropped in value, while prematurely selling winning investments. Grinblatt and Han (2005) explain the disposition effect via Kahneman and Tversky's (1979) prospect theory together with Thaler's (1980) "mental accounting"' framework. They suggest that investors split their assets into two categories based on the past returns and treat them differently, that is, investors are risk loving in the domain of losses and risk averse in the domain of gains, or, in other words, investors tend to ride losses and lock in capital gains. The authors argue that these tendencies in investor behaviour drive the momentum premium by creating an equilibrium in which past losers are overvalued, and past winners undervalued.

Grinblatt and Han's (2005) empirical tests are consistent with their disposition-effect model. They double sort stocks based on past returns and capital gains overhang (difference between current price and the aggregate cost basis). The results show that, after accounting for past returns, the average returns increase with the capital gains quantile. Within the past returns quantiles, the annualized spread between highest and lowest capital gains quantiles ranges from about 6 – 13%. They also find a significant relation between stock's capital gain overhang and expected returns in Fama-Macbeth (1973) regressions. Furthermore, past returns' predictive power disappears when controlling for capital gains (Grinblatt & Han, 2005).

Along the same lines, Frazzini (2006) provides further empirical results regarding the disposition effect. His hypothesis is that the disposition effect causes the underreaction to news and return continuation. He forms a long-short strategy based on cumulative abnormal returns on the most recent earnings announcement and capital gains/losses. The results show that a long-short portfolio that holds the top 20% of positive earnings news stocks with top 20% capital gains and shorts the bottom 20% negative news stocks with bottom 20% of capital gains, yields an abnormal monthly return of 2.433% with a t-statistic of 6.60. In conclusion, the findings exhibit a positive relation between the sign of the news and capital gain overhang. Stock prices tend to underreact to bad news when more investors already carry capital losses and underreact to good news when more investors carry capital gains (Frazzini, 2006).

Alternatively, the momentum premium can be argued of being a compensation for risk under efficient markets and rational investors (Moskowitz, 2010). Fama and French (1996, 2016) study if the three- or five-factor models can explain patterns in average stock returns. In both studies, they find that momentum strategies generate significant alphas and, thus, conclude that both models are unable to capture the momentum premium. Similarly, Jegadeesh and Titman (2001) find that the zero-cost-momentum portfolio yields a significant monthly three-factor alpha of 1.36% with a t-statistic of 7.04.

Conrad and Kaul (1998) present evidence that momentum profits are not attributable to tendencies in returns, but rather to cross-sectional differences in mean returns. They find that momentum strategies tend to buy stocks with high expected returns and sell stocks with low expected returns. The mean returns are also unrelated to the time-series dependencies suggesting that momentum profits are compensation for higher risks rather than the time-series patterns (Conrad & Kaul, 1998). Jegadeesh and Titman (2002) defend the momentum anomaly by noting that Conrad and Kaul (1998) simulations and estimates suffer from small sample biases. Furthermore, they provide empirical evidence that cross-sectional differences in expected returns explain very little of the momentum premium.

Griffin et al. (2003) investigate if business cycle risks could explain the momentum premium. First, contradictory to Asness et al. (2010) they find evidence that momentum profits are not likely to be driven by a common global risk factor since the country correlations of momentum profits are low. In analyzing momentum's macroeconomic sensitivities, they apply the framework of Chen, Roll and Ross (1986) who show that unexpected inflation (UI), changes in expected inflation (DEI), term spread (UTS), changes in industrial production (MP), and default risk premium (URP) are significant for predicting asset returns, providing a basis for investigating momentum strategies' sensitivities to macroeconomic risks. Griffin et al. (2003) conclude that the Chen et al. (1986) model provides a very poor fit for momentum profits with only an average adjusted R2 of 0.012 across all countries. Furthermore, they find that the momentum premium is, on average, positive in all macroeconomic states which further strengthens the claim that momentum profits are independent of macroeconomic risks.

In contrast, Chordia and Shivakumar (2002) show that lagged macroeconomic variables and time-varying risk premia can help to explain momentum premium. They conclude that more focus should be put on time-varying expected returns and business cycle risks in attempt to understand the drivers of momentum. Furthermore, Cooper, Gutierrez, and Hameed (2004), and Sagi and Seasholes (2007) find that momentum profits do seem to be depended on the state of the market. Both studies, find that lagged market return is a relevant predictor of momentum profits.

Johnson (2002) shows that momentum premium can stem from priced firm-level risks, instead of market-level risks. He introduces a single-firm model that provides a plausible mechanism for a strong positive correlation between a firm's past returns and its long-term expected return. The model explains that positive price growth rates mean also greater growth rate risks which subsequently raises current expected returns. This means that high recent-past returns signal improved cashflow growth prospects, while the poor performers signal negative growth prospects. Johnson notes that the point is not to prove that there are not any behavioural reasons for the momentum effect, but rather to illustrate that there can be rational reasons for why the momentum premium might exist.

For more firm-level explanations, Sagi and Seasholes (2007) focus on the determinants of conditional expected returns and questioning what kind of firms might exhibit momentum? They attribute momentum to variation in firm-specific variables, such as a firm's revenues, costs, and growth options. First, their one-firm model rationalizes that firms that have a large part of their value determined by risky growth options face higher risks and thus also exhibit higher expected returns. By using market-to-book ratio as a proxy for this, they find that high market-to-book firms exhibit stronger momentum profits than low market-to-book firms. Second, in their model, operating leverage decreases autocorrelation in returns. They rationalize this by suggesting that positive revenue shocks cause a larger drop in risk and expected returns for firms with high fixed costs. Sagi and Seasholes find that this is supported empirically, as firms with low costs of goods sold produce higher momentum profits than low-margin firms. Third, their model predicts that the momentum premium is more pronounced in high-revenue-volatility firms which is also supported by the data. Based on these implications, they create momentum strategies by first sorting on high revenue volatility firms, high market-to-book firms, and low-cost firms. Their strategies provide an outperformance of approximately 5% per year compared to the traditional momentum strategies.

Traditional asset pricing models predict that firm's beta (risk exposure) is static, Berk, Green, and Naik (1999) propose that firm's beta may be dynamic, if its investment opportunities change over time. Zhang (2004) introduces a model that explains momentum profits via time-varying risk factors. In the model, the momentum premium is driven by the short-term perseverance of investment opportunities, and hence, investment policies. He suggests that when firm adjusts its investment policy and systematic risk exposure according to its predictions of firm-level risks, investors face beta risk (proxy for firm-level risk) in addition to market-level risks. He suggests that a firm with recent good performance might adjust its business so that it faces greater systematic risk exposure in the future, and thus, a larger expected return, and a firm with recent poor performance might face lower systematic risk in the future, and a lower expected return. Furthermore, the model rationalizes size and value premia too (Zhang, 2004).

More recent studies by Arnott, Clements, Kalesnik and Linnainmaa (2019) and Ehsani and Linnainmaa (2019) show that momentum in individual stocks and industries is subsumed by momentum in factor returns. These studies suggest that momentum is not a distinct risk factor, but rather an aggregation of the autocorrelation in factor returns. Using data on 51 factors, Arnott et al. (2019) show that factor momentum is stronger than industry momentum and that it can explain industry momentum profits. The authors find also that factor momentum is not dependent on arbitrary choice of factors, as almost any factor set exhibits positive return autocorrelation. Furthermore, Ehsani and Linnainmaa (2019) show how factor momentum explains all forms of individual stock momentum. By contrast, the other momentum factors do not explain factor momentum. The authors note that momentum profits seem to stem from factor timing, and thus the profitability of momentum strategies essentially boils down to the positive autocorrelations in factor returns. They conclude that momentum profits are not likely to be related to firm-specific news since most factors are so well diversified, washing out the residuals of firm-specific information. They hypothesize that momentum profits are caused by slowly mean-reverting mispricing as arbitrageurs gradually push assets back toward their fundamentals.

In conclusion, the rational explanations of momentum profits require that risks and expected returns rise after positive past returns. Moskowitz (2010) summarizes that the risk-based explanations are based on the suggestion that firms with high (low) returns over the past year will exhibit high (low) current cost of capital because of their increase (decrease) in cash flow risks and/or risk exposures. The increase in cash-flow risks is due to firms' growth prospects or greater discount-rate risk because of their investment opportunities. Furthermore, some studies argue that the correlations across different asset classes and markets imply that there exists some shared economic risk (Asness, Frazzini, Israel & Moskowitz, 2014).

5 Data and methodology

The data used in this paper includes daily share price data from the Nasdaq stock exchange, daily data for the market index and the risk-free rate, as well as monthly returns for the Fama-French factors. This chapter will introduce the data and methodologies used in the empirical analysis of this paper.

5.1 Data

The sample consists of 6308 stocks in the Nasdaq stock exchange between January 1995 and July 2020. The market index used in this study is the Nasdaq Composite Price Index. The stock universe and market index are obtained from the Thompson Reuters Data Stream database. The monthly U.S. Fama-French 5 factors, as well as the risk-free rates (one-month Treasury bill rate) used in this paper are obtained from Kenneth French's database. Furthermore, since this study considers only Nasdaq stocks of the U.S. stock universe, the Fama-French market factor ($R_m - R_f$) which includes all NYSE, AMEX, and NASDAQ firms, is replaced with Nasdaq Composite Price Index's monthly return in excess of the risk-free rate.

5.2 Methodology

5.2.1 Portfolio construction

The aim of this paper is to analyze multi-factor strategies that combine momentum and low-risk factors. All factor measures have been researched in previous literature and have a significant historical track record. The multi-factor portfolios are assembled via two approaches – conditional (sequential) and intersectional (unconditional) approaches described and utilized in Rabener (2018). The conditional approach ranks stocks at the end of the previous month into terciles first on their momentum and then conditionally on the low-risk factor, that is, within the momentum-ranked terciles stocks are sorted into terciles based on the other factor. The intersectional approach simultaneously sorts the stocks at the end of the previous month by both factors and chooses the intersection. In other words, there are two univariate sorts stored into tercile portfolios sorted independently of each other from which the intersection between each tercile is then chosen.

Altogether, at the beginning of each month, both approaches create 9 equal-weighted sub-portfolios for which the monthly returns are then calculated. These sub-portfolios can be denoted as (T_m, T_r) where T_m is the momentum-tercile and T_r is the risk-factor tercile. A graphical illustration of this is provided below in table 1. With this notation the multi-factor long-only portfolio can be expressed as (T_3, T_1) and the long-short portfolio as $(T_3, T_1) - (T_1, T_3)$. The conditional portfolio construction gives more weight to the momentum factor since it is used as the preliminary sorting variable. This is expected to help to capture the strong performance of the momentum factor while still reducing risks via the conditional sort on the low-risk factors.

Table 1. Sub-portfolios

	Sort on low-risk factor		
Sort on momentum	Low	Mid	High
Low	T_1, T_1	T_1, T_2	T_1, T_3
Mid	T_2, T_1	T_2, T_2	T_2, T_3
High	T_3, T_1	T_3, T_2	T_3, T_3

To draw conclusions about the attractiveness of the multi-factor strategies, monthly returns are also calculated for the standalone single-factor strategies (momentum, low SMAX, low volatility and low beta). To construct the single-factor portfolios, at the beginning of each month, stocks are sorted into terciles based on their momentum, volatility, beta, and scaled MAX return, creating three equal-weighted tercile portfolios for each factor. In the empirical analysis, absolute and risk-adjusted returns of the individual the single- and multi-factor sub-portfolios are analyzed. In addition, the long-short portfolios, $(T_3, T_1) - (T_1, T_3)$, that go long the *high momentum-low risk* portfolio and short the *low momentum-high risk* portfolio are analyzed in Fama and French (1993, 2015) factor regressions.

5.2.2 Volatility, beta, SMAX, and momentum computations

The volatility and beta calculations use daily share price data following the corresponding calculations of Asness et al. (2020) as well as Frazzini and Pedersen (2014). The scaled MAX return computation differs slightly from the computations of Asness et al. (2020).

To compute the cross-sectional momentum of a stock, the widely accepted 12-1-1 momentum measure is applied. This measure has been used, for example, by Jegedeesh et al. (1993), Fama and French (1996), and Asness et al. (2013). The 12-1-1 momentum measure is calculated as past 12 month's return skipping the most recent month's return. The most recent month is skipped to avoid shorter-term reversals found in Jegadeesh (1990) and Lehmann (1990). Furthermore, Jegadeesh and Titman (1993) find that, on average, strategies with skipping period generate better returns than strategies without skipping period.

Volatilities are estimated using one-year (252 trading days) rolling windows of daily log-returns. To estimate correlations, five-year rolling (756 trading days) windows of overlapping three-day log-returns, $r_{it}^{3d} = \sum_{k=0}^{2} ln(1 + r_{t+k}^{i})$, are used. Betas are estimated as:

$$\hat{\beta}_i^{TS} = \hat{p}_{im} \frac{\hat{\sigma}_i}{\hat{\sigma}_m} \tag{5}$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities of stock i and the market m and is $\hat{p}_{im}$ the estimated correlation. At least 750 trading days of non-missing return data is required to estimate correlation and 120 trading days of non-missing return data to estimate volatility.

The computation of scaled MAX returns (SMAX) follows roughly the computations of Asness et al. (2020). For each stock, the SMAX is calculated as the past 20 trading days' one-day MAX return divided by the stock's volatility $\hat{\sigma}_i$. In contrast, Asness et al. (2020) calculate SMAX as the average of the five highest daily returns over the last month divided by the stock's volatility. The single-day MAX return (MAX(1)) used in this study in the computation of SMAX is also proven to generate significant statistical and economic effects in Bali et al. (2011). For example, they find that the difference in alphas between the high single-day MAX and low single-day MAX portfolios is −1.18% per month with a Newey–West t-statistic of −4.71. To study the effect of investors' preference for lottery-like returns, the study uses scaled MAX over the MAX since it decomposes MAX to its volatility and return distribution effects. Asness et al. (2020) argue that the MAX return divided by its ex-ante volatility captures a stock's return distribution and investors' preference for lottery-like returns better than the standard unscaled MAX since high maximum returns can be caused by high volatility.

5.2.3 Risk-adjusted performance measures

This study is mainly interested in the risk-adjusted performance of the different strategies. To measure the performances of the long-only portfolios, the study applies Sharpe ratio, Sortino ratio, Information ratio, CAPM alpha, and three-factor alpha. Furthermore, the long-short factor portfolios are analyzed in Fama and French (2015) five-factor regressions.

Sharpe ratio is calculated as:

$$Sharpe_p = \frac{R_p - R_f}{\sigma_p} \tag{6}$$

where R_p is the return of the portfolio, R_f is the risk free rate and σ_p is the standard deviation of the portfolio's excess returns.

One modification of the Sharpe ratio is the Sortino ratio that replaces the standard deviation with the standard deviation of negative portfolio returns. Thus, the Sortino ratio can be expressed as:

$$Sortino_p = \frac{R_p - R_f}{\sigma d_p} \tag{7}$$

where R_p is the return of the portfolio, R_f is the risk free rate and σd_p is the standard deviation of the portfolio's negative returns.

Also, the Information ratio can be present with similar notation, as:

$$IR_p = \frac{R_p - R_b}{\sigma_{(R_p - R_b)}} \tag{8}$$

where R_p is the return of the portfolio, R_b is the benchmark return, and $\sigma_{(R_p - R_b)}$ is the standard deviation of the portfolio's returns excess of the benchmark.

The abnormal returns of the portfolios are measured by using the three asset pricing models presented previously in the section 2.2, i.e., CAPM, three-, and five-factor models.

CAPM alpha is estimated via the following time-series regression equation:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p(R_{m,t} - R_{f,t}) + \varepsilon_{p,t} \tag{9}$$

where α_p is the regression intercept (CAPM alpha), R_p is the return of the portfolio, R_m is the market return, R_f is the risk-free rate, β_p is the beta of the portfolio (systematic risk), and ε_p is the error term.

The Fama and French (1993) three-factor alpha is estimated via the following time-series regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p\left(R_{m,t} - R_{f,t}\right) + s_p SMB_t + h_p HML_t + \epsilon_{pt} \tag{10}$$

where α_p is the regression intercept (three-factor alpha), R_p is the portfolio , R_m is the market return, R_f is the risk-free rate, SMB is the return of the size factor, HML is the return of the value factor, β_p, s_p, h_p are the regression coefficients (factor loadings), and ε_p is the error term.

Similarly, the Fama and French (2015) five-factor alpha (α_p) is estimated via the following time-series regression:

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_p\left(R_{m,t} - R_{f,t}\right) + s_p SMB_t + h_p HML_t + r_p RMW_t + c_p CMA_t + \epsilon_{pt} \tag{11}$$

where RMW is return of profitability factor, CMA is the return of the investment factor, and r_p, c_p are the regression coefficients (factor loadings).

6 Empirical results

Based on the earlier literature on momentum and low-risk anomalies, the double sorted sub-portfolios are expected to yield increasing (decreasing) risk-adjusted returns moving from low to high along the momentum (risk factor) terciles. Thus, the sub-portfolios that rank the highest on momentum and the lowest on risk are expected to yield the best risk-adjusted returns, while the sub-portfolios that rank the lowest on momentum and the highest on risk are expected to yield the worst risk-adjusted returns. The scaled MAX return is referred here as a risk metric, or as a low-risk factor, besides volatility and beta, even though it is expected to generate different effects compared to the volatility and beta factors which measure the total or systematic risk of a stock, while SMAX is intended to capture the idiosyncratic skewness of a stock's return distribution.

Furthermore, the long-short portfolios that bet on high momentum-low risk stocks and short low momentum-high risk stocks are expected to yield significant alphas (unexplained returns) in the Fama and French factor regressions. Overall, the multi-factor portfolios are expected to decrease risk in comparison to pure momentum strategy and present attractive risk-adjusted returns relative to the market index and the single-factor portfolios.

6.1 Sub-portfolio analysis

In this section, risk-adjusted returns of the individually and double-sorted sub-portfolios are analyzed. Table 2 shows risk-adjusted returns (CAPM and three-factor alphas) for the individually sorted sub-portfolios. Tables 3, 4, and 5 show betas and risk-adjusted returns of the sub-portfolios sorted first on momentum and conditionally on the chosen risk factor. In each row, all the sub-portfolios have approximately same momentum but increase in the chosen risk measure from the left column to the right column. Table 6 shows the sub-portfolio Sharpe ratios in a similar manner.

Table 2. Individually sorted sub-portfolios abnormal returns 1995 – 2020.

This table presents CAPM and three-factor alphas for portfolios sorted individually on momentum, volatility, beta, and scaled MAX return. At the end of each month, stocks are allocated into three groups using 33,3th and 66,6th percentiles as breakpoints for each factor. At the beginning of each month, 3 equal-weighted portfolios are formed using the ranking of the end of previous month. T-statistics are shown in parentheses below the estimates, and 5% statistical significance is indicated in bold.

	MOM	VOL	BETA	SMAX
Panel A. CAPM alpha				
Low	-0.003	**0.003**	0.003	0.002
	(-1.27)	(2.04)	(1.78)	(1.37)
Mid	0.000	0.000	0.001	-0.001
	(0.03)	(0.19)	(0.61)	(-0.84)
High	0.003	-0.004	-0.001	-0.002
	(1.29)	(-1.75)	(-0.56)	(-1.29)
Panel B. Three-factor alpha				
Low	-0.004	0.002	0.002	0.002
	(-1.70)	(1.87)	(1.73)	(1.67)
Mid	0.000	0.001	0.001	-0.001
	(0.01)	(0.51)	(0.93)	(-0.91)
High	**0.004**	-0.003	-0.001	-0.002
	(2.00)	(-1.57)	(-0.62)	(-1.37)

Table 2 exhibits risk-adjusted returns for the individually sorted tercile-portfolios where Panel A considers the CAPM alpha and Panel B three-factor alpha. As seen in the table, the risk-adjusted returns for the tercile-portfolios sorted on momentum increase monotonically from low momentum to high momentum, while the risk-adjusted returns for portfolios sorted on risk factors decrease monotonically from low risk to high risk. On a risk-adjusted basis, momentum and volatility sorts produce the strongest economic and statistical effects. The lowest volatility tercile earns significant CAPM alpha of 0.3% per month with a t-statistic of 2.04, but the alpha diminishes when controlled for size (SMB) and value (HML) factors. The highest momentum tercile earns a significant three-factor alpha of 0.4% per month with a t-statistic of 2.00.

Table 3. MOMVOL sub-portfolio betas and abnormal returns 1995 – 2020

This table presents market betas and CAPM and three-factor alphas for portfolios sorted first on momentum and conditionally on volatility. At the end of each month, stocks are allocated into terciles based on 12-1-1 momentum, and within each momentum tercile the stocks are further allocated into terciles based on volatility. At the beginning of each month, 9 equal-weighted portfolios are formed using the ranking of the end of previous month. T-statistics are shown in parentheses below the estimates, and 5% statistical significance is indicated in bold.

	Conditional sort on volatility		
Sort on momentum	Low	Mid	High
Panel A. CAPM betas			
Low	**0.848**	**1.222**	**1.612**
Mid	**0.749**	**1.090**	**1.453**
High	**0.855**	**1.165**	**1.633**
Panel B. CAPM alphas			
Low	-0.0003	-0.001	**-0.008**
	(-0.13)	(-0.44)	(-2.48)
Mid	**0.004**	0.001	**-0.005**
	(2.46)	(0.48)	(-2.04)
High	**0.005**	0.004	-0.001
	(2.75)	(1.57)	(-0.32)

Panel C. Three-factor alphas			
Low	-0.002	-0.002	**-0.008**
	(-0.78)	(-0.69)	(-2.68)
Mid	**0.003**	0.001	**-0.005**
	(2.38)	(0.56)	(-2.00)
High	**0.006**	**0.005**	0.0005
	(3.02)	(2.17)	(0.14)

Panel A in Table 3 considers how ex-ante volatility and momentum sort ex-post market beta, and whether the portfolio returns can be expected to be subject to the theory of leverage constraints. Intuitively, market sensitivity increases from the left column to the right column (low VOL to high VOL) since beta and volatility are highly correlated measures, while the lowest and highest momentum terciles do not exhibit almost any spread in ex-post market risk.

In line with the expectations, Panel B and Panel C show that both CAPM and three-factor alpha decrease as volatility increases or momentum decreases. The conditional sorting on volatility appears to have a strong effect on sub-portfolio abnormal returns as the (T_3, T_1) portfolio yields a CAPM alpha of 0.5% per month and three-factor alpha of 0.6% per month with t-statistics of 2.75 and 3.02, respectively, while the (T_1, T_3) portfolio yields statistically significant -0.8% CAPM and three-factor alphas per month. Furthermore, the conditional sorting procedure provides stronger and more significant risk-adjusted returns and alpha spread than the single-factor MOM and VOL portfolios.

Table 4. MOMBETA sub-portfolio betas and abnormal returns 1995 – 2020

This table presents market betas and CAPM and three-factor alphas for portfolios sorted first on momentum and conditionally on beta. At the end of each month, stocks are allocated into terciles based on 12-1-1 momentum, and within each momentum tercile the stocks are further allocated into terciles based on beta. At the beginning of each month, 9 equal-weighted portfolios are formed using the ranking of the end of previous month. T-statistics are shown in parentheses below the estimates, and 5% statistical significance is indicated in bold.

Conditional sort on beta			
Sort on momentum	Low	Mid	High
Panel A: CAPM betas			
Low	**0.819**	**1.191**	**1.466**
Mid	**0.748**	**1.053**	**1.347**
High	**0.864**	**1.139**	**1.404**
Panel B: CAPM alphas			
Low	-0.0001	-0.001	-0.002
	(-0.03)	(-0.31)	(-0.49)
Mid	**0.004**	0.001	-0.002
	(1.97)	(0.51)	(-1.14)
High	**0.006**	0.003	-0.001
	(2.17)	(1.19)	(-0.28)
Panel C: Three-factor alphas			
Low	-0.001	-0.002	-0.003
	(-0.58)	(-0.65)	(-0.78)
Mid	**0.003**	0.001	-0.003
	(2.09)	(0.50)	(-1.27)
High	**0.006**	0.004	-0.0002
	(2.74)	(1.72)	(-0.09)

Panel A in Table 4 shows, as expected, that sub-portfolios sorted first on momentum and conditionally on beta produce a large ex-post beta spread between the high and low beta terciles. Surprisingly though, the conditional sort on beta produces a lower realized beta spread than the conditional sort on volatility. This can be probably attributed to the different lengths of the rolling windows used in the computations of correlation and volatility.

Panel B and Panel C exhibit CAPM and three-factor alphas for the 9 MOMBETA portfolios. Similar to the results of the MOMVOL portfolios, the risk-adjusted returns increase monotonically from left to right (low to high beta) and from top to down (low to high momentum). The (T_3, T_1) portfolio earns a statistically significant 0.6% CAPM and three-factor alphas per month. Moreover, conditional sorting on beta produces more significant positive alphas than the single-factor high MOM and low BETA portfolios. On the other hand, in comparison to the conditional sort on volatility, the conditional sort on ex-ante beta does not yield statistically significant negative alphas for the (T_1, T_3) (loser-high risk) portfolio.

Table 5. MOMSMAX sub-portfolio betas and abnormal returns 1995 – 2020

This table presents market betas and CAPM and three-factor alphas for portfolios sorted first on momentum and conditionally on scaled MAX return. At the end of each month, stocks are allocated into terciles based on 12-1-1 momentum, and within each momentum tercile the stocks are further allocated into terciles based on scaled MAX return. At the beginning of each month, 9 equal-weighted portfolios are formed using the ranking of the end of previous month. T-statistics are shown in parentheses below the estimates, and 5% statistical significance is indicated in bold.

	Conditional sort on SMAX		
Sort on momentum	Low	Mid	High
Panel A. CAPM betas			
Low	**1.210**	**1.280**	**1.179**
Mid	**1.048**	**1.114**	**1.116**
High	**1.202**	**1.190**	**1.252**
Panel B. CAPM alphas			
Low	0.001	-0.004	**-0.006**
	(0.27)	(-1.41)	(-2.30)
Mid	0.001	-0.001	0.0004
	(0.31)	(-0.85)	(0.22)
High	**0.005**	0.003	0.00003
	(2.03)	(1.32)	(0.01)

Panel C. Three-factor alphas			
Low	-0.00005	-0.004	**-0.007**
	(-0.02)	(-1.76)	(-2.78)
Mid	0.0003	-0.002	0.001
	(0.201)	(-1.02)	(0.32)
High	**0.006**	0.004	0.001
	(2.54)	(1.73)	(0.54)

Panel A in Table 5 shows that the conditional sorting on scaled one-day MAX return does not produce almost any spread in ex-post market betas. This result is not in any contradiction with expectations since the conditional SMAX sort is meant to capture the behavioural and idiosyncratic explanations of the low-risk effect, not the systematic effects. The realized sub-portfolio betas suggest that the difference in MOMSMAX portfolios' abnormal returns is not driven by the theory of leverage constraints. In fact, since the ex-post market betas are larger than one, the theory of leverage constraints implies that these portfolios should have negative alphas.

Sorting on SMAX is supposed to capture investors' lottery demand in a way that is not related to the overall volatility of the stocks, being purely a bet on the shape of distribution of returns. Similar to the two previous tables, Panel B and Panel C show that the CAPM and three-factor alphas increase from left to right and from top to down, producing significant positive alphas for the (T_3, T_1) portfolio and significant negative alphas for the (T_1, T_3) portfolio. The results also exhibit that the conditional sorting procedure produces more attractive risk-adjusted returns than the individual MOM and SMAX sorts. Overall, all three tables show that the conditional sorting increases the risk-adjusted returns and alpha spreads in comparison to the individual sorts.

Table 6. Sub-portfolio Sharpe ratios 1995 – 2020

This table presents Sharpe ratios for portfolios sorted first on momentum and conditionally on volatility (Panel A), beta (Panel B), and scaled MAX return (Panel C). At the end of each month, stocks are allocated into terciles based on 12-1-1 momentum, and within each momentum tercile the stocks are further allocated into terciles based on the chosen risk factor. At the beginning of each month, 9 equal-weighted portfolios are formed using the ranking of the end of previous month.

	Conditional sort on VOL (Panel A), BETA (Panel B), SMAX (Panel C)		
	Low	Mid	High
Panel A: MOMVOL			
Low	0.439	0.430	0.249
Mid	0.774	0.559	0.316
High	0.793	0.642	0.421
Panel B: MOMBETA			
Low	0.450	0.428	0.408
Mid	0.720	0.567	0.416
High	0.731	0.601	0.453
Panel C: MOMSMAX			
Low	0.501	0.346	0.237
Mid	0.547	0.465	0.527
High	0.680	0.614	0.478

Table 6 presents Sharpe ratios for the conditionally sorted MOMVOL (Panel A), MOMBETA (Panel B), and MOMSMAX (Panel C) sub-portfolios. The Sharpe ratios show a similar pattern to the three previous tables. Sharpe ratios increase from low momentum to high momentum and from high risk to low risk. In every case the (T_3, T_1) portfolio generates the highest Sharpe ratio and the (T_1, T_3) portfolio the lowest. Conditional sorting on volatility generates the highest Sharpe ratio for the (T_3, T_1) portfolio of 0.79 as well as the largest (T_3, T_1)—(T_1, T_3) Sharpe-ratio spread. All empirical results presented in this section are consistent and in favour of combining momentum and low-risk strategies to generate abnormal returns.

6.2 Long-only multi- and single-factor portfolios

In this section, the returns of the multi- and single-factor long-only portfolios are examined throughout the examination period. The section considers absolute and risk-adjusted returns as well as different risk and distribution characteristics for the long-only portfolios.

Table 7 provides descriptive statistics for the long-only portfolios. In terms of absolute returns, the strategies that combine momentum and SMAX generate the highest average monthly returns. Overall, all combination strategies outperform the individual low-risk strategies (VOL, BETA, and SMAX) and the market index in absolute returns. The high average returns of MOM and SMAX portfolios are also featured by large standard deviations of returns while low VOL and low BETA portfolios exhibit much smaller standard deviations. In total, the MOMSMAX strategies introduce larger return variability and return range than the MOMVOL and MOMBETA strategies.

When comparing characteristics of the return distributions, the low volatility, beta, and scaled MAX return strategies all exhibit surprisingly negative skewness while the multi-factor strategies have close to zero or positive skewness. The MOMBETA strategies have strikingly large kurtosis and positive skewness when compared to other strategies, especially in comparison to the individual MOM and BETA strategies. Furthermore, the different portfolio construction methods, conditional and intersectional (IS), do not seem to create remarkable differences in descriptive statistics.

Table 7. Long-only descriptive statistics

Statistics	n	mean	sd	me-dian	mad	min	max	range	skew	kurto-sis
MOMVOL	307	0.015	0.065	0.017	0.050	-0.226	0.389	0.615	0.327	4.400
MOMBETA	307	0.015	0.071	0.018	0.052	-0.219	0.487	0.707	0.890	7.860
MOMSMAX	307	0.018	0.091	0.019	0.073	-0.267	0.457	0.725	0.564	3.094
MOMVOL (IS)	307	0.014	0.062	0.016	0.051	-0.200	0.310	0.510	-0.058	2.219
MOMBETA (IS)	307	0.015	0.073	0.017	0.052	-0.207	0.479	0.686	1.000	7.244
MOMSMAX (IS)	307	0.018	0.090	0.017	0.071	-0.283	0.457	0.740	0.542	3.050
VOL	307	0.011	0.054	0.015	0.043	-0.202	0.173	0.375	-0.559	1.674
BETA	307	0.011	0.053	0.016	0.045	-0.222	0.204	0.426	-0.716	2.448
SMAX	307	0.014	0.081	0.014	0.063	-0.235	0.292	0.527	-0.110	0.928
MOM	307	0.015	0.088	0.017	0.069	-0.307	0.502	0.809	0.509	3.986
MKT	306	0.011	0.065	0.017	0.050	-0.229	0.220	0.449	-0.430	1.400

Table 8 shows performance and risk measures for the long-only factor portfolios. Altogether, the conditional MOMVOL portfolio looks the most attractive almost by every measure. It is an attractive combination of high returns as well as low risk. The MOMVOL generates the highest Sharpe, Information, and Sortino ratios and it also exhibits the lowest maximum drawdown and second lowest downside beta.

The results indicate that by combining momentum and low volatility it is possible to capture high average returns affiliated with momentum but with much less risk. The MOMBETA portfolios create similar absolute and risk-adjusted returns, but they exhibit larger dispersion of returns, i.e., standard deviation and kurtosis. As shown in Table 7, the MOMSMAX portfolios generate the highest returns of all the portfolios, but with considerably higher risks measured by standard deviation, drawdowns, and downside beta.

Table 8. Long-only risk-adjusted performance 1995 – 2020

Measure	Sharpe	Sortino	IR	3-factor α	Max drawdown	Avg. Draw-down	Down-side beta
MOMVOL	0.793	1.159	0.462	0.006***	0.488	0.095	0.717
MOMBETA	0.732	1.095	0.347	0.006***	0.520	0.116	0.724
MOMSMAX	0.680	1.048	0.434	0.006**	0.685	0.130	1.022
MOMVOL (IS)	0.761	1.065	0.368	0.004**	0.493	0.095	0.751
MOMBETA (IS)	0.716	1.102	0.337	0.006***	0.504	0.129	0.721
MOMSMAX (IS)	0.678	1.040	0.428	0.006**	0.696	0.136	1.049
VOL	0.716	0.906	0.158	0.002	0.511	0.080	0.733
BETA	0.707	0.872	0.094	0.002	0.499	0.084	0.678
SMAX	0.612	0.839	0.317	0.002	0.701	0.119	1.116
MOM	0.607	0.884	0.287	0.004	0.711	0.144	1.045
MKT	0.569	0.702	-	-	0.750	0.088	-

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The cumulative returns for all portfolios are shown below in Figure 1. The figure shows how all factor portfolios outperform the market. The MOMSMAX portfolios generate the largest cumulative returns, but as the previous tables show, they also experience large drawdowns and surges. In contrast to SMAX, VOL and BETA seem to provide better diversification when combined with momentum, but they do not add absolute returns to the pure momentum strategy. Furthermore, almost all empirical results thus far point to a slight advantage of the conditional strategies over the intersectional strategies that put more weight to momentum in the hope of capturing the strong absolute performance of the momentum factor. But, a bit surprisingly, the results indeed show only a slight advantage, and overall, it seems that there are no remarkable differences in risks or returns between the conditional and intersectional strategies.

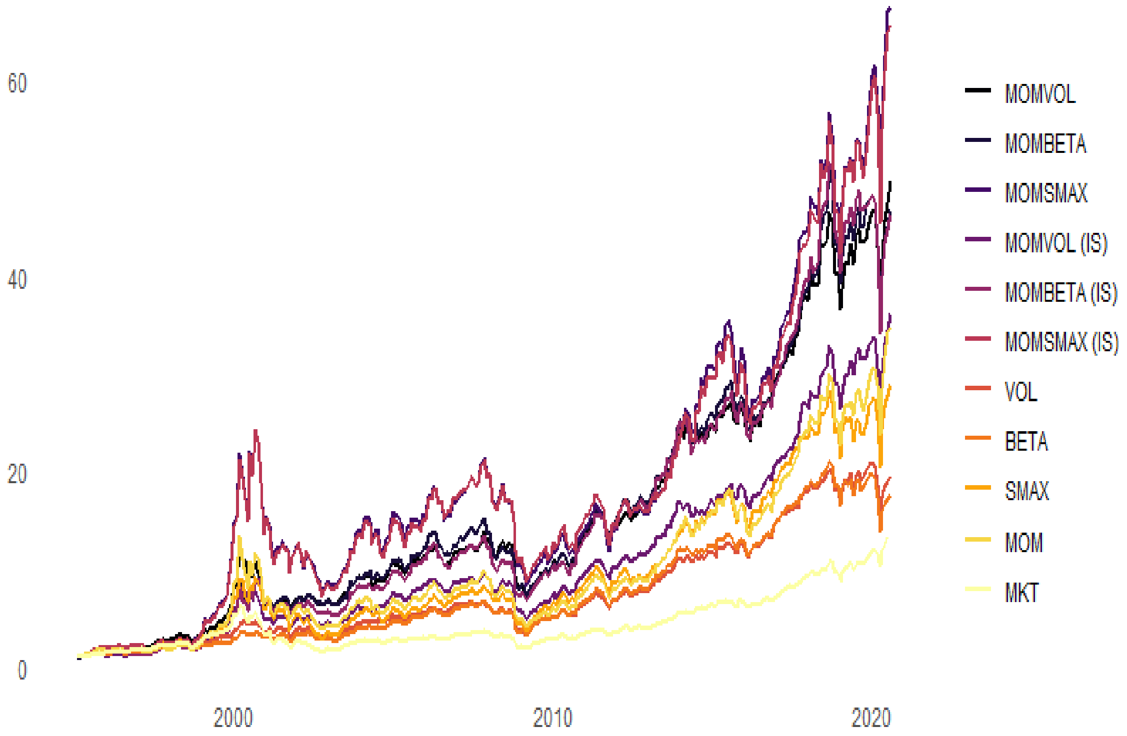

Figure 1. Cumulative returns long-only portfolios

Figure 2 considers how consistent the mean returns of the portfolios have been in different time periods by dividing the 1995 – 2020 period into four five year sub-periods. The figure shows how the MOMSMAX portfolios outperform other strategies in 1995 – 2000, 2000 – 2005, and 2015 – 2020 periods, but yield negative mean returns for the 2005 – 2010 period. In line with the previous findings that show positive risk-adjusted returns for betting against lottery demand, the incorporation of SMAX increases the risk-adjusted returns of the pure momentum strategy. But as the results show, combining SMAX with MOM increases absolute returns without really affecting the risks when comparing the MOMSMAX strategies to the pure MOM strategy. In total, the high average returns and risk-adjusted returns (CAPM and three-factor alphas) related to the exclusion of stocks with lottery-like distributions (high SMAX) increases risk-adjusted returns of the pure MOM strategy, but it does it by increasing returns, not by reducing return variability or drawdowns, which from an investor's perspective can be often seen as desirable. The MOMVOL and MOMBETA strategies, on the other hand, seem to increase consistency and to lower risks for investors while not decreasing the absolute returns of the pure MOM strategy.

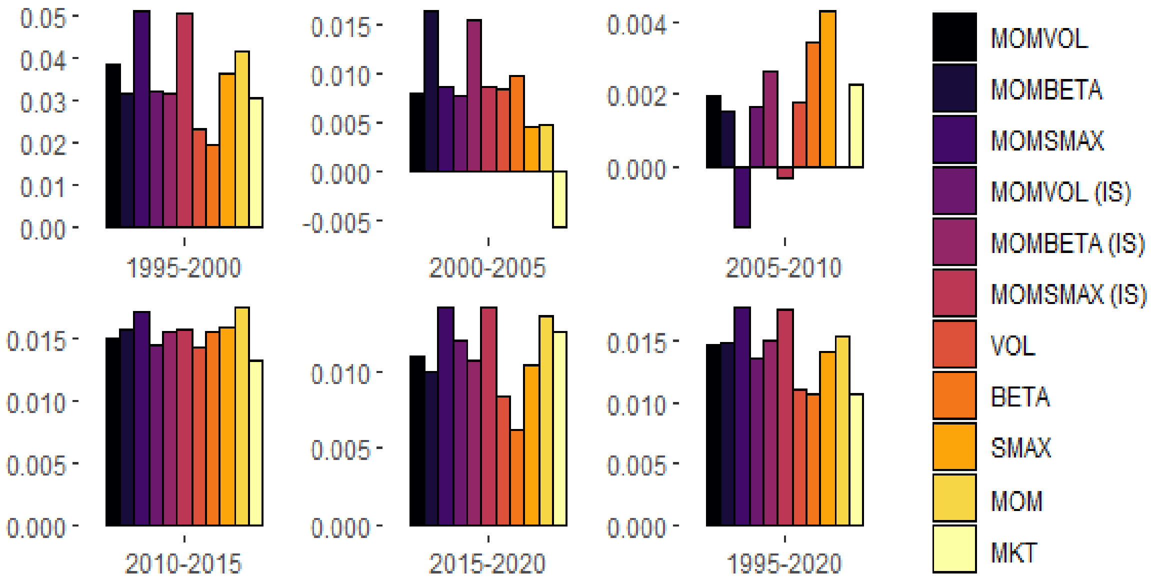

Figure 2. Sub-period average returns long-only portfolios

To further analyze the consistency and attractiveness of the strategies, Figure 3 exhibits the maximum drawdowns for the four sub-periods. The figure shows how the MOMVOL portfolios consistently provide smaller maximum drawdowns than the pure MOM portfolio, suggesting that mixing momentum with low volatility might lessen the steepness of *momentum crashes.* Furthermore, the MOMVOL portfolios experience also the smallest maximum drawdowns for the whole sample period. Especially impressive is how significantly smaller drawdowns the portfolios that invested on low beta or low volatility experienced during the bursting of the “tech bubble” (2000 – 2005) when the maximum drawdown for the market index was as large as 75%. Overall, the attractiveness of the MOMVOL and MOMBETA combination portfolios can be attributed to the strong performance of momentum and to the defensiveness of the low volatility and low beta factors.

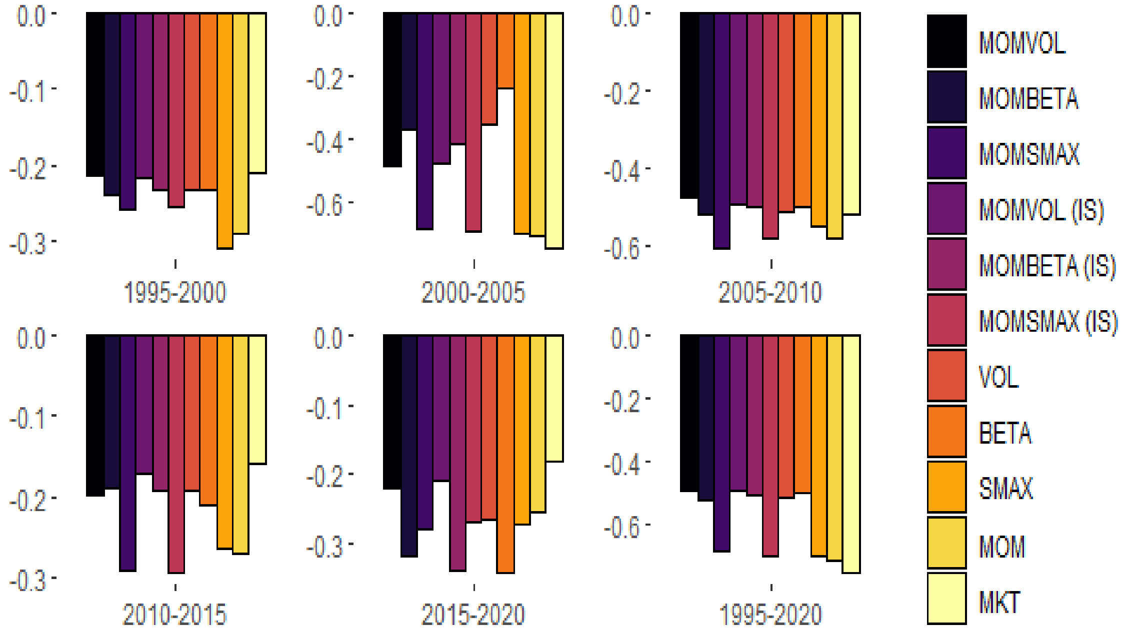

Figure 3. Sub-period max drawdowns long-only portfolios

6.3 Long-short m*omentum-low risk* factor portfolios

In this section, the long-short multi- and single-factor portfolios are examined in Fama and French five- and three-factor regression framework. The analysis thus far suggests that by screening for high-momentum and low-risk stocks investors can generate attractive absolute and risk-adjusted returns. The following analysis provides further insight on the relevance and robustness of this combination, and whether there is a significant difference between the returns of high-momentum low-risk stocks and low-momentum high-risk stocks after controlling for the Fama and French factors. The multi-factor portfolios buy the high-momentum low-risk stocks and short the low-momentum high-risk stocks. The single-factor momentum portfolio buys (shorts) high (low) momentum stocks, and the individual risk-factor portfolios buy (short) low (high) risk stocks.

Table 9. Fama & French three-factor regression

This table reports the three-factor regressions for the long-short portolios. Reported values are regression coefficients from time-series regression where the portfolio returns are regressed on factor returns. Standard errors are in parentheses. Alpha is in monthly terms, not annualized.

	Dependent variable:									
	MOMVOL	MOM-BETA	MOMSMAX	MOMVOL (IS)	MOMBETA (IS)	MOMSMAX (IS)	VOL	BETA	SMAX	MOM
Constant	0.011***	0.007	0.011***	0.009**	0.006	0.011***	0.003	0.002	0.004**	0.006*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
MKT	-0.767***	-0.801***	-0.186***	-0.738***	-0.741***	-0.192***	-0.687***	-0.701***	-0.464***	-0.223***
	(0.071)	(0.081)	(0.068)	(0.067)	(0.076)	(0.068)	(0.045)	(0.047)	(0.036)	(0.061)
SMB	-0.129	0.561***	0.497***	-0.253**	0.533***	0.489***	-0.462***	-0.084	-0.317***	0.491***
	(0.133)	(0.153)	(0.129)	(0.126)	(0.144)	(0.128)	(0.085)	(0.089)	(0.068)	(0.115)
HML	-0.169	-0.492***	-0.603***	-0.047	-0.516***	-0.603***	0.624***	0.271***	0.449***	-0.639***
	(0.133)	(0.152)	(0.128)	(0.126)	(0.144)	(0.128)	(0.085)	(0.088)	(0.068)	(0.115)
Observations	307	307	307	307	307	307	307	307	307	307
R^2	0.352	0.247	0.099	0.391	0.238	0.098	0.677	0.563	0.606	0.126
Adjusted R^2	0.346	0.240	0.090	0.385	0.230	0.089	0.673	0.558	0.602	0.118
F Statistic	54.881***	33.181***	11.060***	64.857***	31.553***	10.964***	211.286***	129.997***	155.315***	14.606***
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 9 shows that both the conditional and intersectional MOMVOL and MOMSMAX long-short portfolios generate significant positive alphas controlled for the Fama and French three-factor model. As in the previous analysis, the conditional and intersectional strategies do not create drastically different return profiles, but the conditional ones perform slightly better. From the single-factor portfolios, only the long-short SMAX portfolio has statistically significant three-factor alpha for the whole examination period. Altogether, double-sorting on momentum and low-risk factors, creates return premium that is not captured by the individual momentum and low-risk factor portfolios.

Turning to the factor loadings, the results show that MOMVOL and MOMBETA portfolios have large and negative market betas while the MOMSMAX portfolios have only a small negative loading on the market factor. This is intuitive since the long-short MOMVOL and MOMBETA portfolios are essentially long (short) stocks with low (high) market risk exposure, while the MOMSMAX portfolios' bet is more exclusively focused on the idiosyncratic skewness of stock's return distribution.

Both the theory of leverage constraints and behavioural explanations predict that low-risk factors should have positive loadings on the value factor (HML) since investors abandon safe stocks because of leverage constraints or behavioural biases. In line with these theories, the individual low-risk factors exhibit significant positive HML loadings, while the momentum portfolio has a significant negative loading on the value factor. The MOMBETA and MOMSMAX strategies seem to be dominated by the MOM factor's large positive SMB and negative HML loadings. Momentum's dominating effect is expected for the conditional strategies since momentum is given more weight in the sorting procedure by using it as the first sorting variable, but it is similarly present in the intersectional MOMBETA and MOMSMAX strategies.

In total, the factor loadings in Table 9 exhibit that all four MOMBETA and MOMSMAX portfolios provide similar SMB and HML loadings as the pure MOM portfolio. They are largely driven by the returns of small growth stocks over large value stocks. In contrast, the MOMVOL strategies provide significantly different SMB and HML factor loadings, suggesting that VOL provides better factor-exposure diversification for momentum investors. The pure MOM portfolio invests in small growth stocks while the VOL portfolio invests in large value stocks. Furthermore, instead of the domination of momentum, these contrasting inclinations (factor exposures) translate into the MOMVOL portfolios.

Table 10. Fama & French five-factor regressions

This table reports the five-factor regressions for the long-short portolios. Reported values are regression coefficients from time-series regression where the portfolio returns are regressed on factor returns. Standard errors are in parentheses. Alpha is in monthly terms, not annualized.

	Dependent variable:									
	MOMVOL	MOM-BETA	MOMSMAX	MOMVOL (IS)	MOMBETA (IS)	MOMSMAX (IS)	VOL	BETA	SMAX	MOM
Constant	0.008**	0.006	0.011***	0.006	0.006	0.011***	-0.001	-0.001	0.0001	0.007*
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)
MKT	-0.654***	-0.765***	-0.201**	-0.623***	-0.725***	-0.200**	-0.507***	-0.630***	-0.303***	-0.268***
	(0.089)	(0.103)	(0.087)	(0.084)	(0.098)	(0.087)	(0.053)	(0.057)	(0.042)	(0.078)
SMB	0.018	0.614***	0.509***	-0.085	0.577***	0.496***	-0.237***	0.115	-0.131**	0.437***
	(0.142)	(0.164)	(0.139)	(0.133)	(0.155)	(0.138)	(0.084)	(0.090)	(0.066)	(0.124)
HML	-0.301*	-0.531***	-0.568***	-0.171	-0.522***	-0.583***	0.406***	0.253**	0.246***	-0.584***
	(0.165)	(0.191)	(0.162)	(0.155)	(0.181)	(0.161)	(0.098)	(0.105)	(0.077)	(0.145)
RMW	0.593***	0.204	0.005	0.653***	0.146	0.004	0.920***	0.651***	0.781***	-0.222
	(0.204)	(0.237)	(0.200)	(0.192)	(0.224)	(0.199)	(0.121)	(0.130)	(0.095)	(0.179)
CMA	0.025	-0.012	-0.116	-0.041	-0.082	-0.065	0.081	-0.380**	0.124	-0.030
	(0.263)	(0.304)	(0.257)	(0.247)	(0.288)	(0.256)	(0.155)	(0.167)	(0.123)	(0.230)
Observati-ons	307	307	307	307	307	307	307	307	307	307
R^2	0.370	0.249	0.099	0.415	0.240	0.098	0.730	0.610	0.678	0.131
Adjusted R^2	0.360	0.237	0.084	0.405	0.227	0.083	0.725	0.603	0.673	0.116
F Statistic	35.393***	19.987***	6.641***	42.710***	18.966***	6.550***	162.537***	94.093***	126.873***	9.061***
Note:										*p<0.1; **p<0.05; ***p<0.01

Table 10 provides results for the Fama and French five-factor regressions. The MOMVOL and MOMSMAX remain as the most robust factor combinations. The conditional MOM-VOL and both MOMSMAX strategies (conditional and intersectional) earn significant five-factor alphas of 0.8%, 1.1%, and 1.1% per month, respectively.

In line with previous studies (Novy-Marx, 2014: Fama and French, 2016), the RMW and CMA factors increase the explanatory power of the regressions. Profitability has significant power in explaining the low-risk effect. The positive RMW loadings are significant especially for the standalone low-risk factor portfolios, as well, as for the MOMVOL portfolios, weakening the abnormal returns of these portfolios in comparison to the previous three-factor regression. The positive RMW loadings are not surprising, as noted by Asness, Frazzini, and Pedersen (2019) who argue that RMW is just an accounting-based method for measuring stock's safety (low risk). In turn, the MOMSMAX strategies are not driven by the profitability and investment factors, maintaining their strong abnormal returns.

Furthermore, what makes the mixing of momentum and low-risk factors particularly attractive is how the level of correlation between the low-risk factors (especially VOL) and momentum changes across time. This diversification benefit is illustrated below in Figure 4 that shows the 24-month rolling correlation between momentum and the low-risk factor long-short portfolios.

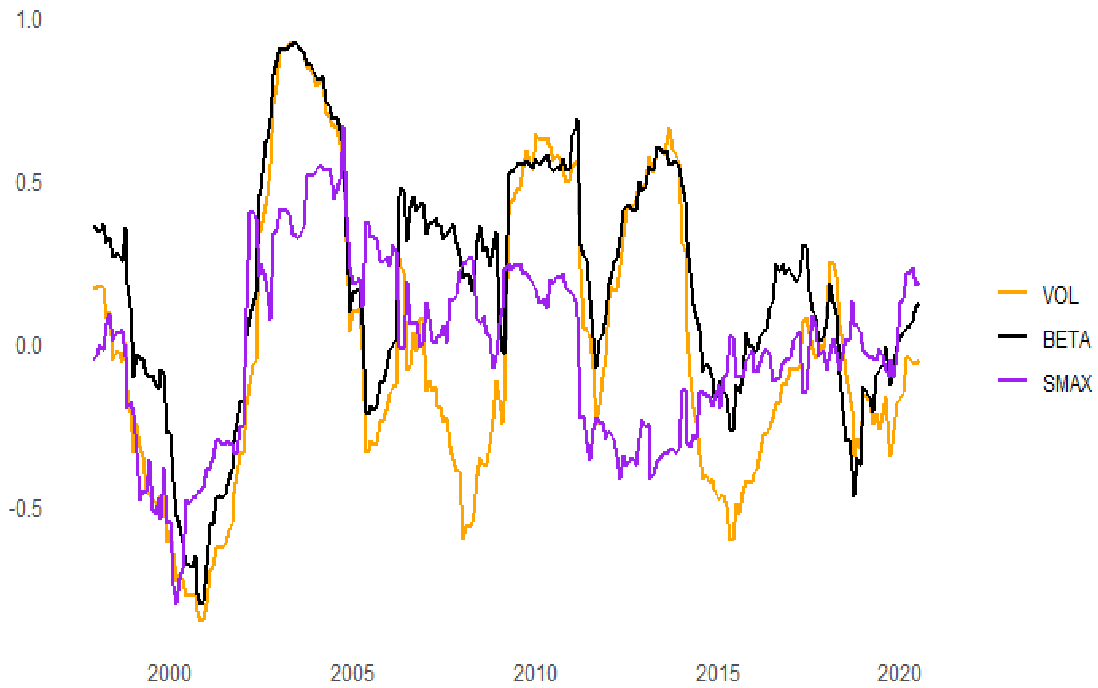

Figure 4. Rolling correlations momentum and low-risk factors

As the previously presented tables already suggest, combining momentum and betting against volatility or beta strategies can provide diversification benefits for investors. This claim is further verified by Figure 4 that shows how the correlation between the low-risk factors and momentum decreases when diversification is especially beneficial, that is, in periods of market turmoil. In line with the previous results, this correlation dynamic is the strongest for the VOL factor. Correlation between the MOM and VOL portfolios is clearly positive in stable and rising market conditions but negative in distressed market conditions, like in the "tech bubble" or the 2008 financial crisis. Similar findings are presented, for example, in Rabener (2020) and in Garcia-Feijóo et al. (2015).

6.4 Possible limitations and shortcomings

There are some possible limitations regarding the data and methodology used in this study. First, the data is limited to only the Nasdaq stock exchange, and the results might vary with broader or otherwise different samples. Furthermore, Nasdaq is known for its orientation towards the technology sector which might have an effect on the empirical results. Second, the portfolios formed in this study are equal-weighted while the Fama and French factors are value-weighted. There is evidence that equal-weighted returns can be crucial for the performance of different factor strategies and that controlling for microcaps can diminish the abnormal returns affiliated with different strategies (Hou, Xue & Zhang, 2018; Novy-Marx & Velikov, 2018). For example, Hou et al. (2018) note that microcaps have the highest equal-weighted returns as well as the highest dispersions in returns and in anomaly variables. Third, the study does not account for transaction costs which might diminish the abnormal returns achieved in this study, especially since equally weighted returns can lead to overweighting microcap stocks with restricted liquidity.

7 Conclusions

The empirical results show that pure momentum and low-risk strategies provide better risk-adjusted returns than simple market exposure but after controlling for the common risk factors the abnormal returns of these pure-play strategies tend to disappear. In turn, by combining momentum and low volatility factors or momentum and low SMAX factors, significant abnormal returns are obtained. Furthermore, all combination strategies increase Sharpe ratios and other risk-adjusted return measures in comparison to the single-factor strategies. In general, stocks with strong momentum and low risk tend to outperform stocks that exhibit just strong momentum or low risk.

More specifically, the results show that combining momentum with a factor capturing investors lottery demand (SMAX) increases risk-adjusted returns, and especially, regression alphas (abnormal returns). However, the increase in risk-adjusted returns is due to higher returns without decreases in portfolio volatility, drawdowns, or downside beta. Incorporating low volatility or low beta into momentum, on the other hand, provides significant diversification benefits, reduction in risks, and attractive risk-adjusted returns. By combining momentum with low volatility or low beta factors, investors can achieve the high returns affiliated with momentum but with considerably lower risks.

All long-only combination portfolios earn statistically significant Fama and French three-factor alphas. In addition, analysis on the double-sorted sub-portfolios reveals that the risk-adjusted returns (CAPM & three-factor alphas & Sharpe ratios) increase monotonically from low momentum to high momentum and decrease monotonically from low risk to high risk for all low-risk factors. Moreover, the long-short MOMVOL and MOMSMAX strategies yield significant three-factor alphas, representing a significant spread in the abnormal returns between *high momentum-low volatility/SMAX* and *low momentum-high volatility/SMAX* firms. However, the unexplained returns for the long-short *momentum-low volatility* portfolios decrease considerably in Fama and French five-factor regressions due to large compensation (loading) for profitability (RMW).

Altogether, the abnormal and risk-adjusted returns indicate that combining momentum and low risk strategies can add value to simple market exposure and to pure momentum or pure low risk strategies. *Momentum-low risk* portfolios are also able to generate attractive absolute returns. Furthermore, correlation dynamics, drawdowns, factor loadings, and performance stability promote diversification benefits between momentum and low volatility/beta factors. The attractive overall performance and interplay of the investigated factors can provide useful suggestions for constructing compelling multi-factor strategies and for portfolio management more broadly. From a practical point of view, combining momentum and low volatility/beta factors can help to alleviate investors' "fear of missing out" without subjugating them to considerable crash risks by creating a portfolio of trending (easy to hold) stocks with relatively low risk.

Finally, future research could be done with broader samples and with longer investigation periods to produce more evidence on the profitability and robustness of the investigated factor combinations. Also, future studies could focus on finding the optimal *momentum-low risk* factor combinations by exploring different estimation periods for momentum as well as for the low-risk factors. Issues regarding the use of equal-weighted *momentum-low risk* portfolios versus value-weighted risk factors and transaction costs could also be examined in the future for more decisive conclusions.

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