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„Value and Momentum as Asset Allocation Indicators"

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0 Introduction

The objective of this thesis is to analyze two risk premia and their benefits for asset allocation and diversification: value and momentum. Risk premia have gained attention after the 2007-2009 liquidity crunch and collapse of asset prices, when correlations among asset classes rose and portfolio diversification often proved to be insufficient. By identifying and managing risk factors more effectively, it is possible to improve diversification strategies such as the 60/40 portfolio. By analyzing systematic risk factors such as value and momentum across asset classes it can be shown that even simple asset allocation approaches provide superior diversification benefits.

Upon this stage, research (single and multi-factor models) mainly focused on equity[1], while momentum and trend following[2] have been studied most intensely for commodities[3]. Inspired by Asness, Moskowitz and Pedersen[4] this thesis will endorse a comprehensive approach across asset classes.

First, the risk premia and their time-varying characteristics are discussed thoroughly. Also, light will be shed on the migration process of anomalies into risk factors in the setting of multi-factor models. Well-known multi-factor asset pricing models such as the Fama-French three-factor model and the Carhart four-factor model are examined. While these models concentrate on equities, the application of value and momentum across asset classes by Asness, Moskowitz and Pedersen will be presented subsequently. Concluding, the findings will be discussed in the context of different diversification strategies.

In the practical part, certain theoretical findings will be tested empirically. First, value and momentum factor-mimicking portfolios are constructed for international equity indices, government bonds and currencies. The profitability of both investment styles can be confirmed. Second, the explanatory power of value and momentum measures for asset returns is tested in a multiple regression. Based on forecast returns and mean-variance optimization an asset allocation model is constructed. This approach is back-tested out-of-sample for 5 years and 11 months, producing substantial Sharpe ratios of up to 1.50, in contrast to 0.39 for the equally weighted portfolio.

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[1] Fama/French (1993) apply the three factors (Value, Size, Market) to the cross section of government and corporate bond returns, but do not find a significant relation. Only low grade corporate bonds load on the market factor. For further discussion of this paper see section 2.
[2] While momentum refers to the cross-section of return (across assets), trend following is time dependent (corresponding to a longitudinal analysis). See Moskowitz/Ooi/Pedersen (2012).
[3] See Ilmanen (2011), pp. 293-305.
[4] See Asness/Moskowitz/Pedersen (2011).

The outline for this thesis is as follows: in section 1, the notion of time varying risk premia will be discussed in the setting of modern portfolio theory. Empirical evidence for value and momentum as well as explanatory factors will be discussed profoundly. In section 2, the Fama-French multi-factor model and Carhart's extension will be introduced. In section 3, the application of multi-factor models across asset classes by Asness, Moskowitz and Pedersen will be examined. Section 4 summarizes the theoretical findings and links them to the context of diversification. In section 5 and 6, the empirical part and the conclusion follow.

1 Risk Premia and the Cross-Section of Returns

The cross-section of returns and portfolio attribution have been among the most focal research topics in investment finance in recent decades. Modern portfolio theory established by Markowitz[5] targets on two levers: mean expected asset returns and variance. Thus, studying cross-sectional return patterns in a portfolio context also means studying risk factors. This leads to the question, which underlying risk factors are driving portfolios?

The Capital Asset Pricing Model (CAPM, Sharpe 1964[6], Lintner 1965[7]) distinguishes between unsystematic and systematic risk. While systematic risk (e.g. the market beta) is rewarded with excess return, bearing unsystematic risk is not rewarded: it can and should be diversified away. The "right kind of diversification"[8] depends on the characteristics of the co-variance matrix. Therefore, correlations unexpectedly rising across asset classes during major economic and financial crises pose a serious challenge to portfolio selection.

The first model to identify systematic risk was a one-factor model, the unconditional CAPM: a constant market beta is the only (passive) factor explaining returns in excess of the risk-free rate of return. The intercept of the regression is attributed to active management and thus to the ability of the manager to beat the market. Therefore, varying excess returns are attributed to a) manager ability and b) market risk exposure.[9] Risk-averse investors are positioned along the capital market line, choosing their market risk exposure. They are rewarded with a price of time, which is the riskless rate of return and a price of risk, the equity premium.[10] Put differently, the equity premium is the reward of bearing equity risk in contrast to holding (assumingly) riskless assets such as government bills. During 1927-2010, the equity premium averaged at 5.8% p.a.[11]

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[5] See Markowitz (1952).
[6] See Sharpe (1964).
[7] See Lintner, John (1965): The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, The Review of Economics and Statistics, Vol. 47, No. 1, pp. 13-37.
[8] Markowitz (1952), p. 89.
[9] The most prominent critic of the CAPM is Richard Roll (1977): A Critique of the Asset Pricing Theory's Tests Part I: On past and potential testability of the theory, The Journal of Financial Economics Vol. 4, No. 2, pp. 129–176. Roll showed that it is not possible to test the CAPM due to a) the mean-variance tautology and b) due to the unobservable nature of the market portfolio, which includes every price of every existing asset that can be acquired.
[10] See Sharpe (1964), p. 425.
[11] See Ilmanen/Kizer (2012), p. 17.

Multi-factor models identify additional systematic risk premia: size, term, default, value and momentum. The size premium rewards for higher risks to hold small-cap instead of large-cap stocks. The term premium rewards investors for holding long term relative to short term government bonds. Notably, this premium is less stable than the equity premium. The default premium is the spread of investment-grade corporate and government bonds with equal maturities. The sources for value and momentum premia will be analyzed thoroughly in subsequent sections. While value and momentum premia are considerably high (3.9% and 7.7% p.a.), term and default premia only paid 1.8% and 0.2% p.a. in the US between 1927 and 2010.[12]

Contrary to the unconditional (static) CAPM, conditional models have been developed, which allow time varying risk premia and take into account changing return expectations.[13] Also, in conditional models the relation between the risk premium and the dependent variable (the return) is not necessarily linear.[14]

1.1 Value and Momentum as Risk Premia

This thesis concentrates, based on the research done by Asness, Moskowitz and Pedersen[15], on the value and the momentum factor. The value premium is the reward for investing in value in contrast to growth assets. In equities, it is measured via fundamental valuation multiples like book-to-market or P/E. While value firms exhibit high book-to-market ratios, growth firms are characterized by low book-to-market ratios.[16]

The momentum premium is the return difference of high (past winners) to low (past losers) momentum assets. It is characterized by past performance, usually the cumulative past one-year asset return. Due to a short term reversal effect the return of the most recent month is usually not considered.[17] The influence of value and momentum on the cross-section of returns has been examined using the multiple or measure itself or using zero-

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[12] See Ilmanen/Kizer (2012), p. 17.
[13] Contrary to unconditional models, current and therefore changing expectations of future returns of conditional models are taken into account, leading to a conditional risk concept. See Vosilov/Bergström (2010).
[14] The Arbitrage Pricing Theory (APT) – by Richard Roll and Stephen A. Ross – is, like the CAPM, an equilibrium model. Contrary to the CAPM it is not based on a regression. Moreover, it is a multifactor model, which takes into account changing inflation expectations, changing production levels for specific industries, risk premia and interest rate term structures.
[15] See Asness/Moskowitz/Pedersen (2011).
[16] See Ilmanen (2011), pp. 249 f.
[17] See Asness/Moskowitz/Pedersen (2011), p. 9; Carhart (1997), p. 61; Ilmanen (2011), pp. 293f.

investment, factor-mimicking portfolio returns: HML (High Minus Low)[18] and PR1YR (one-year momentum)[19].

In the setting of the Efficient Market Hypothesis (EMH) and the CAPM, value and momentum are anomalies. Fama and French[20] show that the market factor alone is insufficient in explaining the cross section of stock returns. Two factors, value and size, in combination with the market factor satisfyingly lower the intercept and thus the part of the return attributed to active management. Carhart further enlarges the Fama-French model with a fourth factor, momentum.[21] Step by step quantifiable risk factors are lowering alpha. Extensive empirical research comprehensively capturing risk factors changes the perception of anomalies towards risk related rewards.

Value and momentum returns are shaped by similar patterns: assuming that prices behave according to a log normal distribution, buying value targets on long term mean reversion. The compensation for value is therefore the (ex ante) premium for bearing the risk, that prices will not mean-revert in the short term. On the other hand, momentum compensates for reversal risk.[22] The resulting negative correlation of value and momentum is benign for diversification and timing facing changing macro environments and the economic cycle.[23] This diversification effect pushes a strategy combining value and momentum closer to the efficient frontier by reducing volatility.[24]

Comparing value and momentum, Asness states that "each of these strategies is nearly monotonically weaker among stocks found increasingly attractive by the other strategy"[25]. Put differently, a good momentum firm is a weak value firm and vice versa. Consequently, opposing the two styles is counterproductive: instead, the time patterns of value and momentum have to be considered: value is an inherently long- whereas momentum is a short term strategy.

Value and momentum are naturally long-short strategies; however, as shown in Mesomeris et al. they can also be employed long only, reducing ex post returns.[26] In the empirical analyses, I focus on the long-short approach assuming no managerial restrictions and transaction costs.

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[18] See Fama/French (1993).
[19] See Carhart (1997).
[20] See Fama/French (1992 & 1993).
[21] See Carhart (1997).
[22] See Ilmanen (2011), p. 265 and p. 294.
[23] See Asness/Moskowitz/Pedersen (2011), p. 41. See Ilmanen (2011), p. 249.
[24] See Asness/Moskowitz/Pedersen (2011), pp. 4f.
[25] Asness (1997), p. 34.
[26] See Mesomeris et al. (2011), pp. 44-45.

1.2 Alternative Risk Premia

Risk premia can be categorized into investment style, beta and macro risks. Value, momentum, carry, volatility[27] and illiquidity[28] are counted as investment style premia. Beta premia for different asset classes include bond duration, credit, equity, commodity and alternatives risk. Macro premia include illiquidity, sovereign, growth and inflation volatility risk.[29]

Investment style risks and macro risks interact: specifically, Asness, Moskowitz and Pedersen discuss illiquidity as a global macro risk factor that could influence the "correlation structure and some of the return premia"[30] of value and momentum across asset classes.[31] Especially since the liquidity crunch in 2007 – 2009 illiquidity premia have gained importance in research. During the financial crisis, illiquidity premia and thus ex ante return spreads of illiquid assets to liquid assets escalated. While more pronounced during recessions and stock market turmoil, the liquidity spread is generally explained by illiquid assets' higher transaction costs and/or a higher "sensitivity to a systematic risk factor"[32]. This exposure is associated with adverse performance during crises, leading investors to demand a premium.[33]

Liquidity is a vague notion: it describes the monetary environment as well as the corporate sector's balance sheets. This sections focuses on funding liquidity (financing of investments, often trader specific[34]) and financial market liquidity. Liquid financial markets exhibit low transaction costs, low bid-ask spreads and no or little impact by large trades. Liquid assets comprise a put option for the holder, since they generally can be sold without a significant discount.[35] Importantly, illiquidity can be aggravated by agency conflicts and information asymmetry. If transparency and confidence in market prices decline, liquidity dries up. Also, privately held contrary to publicly traded securities are typically more illiquid, which is partly due to higher information asymmetry.[36]

Similar to value and momentum premia, illiquidity premia vary over time due to changing liquidity conditions and varying demand for liquidity. Historically, market

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[27] In options trading, this applies to the difference between the implied and the realized volatility.
[28] A popular example of the illiquidity or endowment style is the Yale portfolio. Based on modern portfolio theory the Yale endowment heavily invests in alternative, typically illiquid, assets.
[29] See Jones (2012), p. 7.
[30] Asness/Moskowitz/Pedersen (2011), p. 31.
[31] See Section 3.
[32] Ilmanen (2011), p. 361.
[33] See Ilmanen (2011), pp. 360f.
[34] See Ilmanen (2011), p. 360.
[35] See Ilmanen (2011), pp. 359-360.
[36] See Ilmanen (2011), p. 360.

illiquidity rises before recessions and decreases before recessions end. Further studies of funding and market liquidity confirm the procyclical nature of liquidity.[37] Naturally, illiquidity premia appeal to long term investors like endowments. David Swensen's Yale model, based on modern portfolio theory, heavily relies on illiquid assets. The popularity of the Yale model overcrowded this investment style and led to diminishing liquidity premia in advance of the financial crisis in 2007-2009.[38]

Both funding and market liquidity risk factors are analyzed by Asness, Moskowitz and Pedersen in terms of their significance for value and momentum. However, only funding liquidity is able to partly explain value and momentum returns as well as correlations. Notably, funding liquidity risk is related negatively to value and positively to momentum. Hence, funding liquidity is especially costly for crowded, recently successful trades such as assets with high positive momentum. On the other hand, value performs poorly in times of rising funding liquidity. Thus, the negative correlation of value and momentum is related to funding liquidity risk. However, funding liquidity risk does not explain positive value returns. High Sharpe ratios of 1.36 and 1.45 for strategies combining value and momentum (global all asset classes) are evidence that a combination partly protects against funding liquidity risk.[39]

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[37] See Ilmanen (2011), pp. 361-364.
[38] See Ilmanen (2011), p. 373.
[39] See Asness/Moskowitz/Pedersen (2012), pp. 19-21, p. 51. See section 3 on the findings of Asness/Moskowitz/Pedersen (2011 & 2012).

1.3 Value

The value effect has been first described by Graham and Dodd in 1934 and then by Dreman in 1977[40]. It is one of the longest known anomalies or risk factors reflecting economic or investment risk. For US stocks, Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) were the first authors to describe the value effect via book-to-market ratios. Basu (1983) then showed that the returns of U.S. stocks were influenced by the E/P ratio (earnings-to-price).[41] Researchers first concentrated on the stock market in developed markets, i.e. the US and Japan, most prominently Fama and French (1992 & 1993) and Lakonishok, Shleifer and Vishny (1994). While concentrating on the stock market, interesting findings include sector neutrality. In value, a relative sector neutral approach has outperformed selecting cheap stocks over all sectors.[42]

In this and the following section possible explanations for value and momentum (from an economic, behavioral and institutional point of view) will be discussed. Generally, economic explanations are in line with the EMH. Proponents of behavioral explanations, on the other hand, point out the importance of limits-to-arbitrage and human behavior in general. While observable human behavior distinctly differs from the assumptions under the *homo oeconomicus* hypothesis, limits-to-arbitrage (e.g. high transaction costs, agency conflicts, regulations for institutional investors) prevent rational investors from gaining from anomalies and lead to sustained market inefficiencies. Although limits-to-arbitrage is in conflict with the purest form of the EMH, most EMH proponents accepted it.[43]

Thus, given strong empirical evidence of the value effect, explanations of its existence are still diverse. For instance, assuming that security prices move along a log normal distribution, mean reversion will (eventually) lead to the underperformance of glamour or growth assets. This is compatible with the EMH and random price movements. However, if mean reversion is the consequence of previous investor overreaction and overvaluations a behavioral approach is at hand. Therefore, in the following, economic, behavioral and institutional explanations will be contrasted.

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[40] See Lakonishok/Shleifer/Vishny (1994), p. 1541. Fama/French (1992), p. 427, refer to Stattman (Stattman, Dennis (1980): Book values and stock returns, The Chicago MBA: A Journal of Selected Papers, Vol. 4, pp. 25-45) and to Rosenberg et al. (Rosenberg, Barr; Reid, Kenneth; Lanstein, Ronald (1985): Persuasive evidence of market inefficiency, The Journal of Portfolio Management, Vol. 11, pp. 9-17) for the US stock market and to Chan et al. (Chan, Louis K.; Hamao, Yasushi; Lakonishok, Josef (1991): Fundamentals and stock returns in Japan, The Journal of Finance, Vol. 46, pp. 1739-1789) for the Japanese stock market.
[41] See Fama/French (1992), pp. 427-428.
[42] See Ilmanen (2011), p. 249.
[43] For a discussion of the behavioral angle see Ilmanen (2011), pp. 87-107.

The long history of value as an anomaly and investment style poses the question why the wide awareness and popularity did not diminish excess returns significantly.[44] Instead, recent research suggests that value premia reward for fundamental economic risk factors. In neoclassical models value is increasingly considered as a systematic risk factor.[45] Put differently, the price of a value investment is assumed to be comparatively low for an economic, measurable reason.

Fama and French argue that value is a compensation for distress risk, which is missed by the CAPM.[46] The evidence of value not only driving US but also international equity returns, supports the notion of a common equity risk factor like distress risk.[47] Moreover, the negative correlation of equity momentum and value can be explained by distress risk: growth stocks or stocks with high positive momentum are less likely to be in financial distress.[48]

Quantifiable risk factors attributable to equity value were put forward by Zhang's study about the value premium[49], helping to migrate value from an anomaly into a systematic risk factor. In a neoclassical framework the author constructs a benchmark model based on an industry equilibrium model, assuming aggregate uncertainty, to explain value stocks' higher expected returns with asymmetric adjustment costs[50] and the varying, countercyclical price of risk. In Zhang's model, focusing on production, firms arrive at investment plans based on current productivity and growth options. While value stocks exhibit higher capital in place, growth stocks implicitly bear higher productivity and growth options. Zhang estimates the impact of aggregate and idiosyncratic productivity shocks, generating heterogeneity among firms with the latter. Thereby, his model links risk and expected return.[51]

The benchmark model generates a value premium similar to empirical findings. In sensitivity tests Zhang shows that the explanatory power relies upon the combination of both assumptions: asymmetric adjustment costs and the countercyclical price of risk. The expected value premium and value spread are countercyclical: therefore, value is riskier

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[44] See Ilmanen (2011), p. 250.
[45] See Zhang (2005).
[46] See Fama/French (1992), pp. 450-451.
[47] See Fama/French (1998), p. 1975.
[48] See Asness (1997), p. 29.
[49] See Zhang (2005), p. 89. Zhang defines the value premium as the value spread times the price of risk.
[50] The adjustment cost function is asymmetric and quadratic during crises because it is more costly to reverse investment decisions than to expand the balance sheet. This directly affects the volatility of current dividends, thereby increasing risk.
[51] See Zhang (2005), pp. 70f.

than growth, especially in bad times. During good times, the value premium is low.[52] The economic intuitive behind it is that value firms disinvest more than growth firms during recessions and invest less during good times.[53]

Zhang confirms the positive relation between HML and average returns. HML (4.87%), as predicted by the benchmark model, is very similar to the empirical HML (4.68%). Albeit experiments with a wide range of parameter values (idiosyncratic productivity volatility, fixed costs, pace of adjustment) show that the value premium increases with higher volatility, higher fixed costs and slower adjustment, asymmetric adjustment costs and varying price of risk cannot be duplicated.[54]

The results indicate that the value premium can be derived by productivity differences, which explain differences in risk. Particularly, idiosyncratic productivity risk accounts for heterogeneity among firms in Zhang's model and therefore for value or growth characteristics and firm profitability.[55] Figure 1 illustrates this relation, measuring profitability by return on equity. In panel A the profitability patterns of value and growth stocks around the portfolio formation date are depicted. At the formation date, value stocks consistently exhibit lower productivity than growth stocks. This pattern reverses in subsequent years. Panel B shows the times series of profitability of growth and value stocks. Growth stocks display persistently higher profitability ratios than value stocks.
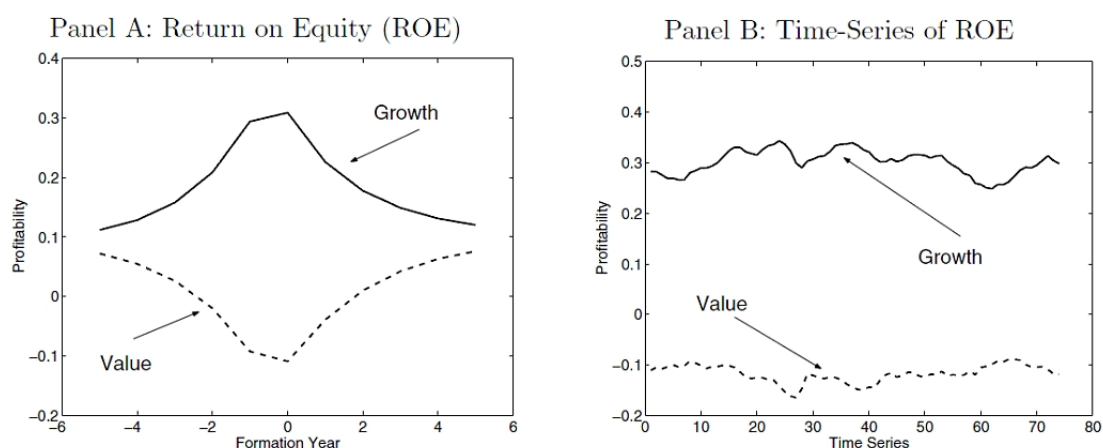

Figure 1, The Value Factor in Profitability (ROE). Source: Zhang (2005), p. 84.

Assuming differing growth options, capital investment decisions are made based on a firm's profitability. Therefore, value and growth firms differ in their optimal investment

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[52] See Zhang (2005), pp. 68-69.
[53] See Zhang (2005), p. 78.
[54] See Zhang (2005), p. 81.
[55] See Zhang (2005), p. 84.

decisions. In times of high aggregate productivity the level of optimal investment is high. Expanding growth stocks exhibit high adjustment costs, while value stocks with lower investments bear lower adjustment costs. However, during bad times, this relation changes: under the benchmark model, value firms are more likely to disinvest, thus exhibiting higher adjustment costs than growth firms.[56] Consequently, the degree of flexibility to ensure stable dividend payouts is impaired for value firms. Value firms find themselves burdened with unproductive capital on their balance sheets. A countercyclically moving price of capital influences adjustment costs and further decreases flexibility. This pattern explains the countercyclicality of the value premium; defined as the value spread times the price of risk, in bad times, both the value spread and the price of risk are high.[57]

While Zhang's study concentrates on equity, Asness, Moskowitz and Pedersen examine value across asset classes: the correlation structure of value and momentum across asset classes indicates that common risk factors move value and momentum.[58] Indeed, increased distress risk can be observed during economic crises, often in combination with lower liquidity and rising macroeconomic risk factors like growth, inflation and sovereign risks. From this point of view, an equity-related explanation of value can be translated into a broader set applicable to various asset classes. A deleveraging cycle in a weak economy puts further downward pressure on risky investments like value stocks, increasing volatility for these assets. Consequently, the value premium should also reward for volatility risk.[59]

1.3.1 Value: a Contrarian Investment

In the light of behavioral explanations, value is regarded as an anomaly. Behaviorists identify cognitive failures and deviations from the *homo oeconomicus* as reasons for inefficient markets and the value effect.

One important example is the extrapolation of price movements and the overweighting of recent performance on the cost of long run performance (judgment error)[60]; another is the overreaction to certain information instead of regarding fundamental ratios as proxies for higher future returns.[61] Consequently, some stocks are "oversold" and thus "underpriced", because investors underestimate the power of mean reversion,

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[56] See Zhang (2005), pp. 85-86.
[57] See Zhang (2005), pp. 86-89.
[58] See Asness/Moskowitz/Pedersen (2011), pp. 3f.
[59] See Mesomeris et al. (2012), p. 16.
[60] See Lakonishok/Shleifer/Vishny (1994), pp. 1559-1561.
[61] See Lakonishok/Shleifer/Vishny (1994), p. 1551.

explaining asset bubbles.[62] Furthermore, the propensity to fall for glamour investments is aggravated by the lottery ticket effect – low diversification and the hope for a very unlikely outcome.[63] One finding points to economic and behavioral explanations: the fact that the value effect is least prominent in the large cap market[64], which is the mostly covered and liquid market, could be interpreted in terms of limits-to-arbitrage, information asymmetry as well as the attention effect. The latter is caused, for instance, by enthusiastic media reports and intense coverage by investment banks.[65]

In their 1994 article "Contrarian Investment, Extrapolation, and Risk" Lakonishok, Shleifer and Vishny discuss value - or contrarian, as opposed to momentum or trend – investing from a behavioral perspective. Whereas Fama and French concentrate on the book-to-market ratio[66], Lakonishok, Shleifer and Vishny consider a range of ratios. Fundamentals, such as earnings, dividends, book assets, cash flow, sales and past growth of sales are related to the price of market equity.[67] Time series of NYSE and AMEX stock returns start in 1963 and end in 1990.[68] The authors imply a long term investment horizon of 5 years, related to the long term nature of value. The return difference of glamour and value stocks is continuously high (using the book-to-market ratio: 10.5% p.a.), decreasing size-adjusted (7.8%).[69] Since – according to the authors – the book-to-market ratio is not "a clean variable"[70] other ratios such as cash flow/price are preferred from a theoretical viewpoint and lead to better results.

The authors contradict the tenets of the EMH suggesting that market prices overestimate future growth paths. Put differently, high expected future growth rates for growth stocks – signaled by low ratios (C/P for instance) – are contrasted with higher than expected ex post returns for value stocks.[71]

The behavioral approach of the Lakonishok, Shleifer and Vishny paper is based on previous research done by De Bondt and Thaler, who also applied "irrational" explanations

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[62] See Akerlof/Shiller (2009), pp. 188-222.
[63] See Mesomeris et al. (2012), p. 16.
[64] See Lakonishok/Shleifer/Vishny (1994), p. 1555.
[65] See Mesomeris et al. (2012), p. 16.
[66] See Fama/French (1992 & 1993).
[67] See Lakonishok/Shleifer/Vishny (1994), p. 1541.
[68] The portfolios are rebalanced every April from 1968 to 1989.
[69] The authors also test for the affect of size on value by only testing the 20% and 50% largest firms of the sample. The results confirm that value also exists in the large capitalization segment.
[70] For example, the book-to-market ratio can be distorted if intangible assets are dominant in the balance sheet.
[71] See Lakonishok/Shleifer/Vishny (1994), pp. 1547-1548.

such as investors' overreaction to the value effect.[72] Studying individual investor and market behavior, De Bondt and Thaler empirically tested and confirmed the overreaction hypothesis, finding asymmetric return patterns, such that the overreaction is larger for losers than for winners.[73]

Lakonishok, Shleifer and Vishny reason that higher returns of the value strategy are due to the "suboptimal behavior of the typical investor"[74]. While investors underrate mean reversion, empirical data show that the market's expectation of glamour firms' superior growth is confirmed in the short term (2 years) and disconfirmed in the longer term (5 years).[75] The authors argue that superior returns are not linked to higher fundamental risks. Surprisingly, value outperforms glamour even during crises, when "the marginal utility of consumption is high".[76] However, newer studies found that value often underperforms during recessions.[77] Instead, the findings of Lakonishok, Shleifer and Vishny – value stocks are not riskier than growth stocks in terms of beta and standard deviation[78] – rather indicate that both are inaccurate measures of value risk.

1.3.2 Institutional Explanations

Next to economic and behavioral, also institutional explanations and agency conflicts are taken into account as explanations for value. Since institutional investors strive to appear prudent choosing less volatile stocks, there is a tendency towards growth stocks. Also, individual managers are led by career concerns focusing on meeting respectively beating the benchmarks, which are by construction exposed to growth stocks[79]. The empirical evidence suggests superior performance of equally weighted indices due to the advantage of overweighting value stocks relative to growth stocks, resulting in higher returns during tail or worst case events.[80]

Also, in an agency context, managers have shorter time horizons than their principals, such as endowments and pension funds. This is problematic since value is an inherently long term investment. This conflict could exaggerate the value effect.[81]

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[72] See Lakonishok/Shleifer/Vishny (1994), p. 1542.
[73] See De Bondt/Thaler (1984), pp. 799f.
[74] Lakonishok/Shleifer/Vishny (1994), p. 1541.
[75] See Lakonishok/Shleifer/Vishny (1994), p. 1551 and p. 1563.
[76] Lakonishok/Shleifer/Vishny (1994), p. 1564. See pp. 1564-1574.
[77] See Ilmanen (2011), p. 249.
[78] See Lakonishok/Shleifer/Vishny (1994), pp. 1569-1574.
[79] Although indices based on fundamental data (e.g. GDP or book value) are gaining popularity, usual benchmarks are market cap weighted.
[80] See Asness/Israelov/Liew (2011), p. 33.
[81] See Lakonishok/Shleifer/Vishny (1994), pp. 1542-1543 and 1575-1577.

Additionally, stocks with little institutional ownership more likely exhibit significant value premia. Since these stocks mostly are small-cap securities, arbitrage is more costly, thus mispricing more likely.[82] Moreover, agency conflicts play a role: since corporations with high shares of institutional shareholders are often subject to higher corporate governance standards and shareholder action, they provide a level of transparency, that corporations with less vigilant shareholders cannot. Thus, a premium for accepting less transparency seems straightforward.

Moreover, the use of Value at Risk (VaR) as a risk management tool could contribute to the value effect, since it is a very procyclical investment style, while value is distinctly countercyclical.[83]

Concluding rational, behavioral and institutional explanations, value assets are rationally perceived to be riskier investments. According to Ilmanen, one reason for this is the history of the volatile 1930ies. The author points out that the market beta of value stocks has been clearly positive in the 1930ies, turning negative between 1980 and 2005.[84] At one time indeed, investors' memories seem to be too long. However, since the value effect is one of the most popular and well documented investment strategies, it is fair to assume that informational inefficiencies do not play a decisive role. Contrary, it is more likely that underlying risk factors dominate value, as Asness, Moskowitz and Pedersen[85] suggest.

1.3.3 Measuring the Value Premium

Value stocks can be defined by their equity market value relative to some fundamental value, such as the book value of assets, earnings (the 12-month trailing vs. forward earnings yield, which takes into account estimated earnings from analysts instead of realized, past earnings), dividends, sales, historical prices or any measure of a firm's intrinsic value.[86] While Fama and French[87] use book-to-market and E/P for identifying the value effect, Lakonishok, Shleifer and Vishny[88] also include cash flow-to-price (CF/P) and sales growth (GS)[89]. Another ratio is Tobin's q, which is the market value of a corporation in relation to the replacement value of all corporate assets. Tobin's q not only considers the

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[82] See Ilmanen (2011), p. 258.
[83] See MacKenzie (2006), p. 232. MacKenzie underlined the procyclical role VaR played during the LTCM crisis.
[84] See Ilmanen (2011), p. 253.
[85] See Asness/Moskowitz/Pedersen (2011).
[86] See Lakonishok/Shleifer/Vishny (1994), p. 1541.
[87] See Fama/French (1992 & 1993).
[88] See Lakonishok/Shleifer/Vishny (1994).
[89] See Lakonishok/Shleifer/Vishny (1994), pp. 1546-1577.

equity market value, but the enterprise value (including the value of debt). Certain value indicators are not fully applicable to financial stocks. For example, the book-to-market ratio overstates a bank as a value stock since the high leverage is not depicted. For this reason, financial stocks are usually excluded in asset pricing studies.[90]

The value factor HML is then constructed as the return on a zero investment portfolio based on one fundamental ratio. It has three sources: a) high returns on value stocks that turn to growth stocks, b) low returns on growth stocks that turn to value stocks and c) higher returns for non-migrating value and growth stocks.[91]

Analyses based on historical data show that value paid a substantial premium in the past[92], referred to as the ex post value premium. According to Ilmanen, the long run ex post value premium (1926-2009) is 4.1% p.a. vs. 5.7% p.a. equity premium.[93] Contrary to the ex post risk premium, the ex ante premium measures what future returns are expected to be, often based upon past price movement. Ex post and ex ante returns vary because prices deviate from historic paths. For instance, in a bull market, high capital gains and rising valuations lower ex ante returns. However, if the bull market continues, realized returns will exceed ex ante returns.[94] Consequently, ex post and ex ante risk premia are varying over time. Since price reversal cannot be predicted precisely, the timing of value is of special importance. However, the multi-factor models discussed here focus on constant risk factors.[95] Varying time dependent value premia make necessary dynamic factor allocation, which will be briefly described in section 4.

The timing of the value strategy poses several questions: when does value work particularly well or bad? Are there cross-country differences? First, value is especially pronounced in January, but, unlike the size effect, strong throughout the whole year.[96] Second, lasting booms with ever higher multiples are natural enemies of the value strategy. In advance of the dotcom bust or the subprime crisis value performed very poorly for years. Consequently, there exists a momentum in investment strategies themselves. The popularity of an investment style lowers ex ante risk premia.[97]

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[90] See Ilmanen (2011), p. 256.
[91] See Ilmanen (2011), p. 255. Similar to Lakonishok, Shleifer and Vishny (1994) Ilmanen reasons that the market's expectation of slower growth for value stocks is exaggerated.
[92] See introduction of section 1. See Fama/French (1992 & 1993) and Lakonishok/Shleifer/Vishny (1994).
[93] See Ilmanen (2011), pp. 251-252.
[94] See Ilmanen (2011), pp. 258-261.
[95] See Fama/French (1992 & 1993 & 1998) and Lakonishok/Shleifer/Vishny (1994).
[96] See Fama/French (1992), p. 448.
[97] See Ilmanen (2011), pp. 252-253. For instance, in 2007-2009, during the liquidity crunch, hedge funds, using similar trading strategies, tried to exit trades simultaneously.

In accordance with risk based explanations for value and momentum the economic cycle is a natural force shaping risk premia. Risk premia like value move with the economic cycle in a countercyclical way; thus they reward for bearing the risk of economic downturns.[98] The countercyclicality of value was also described by Zhang: the correlation between HML and aggregate productivity is negative (-0.25).[99]

Forecasting value premia is mostly based on economic and financial markets data, but often subject to "spurious ex post relationships"[100]. Zhang, examining the applicability of style timing for value, finds high predictive power for the value premium in the value spread.[101] Asness, Friedman, Krail and Liew divide the ex ante value spread into 1) a spread in valuation multiples and 2) the earnings growth spread of value and growth assets, which is negative throughout time. This understanding is based upon the Gordon model, which states that expected returns are a function of current valuations (E/P) and earnings growth. The ex ante valuation and earnings spreads are important indicators for the timing of the value strategy. For instance, if the valuation spread is very high, value has been doing poorly a while and the ex ante value premium rises. A wide dispersion in price levels also raises the chances to find undervalued stocks. If the value spread is not justified by growth expectations it should narrow and thus raise the ex post premium. For instance, the earnings growth spread historically varied between -3.9 to -15.5%.[102] Notably, next to earnings differentials, other forces must drive valuation spreads, either rational or irrational or possibly a combination.[103]

In his 2012 paper Kim confirms the existence of a value premium (via E/P) across developed and emerging equity markets. The author shows that the E/P spread and return dispersion have predictive power for cross-country value premia, albeit only in emerging markets. This is possibly due to higher heterogeneity in emerging markets: value premia range from -4% to 11% for developed markets, but from -2.5% to 17% among emerging markets.[104]

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[98] See Ilmanen (2011), pp. 262-265 and pp. 87-106.
[99] See Zhang (2005), pp. 90-92.
[100] Asness/Friedman/Krail/Liew (2000), p. 50.
[101] See Zhang (2005), pp. 90-92. The value spread is defined as the log book-to-market difference between value and growth firms. Therefore, it is the spread of valuation multiples and no return spread. Zhang also tests the earnings growth spread, which is the difference in log return on book equity, finding weaker relations.
[102] See Asness/Friedman/Krail/Liew (2000), pp. 51-55.
[103] See Asness/Friedman/Krail/Liew (2000), pp. 56, 58.
[104] See Kim (2012), pp. 75f.

1.4 Momentum

This section discusses the momentum effect, which is one of the most prevailing investment styles.[105] It is a strategy, which naively sells recent losers and buys recent winners. If momentum is seen as an anomaly, superior returns should be arbitraged away very quickly. However, the persistence of momentum suggests the existence of underlying risk factors, which justify a momentum premium. As a strategy, momentum is consistently negatively correlated with value, indicating that common forces drive value and momentum.[106] Research on momentum mostly concentrated on commodities, but it exists across asset classes.[107]

In their 1993 paper, Jegadeesh and Titman analyze the momentum effect in 1965-1989 and confirm its robustness over time. While a premium for contrarian trading was academically well supported in 1993, superior returns by „relative strength trading rules"[108] were applied by practitioners, but not intensely studied. The reconciliation of these adverse trading strategies can be done by considering different time horizons. Very short term return reversals (1 week to 1 month) and very long term return reversals (3 to 5 years) are contrasted with return momentum based on past price movement of previous 3-12 months. After 12 months, the past winners' superior returns are shrinking.[109]

Jegadeesh and Titman don't see systematic risk, but investors' overreaction behind momentum. Notably, momentum is not due to delayed stock price reactions to information about a common factor, but to "firm specific information".[110] Specifically, returns around earnings announcement dates show that information only slowly migrates into prices. For 1980 to 1989, stocks are sorted into deciles based on their previous 6-month return. The differences of the 3-day quarterly earnings announcement returns are then examined.[111] The results confirm the slow incorporation of information in market prices: for 6 months, 3-day announcement day returns are significantly higher for past winners. During the subsequent 13 months past winners underperform significantly. In the final phase of the 36 month observation period the return difference is still negative but with declining significance. The findings of the earnings announcement analysis are consistent with the results of the relative strength analysis and with previous research on earnings surprises:

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[105] See Mesomeris et al. (2012), p. 22.
[106] See Asness/Moskowitz/Pedersen (2011).
[107] See Ilmanen (2011), p. 294.
[108] Jegadeesh/Titman (1993), p. 66.
[109] See Jegadeesh/Titman (1993), pp. 66-67.
[110] Jegadeesh/Titman (1993), p. 67.
[111] The 3-day return is calculated from day -2 to day 0 of the quarterly earnings announcement.

the likelihood of positive returns around earnings announcement dates is higher if there was a positive earnings surprise in the preceding quarter. This momentum is reversing 4 quarters after the positive earnings surprise.[112] Earnings momentum, defined as the change of the EPS growth rate, and price momentum are therefore closely tied and possibly related to investor underreaction.[113]

In 1996, Asness, Liew and Stevens publicized that momentum, value and size are robust even when using country instead of individual stock returns.[114] Extending the Fama-French three-factor model the authors examine risk factors on a country return level. Country and individual US stock risk premia only exhibit low albeit positive correlations. Consequently, different forces are shaping domestic and global risk factors (for example domestic tax regulations in contrast to global macroeconomic risks). While distress risk also relates to country value and size, it is not affiliated to country momentum.[115]

1.4.1 What drives Momentum Returns?

Momentum can be explained by economic distress and consumption risk; both affect sustained price movements across asset classes via slow transmission processes and feedback-loops.[116]

Mostly virulent for storable commodities are explanations related to business cycles and seasonal effects. Producers of storable commodities cannot instantly adapt to price changes (especially in hard commodities). Therefore, inventories serve as a buffer, reflecting past price movements and price expectations. For instance, high current prices and positive expectations cause sustained price momentum and well-filled inventories. On the other hand, declining prices incentivize lower production volumes finally reducing inventories – with a time lag causing downward price momentum.[117] Furthermore, storage costs and the convenience yield[118] influence inventories and shape commodity futures curves. High storage costs (or interest rates) lead to low inventory levels and rising convenience yields, diminishing momentum returns. In this scenario, the futures curve is in backwardation.[119] Concluding, demand-supply and storage costs help to explain the

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[112] See Jegadeesh/Titman (1993), pp. 86-89.
[113] See Ilmanen (2011), p. 305.
[114] The existence of a January seasonal effect on the country level contradicts suspicions of data mining.
[115] See Asness/Liew/Stevens (1997), p. 79-86.
[116] See Mesomeris et al. (2012), p. 16.
[117] See Ilmanen (2011), pp. 293-301.
[118] See Ilmanen (2011), p. 221. The convenience yield is the intangible benefit derived from the consumption value of a commodity. The futures holder only pays for the deferred value of the commodity.
[119] See Ilmanen (2011), pp. 220-221.

dominance of momentum in commodities but do not enlighten momentum in other asset classes.

The hedging pressure hypothesis applies to commodities and to currencies. Although it receives little empirical support[120], it provides intuitive explanations. Generally, producers create more hedging pressure than consumers. By selling futures producers hedge against price drops, pushing futures prices below the spot price. On the other side of the trade are speculators acting as risk insurers profiting from sustained momentum while producers are short momentum. In that scenario, the commodity futures curve is in backwardation.[121]

Contrary to cross-sectional momentum, time series momentum is related to hedging pressure. In their 2012 paper, Moskowitz, Ooi and Pedersen explain time series momentum with speculative positioning and the shape of the futures curve. While the authors dismiss standard factors (i.e. distress risk) and crash risk as forces driving momentum, patterns show that "initial underreaction and delayed overreaction"[122] play a dominant role.[123]

Indeed, behaviorists observe underreaction to fundamentally important news as well as overreaction and extrapolation of past returns. Also, investors attach to much attention to stories in contrast to fundamental data. An example is conservatism, which – also affecting value – tempts investors to buying growth assets. Overconfidence, combined with an attention or cognitive bias, undermines critical thinking regarding past success stories. This is exaggerated by firms' information policies (gradual diffusion of firm-specific information) and investment banks' coverage bias.[124] Furthermore, investors tend to avoid realizing losses/capitalizing gains, consequently trades are held too long. The resulting capital loss/gains overhang (the difference between the spot and historical price, at which the average buyer bought) further adds to momentum. Subject to game theory is herding behavior (is it rational to be part of the crowd?), which substantially contributes to momentum.[125]

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[120] See Ilmanen (2011), p. 300.
[121] See Ilmanen (2011), p. 220.
[122] Moskowitz/Ooi/Pedersen (2012), p. 227.
[123] See Moskowitz/Ooi/Pedersen (2012), pp. 227-229.
[124] See Mesomeris et al. (2012), p. 16 and Ilmanen (2011), pp. 90-94.
[125] See Mesomeris et al. (2012), p. 16.

1.4.2 Institutional Explanations

One systematic risk factor on an institutional level is portfolio insurance, which played a role during the crash of October, 1987. Portfolio insurance installs a floor for the portfolio value by setting the proportion of risky and riskless assets with constantly changing allocations. The proportion of the risky asset declines with its price until the portfolio contains 100% riskless assets. By then, the portfolio cannot profit from any price reversal. By construction, the procyclicality of portfolio insurance contributes to feedback loops, especially in combination with high trading volumes.[126]

Today, the value at risk (VaR) and risk budget concept is the most common risk management tool and inherently procyclical as well. In an institutional environment, where risk management is object to stringent legal regulations, VaR poses systematic risks if it causes substantial price movements without incorporating new information. Concluding, although it is well-known that investors suffer from informational deficiencies and that price movements are driven by risk management trades, the actual influence of each is unknown and cannot be arbitraged away completely.[127]

Moreover, institutional investors are typically index trackers. Individual managers often minimize career risk by "hugging the benchmark"[128]. While market capitalization weighted indices inhibit momentum themselves, no-information trades such as the inclusion or removal of index constituents support price momentum – in contradiction to the EMH. Indeed, momentum is the only risk premium which gains power once more investors are adopting this style. The increasing volatility of an overcrowded momentum strategy is destabilizing for financial markets.[129]

1.4.3 Measuring the Momentum Premium

Momentum can be measured via past asset returns, but also via analysts' revisions of earnings forecasts.[130] Instead of taking simple past returns it is also possible to use the moving average as a signal. By smoothing current observations the choice of an appropriate time frame is less critical than for simple past returns. In addition, Ilmanen points out the validity of the signal's strength, such as consistency and sharp movements.[131]

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[126] See MacKenzie (2006), pp. 179-200.
[127] See MacKenzie (2006) and Ilmanen (2011).
[128] Mesomeris et al. (2012), p. 16.
[129] See Ilmanen (2011), pp. 401-403.
[130] See Mesomeris et al. (2012), pp. 22f.
[131] See Ilmanen (2011), pp. 295-296.

The most common momentum measure is the past one year's cumulative return skipping the most recent month, because "liquidity and microstructure cause short-term reversals at the one month level"[132] and because of a short term "bid-ask bounce"[133]. One possible explanation for short term reversal is that prices are moving back to their fair value after large trades led to distortions. This is underlined by the finding that this pattern is even stronger in shorter time horizons like weeks or days and in illiquid markets. Asset classes like currencies are more liquid than commodities and thus are less prone to short term reversal.[134]

Momentum (across asset classes) is stronger for months 6-12 than for months 2-6. After 12 months the long term reversal effect is taking asset prices, according to the behavioral theory, to fair levels.[135] Concluding, in contrast to value, momentum is an inherently short term strategy.

In general, the momentum strategy involves higher turnover and thus higher transaction costs than value strategies. Prolonging the time frame can reduce trading costs, although it risks trading into the long time reversal phase starting after 12 months.[136] Many empirical studies do not account for transaction costs.[137] Also, neglecting volatility can lead to misjudgments due to substantial volatility differences, e.g. for commodities (gold vs. natural gas). Contrary to value, momentum is inherently long volatility (in combination with a high market beta exposure). Similar to value, momentum is a long-short strategy. Shorting constraints for many institutional investors – as a limit-to-arbitrage – thus can be the reason why momentum is more pronounced on the short side.[138]

Similar to value, momentum is more pronounced for small firms[139], which are less liquid in general. Empirical studies suggest that illiquid assets are more prone to momentum, since the slow movement of information adds to momentum and underreaction plays a greater role. Also, illiquid assets have higher trading costs and are covered less intensely. Poor fundamental anchors add to momentum since uncertainty about the fair

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[132] Mesomeris et al. (2012), p. 23, see also Jegadeesh/Titman (1993).
[133] Fama/French (1996), p. 66.
[134] See Asness/Moskowitz/Pedersen (2011), pp. 9f and Ilmanen (2011), p. 304.
[135] See Ilmanen (2011), pp. 303-304.
[136] See Jegadeesh/Titman (1993), pp. 66-67.
[137] See Carhart (1997), p. 58. Transaction costs eliminate profits on the momentum strategy. Transaction costs are not accounted for in many back-tests, for instance Asness/Moskowitz/Pedersen (2011). Importantly, transaction costs are lower for certain asset classes like currencies.
[138] See Ilmanen (2011), pp. 293-301.
[139] See Rouwenhorst (1998), pp. 268f.

asset value is higher providing greater scope for exuberance. Accordingly, good substitutes (for example in commodities and equities) diminish momentum.[140]

Momentum as a time varying risk premium is closely tied to investor sentiment and economic feedback loops. It performs well in times of rising volatility, when volatility has been low before. Concluding, momentum is a benign diversifier against crash risk. Interestingly, trend-following strategies are not prone to positive momentum themselves. Like value, momentum exhibits seasonal effects: due to "year-end tax loss selling and window-dressing"[141], it works best in December and bad in January.[142]

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[140] See Ilmanen (2011), pp. 293-301.
[141] Ilmanen (2011), p. 299.
[142] See Ilmanen (2011), p. 299.

2 Multi-Factor Models

After discussing the value and momentum effect mostly in terms of investment strategies, in the following the Fama-French three-factor model[143] and Carhart's survey of mutual fund returns including momentum[144] will be discussed. Both models mainly concentrate on stocks, although Fama and French include bonds in their 1993 study. In section 3, the multi-factor model extension across asset classes by Asness, Moskowitz and Pedersen[145] will be examined.

The three- and four-factor asset pricing models shed light on value and momentum as risk factors shaping the cross section of asset returns. The factor models attribute portfolio returns to risk drivers reducing the return ascribed to alpha and manager ability, respectively. Factor-based asset allocation popular after the 2007-2009 crisis focuses on portfolio selection along risk factors rather than asset class silos and is "a natural extension of portfolio attribution analysis"[146]. Portfolio attribution analysis was made popular by Sharpe, determining an investor's actual asset mix by "measuring exposures to variations in returns of major asset classes"[147] and to evaluate the manager's ability.

2.1 The Fama-French Three-Factor Model

The CAPM explains the cross section of stock returns with the assets' correlations to the market portfolio. Returns are divided into an active (alpha) and a passive (beta) factor. For US stocks from 1941-1990, Fama and French show that the CAPM leaves a considerable part of the excess return share unexplained, resulting in high alpha values.[148]

Since value pays a positive risk premium, according to the CAPM, value firms should exhibit higher beta values than growth firms. Nevertheless, Fama and French find the opposite to be true: the betas for value portfolios' are less than one, while the growth portfolios' betas are above one.[149] According to the CAPM, value stocks are not riskier than growth stocks. Consistent excess returns of the value strategy are therefore regarded as anomalies.

Examining beta, in their 1992 paper Fama and French find that the traditional calculation of beta is closely tied to size, since betas are assigned to size sorted portfolios.

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[143] See Fama/French (1992 & 1993).
[144] See Carhart (1997).
[145] See Asness/Moskowitz/Pedersen (2011).
[146] Mesomeris et al (2012), p. 12.
[147] Sharpe (1992), p. 7.
[148] See Fama/French (1992), pp. 459f.
[149] See Fama/French (1998), p. 1984.

Beta is therefore distorted, comprising elements of size as well. Therefore, Fama and French construct 100 size and historical beta sorted portfolios, producing a much wider range of beta values in size portfolios. Immediately, homogeneous returns illustrate the weak explanatory power of beta. Afterwards, the 100 portfolios are assigned post-ranking, historical beta values, which are then used for the Fama-MacBeth cross-sectional regression. Again, size-unrelated beta has little explanatory power, even if it is the only explanatory variable. The relation between average returns and beta is more or less flat.[150]

The Fama-French three-factor model[151] is the first model including three factors explaining the cross-section of returns on a portfolio basis. Both value and size (first studied by Banz in 1981[152]) can diminish the explanatory power of beta. Importantly, the value measure BE/ME is not a function of beta: BE/ME ranked portfolios exhibit similar betas.[153] The Fama-French three-factor model transforms size and value into risk factors or "state variables of special hedging concern to investors"[154]. Accordingly – contrary to Lakonishok, Shleifer and Vishny[155] - Fama and French focus on fundamentals explaining the size and the value effect. According to the authors, value stocks' excess return is due to higher distress risk and not due to investors' overreaction. Underperforming firms, thus firms with high BE/ME, are more likely to be in financial distress.[156] Similarly, also the size effect is linked to fundamental risk factors like default risk.[157]

In the following, the Fama-French three-factor model (equation 1) and its variables will be described thoroughly. The dependent variables are the average monthly returns on the NYSE. The explanatory variables are β, size (ln ME) and value (ln BE/ME). The inclusion of value and size in the multi-factor regression causes R^2 to rise substantially.

$$R_{it} = \alpha_i + b_{1t}\beta_{it} + b_{2t}\ln(ME_{it}) + b_{3t}\ln(BE/ME_{it}) + \varepsilon_{it} \qquad (1)[158]$$

The BE/ME ratio has more explanatory power than the size effect: the spread between the portfolio with the highest and the lowest BE/ME (1.53% per month) is double the spread of the size portfolios. However, size is still significant even if value is

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[150] See Fama/French (1992), pp. 431-433. This applies to a longer time frame as well, as the authors prove in the appendix, p. 452.
[151] See Fama/French (1992 & 1993).
[152] See Fama/French (1992), p. 427: Banz, Rudolf W. (1981): The relationship between return and market value of common stocks, The Journal of Financial Economics, Vol. 9, pp. 3-18.
[153] See Fama/French (1992), p. 441.
[154] Fama/French (1996), p. 57
[155] See Lakonishok/Shleifer/Vishny (1994).
[156] See Fama/French (1992), p. 428.
[157] See Fama/French (1992), pp. 450-451.
[158] Fama/French (1992), p. 448.

included.[159] A possible explanation is the negative correlation (-0.26) between value and size. Concluding, small sized firms tend to have high BE/ME values, poor growth prospects and high ex ante risk premiums.[160]

BE/ME captures the effect of the earnings yield (E/P), while E/P does not capture BE/ME. Consequently, the explanatory power of E/P is due to its link to BE/ME. Additionally, forecasting returns with E/P only makes sense if the ratio is positive, which is not the case for BE/ME. This fact is reflected in the U-shaped returns of E/P-ranked portfolios, while average returns for BE/ME-ranked portfolios steadily increase.[161] Moreover, BE/ME also captures the effect of leverage. Leverage is measured by A/ME (market leverage) and A/BE (book leverage). While market leverage is significantly positively related, book leverage is significantly negatively related to average returns. The ratio of market and book leverage corresponds to the BE/ME ratio. A high A/ME indicates "involuntary, market imposed leverage"[162]. Thus, high A/ME and BE/ME ratios implicate distress risk premia.

High BE/ME firms exhibit superior ex post returns, accounting for low future earnings prospects and "relative distress risk"[163] priced in the market. Thus, investors approximate high BE/ME ratios for distress risk and demand high (ex ante) premia for holding high BE/ME stocks. Since not every high BE/ME firm is distressed, value leads to higher average (ex post) returns. Thus, the Fama-French three-factor model is consistent with rational asset pricing theories. However, the authors also point out irrational explanations for value like over- and underreaction.[164] Summarizing, Fama and French find that beta cleared of the size effect does not satisfactorily explain average returns in 1963-1990. Second, BE/ME accounts for leverage effects. Third, E/P is absorbed by ME and BE/ME.[165]

In their 1993 paper, Fama-French transform the regressors to factor-mimicking portfolios and include two bond factors: TERM and DEF. Instead of valuation multiples, SMB (Small Minus Big) and HML (High Minus Low) are used as explanatory variables in a multifactor regression on the cross-section of stock and bond returns. SMB and HML are returns on zero-investment, long-short portfolios based on ME (SMB) and the ratio of book

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[159] See Fama/French (1992), pp. 440-441.
[160] See Fama/French (1992), p. 446.
[161] See Fama/French (1992), p. 441.
[162] Fama/French (1992), p. 444.
[163] Fama/French (1992), p. 441.
[164] See Fama/French 1992, pp. 441-444.
[165] See Fama/French (1992), p. 445.

equity (BE) to market equity (ME, HML). Equation (2) depicts the multiple regression with excess asset returns on the left hand side and alpha, the market, size and value return factors on the right hand side of the equation.

$$R_{it} - rf_t = \alpha_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + \varepsilon_{it} \quad (2)[166]$$

In their 1996 paper, Fama and French perform asset pricing tests with cash flow/price, sales growth, as well as long and short term past returns – confirming momentum and a long term reversal effect.[167] The three-factor model as in (2) is able to explain proxies for value such as long term past returns. The economic explanation is that long term losers are more likely to be small, distressed stocks. However, the continuation of short term past returns, i.e. momentum, is not captured by the three-factor model. Instead, it predicts the reversal of both short and long term returns.[168] The authors conclude that the assumption of rational asset pricing can be maintained, but that the three-factor model misses one risk factor.[169]

2.2 Carhart's Four-Factor Model

While Fama and French are reluctant to add an additional factor to their three-factor asset pricing model, Carhart publicizes a four-factor model including momentum in his 1997 paper on the persistence of mutual fund performance.[170] He finds that common risk and expense factors are driving fund return persistence. Analyzing fund managers' abilities, Carhart attributes performance persistence to a passive momentum strategy, instead of individual manager ability. Consequently, some "mutual funds just happen by chance to hold relatively larger positions in last year's winning stocks"[171], so the outperformance is not persistently repeated. Funds actively pursuing a one-year momentum strategy[172] are found to underperform after expenses due to frequent portfolio rebalancing.[173]

Carhart compares the CAPM, the Fama-French three-factor model and a four-factor model including one-year momentum (PR1YR). While the three-factor model exhibits lower pricing errors, thus higher validity, than the CAPM, it leaves short term past returns largely unexplained. Moreover, returns predicted by the three-factor model are not

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[166] Fama/French (1993), p. 24
[167] See Fama/French (1996), pp. 63f.
[168] See Fama/French (1996), pp. 66-68.
[169] See Fama/French (1996), pp. 81-82.
[170] See Carhart (1997).
[171] Carhart (1997), p. 58.
[172] Since the exact mutual fund strategies are not published, this is an assumption made by Carhart.
[173] See Carhart (1997), pp. 57-58.

economically different from returns predicted by the CAPM.[174] The four-factor model attributes performance to the excess market return RMRF, SMB (size), HML (value) and PR1YRt (momentum) as depicted in equation (3).

$$R_{it} - rf_t = \propto_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + p_i PR1YR_t + \varepsilon_{it} \quad (3)\text{ [175]}$$

The dependent variables on the left hand side of the equation represent the excess portfolio return. RMRF is the Fama-French value weighted market proxy. SMB and HML are the Fama-French value weighted, zero-investment, factor-mimicking portfolios. PR1YR is calculated based on equally weighted US stock returns[176] (12-1 months), underweighting big and recently successful firms. The momentum premium is calculated as the spread of the 30% best and worst performers.[177] The results of the four-factor model exhibit high variance of and low correlations among RMRF, SMB, HML and PR1YR. The model improves the pricing errors of the CAPM and the Fama-French three-factor model, thus captures returns satisfactorily.[178]

In the next section Carhart forms deciles-ranked, annually rebased portfolios of mutual funds' lagged one-year performance. The spread of the worst and best performers is 1% per month. Since the betas of the portfolios (return-unrelated) are very similar, the CAPM cannot explain this return variation, which is why alpha (interpreted as the manager's ability) fills the gap. Indeed, the CAPM suggests an outperformance of the best decile by 2.6% p.a. (equivalent to alpha) and an underperformance of -5.4% for the worst decile. Thus, while best and worst funds are at the same information level and bear similar market risk, "worst funds appear to use this information perversely to reduce performance".[179]

Multi-factor models diminish alpha. Momentum alone explains half of the return spread of the top and the bottom decile (67 basis points). Interestingly in terms of active momentum strategies, Carhart tests, albeit not significantly, show that the bottom decile funds are subject to higher expenses and higher turnover than the best performers. Nevertheless, these factors cannot explain the return difference.[180]

The analysis of fund ranking time series exhibits persistency, since funds in the very top and in the bottom decile tend to be the best respectively the worst funds in the

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[174] See Carhart 1997, pp. 61-62.
[175] Carhart (1997), p. 61.
[176] NYSE, Amex and Nasdaq (1963-1993).
[177] See Carhart (1997), pp. 61-62.
[178] See Carhart (1997), p. 62.
[179] See Carhart (1997), p. 63.
[180] See Carhart (1997), pp. 67-68.

next year (Figure 2). Superior performance reverses more quickly than underperformance. However, 80% of funds are in different deciles in subsequent time periods.[181]
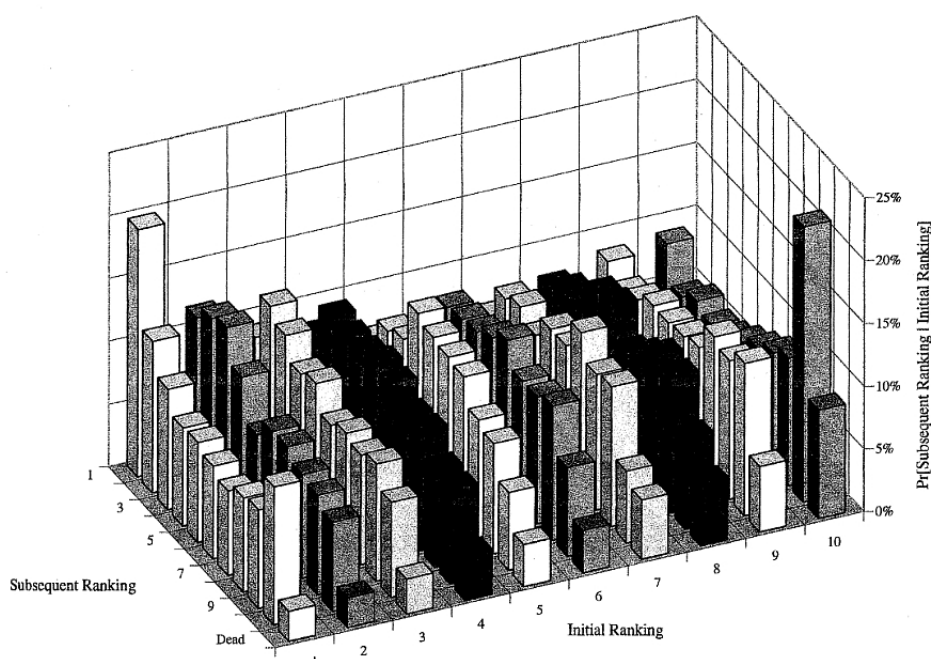

Figure 2, Contingency Table of Initial and Subsequent One-Year Performance Rankings. Source: Carhart (1997), p. 71.

The hypothesis that active momentum strategies earn abnormal returns is rejected, since momentum is "not an investable strategy at the individual security level"[182]. Carhart concludes that the top mutual funds follow passive momentum "strategies", so by not rebalancing they hold winning stocks in higher proportions and save transaction costs.[183]

2.3 Conclusion Multi-Factor Models

Both the three-factor model proposed by Fama and French and the extended four-factor model by Carhart help to diminish alpha. Alpha, left to the manager's investment secrets, is justifying high management fees and a sense of mystery. Concluding, from an individual investor's perspective, these and further models increase transparency and cost efficiency of mutual funds' performance, for example in comparison to passive investing.

Based on the Fama-French multi-factor approach, various models have been constructed. For instant, similar to Zhang[184], Chen et al. establish a multi-factor model for equities, linking investment and profitability. The authors claim that their model "reduces

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[181] See Carhart (1997), pp. 71-72.
[182] Carhart (1997), p. 73.
[183] See Carhart (1997), p. 73.
[184] See Zhang (2005).

[…] abnormal returns of […] anomalies-based trading strategies"[185]. According to Chen et al., the Fama-French three-factor model does not account for market anomalies like momentum and earnings surprises or financial distress and net stock issues. Their model includes a market, an investment and a return-on-equity factor. The model is based on the assumption that firms invest during times of high profitability. On the other hand, low investment firms had lower past returns and low current valuations. This characterizes a value stock with typically higher future ex post returns. Moreover, controlling for investment higher profitability (higher ROE) leads to higher expected returns.[186]

However, the applicability of the referred as well as similar studies is limited due to its restriction to equity. Since value and momentum exist across markets and asset classes, the interpretation of value in terms of investment risk, for instance, is flawed. Asness, Moskowitz and Pedersen demand that value and momentum should be discussed in a global, asset class comprehensive approach.[187] Their research is the result of a step-by-step extension of the original Fama-French three-factor model.

In 1998, Fama and French examine and find evidence of a value premium in international equity markets. The authors deploy a two-factor model on developed and emerging equity markets.[188] Contrary to Fama and French (1992 & 1993), they set up, next to the market factor, just one relative distress factor (the global value spread captured by BE/ME). The authors also test for Earnings/Price, Cash Flow/Price and Dividends/Price. However, every ratio produces a premium that can „be described as compensation for a single common risk"[189]. They find that, contrary to the international CAPM which explains well local market returns, a two-factor model – via a time series regression – also captures the performance of local value portfolios. More specifically, global value can explain value on a country level. This is supportive for the existence of a globally inherent risk factor, since between 1975 and 1995, 75% of the global portfolio consisted of US and Japanese stocks. However, correlations for value premia are low, albeit positive (0.09 on average). Still, 75% of the global market and value factor's variance is explained by country co-variances.[190]

[185] Chen et al. (2011), p. 1.
[186] See Chen et al. (2011), pp. 2f.
[187] See Asness/Moskowitz/Pedersen (2011), p. 2.
[188] See Fama/French (1998), pp. 1984f.
[189] Fama/French (1998), p. 1985.
[190] See Fama/French (1998), pp. 1981f.

3 Value and Momentum in Every Asset Class

This section analyzes the extension of multi-factor models by Asness, Moskowitz and Pedersen [191] to other asset classes, namely international individual equities, international equity indices, government bonds, commodities and currencies.

Momentum is measured across asset classes as the "past 12-months cumulative raw return on the asset […], skipping the most recent month's return"[192]. For value, the measurement is less obvious. While equity value is measured via book-to-market, value for commodities, government bonds and currencies is defined as the negative 5-year return. Value in currencies is adjusted for the net interest earned.[193] The dataset is comprised of 4 individual country stock returns, 18 country index futures, 10 spot exchange rates[194], 10 government bond returns and 27 commodity futures.[195]

Funding liquidity is measured by the TED spread (local 3-month LIBOR minus local 3 month T-Bill rate), the LIBOR – term repo spread (local 3-month LIBOR minus local term repurchase rate) and the Swap – T-Bill spread (interest rate swaps minus local T-Bill). One possible measure for market liquidity is the on-the-run – off-the-run spread.[196]

Asness, Moskowitz and Pedersen detect a common, underlying risk factor, which is driving asset class returns. Assuming rational asset pricing, value and momentum risk premia therefore compensate for this underlying risk factor. Apparently, this common factor exposure is best made visible by comparing value or momentum throughout markets and asset classes.[197]

The research questions are 1) the co-movement of value and momentum across markets and time; the correlations of value and momentum and of a combination strategy over time, 2) how factor diversification can be obtained by value and momentum, 3) what economic drivers and dynamics shape value and momentum returns and their correlations and 4) the implementation of an empirical model capturing cross-sectional returns.

Asness, Moskowitz and Pedersen demonstrate the persistence of value and momentum premia over time. They show that value and momentum strategies, respectively, are positively correlated across asset classes. These relationships are stronger

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[191] See Asness/Moskowitz/Pedersen (2011 & 2012).
[192] Asness/Moskowitz/Pedersen (2011), p. 9.
[193] See Asness/Moskowitz/Pedersen (2011), pp. 9-10.
[194] The currency returns are computed based on currency forward contracts and are USD denominated.
[195] A total return index is calculated based on daily excess returns of the most liquid futures contract, which is typically the nearest to delivery contract. See Asness/Moskowitz/Pedersen (2011), pp. 5f.
[196] See Asness/Moskowitz/Pedersen (2012), p. 19.
[197] See Asness/Moskowitz/Pedersen (2011), pp. 1f.

than the correlations of the asset classes themselves. Moreover, value and momentum are negatively correlated across and within asset classes. This pattern is remarkable due to the differing investment backgrounds of the asset class universe, such as market and informational structures. Due to the negative correlation of value and momentum, a combination of both factors outperforms the single strategies (the Sharpe ratio of the global all asset classes strategy is 1.45). This superior performance indicates that the combination strategy hedges a certain risk factor. Meanwhile, the global single strategy Sharpe ratios are higher than the local single strategy Sharpe ratios, suggesting the existence of an underlying risk factor.[198] The analysis of value and momentum over time exhibits declining profitability of value and momentum strategies, though they are becoming "more (negatively) correlated across asset classes"[199], which stabilizes Sharpe ratios. In equities, the average correlation between value and momentum factors is -0.64, for other asset classes it is -0.55.[200]

Asness, Moskowitz and Pedersen perform a principle component analysis for individual stocks in the US, UK, Europe (ex. UK) and Japan and for value and momentum strategies in individual stocks globally, country equity indices, currencies, government bonds and commodities. Figure 3 depicts the largest eigenvector values of the co-variance matrix (returns to value and momentum strategies) for all assets.[201] While the first principle component loads in one direction for value strategies, it loads in the other direction for momentum strategies. It accounts for 53.6% of the co-variance matrix of global equity value and momentum portfolios and for 22.7% for all asset classes. It can be interpreted as the (either long or short) momentum-value factor.[202] While an underlying factor seems to have been detected, there is still a need for a name. Many style- and asset class-specific factors, which have been discussed (consumption, business cycle or distress risk), are not applicable, since this factor has to apply to all asset classes.

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[198] See Asness/Moskowitz/Pedersen (2012), pp. 11f, p. 51.
[199] Asness/Moskowitz/Pedersen (2011), p. 4.
[200] See Asness/Moskowitz/Pedersen (2012), pp. 50-51.
[201] See Asness/Moskowitz/Pedersen (2011), p. 35.
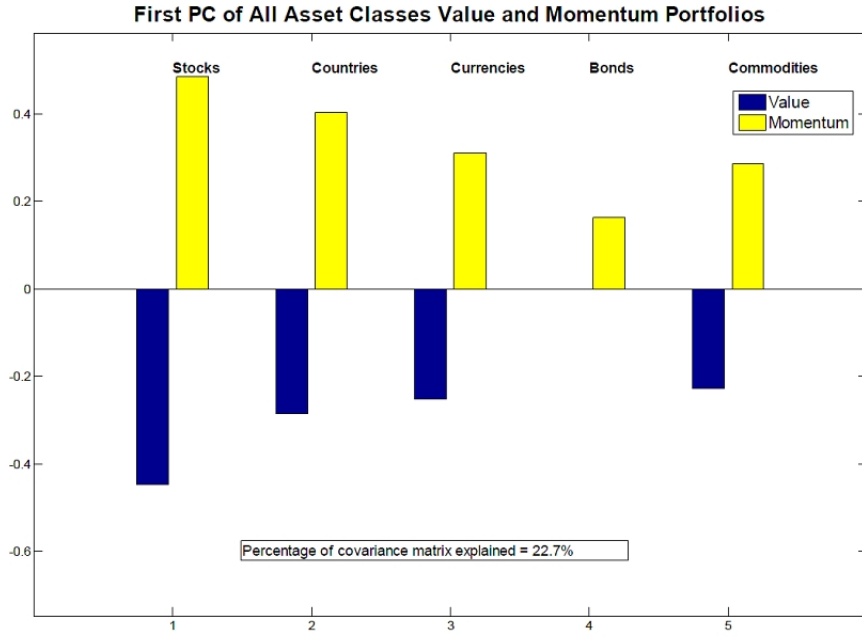[202] See Asness/Moskowitz/Pedersen (2012), p. 41.

Figure 3, First Principal Component of All Asset Classes. Value and Momentum Portfolios. Source: Asness/Moskowitz/Pedersen (2012), p. 41.

Liquidity risk is examined as a possible risk factor driving value and momentum returns. The positive relation of liquidity to momentum and the negative relation to value help to explain the correlation structure of value and momentum. While both market and funding liquidity risk are discussed, only global and local funding liquidity partly explain value and momentum returns. However, positive returns of the 50/50 value/momentum combination strategy indicate that asset returns also include a premium for another risk factor next to liquidity risk.[203]

In the following section, the calculations are being expounded. The authors construct value and momentum factors based on asset returns. Rather than using factor-mimicking portfolios based on spreads, the returns are weighted according to equation (4). The portfolios are then constructed as zero-cost long-short portfolios. Each asset return in each asset class is giving a non-zero weight. Due to this and due to the positive linear relation of the weight and the signal, the factors outperform the simple factor-mimicking portfolios.[204] Additionally, 50/50 value-momentum combination portfolios and a zero-cost return spread (high-low) portfolio are tested.

$$w_{it}^{SIGNAL} = c_t(rank(SIGNAL_{it}) - \sum_i rank\ (SIGNAL_{it})/N) \quad (4)^{[205]}$$

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[203] See Asness/Moskowitz/Pedersen (2011), p. 3.
[204] See Asness/Moskowitz/Pedersen (2011), pp. 11, 19.
[205] Asness/Moskowitz/Pedersen (2011), p. 11.

In cross-sectional regressions, 48 portfolio returns are examined as dependent variables (equation 5): high (best 30%), middle, low (lowest 30%) value and momentum portfolios for 8 asset classes (individual equity portfolios for the US, UK, Europe ex. UK, Japan, equity indices, government bonds, currencies and commodities). Value or momentum in one asset class is tested against value and momentum in all other asset classes. Therefore, the dependent variable is not part of the explanatory variable VAL or MOM. An R^2 of 0.55 and an average absolute alpha of 22.6 basis points confirm the forecasting power of value and momentum across asset classes.

$$R_{it}^p - rf_t = \alpha_i^p + \beta_i^p RMRF_t + v_i^p \sum_{j \neq i} w_j VAL_{jt} + m_i^p \sum_{j \neq i} w_j MOM_{jt} + \varepsilon_{it}^p, \quad (5)^{206}$$

$$\forall i \in (US, UK, EU, JP, EQ, FX, FI, COM)$$

$$\forall p \in \left(Val^{low}, Val^{mid}, Val^{high}, Mom^{low}, Mom^{mid}, Mom^{high}\right)$$

Referring to Fama-French (1993) and Carhart (1997), the authors perform a second regression using constant zero-cost, signal and equal volatility weighted[207] value and momentum factors. Similar to Fama-French the factors are long-short portfolio returns, but contrary to spread portfolios every asset return is given a non-zero weight.

$$R_{it}^p - rf_t = \alpha_i^p + \beta_i^p RMRF_t + v_i^p VAL_t^{everywhere} + m_i^p MOM_t^{everywhere} + \varepsilon_{it}^p \quad (6)^{208}$$

48 excess portfolio returns are regressed against global value and momentum. Since the regressors are the same in every regression, R^2 rises to 0.71 with an average absolute alpha of 18 basis points. In addition, the authors test their model against the CAPM, the four-factor model and a six-factor model including a default (DEF) and a maturity (TERM) factor. DEF and TERM were introduced by Fama and French in their 1993 paper as bond risk factors. Although stock factors only play a limited role for bond returns (except for low-grade corporate bonds), Fama and French found a link between the stock and bond market via the term factor.[209]

The results show that the three-factor model by Asness, Moskowitz and Pedersen (AMP-model) has greater explanatory power than preceding models. The R^2, for example, is substantially higher for the AMP model than for the CAPM (0.449), the four-factor (0.554) and the six-factor model (0.601). However, the Fama-French dataset is comprised of US stocks and bonds, while the AMP-factors are based on global and asset class

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[206] Asness/Moskowitz/Pedersen (2011), p. 18.
[207] Every asset class equally contributes to total portfolio volatility by weighting the asset class by the inverse of the in-sample volatility.
[208] Asness/Moskowitz/Pedersen (2011), p. 19.
[209] See Fama/French (1993), pp. 51f.

comprehensive data. Referring to this objection, Asness, Moskowitz and Pedersen test the 4 models on the Fama-French 25 size-value and 25 size-momentum portfolios of US stocks[210], which naturally results in much better results for the four- and six-factor Fama-French models (R^2 of 0.772 and 0.766 respectively). Still, the AMP has much greater explanatory power (R^2 of 0.642) than the CAPM (-0.316). The R^2 of value-momentum combination portfolios decreases to 0.36, which indicates that by combining value and momentum, a substantial part of the underlying risk can be diversified away. Therefore, only a small fraction of return variance of the combination portfolio can be explained by value and momentum *everywhere* factors.[211]

In the following, Asness, Moskowitz and Pedersen analyze possible macro risks as return drivers. The most prominent effect is found for the TERM and DEF factors in all asset classes. While global equity momentum is significantly negatively related to DEF, global equity value loads positively on it. Furthermore, also GDP growth and recessions exhibit a significant negative relation to momentum in all (non equity) asset classes.[212]

Furthermore, funding and market liquidity risk approximations[213] are tested as possible risk sources. Funding liquidity risk is negatively related to value but positively to momentum, which may in part explain their negative correlation. Moreover, funding liquidity risk may be the reason or the result of rising risk aversion and rising risk premia. The combination strategy of value and momentum exhibits lower relation to funding risk. Therefore, the combination portfolio hedges funding liquidity risk. The excess return after accounting for funding liquidity indicates that liquidity risk does not capture the whole picture. On the other hand, US market liquidity risk shows a positive but weak relation to value, while global liquidity risk factors seem to be unrelated to value and momentum.

Furthermore, more evidence on the effect of funding liquidity is detected in a Fama-MacBeth regression of several macroeconomic factors on 48 value and momentum portfolios. First, being the only explanatory variable, liquidity risk pays a significant, substantial premium of 24 basis points per month. In a second regression, only GDP growth, long term consumption growth, TERM and DEF are tested. TERM and DEF are strong with t-statistics of 2.19 and 2.18 respectively. Third, liquidity risk is added to these

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[210] The 25 size-value and 25 size-momentum portfolios and the Fama-French portfolios are designed from the same data set.
[211] See Asness/Moskowitz/Pedersen (2011), pp. 19f.
[212] See Asness/Moskowitz/Pedersen (2011), p. 45.
[213] Liquidity shocks are calibrated for instance for the TED spread, LIBOR-Term Repo spread, interest rate swap-T-Bill spread and the off-the-run – on-the-run government note spread. Moreover, the first principle component of a correlation matrix of funding shocks is tested as well.

four risk factors, diminishing the power of TERM and DEF. Compared to the single factor regression the explanatory power of liquidity decreases (2.29 t-statistic vs. 3.05). Finally, market, value and momentum factors (the volatility weighted average of all value/momentum strategies) are included. Liquidity is less significant in this eight-factor regression, while value and momentum exhibit strong and significant t-statistics. Thus, value and momentum proxy for risks first attributed to global funding liquidity risk.

The analysis of the correlation structure of value and momentum reveals that both value and momentum became more correlated across asset classes over time, while the correlation of value to momentum became more negative. This is even more pronounced when Sharpe ratios and correlations before and after the 1998 Long Term Capital Management (LTCM) crisis, as a major liquidity event, are compared. After 1998, only the Sharpe ratios and correlations of the individual value and momentum strategies changed, while the combination strategy's Sharpe ratio remained stable. [214]

Moreover, the effects of recessions are tested on correlations and Sharpe ratios over time: value performs better during recessions than momentum, exhibiting relatively stable correlations to momentum. [215] Conversely, other evidence suggests that value stocks often underperform in times of low liquidity, often coinciding with recessions. [216] The combination strategy exhibits similar Sharpe ratios for recessions and non-recessions (1.52 and 1.35) and thus consistent performance irrespective of the economy's state. What is more, negative funding liquidity shocks see rising Sharpe ratios for value, while the contrary is true for momentum. However, this is only true after the 1998 LTCM crisis. Underlining this finding, the authors test the explanatory power of funding liquidity shocks for the correlations of value, momentum and value-momentum. Only after 1998 a relation of liquidity to momentum can be confirmed. Accordingly, the LTCM crisis was a major turning point for the characteristics of value and momentum in separate. During that time, value and momentum, as well as highly levered quantitative trading strategies gained more popularity. The liquidity drain of 1998 and the transformed characteristics of value and momentum point to an underlying factor such as liquidity risk, which drives part of the returns. Also, limits-to-arbitrage will prevent the exploitation of these effects and are linked to funding liquidity risk. [217]

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[214] See Asness/Moskowitz/Pedersen (2011), p. 29.
[215] See Asness/Moskowitz/Pedersen (2011), p. 29.
[216] See Ilmanen (2011), p. 249.
[217] See Asness/Moskowitz/Pedersen (2011), pp. 30f.

Summing up, by studying average, global value and momentum returns jointly within eight asset classes, Asness, Moskowitz and Pedersen detect common factor exposure due to higher cross-sectional variance in a global portfolio than in a single local portfolio. The influence of funding liquidity on value and momentum effects thus can only be observed by looking at global value and momentum factors across markets and asset classes. However, the positive value premium and the convincing Sharpe ratio of the value-momentum combination portfolio are left mostly unexplained. Moreover, for government bonds, value and momentum effects are first being confirmed. A value premium is first being detected for currencies and commodities.[218]

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[218] See Asness/Moskowitz/Pedersen (2011), p. 12.

4 Diversification Context

In the first part of the thesis, value and momentum risk premia and their possible sources were analyzed. Models assuming rational or irrational asset pricing have been distinguished. The characteristics of ex ante and ex post risk premia have been discussed, as well as the time dependency of risk premia. The migration of value and momentum – from anomalies in a CAPM setting – into risk factors in multi-factor models by Fama and French, Carhart as well as Asness, Moskowitz and Pedersen was depicted. In the following, the findings will be presented in an asset and factor allocation context.

The objective of portfolio selection is to attain diversification. Diversifying unsystematic risk reduces portfolio volatility without reducing the expected return, or increases the expected return without raising portfolio volatility. While diversification reduces downside risk in the long term, rising asset correlations can cause failure in the short term during severe crises. In the aftermath of 2007-2009, traditional diversification approaches alongside asset class silos have been questioned.

First asset allocation generations were based upon modern portfolio theory and its concept of mean-variance optimization and its distinction between systematic and idiosyncratic risk. Portfolios were built around expected returns and co-variances.[219] Selecting market risk exposure along the capital market line, the traditional 60/40 policy portfolio consists of 60% equity and 40% government bonds. By rebalancing the fixed weights growth assets are underweighted, introducing a value component. Moreover, in the traditional 60/40 policy portfolio, volatilities and correlations are assumed to be stable, neglecting changing risk premia as argued in section 1. An important risk source of the traditional 60/40 portfolio is high market directionality, which even increases during market turmoil due to higher equity volatility. Also, the bond-stock correlation is positive (0.1 in the US since 1900) during normal times and even rises during crises.[220] Apparently, this high equity risk exposure has been misjudged during the 2007-2009 crisis.[221]

The second asset allocation generation is the extension of the local 60/40 portfolio to a global 60/40 portfolio. While market directionality is still high, global portfolios hedge country-specific risk factors. In their 2011 paper Asness, Israelov and Liew study

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[219] See Mesomeris et al. (2012), p. 4.
[220] See Jones (2012), pp. 7f and Mesomeris et al. (2012), pp. 4-5.
[221] See Ilmanen/Kizer (2012), p. 15.

international diversification benefits for local investors.[222] Overcoming the home bias can protect long term investors from portfolio concentration. Indeed, in the long term country specific growth is more important than short term market turmoil.[223] However, in the short term international diversification reduces volatility, but increases negative skewness. The volatility reduction incentivizes investors to increase their market exposure. Adversely, such diversified portfolios are becoming even riskier.[224]

Over the long term international diversification benefits increase. Indeed, negative skewness is more pronounced in the short term. For the long term (longer than 3.5 years) the difference in skewness vanishes. An analysis of returns, decomposed into multiple expansion or contraction (i.e. capital gains or losses) and actual economic growth proves that multiple expansion is important in the short term, but over the long term economic growth gains in importance. In fact, multiple expansion explains 96% of quarterly returns, but over 15 years, country-specific growth explains 39% of returns. Thus, international diversification protects against portfolio concentration in countries with poor long term growth paths. Concluding, while internationally diversified portfolios exhibit short term weakness due to rising correlations, long term portfolio return is driven by long term country growth differentials.[225]

The third generation is the endowment model, investing in typically illiquid alternative asset classes. The endowment model states that high competition and liquid markets make it harder to gain superior returns simply by fundamental research. But for alternative assets, such as real assets, venture capital and private equity, fundamental research can provide an edge. The specialty of the endowment model is the long term horizon, which allows investors to accept short term mark-to-market losses.[226]

The fourth generation allocates alongside risk factors. Risk allocations to macro factors such as growth, inflation and liquidity can be modeled by exposure to value, momentum, carry and trend-following. This strategy is comparable to the risk parity approach, which targets "*balanced* contributions of various risk exposures to portfolio risk"[227]. Still, diversification takes place alongside asset class silos rather than risk factors.[228]

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[222] See Asness/Israelov/Liew (2011).
[223] See Asness/Israelov/Liew (2011), p. 24.
[224] See Asness/Israelov/Liew (2011), p. 26.
[225] See Asness/Israelov/Liew (2011), pp. 29-34.
[226] See Ang (2011), pp. 6-8.
[227] Ilmanen/Kizer (2012), p. 16.
[228] See Ilmanen/Kizer (2012), pp. 16-17.

Ilmanen and Kizer test diversification benefits of factor and asset class diversification. The asset class diversification portfolio exhibits a slightly higher but unimpressive Sharpe ratio of 0.48 due to the high correlations between portfolio constituents (+0.38). Contrary, the factor diversification portfolio has a Sharpe ratio of 1.44, which can be explained in regard to low correlations between the portfolio constituents (-0.02). Notably, transaction costs, which are larger for factor strategies, are not accounted for. The factor-diversified portfolio implies less equity exposure, thus lower market directionality: its correlation to US stocks is 0.64 instead of 0.87 for the asset class diversified portfolio. Consequently, the factor diversified portfolio exhibits smaller drawdowns, but disadvantageous skewness and kurtosis. Still, it has higher returns during recessions than the asset class diversified portfolio and similar returns during expansions.[229] Figure 4 depicts average pair-wise correlations among the constituents of the asset class diversified and the factor diversified portfolio.
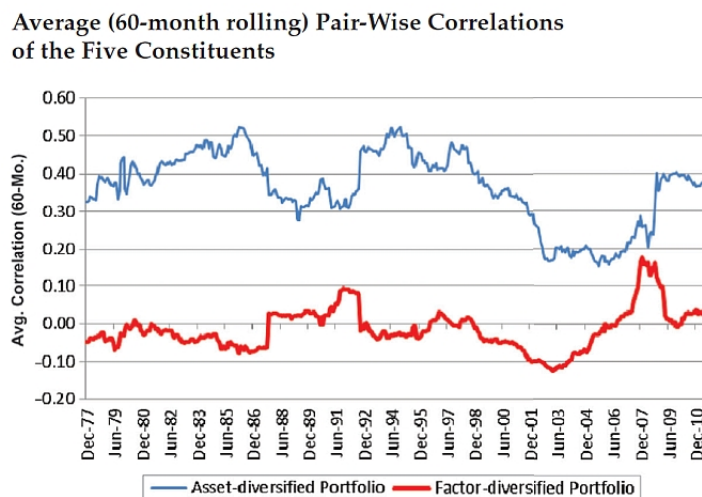
Figure 4, Average (60-month rolling) Pair-Wise Correlations of the Five Constituents. Source: Ilmanen/Kizer (2012), p. 21.

While the factor-diversified portfolio still exhibits common liquidity risk – the dry up of liquidity can make previously uncorrelated factors correlated –, Ilmanen and Kizer claim it to be "more manageable than concentration risk".[230] While factor diversification as an elaborate diversification approach implies high transaction costs, there is evidence that also simple international diversification provides an edge. Rising correlations across

[229] See Ilmanen/Kizer (2012), pp. 20-21.
[230] Ilmanen/Kizer (2012), p. 23.

countries during economic downturns had questioned the advantage of global investing, because of "more severe tail events in global portfolios than in local portfolios"[231].

Ang and Bekaert empirically examine this pattern and show that the reluctance of investors to invest globally is due to a home bias and not to rising volatility and correlations during economic downturns. Assuming time-varying risk premia, correlations and volatility, investors' exposure to global markets during regime changes are relatively stable. Different regimes refer to times of high correlation and low returns (crisis) and to times of low correlation and higher mean returns (expansion).[232]

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[231] Asness/Israelov/Liew (2011), p. 25.
[232] See Ang/Bekaert (2002), pp. 1137-1139, p. 1180.

5 Empirical Analysis

The empirical analysis is conducted in two parts. First, a scoring analysis is performed. Via zero-cost portfolios value and momentum premia are examined in three asset classes: equity indices, government bonds and currencies. The underlying assumption of the scoring approach is the persistence of value and momentum.

Second, an asset allocation model is applied. It combines forecasting asset returns via multiple regressions and mean-variance optimization. Lagged value and momentum valuation measures (rather than factor-mimicking portfolios) predict asset returns. The single expected asset returns are summarized by asset class. Then, the asset allocation is optimized based on the risk/return profiles using historic co-variances (1995/1996-2006).

The validity of this approach depends on the one hand on the predictive power of value and momentum: are value and momentum coefficients significant? It will be shown that the usage of yearly overlapping instead of monthly returns considerable improves the significance of the coefficients. While this may partly be due to the use of overlapping data, the relative strength of value in particular over longer time periods is not surprising.

On the other hand, the outcomes depend on mean-variance optimization and its restrictions. As can be seen in Figure 7 and Figure 8, mean-variance optimization can lead to extreme allocations and high portfolio turnover. The approach selected in this thesis minimizes volatility while setting the return constraint at historic mean portfolio returns.

5.1 Data

In the following, the data set used in the empirical analysis will be described. Monthly as well as yearly overlapping equity index, government bond and currency returns are analyzed. In equity, six MSCI indices (all measured in USD) are used; three developed and three developing country indices, namely MSCI North America, MSCI EAFE, MSCI Pacific[233], MSCI Emerging Europe, MSCI Latin America and MSCI Emerging Asia. The monthly returns are derived from the total return index.

For government bonds, data are obtained from Citigroup's currency hedged total return indices (measured in USD) for bonds with maturities from 7 to 10 years. The time series starts in 1995, which means that the first value measure is only obtainable in 2000. Twelve government bonds are included: Australia, Canada, Denmark, France, Germany,

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[233] MSCI EAFE includes developed Europe, Australia and Far East. MSCI Pacific includes developed countries such as: Australia, Hong Kong, Japan, New Zealand, and Singapore. http://www.msci.com, 22.02.2013.

Italy, Japan, Norway, Sweden, Switzerland, UK and US. Finally, ten currencies are measured via spot rates against the USD, concentrating on industrial countries currencies: AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD and SEK.

The dataset ends in 30.11.2012. The data availability for certain asset classes is limited, therefore time series differ in their starting point, Were possible, I made use of the longer time series (for example in Table C and Table D) to include as much information as possible. In the scoring part, the zero-investment value and momentum factors in currencies are first available by 31.07.1990; for equities by 31.07.1995 and for government bonds by 31.07.2000. Yearly rebalancing takes place at the end of June. Only for reasons of completeness it should be noted that momentum in government bonds is available as early as 31.07.1996, which is depicted in Figure 5, but not included in the calculations.

Since yearly rebalancing is not necessary in the forecasting model, value and momentum valuation multiples are first at hand for currencies by 1990, for equities by 1995 and for government bonds by 2000.

5.2 Value and Momentum Measures

In the following it will be described how value and momentum are measured both in the scoring and the forecasting part of the analysis. In equities, value is measured threefold: well-known ratios such as E/P and B/P[234] are contrasted with negative 5-year returns.[235] However, it will be shown that this last measure severely underperforms E/P and B/P. Also, it negatively correlates with E/P and B/P, which is not supported in the literature. Due to the existent research on this topic[236], the extent of the underperformance of negative 5-year returns in contrast to E/P and B/P is surprising. It is probably due to the limited time window and due to a possible distortion caused by the aggregated information level supplied by the indices.

The inverse of the first value ratio, E/P, is provided by Bloomberg and calculated on the basis of the last price divided by trailing 12 months earnings per share before extraordinary items. Notably, E/P ratios based on 12 months trailing earnings are more volatile than the well-known Shiller P/E, which accounts for 10 years of trailing earnings, thus one or two business cycles.[237] The inverse of B/P is also provided by Bloomberg and calculated with the latest available price (similar to E/P) and the most recently reported

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[234] For computing reasons, in the scoring part, the inverse of P/E and P/B will be applied.
[235] See Asness/Moskowitz/Pedersen (2011), p. 10.
[236] See Fama/French (1996), pp. 63ff.
[237] See. Asness (2012), p. 2.

data (which may be quarterly, semi-annually or annually) on the book value per share. For government bonds and currencies the negative 5-year return is used as a value measure. In all asset classes the return is based on the average spot price of 5 years earlier plus/minus one month.

Similar to Asness, Moskowitz and Pedersen, the measure for momentum is the same in every asset class. It is calculated as the twelve months return skipping the most recent month.[238]

5.3 Scoring Analysis

In the scoring part, it will be tested whether value and momentum exist in the selected asset classes by establishing zero-cost long-short portfolios (without leverage). The portfolios are yearly rebalanced in the end of June. Returns are measured monthly. The breakpoints are the 30th and 70th percentile of the value and momentum range.

For reasons of comparability and to enrich the equity space of the analysis, the Fama-French value (HML) and momentum (WML) factors for developed markets published on Kenneth R. French's website[239] are included to study these factors' interaction with the factors calculated independently. The factors are available from June 1990 to January 2013 and are in USD. The breakpoints for the Fama-French value and momentum factors are the 30th and the 70th percentile. Rebalancing takes place once a year in the end of June. The returns of HML and WML are equally weighted, hence independent of market capitalization. Fama-French measure HML via the book-to-market ratio. WML is the "stock's cumulative return for month t-12 to month t-2"[240]. Contrarily, my momentum factor is based upon the return for month t-13 to t-2.

	FF Value	FF MOM	E Value B/P	E Value E/P	E Value	E MOM	GB Value	GB MOM	FX Value	FX MOM
FF Value	1,00									
FF MOM	0,04	1,00								
E Value B/P	-0,06	-0,06	1,00							
E Value E/P	-0,04	-0,11	0,37	1,00						
E Value	0,08	0,08	-0,03	-0,79	1,00					
E MOM	-0,02	-0,08	-0,03	0,50	-0,68	1,00				
GB Value	0,04	-0,08	-0,02	-0,05	0,04	-0,03	1,00			
GB MOM	0,03	0,04	0,19	0,18	-0,22	0,13	-0,15	1,00		
FX Value	0,10	-0,13	0,09	-0,15	0,32	-0,22	0,16	-0,09	1,00	
FX MOM	-0,07	0,18	0,06	-0,05	0,11	-0,09	-0,07	0,11	-0,34	1,00

Table A, Factor Correlations across Asset Classes.

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[238] See Asness/Moskowitz/Pedersen (2011), p. 9.
[239] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html, 20.02.2013. See Fama, Eugene F.; French, Kenneth R. (2012): Size, Value, and Momentum in International Stock Returns, The Journal of Financial Economics, Vol. 105, No. 3, pp. 457-472.
[240] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_developed.html, 20.02.2013.

Table A summarizes the correlations of the zero-cost factor-mimicking portfolio returns. It shows very low correlations of FF value and the other value/momentum factors. The same is true for FF momentum, although both FF factors nicely interact with FX value and momentum. Expectedly, B/P and E/P are positively correlated. However, both are negatively correlated to equity value measured by negative 5-year returns. E/P is positively correlated to equity momentum, and both E/P and B/P are positively related to GB momentum. This is consistent due to the negative correlations of value and momentum factors in each asset class, specifically in equity when using negative 5-year returns. Although correlations are low in general, Table B clarifies that there is some connection between value and momentum throughout the asset classes. The correlations across asset classes are comparable to the results by Asness, Moskowitz and Pedersen: the average individual stock value/momentum strategy is 0.15/0.37 correlated with the average non-stock value/momentum strategy.[241]

	Value Equity	Value GB	Value FX			Momentum Equity	Momentum GB	Momentum FX
Value Equity	1,00				Momentum Equity	1,00		
Value GB	0,04	1,00			Momentum GB	0,13	1,00	
Value FX	0,32	0,16	1,00		Momentum FX	-0,09	0,11	1,00

Table B, Correlations of Value and Momentum.

In Table C the long-short portfolios' annualized returns are summarized. The returns achieved show substantial outperformance of some of the well-known value and momentum factors, albeit single factors substantially underperform, especially negative 5-year return. Since there are differences in the data availability, for equity and currencies there are longer time windows accessible (row 1). In the second row the time window is the same for every asset class (31.07.2000-30.11.2012).

	Returns Zero-Cost Long-Short Portfolios (p.a.)							
	Equity				Government Bonds		Currencies	
	Value			Momentum	Value	Momentum	Value	Momentum
	B/P	E/P	Neg. 5yr Return	12-1M	Neg. 5yr Return	12-1M	Neg. 5yr Return	12-1M
Longest Time Window*	0,34%	6,64%	-4,97%	3,42%	0,45%	0,32%	4,39%	-3,56%
Standard Time Window**	4,39%	9,01%	-6,70%	1,05%	0,45%	0,32%	3,22%	-1,66%

* Equity: Start 31.07.1995. Currencies: Start 31.07.1990.
** 31.07.2000 - 30.11.2012

Table C, Returns for Value and Momentum Factor-Mimicking Portfolios.

Table C shows that the time window makes a substantial difference. Skipping the years 1995-2000 leads to a major improvement for B/P while momentum returns decrease

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[241] See Asness/Moskowitz/Pedersen (2012), p. 15.

by a sizeable amount. This can be interpreted in terms of time-varying risk premia – therefore the years 1995-2000 saw good momentum, but little value, measured by B/P. Notably, value measured by negative 5-year return fails to perform, but doesn't change a lot in a longer time frame. Returns for government bonds are small for value and momentum. In currencies only the value strategy works. Table D shows the Sharpe ratios for the zero-cost portfolios. In general, value produces considerable Sharpe ratios, especially equity (E/P) and currency value.

	Sharpe Ratios Zero-Cost Long-Short Portfolios							
	Equity				Government Bonds		Currencies	
	Value			Momentum	Value	Momentum	Value	Momentum
	B/P	E/P	Neg. 5yr Return	12-1M	Neg. 5yr Return	12-1M	Neg. 5yr Return	12-1M
Longest Time Window*	0,08	1,28	-1,09	0,77	0,73	0,45	1,86	-1,43
Standard Time Window**	1,15	1,91	-1,44	0,25	0,73	0,45	1,46	-0,71

* Equity: Start 31.07.1995. Currencies: Start 31.07.1990.
** 31.07.2000 - 30.11.2012

Table D, Sharpe Ratios for Value and Momentum Factor-Mimicking Portfolios.

As is visible in Table C and Table D, value generally outperforms momentum. Momentum and value returns are comparable only in the case of government bonds, where both strategies are weak. When selecting an equity value ratio for the forecasting part of this study, E/P seems to be the most promising. The time series of cumulative value and momentum strategy returns are depicted in Figure 5 and Figure 6.
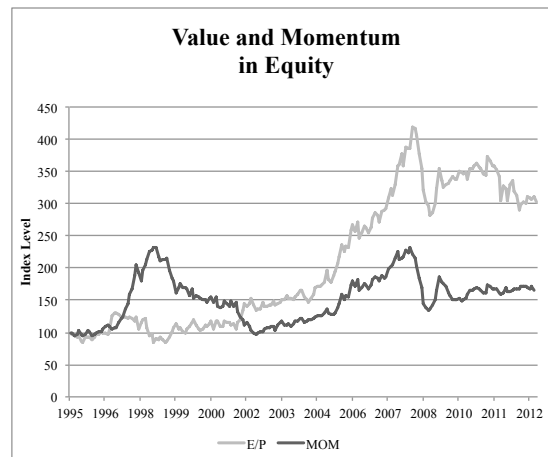

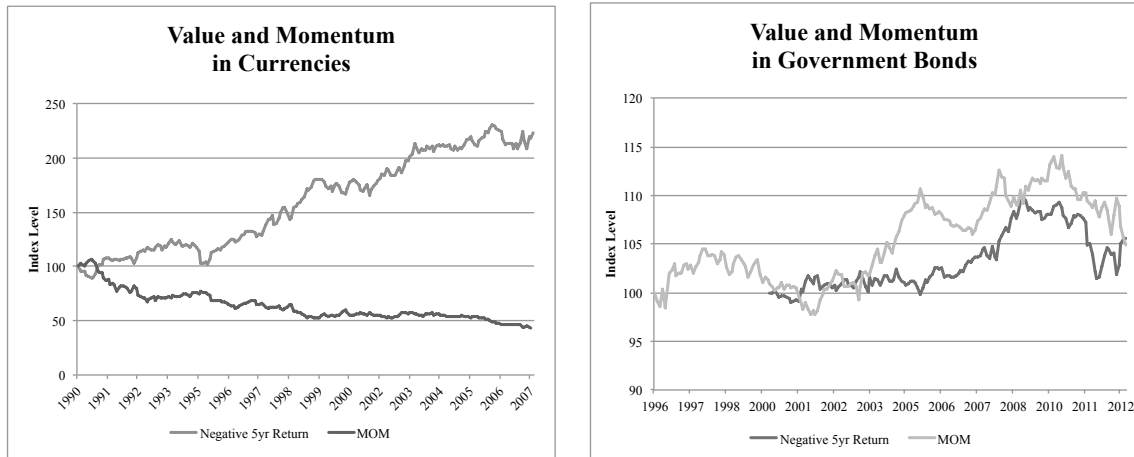Figure 5, Cumulative Returns on Value and Momentum in Equity.

Figure 6, Cumulative Returns on Value and Momentum in Currencies and Government Bonds.

Summarizing, value and momentum factors exist in the given dataset, except for currency momentum. The finding of value and momentum in government bonds is backed by the results of Asness, Moskowitz and Pedersen, as well as the value premium in currencies.[242]

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[242] See Asness/Moskowitz/Pedersen (2011), p. 12.

5.4 Forecasting Model

In this section, a forecasting model combined with an asset allocation approach will be applied. The assets and the asset classes are the same as before, therefore monthly returns for 28 assets are used (6 equity indices, 12 government bonds, and 10 currency pairs). While the time series length differs for equities, government bonds and currencies, the data points within each asset class are uniform. Based on the findings of the first part of the empirical analysis, P/E is used as an equity value measure. Value in government bonds and currencies is depicted via the negative 5-year return. Momentum in every asset class is the previous 12-months return skipping the most recent month.

The returns (the dependent variable) used in the forecasting model (until 2006) are referred to as ex post returns subsequently. Based on the results of this multiple regression, future returns are estimated, starting in 2007, and are referred to as ex ante returns. The multiple regression and the calculation of the ex ante returns will be described in the following section.

5.4.1 Multiple Regression Analysis

First, the significance of the value and momentum indicators for each asset's monthly realized return (ex post) is tested by a multiple regression analysis. The value and momentum coefficients are estimated using the relevant time series until 2006[243].

$$R_{it,monthly} = \propto_i + \beta_{1i}Value_{i,t-1} + \beta_{2i}Momentum_{i,t-1} + \varepsilon_{it} \qquad (7)$$

The endogenous variable is the return of asset i in month t. The exogenous variables are the respective value and momentum measures as described above, at time t-1. Contrary to Fama-French (1993) and Asness, Moskowitz and Pedersen (2011) the regressors are valuation multiples and not returns.[244]

While equation (7) refers to the month-to-month effect, in a second step also overlapping yearly returns will be used to capture long term return reversal patterns. More specifically, the yearly return in month t of asset i will be tested on the value and momentum indicator available in month t-12. The usage of overlapping yearly returns is necessary due to the limited data range of some time series, especially government bonds.

$$R_{it,yearly} = \propto_i + \beta_{1i}Value_{i,t-12} + \beta_{2i}Momentum_{i,t-12} + \varepsilon_{it} \qquad (8)$$

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[243] For equities, the time window starts at 02/28/1995. For government bonds, it starts at 05/30/2000. For currencies, the first date, when value and momentum measures are available, is 03/30/1990.
[244] See Fama/French (1992).

The beta coefficients for value and momentum calculated by these multiple regressions in combination with the resulting intercepts are used to obtain ex ante returns (equations 9 & 10). The calculation of value and momentum measures is unchanged.

$$E(R_{it,monthly}) = \propto_i + \beta_{1i}Value_{i,t-1} + \beta_{2i}Momentum_{i,t-1} \qquad (9)$$

$$E(R_{it,yearly}) = \propto_i + \beta_{1i}Value_{i,t-1} + \beta_{2i}Momentum_{i,t-1} \qquad (10)$$

Monthly and yearly overlapping returns exist for each asset from January 2007 to November 2012. On the basis of these estimated returns an asset allocation model will be applied. For reasons of clarity and comprehensibility, the assets' returns will be aggregated on an asset class level (equally weighted average returns).

For each month from January 2007 to November 2012, a mean-variance optimization is applied, using historic co-variances (for 1995 – 2006 for the monthly return part and 1996 – 2006 for the yearly overlapping return part). This asset allocation will be back-tested with monthly ex post returns for each asset class. The asset class ex post returns are the equally weighted average returns of each asset in the respective asset class. Thus, the asset allocation model and the forecasting power of value and momentum will be tested out-of-sample for 5 years and 11 months.

The results of regression (7) are summarized in Table E. The results (beta coefficients, t-statistics, p-values) for value are depicted in columns 1-4. In column 4, the significance levels of the beta coefficients are illustrated by *, ** or *** for alpha at 10%, 5% and 1%. Significances are very low except for equities. The signs of the coefficients are negative for Equity North America and EAFE since P/E and not E/P is used in this regression. The coefficients' signs for value as negative 5-year return should be positive, which is the case for currencies, albeit not significant. Most government bonds exhibit negative coefficients. It will be shown that this pattern is consistent throughout this data sample. While value is weak, momentum turns out to have slightly more forecasting power on the month-to-month level (columns 5-8). Government bonds show significance levels in four cases at α = 10% and in one case at α = 5%. Still, similar to value, the coefficients' signs are negative. These results imply that the selected government bonds in the referred time window exhibit negative value and momentum: thus the returns tend to reverse in the short term with sustained long term momentum. However, this pattern is less surprising in regard of the secular interest rate cycle and of long term capital gains for government bonds, seen in 1990 to 2000.

		Significance Levels (Monthly Returns)							
		Value				Momentum			
		ß1	t-stat.	p-value		ß2	t-stat.	p-value	
Equity	North America	-0,0022	-2,7069	0,0076	***	0,0337	1,6191	0,1077	
Equity	EAFE	-0,0004	-2,4700	0,0147	**	0,0045	0,1993	0,8423	
Equity	Pacific	0,0000	0,3293	0,7425		0,0195	1,0103	0,3142	
Equity	Emerging Europe	0,0007	0,5654	0,5728		-0,0024	-0,0949	0,9245	
Equity	Latin America	-0,0007	-0,5239	0,6012		0,0143	0,6404	0,5229	
Equity	Emerging Asia	0,0006	1,3083	0,1932		0,0159	0,6927	0,4898	
GB	Australia	-0,0154	-1,2726	0,2070		-0,0542	-1,1705	0,2454	*
GB	Canada	-0,0145	-0,8263	0,4112		-0,1015	-1,8910	0,0624	*
GB	Denmark	-0,0125	-1,0421	0,3007		-0,0578	-1,6887	0,0954	*
GB	France	-0,0173	-1,2843	0,2029		-0,0667	-1,7652	0,0815	*
GB	Germany	-0,0170	-1,1341	0,2603		-0,0705	-1,7775	0,0795	
GB	Italy	-0,0087	-1,1768	0,2429		-0,0553	-1,5770	0,1189	
GB	Japan	-0,0119	-1,2389	0,2192		-0,0315	-0,8506	0,3977	
GB	Norway	0,0253	1,3912	0,1682		-0,0402	-1,0003	0,3204	
GB	Sweden	-0,0029	-0,3698	0,7125		-0,0345	-1,0257	0,3083	**
GB	Switzerland	-0,0322	-1,7960	0,0765	*	-0,0840	-2,6404	0,0100	
GB	UK	-0,0122	-1,0106	0,3154		-0,0431	-0,9877	0,3264	
GB	US	0,0185	0,8833	0,3791		-0,0007	-0,0214	0,9830	
FX	GBPUSD	0,0029	0,2224	0,8242		-0,0218	-0,9094	0,3642	
FX	DKKUSD	0,0019	0,2060	0,8370		0,0150	0,7064	0,4808	
FX	EURUSD	0,0005	0,0596	0,9525		0,0129	0,5854	0,5589	
FX	NOKUSD	0,0027	0,2494	0,8033		0,0032	0,1383	0,8901	
FX	SEKUSD	0,0025	0,2264	0,8211		0,0152	0,7130	0,4767	
FX	CHFUSD	0,0027	0,2703	0,7872		0,0068	0,2881	0,7736	
FX	CADUSD	0,0045	0,5211	0,6029		0,0395	1,6023	0,1107	
FX	JPYUSD	0,0061	0,5959	0,5519		0,0070	0,3037	0,7616	
FX	AUDUSD	0,0071	0,7518	0,4531		0,0319	1,5851	0,1145	***
FX	NZDUSD	0,0085	1,2514	0,2123		0,0466	2,8120	0,0054	

Table E, Regression Results, Monthly Returns.

Summarizing the regression results of equation (7), value and momentum in general possess rather weak predictive power on the month-to-month level. For this reason, the same value and momentum measures will be used to explain overlapping yearly returns (equation 8). The results of this multiple regression are shown in Table F. Columns 1-4 summarize the value coefficients for each asset class, including t-statistics and p-values. In general, significance levels are noticeably higher than before. All currency pairs exhibit highly significant value coefficients. While value is less pronounced for equities, the majority of government bonds are featuring significant value effects. As before, however, the value coefficients' signs are negative. It should be noted that the usage of overlapping data might contribute to higher significance levels for yearly returns due to a look-ahead bias. Nevertheless, it is obvious that value as a long term strategy becomes stronger over longer time windows.

		Significance Levels (Yearly Returns)							
		Value				Momentum			
		ß1	t-stat.	p-value		ß2	t-stat.	p-value	
Equity	North America	-0,0251	-8,8533	0,0000	***	0,3617	5,3304	0,0000	***
Equity	EAFE	0,0001	0,1291	0,8974		0,2064	2,0114	0,0464	**
Equity	Pacific	0,0000	0,2056	0,8375		-0,0690	-0,6651	0,5072	
Equity	Emerging Europe	-0,0094	-1,8250	0,0706	*	-0,1068	-1,0030	0,3179	
Equity	Latin America	-0,0043	-0,8480	0,3980		0,0341	0,3599	0,7195	
Equity	Emerging Asia	0,0028	1,3434	0,1818		-0,1306	-1,1341	0,2591	
GB	Australia	-0,1857	-6,7976	0,0000	***	-0,7066	-7,5327	0,0000	***
GB	Canada	-0,0605	-1,7149	0,0911	*	-0,4885	-4,1515	0,0001	***
GB	Denmark	0,0150	0,5451	0,5876		-0,9203	-10,7848	0,0000	***
GB	France	-0,0251	-0,7777	0,4396		-0,8463	-8,8338	0,0000	***
GB	Germany	-0,0254	-0,7261	0,4704		-0,8239	-8,4646	0,0000	***
GB	Italy	-0,0386	-2,0191	0,0476	**	-0,8239	-8,1736	0,0000	***
GB	Japan	-0,2091	-4,9208	0,0000	***	-0,5970	-4,2483	0,0001	***
GB	Norway	0,3719	10,5946	0,0000	***	-0,1916	-2,3445	0,0221	**
GB	Sweden	0,0356	1,7647	0,0823	*	-0,6719	-7,4020	0,0000	***
GB	Switzerland	-0,0554	-0,9440	0,3486		-0,6786	-6,7304	0,0000	***
GB	UK	-0,1468	-4,5507	0,0000	***	-0,7380	-6,7417	0,0000	***
GB	US	0,2641	2,2779	0,0250	**	-0,2533	-2,4555	0,0159	**
FX	GBPUSD	0,2109	5,2178	0,0000	***	0,0187	0,2648	0,7915	
FX	DKKUSD	0,0891	2,4133	0,0168	**	0,0299	0,3618	0,7179	
FX	EURUSD	0,0845	2,3919	0,0177	**	0,0767	0,9224	0,3575	
FX	NOKUSD	0,1227	2,8219	0,0053	***	0,0264	0,3206	0,7488	
FX	SEKUSD	0,1754	3,7158	0,0003	***	0,0922	1,1065	0,2699	
FX	CHFUSD	0,1151	3,2564	0,0013	***	0,0345	0,4287	0,6686	
FX	CADUSD	0,0615	1,7543	0,0810	*	0,5118	5,8285	0,0000	***
FX	JPYUSD	0,0660	1,9632	0,0511	*	0,0899	1,1761	0,2410	
FX	AUDUSD	0,2459	5,6712	0,0000	***	0,3361	4,3604	0,0000	***
FX	NZDUSD	0,2856	9,8620	0,0000	***	0,5883	9,1059	0,0000	***

Table F, Regression Results, Yearly Returns.

As for value, also the predictive power of momentum (columns 5-8) increases over the one year horizon. In equities, both value and momentum seem to work best for MSCI North America. This is not surprising, since it is the most liquid and most intensely observed market. The coefficients for government bonds are all significant, mostly at $\alpha = 1\%$. As before, the sign is negative, which implies that short term reversal is a highly significant factor for government bonds. Finally, the coefficients for currencies are not significant, except for CAD, AUD and NZD, but all are positive. Momentum for CAD, AUD and NZD is significant at the 1% level.

The regression results of equation (8) indicate that the predictive power of value and momentum can be considerably increased by using overlapping 12 month returns. Despite this evidence, both monthly and yearly expected returns will be used for separate mean-variance optimization and out of sample back-testing.

5.4.2 Mean-Variance Optimization

The mean-variance optimization is calibrated based on the following assumptions. First, it is assumed that historic co-variances (1995 – 2006) are representative until 11/2012, which is the end of the back-testing period. Second, the return restriction is the historic average equally weighted return. In combination with minimizing portfolio volatility, the derived asset allocation does not capture sustained aggregate price developments (Figure 7 and Figure 8).

First, the results of the mean-variance optimization using monthly expected returns calculated with value and momentum coefficients derived from equation (9) will be described. The expected returns per asset class are the equally weighted expected returns of each asset in the particular asset class. The optimization minimizes the portfolio variance; therefore the constraint for the portfolio return is set at the average ex post return until the end of 2006, which is the return an equally weighted portfolio would have offered on average (0.53% per month, 6.54% p.a.). In Figure 7, the thereby achieved asset allocation for each month is depicted. Expectably, the mean-variance optimization leads to quite extreme allocations, for example in 2009 and 2012. Government bonds are given a high weight throughout the time period due to their benign risk-return profile. While the optimization would never indicate going short equities, the suggested equity allocation is near zero in the first half year of 2010 and in summer/autumn 2011. Finally, currencies are least effective in terms of risk-return, which results in substantial negative allocations during 2009 and 2012.
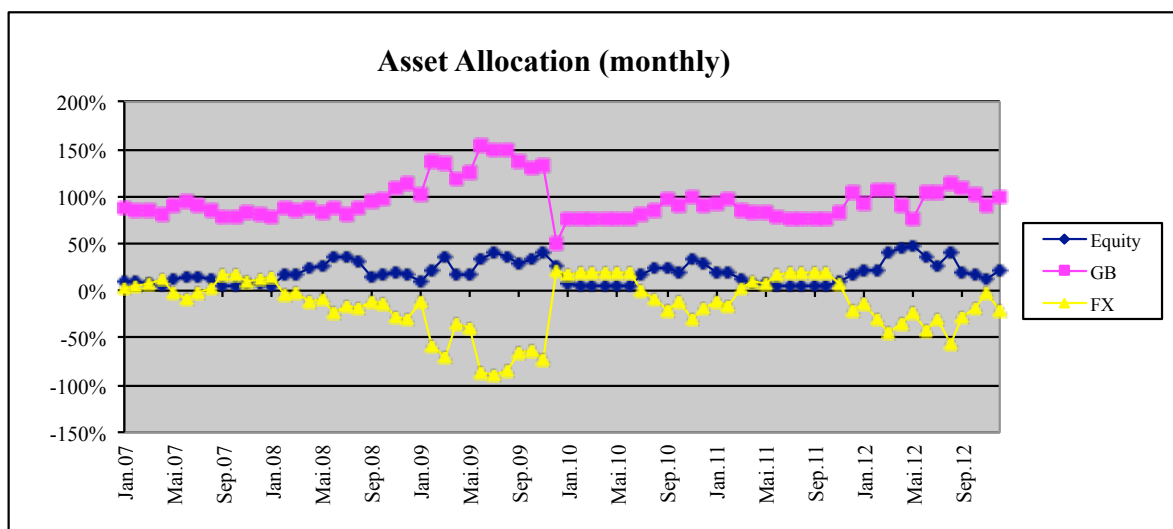

Figure 7, Asset Allocation based on Monthly Data.

In contrast, the asset allocation model using yearly returns and coefficients (Table F and Figure 8) leads to different results, based on a return constraint of 6.66% p.a. As visible in Figure 8, government bonds are again given substantial allocations due to their benign risk-return profile. Furthermore, equity takes a stable but clearly smaller portion of the portfolio. Again, FX is the only asset class that is being shorted during the observed time span. Generally noticeable in comparison to Figure 7 is that the allocations are less extreme when using yearly data (overlapping returns).
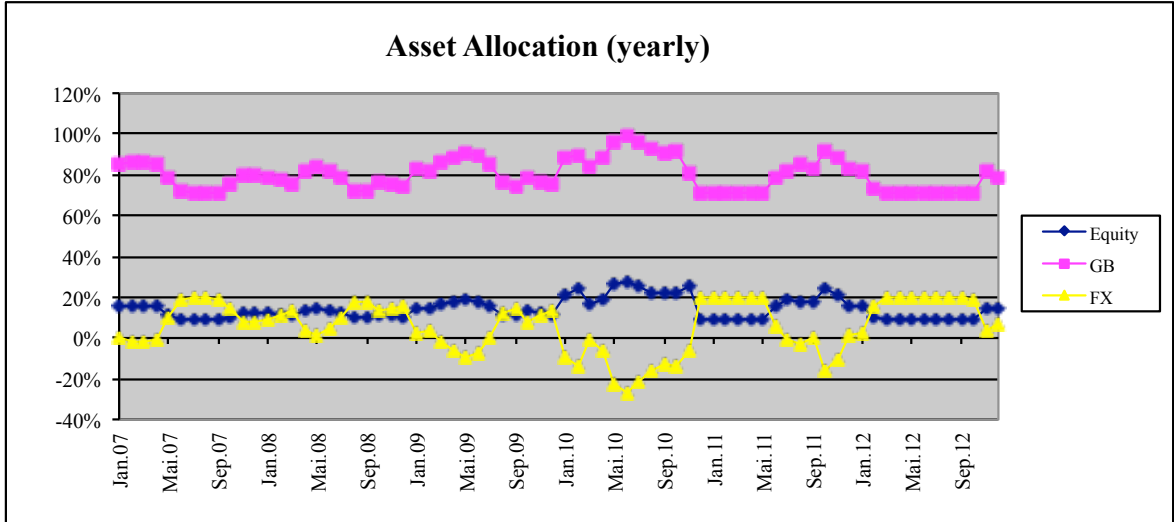

Figure 8, Asset Allocation based on Yearly Data.

In the next part of the analysis, the optimized portfolios are back-tested out-of-sample for January 2007 - November 2012. The results are illustrated in Table G. It is stated in the first row whether yearly or monthly expected returns were used in the mean-variance optimization. The second row specifies the ex post returns for the back-testing part: the portfolios were tested with monthly and yearly returns. Columns 1 and 2 refer to the asset allocation in Figure 7, while column 4 refers to Figure 8. Columns 3 and 5 display portfolios, where each asset class is equally weighted. The returns are displayed as average ex ante or ex post returns per year, respectively. In the last row, a risk, more specifically, volatility adjusted return is calculated based on the assumptions that the asset allocation portfolios can be levered up to the volatility of the equally weighted portfolios.

Returns Asset Allocation Model vs. No Model					
Expected Returns Ex post Returns Model	monthly monthly AA Model	yearly monthly AA Model	- monthly NO Model	yearly yearly AA Model	- yearly NO Model
Ex Ante Return p.a.	6,71%	5,69%	6,51%	7,06%	6,05%
Ex post Return p.a.	5,90%	6,15%	4,18%	6,99%	5,79%
Volatility p.a.	4,64%	4,10%	10,65%	5,06%	15,13%
SR	1,27	1,50	0,39	1,38	0,38
Risk Adjusted Return	13,66%	16,33%	4,18%	20,46%	5,79%

Table G, Back-Testing Results.

By definition, ex ante the optimized portfolios outperform the equally weighted portfolios, except for column 2, where the asset allocation is estimated based on yearly data but tested with monthly returns. Indeed, the outperformance even increases ex post and ranges from 120-197 basis points. Moreover, the volatility and thus the Sharpe ratios are very benign in comparison to the equally weighted portfolios. Every asset allocation portfolio has a Sharpe ratio substantially higher than 1. The Sharpe ratios for the equally weighted portfolios of 0.38 and 0.39 are in line with historic average Sharpe ratios of 0.43[245]. Levered asset allocation portfolios yield 13.66-20.46% p.a.

The yearly asset allocation model (Figure 8) is tested with ex post monthly as well as yearly returns (January until December). While the ex ante and ex post yearly returns are higher than monthly returns, the volatility still is higher, resulting in a lower Sharpe ratio (1.38 vs. 1.50). In each case the asset allocation model outperforms the simple equally weighting approach (NO Model). While the Sharpe ratios for both equally weighted portfolios are similar, the Sharpe ratio for yearly data with monthly rebalancing is considerably higher than for yearly rebalancing. This suggests an advantage for portfolios with monthly rebalancing in terms of timely information flows. Sharpe ratios of 1.27-1.50 indicate that value and momentum effectively captured risk factors between 2006 and 2012.

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[245] See Zhang (2005), p. 80.

5.5 Summary Empirical Findings

The persistence of value and momentum in three asset classes could be demonstrated via zero-cost portfolios. It could be confirmed that value or momentum, respectively, were positively correlated across asset classes. Value and momentum within and across asset classes were negatively correlated in general. Hence, the results of the first part of the analysis were alongside expectations.

In the second part, a multiple regression was applied to analyze the predictive power of value and momentum for asset returns. The results suggest that value as well as momentum have more meaningfulness for yearly rather than monthly returns. However, significance levels might be overstated due to the usage of overlapping data. While value and momentum were confirmed by the regression analysis for equity and currencies, the coefficients' signs for government bonds are negative for both yearly overlapping and monthly returns, but highly significant in general. Negative value can be explained by sustained capital gains in this asset class in the referred time period. This explanation is less convincing for the existence of negative momentum.

Finally, the results of the asset allocation models in comparison to simple equally weighted portfolios are tested for a period of more than (in two cases exactly) 5 years, producing impressive Sharpe ratios between 1.27-1.50. Briefly, albeit the surprising behavior of government bond returns, the empirical analysis largely confirms the findings cited in previous sections.

6 Conclusion

This thesis analyzes value and momentum as time-varying risk premia, regarding them as rewards for investors to bear specific risks. These risk factors are associated with common, underlying macroeconomic factors such as liquidity and growth. Both rational and irrational asset pricing assumptions are examined. Expected, i.e. ex ante risk premia are contrasted with ex post, i.e. realized risk premia. It is shown in the context of portfolio attribution and multi-factor models that risk premia can be used to effectively diversify common underlying macroeconomic factors, such as liquidity risk.

Binary financial markets force the rethinking of traditional diversification approaches, leading the way to risk factor allocation. Unforeseen high asset correlations during recessions and market turmoil in combination with higher than expected portfolio exposure to the (developed) equity market are the motivation for this most recent strand of literature on diversification.

Empirically, it can be shown that reversal and momentum forces exist in global equity indices, government bonds and currencies. Positive correlations of value or momentum, respectively, across asset classes exhibit common factor exposure driving portfolio returns. Also, it can be shown that value and momentum have predictive power forecasting asset returns. A simple asset allocation approach – mean-variance optimization[246] – is applied using forecast returns and historic co-variances. The out-of-sample back-tests confirm superior returns: the Sharpe ratios of the asset allocation models range between 1.27-1.50, in comparison to Sharpe ratios of 0.38-0.39 for the equally weighted portfolios.

While this approach is simple and still diversifies along asset class silos, it implicitly uses the benign characteristics of value and momentum as risk factors. Concluding, value and momentum capture risk factors, which drive asset returns. In combination, they provide substantial diversification benefits.

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[246] See Markowitz (1952).

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8 Appendix

8.1 Curriculum Vitae

10/2010 – 06/2012	**Portfolio Management Program**
	The Research Institute for Capital Markets, ISK (Vienna)
03/2009 –	**MSc Business Administration**
	University of Vienna
	Corporate Finance, Energy and Environmental Management
10/2005 – 03/2012	**BA History of Art**
	University of Vienna
10/2005 – 01/2009	**Bakk.rer.soc.oec. Business Administration**
	University of Vienna
	09/2007 – 12/2007: Exchange Semester
	Hanken School of Economics (Helsinki)

8.2 Abstract in English

This thesis analyzes value and momentum as time-varying risk premia. Risk premia are used for effective diversification in the context of multi-factor models. Factor and asset allocation are examined in the light of discussions about the reliability of traditional diversification approaches in times of binary financial markets. It can be shown empirically that reversal and momentum forces exist in global equity indices, government bonds and currencies. Also, superior returns can be gained by combining the forecasting power of value and momentum and simple portfolio allocation models like Markowitz's mean-variance optimization.

8.3 Abstract in German

Value und Momentum als zeitvariable Risikoprämien können im Kontext von Multi-Faktor Modellen nicht nur den Querschnitt der Rendite unterschiedlicher Anlageklassen erklären, sondern auch zur Diversifikation durch effektive Risiko-Allokation genutzt werden. Die Portfolio Allokation nach Asset Klassen oder Risikofaktoren wird im Lichte der Debatte um Diversifikation angesichts zunehmend binärer Finanzmärkte diskutiert. Empirisch werden Value und Momentum in globalen Aktienindizes, Staatsanleihen und Währungen untersucht. Die Vorhersagekraft von Value und Momentum wird in Kombination mit einer Mittelwert-Varianz Optimierung nach Markowitz zur Asset Allokation genutzt.