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Navn:	Anders Bostad Borg og Emil Pay

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Master Thesis

Momentum and Autocorrelation Patterns

in the US Stock Markets

Anders Borg Emil Pay

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Author 1

Author 2

Abstract

This paper seeks to investigate the role of autocorrelation and cross-serial correlation for momentum in stock returns. Using different momentum portfolios applied to the US stock market from January 1941 to December 2021, we find that negative cross-serial correlation drives momentum profits over longer return horizons, while negative autocorrelations act as a reducing factor. However, when the return horizons are shortened, their roles change as autocorrelations become more positive, while cross-serial correlations become less negative. We conclude that underreaction as an explanation of momentum can co-exist alongside negative autocorrelation since the value of serial-correlation varies with different return horizons.

Keywords: momentum, autocorrelation, cross-serial correlation, underreaction, overreaction

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1 Introduction and Motivation

Momentum refers to the empirically observed tendency for asset prices that previously have risen (fallen) to sustain their current trend. The existence of this tendency is an anomaly that financial theory struggles to explain. The issue lies within the efficient market hypothesis, which states that previous price action in asset prices should not warrant future price movements. Some of the earliest research done on the momentum anomaly was conducted by Jegadeesh and Titman (1993). Similar research has been conducted for several international markets, and the momentum anomaly tends to hold, also in more recent studies, e.g. Fama and French (2008), Barroso and Santa-Clara (2015) and Ottaviani and Sørensen (2015).

Our research aims to explore the source of momentum by looking at autocorrelation patterns in returns in light of behavioral models of overreaction and underreaction. Specifically, our research question states: *What is the role of autocorrelation and cross-serial correlation for momentum in stock returns, and does this role change with different return horizons?* Through this research question, our thesis seeks to improve the understanding of the mechanisms behind momentum. Looking back on previous findings on the momentum anomaly is essential. It helps gain a better fundamental and theoretical understanding of momentum and how it stands the tests of time. By better understanding the role of autocorrelation and cross-serial correlation in momentum strategies, policymakers can improve market stability and efficiency. Deeper understanding of the mechanisms behind the anomaly could also be beneficial for investment decision making and asset pricing. As an investment strategy, momentum is a thumb in the eye of the efficient market hypothesis, one of the central tenets of modern finance, which has made passive investing incredibly popular over the last 20 years. Yet, various styles of momentum investing continue to reward their investor practitioners with above-average returns.

Consider the iShares Edge MSCI USA Momentum Factor exchange-traded

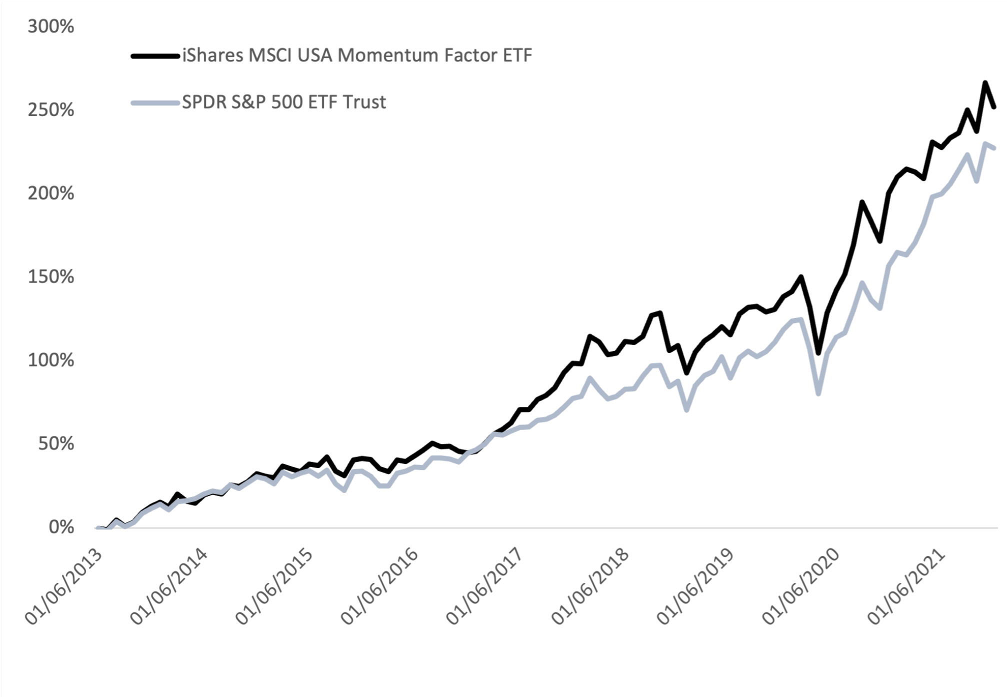

Figure 1.1: iShares Edge MSCI USA vs. SPDR SP 500 ETF Trust. Data collected from Yahoo Finance for the period April 18th 2013 to December 31st 2021.

fund (ticker symbol: MTUM). Launched in 2013, the fund has grown to $10 billion in assets by convincingly outperforming the benchmark Standard & Poor's 500 index for most of the last five years. The last couple of decades have also seen a rise of smart beta funds, factor investing and momentum strategies. In Europe alone, the share of institutional investors adopting these strategies have gone from 40% in 2014 to 60% in 2017, and are being considered a mega-trend according to the FTSE Russel. (FTSE-Russell, 2017).

While there is no question of the existence of momentum and its role as a serious investment strategy, the explanation and extent remain obscure. Different studies propose different answers based on different proxies and variables. One way to analyze the anomaly relates momentum to different factors driving the cross-section of expected returns. Using this approach, Lewellen (2002) suggested that cross-serial covariance drive momentum in stock returns. He found that both the autocovariance and the cross-serial covariances are negative, but the former is less negative than the latter. Based on these findings, he concluded that the profitability of portfolio-based momentum strategies is primarily driven by cross-serial correlations among portfolio returns. Interestingly, these results go against behavioral theories that imply positive autocorrelation in stock returns.

To evaluate our research question, we follow the approach of Lewellen (2002) and utilize the momentum decomposition of Lo and MacKinlay (1990) to industry, size, and book-to-market portfolios for the 1941–2021 sample period. We formulate the portfolio-specific momentum strategies with formation periods of 1, 3, 6, and 12 months and examine the autocorrelation patterns for up to 18 months after formation. We include individual stocks only for our first set of tests but omit them when evaluating autocorrelation patterns of return. This is the most glaring omission of this thesis. In order to better understand the roles of autocorrelation and cross-serial correlation in momentum strategies, we utilize both long- and short-term return horizons.

2 Literature Review

The pioneering research on the momentum anomaly was a 1993 study by Jegadeesh and Titman. Using data from the U.S. market, Jagadeesh and Titman examined various momentum strategies that go long stocks with relatively high returns over the last 3 to 12 months, and short stocks with relatively poor returns. At the end of each month, all stocks that has a return history of minimum 12 months are ranked into deciles based on their past J-month return (j=3,6,9,12). They are then assigned to one out of ten relative strength portfolios. These portfolios are equally weighted at formation and held for K subsequent months (K=3,6,9,12). During this time the weights are not rebalanced. They noted that such strategies earn profits around 1% per month for the following year. For example, portfolios which picked stocks based on their previous semi-annual returns, for then to hold them for 6 months, would generate an extra 1% per month above what was to be expected. More recent research still finds momentum to be a valid investment strategy that generates positive returns in excess of the market, e.g. Bali et al. (2012) and Jegadeesh and Titman (2011). Similar research has also been conducted for several international markets and generally tends to hold. E.g., Rouwenhorst (1998) found evidence of momentum returns in different European markets, constructing their model after Jegadeesh and Titman (1993). This was later substantiated by Barroso and Santa-Clara (2015) who found evidence in the French, German, Japanese and UK markets using a similar approach.

There are several proposed explanations behind the success of momentum investing, most fall into one out of two categories. The first category belongs to rational thinkers who believe that momentum premium is the compensation for the high risk taken by momentum traders. Academic studies suggest plausible risk-based momentum models (Conrad and Kaul (1998); Berk et al. (1999); Moskowitz and Grinblatt (1999); Johnson (2002); Bansal et al. (2004); Ruenzi and Weigert (2018)). The second category consists of two subcategories of behavioral models: Investors either overreact or underreact to important information. Behavioral explanations such as Da et al. (2014) argued using data from the US stock market that momentum arises because investors underreact to information arriving in small bits. Their research showed that stocks where past returns gradually accumulate will exhibit more momentum than stocks where returns are collected in a volatile fashion. Using all common stocks listed on the NYSE and AMEX over the sample period February 1967 to December 2008, Antoniou et al. (2013) argued that momentum stems from classic cognitive dissonance: investors react correctly to the news that confirms their beliefs, but underreacts to new information which refutes their ideas. Also utilizing the models of Jegadeesh and Titman (1993), the study showed that momentum generally arise in bullish periods since investors underreact to bad news.

Using CRSP stock-return data for the period 1971 to 2004, Hong et al. (2007b) suggested that investors utilize overly simplified models when they evaluate stocks. For example, investors may believe that stock prices are vital for big-picture financial data. An investor trusting in a particular model might use this model while making persistent forecast errors as it ignores more relevant information, leading to momentum. Based on research conducted on all NYSE and AMEX stocks in the period 1962 to 1996, Grinblatt and Han (2005) proposed that investors natural reluctance to short losers and their eagerness to sell winners causes underreaction to new fundamental information. Based on US-stock market returns, Hong and Stein (1999) suggested that the mechanical trading of momentum investors causes an overreaction to new information since investors continue to place directional bets even after fully incorporating new information into the stock price.

Different studies suggest different explanations based on distinct samples, proxies, and variables. One approach to examining momentum sources is relating momentum to other factors that drives the cross-section of expected stock return. Following this approach, Lewellen (2002) had two sets of findings. First, looking at industry, size, and B/M portfolios, buying past winning portfolios and selling past losing portfolios, will generate positive returns for about one year. Using NYSE, AMEX and Nasdaq common stocks in the time-period 1941 to 1999, Lewellen found that size and book-to-market portfolios exhibit momentum distinct from momentum in individual stocks and industries, but similar in magnitude. The second set of findings was based on Lo and MacKinlay (1990), who observed that the expected profit of a momentum strategy might come from three different sources. Based on a sample of 551 NYSE and AMEX stocks in the period 1962 to 1989, Lo and MacKinlay (1990) found that stocks that was performing well relative to others might continue to do so because; (1) the stock has a high unconditional mean relative to other stocks, (2) the stock return is positively correlated, so its past return predicts high future returns, and (3) the stock return is negatively correlated with lagged returns on other stocks (negative cross-serial covariance), so their poor performance predicts high future returns.

Lewellen used raw returns to separately calculate the auto- and cross-serial covariances among industry, size, and book-to-market (B/M) portfolios. For each set of portfolios, the average autocovariance is slightly negative, however not statistically significant. The corresponding average of the cross-serial covariances tends to be more negative but neither these are usually statistically significant. Lewellen drew two conclusions based on these results. First, the negative autocovariances is proof that industry, size, and B/M momentum is not a result of past winners continuing to outperform past losers. This claim contradicts the underreaction theory and the behavioral models of momentum like Hong and Stein (1999), which propose that positive autocorrelation in stock returns drives momentum. Second, momentum in industry, size, and B/M portfolios stems from negative cross-serial correlations. This corresponds to an overreaction hypothesis where specific stocks overreact to a common factor while others don't.

Despite different theories regarding underlying behavioral investor biases, many of the previous proposed theories generally attribute momentum to return continuations, e.g., Da et al. (2014), Antoniou et al. (2013) Hong and Stein (1999). They all suggest a close relation to positive autocorrelation in short horizons. This is either due to underreaction to news, or continued overreaction. However, the results of Lewellen (2002) document negative autocorrelation. While behavioral models generally do not explicitly define any return horizon (Pan (2010)), it would be reasonable to expect underreaction or overreaction at time horizons shorter than those examined in Lewellen (2002). This is a gap which our thesis aims to explore, and possibly reconcile these conflicting results. We follow the same methodology as Lewellen (2002) and utilize the Lo and MacKinlay (1990) decomposition, adding shorter return horizons to the analyses. Our data slightly differs from that of Lewellen (2002), which is discussed in detail in Section 4.3. We have utilized research portfolios exported from the Ken French data library. The portfolio construction of the industry, size, B/M and size-B/M portfolios are explained in detail in Section 4.1.

3 Methodology

3.1 Hypothesis

Our research question states: *What is the role of autocorrelation and cross-serial correlation for momentum in stock returns, and does this role change with different return horizons?* In order to answer this, we report two sets of tests. We first look at the profitability of portfolio-based momentum strategies, before further exploring autocorrelation patterns in returns.

1. Assessing profitability of portfolio-based momentum

We use individual stocks, industry, size, and B/M portfolios for our momentum strategy to see whether momentum still generate statistically significant returns[1]. Using portfolio-based strategies we can also see whether momentum can be attributed to firm-specific events or not. These momentum portfolios are constructed as explained in Section 3.2. We will test the hypothesis over different lags, for up to 18 months after formation. Formation period for these tests is constant at 12 months. As we can't be certain that we will achieve positive returns, we use a two-sided test.

Hypothesis 1: Profitability of portfolio-based momentum:

$$H_0 : \bar{r}_w - \bar{r}_L = 0$$
$$H_A : \bar{r}_w - \bar{r}_L \neq 0$$

The hypothesis answer whether portfolio-based momentum strategies generate statistically significant return in the US stock market for the time-period January 1941 to December 2021. In order to generate positive return, the winners ($\bar{r}_w$) must outperform the losers ($\bar{r}_L$). If the momentum return of these portfolios are significant, we can argue that there are other sources for momentum besides portfolio-specifics.

[1]These portfolios are constructed as shown in Section 4.1.

2. Autocorrelation patterns

For the second set of tests, we focus on cross-serial correlations and autocorrelation patterns in return. We utilize Pearson's correlation coefficient to assess the linear correlation between two data sets. Statistical inference is drawn using bootstrapping as described in Section 3.3.1. The aim is to test the null hypothesizes that the true correlation coefficient ρ is equal to 0, based on the sample correlation coefficient.

Hypothesis 2.1: Autocorrelations:

$$H_0 : \rho(r_{i,t}, r_{i,t+k}) = 0$$
$$H_A : \rho(r_{i,t}, r_{i,t+k}) \neq 0$$

This hypothesis test whether the correlation between the formation period return of asset i ($r_{i,t}$) and its return k months after formation ($r_{i,t+k}$) is equal to zero.

Hypothesis 2.2: Cross-serial correlations:

$$H_0 : \rho(r_{i,t}, r_{j,t+k}) = 0$$
$$H_A : \rho(r_{i,t}, r_{j,t+k}) \neq 0$$

This hypothesis test whether the correlation between the formation period return of asset i ($r_{i,t}$) and other assets return k months after formation ($r_{j,t+k}$) is equal to zero.

While several authors have provided guidelines on the interpretation of the correlation coefficient's size (Buda and Jarynowski, 2010), such interpretations are in some ways arbitrary, (Cohen, 1992). The size and value depend on context and purposes. Qualitative analysis is therefore also made with respect to the size and value in relation to the models of momentum returns as described in Section 3.5.

To further investigate the role of autocorrelation, we look at each lag individually. More specifically, we test whether the strategies generate autocorrelations statistically different from zero at each lag of the given horizon. We utilize an autoregressive model (i.e. $y_t = \beta_0 + \beta_1 y_{t-1} + \epsilon_t$) and estimate the slope coefficient when a portfolio's monthly return is regressed on its lagged formation period return[2]. We use two-sided tests.

Hypothesis 2.3: Individual lags

$$H_0 : \beta_1 = 0$$
$$H_A : \beta_1 \neq 0$$

3.2 Momentum Portfolios

To conduct our tests, we construct portfolios that buy past winners, and sell past losers. We construct strategies which hold assets in proportion to their market-adjusted returns. For simplicity the following formulation focuses on one period returns. The results are however easily adopted to multiple-period returns (as seen in footnote 4).

$$w_{i,t} = \frac{1}{N}\left(r_{i,t-1} - r_{m,t-1}\right) \tag{3.1}$$

N is the total number of stocks, $r_{i,t-1}$ equals the return in month t-1 for asset i, while $r_{m,t-1}$ is the equal-weighted index return in month t-1. We assume that returns have unconditional means given by: $\mu \equiv E\left[r_t\right]$, and the autocovariance matrix; $\Omega \equiv E\left[\left(r_{t-1} - \mu\right)\left(r_t - \mu\right)'\right]$. We can then express the portfolio return in any month t as:

$$\pi_t = \sum_i w_{i,t} r_{i,t} = \frac{1}{N}\sum_i \left(r_{i,t-1} - r_{m,t-1}\right) r_{i,t} \tag{3.2}$$

Then we can further express the *expected* profit as:

$$E\left[\pi_t\right] = \frac{1}{N} E\left[\sum_i r_{i,t-1} r_{i,t}\right] - \frac{1}{N} E\left[r_{m,t-1}\sum_i r_{i,t}\right] \tag{3.3}$$

We write in terms of autocovariance for asset i and the equal-weighted portfolio (ρ_i, ρ_m):

$$E\left[\pi_t\right] = \frac{1}{N}\sum\left(\rho_i + \mu_i^2\right) - \left(\rho_m + \mu_m^2\right) \tag{3.4}$$

Equation 3.4 illustrates how profit depends on the magnitude of asset autocovariance relative to the markets autocovariance.

In matrix notation, the average autocovariance is given by $\frac{\mathrm{tr}(\Omega)}{N}$, while $\frac{\iota'\Omega\iota}{N^2}$

[2] We also report the Ljung-Box Q-Test for these estimates

is the autocovariance of the market portfolio[3]. We can then decompose expected momentum return into three different components:

$$\begin{aligned} E\left[\pi_t\right] &= \tfrac{1}{N}\operatorname{tr}(\Omega) - \tfrac{1}{N^2}\iota'\Omega\iota + \sigma_\mu^2 \\ E\left[\pi_t\right] &= \tfrac{N-1}{N^2}\operatorname{tr}(\Omega) - \tfrac{1}{N^2}\left[\iota'\Omega\iota - \operatorname{tr}(\Omega)\right] + \sigma_\mu^2 \end{aligned} \tag{3.5}$$

Equation 3.5 locates the potential sources of momentum that our hypothesises are based upon[4]. First, stocks can inherit positive autocorrelation: $\left(\frac{N-1}{N^2}\operatorname{tr}(\Omega)\right)$. This implies that firms with positive returns are expected to continue to have so in the future. Second, momentum could stem from negative lead-lag relations: $\left(-\frac{1}{N^2}\left[\iota'\Omega t - \operatorname{tr}(\Omega)\right]\right)$. This implies that if a firm does well today, then other firms will be negatively affected. The last term $\left(\sigma_\mu^2\right)$ arises as momentum strategies by nature tends to go long stocks with high unconditional means on average. As stocks with the highest unconditional means also have the highest realized return, profits could still be positive, even in the absence of time-series predictability, (Lewellen, 2002).

3.3 Pearson's Linear Correlation Coefficient

We utilize Pearson's linear correlation coefficient to test for correlation effects and achieve the autocovariance matrix Ω used in our hypotheses. For column X_a in matrix X and column Y_b in matrix Y, having means $\bar{X}_a = \sum_{i=1}^{n}\frac{X_{a,i}}{n}$ and $\bar{Y}_b = \sum_{j=1}^{n}\frac{X_{b,j}}{n}$, Pearson's linear correlation coefficient $(r_{a,b})$ is defined as:

$$r_{a,b} = \frac{\sum_{i=1}^{n}\left(X_{a,i} - \bar{X}_a\right)\left(Y_{b,i} - \bar{Y}_b\right)}{\left\{\sum_{i=1}^{n}\left(X_{a,i} - \bar{X}_a\right)^2 \sum_{j=1}^{n}\left(Y_{b,j} - \bar{Y}_b\right)^2\right\}^{1/2}} \tag{3.6}$$

Where n is the length of each column. Values of the correlation coefficient can range from –1 to +1.

[3] ι is a vector of ones. $\operatorname{tr}(\Omega)$ is the sum of the diagonal of the autocovariance matrix

[4] The tests consider strategies based on past 12-month returns and held for 1-18 months. Suppose annual return has unconditional mean γ and the covariance between month t+k returns and lagged 12-month return equals $\Delta_k \equiv E\left[\left(r_t^{12} - \gamma\right)\left(r_{t+k} - \mu\right)'\right]$. The expected profit in month t+k is $E\left[\pi_{t+k}\right] = \operatorname{tr}\left(\Delta_k\right)/N - \iota'\Delta_k\iota/N^2 + \sigma_{\mu\gamma}$

3.3.1 Bootstrap Simulations

We want to test our null hypotheses that the true correlation coefficient ρ is equal to 0 based on the value of the sample correlation coefficient $r_{a,b}$. We use bootstrap simulations to construct confidence intervals for Pearson's correlation coefficient to assess them in accordance with Hypothesis 2.1 and 2.2.

In the non-parametric bootstrap, n pairs $(X_{a,i}, Y_{b,i})$ are resampled with replacements from the observed set of n pairs, and the correlation coefficient $r_{a,b}$ is calculated based on the resampled data. This process is repeated 1000 times, and we can use the empirical distribution of the resampled correlation coefficients to approximate the sampling distribution of the statistic. I.e., the 95% confidence interval for ρ is defined as the interval spanning from the 2.5th to the 97.5th percentile of the resampled $r_{a,b}$ values.

3.4 Statistical Significance

3.4.1 Student's T-test

Our preferred method of testing the null hypothesis that the sample mean is equal to a specified value μ_0, is the one-sample student's t-test:

$$t_{stat} = \frac{\bar{x} - \mu_0}{\frac{s}{\sqrt{n}}} \tag{3.7}$$

where $\bar{x}$ is the sample mean, μ_0 is the hypothesized population mean, s is the sample standard error, and n is the sample size. As we do not know if the tests will produce positive or negative estimates, we will use two-sided tests throughout the thesis.

Once the t value and degrees of freedom are determined, we find a p-value using a table of values from Student's t-distribution. If the calculated p-value is below the threshold chosen for statistical significance[5], then the null hypothesis is rejected in favor of the alternative hypothesis.

[5] In order to stay consistent with Lewellen (2002) we utilize a 10% significance threshold.

3.4.2 Ljung-Box Test

We also report the formal Ljung-Box Q-Test to test whether or not observations over time are random and independent. In particular, for a given lag m, it tests whether the autocorrelations up to lag m are all 0. The Ljung-Box test statistic is given by:

$$Q(m) = N(N+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{N-k} \tag{3.8}$$

where n is the sample size, $\hat{\rho}_k^2$ is the sample autocorrelation at lag k, and m is the number of lags being tested.

3.5 Models for Momentum Return

We now turn to the theoretical models. As mentioned in the literature review, underreaction theory along with positive autocorrelation is a common interpretation of momentum, [e.g. Moskowitz et al. (2012), Ottaviani and Sørensen (2015)]. We present two models of underreaction and overreaction as explanations of momentum return proposed by Lewellen (2002)[6].

His model of underreaction (Section 3.5.3) explains how the idea that prices react slowly to news leads to positive autocorrelation and cross-serial correlation. The second model (Section 3.5.4) explains how investors can overreact to information about one firm when evaluating the prospects of others. The overreaction model contains excess covariance, meaning that prices covary more strongly than dividends. The model further shows how as long as the overreaction described is not too large, momentum profits will be positive.

[6]Lewellen (2002) also proposed a model of Time Varying Risk Premium as an explanation of momentum. In this thesis we have focused solely on basic interpretation of the underreaction and overreaction explanations

3.5.1 Stock Prices

We use a basic representation of stock prices based on Fama and French (1988). We assume that the vector of log prices (p_t) can be separated into a permanent and a transitory component:

$$p_t = q_t + \epsilon_t \tag{3.9}$$

q_t follows a random walk and ϵ_t is a stationary process with mean zero. Changes in q_t should be interpreted as new information regarding dividends. Changes in ϵ_t can be thought of as new information regarding expected return. The vector q_t then follows the process:

$$q_t = \mu + q_{t-1} + \eta_t \tag{3.10}$$

Expected drift is represented by μ. η_t is the white noise with mean zero and covariance matrix $\sum$. This yields continuously compounded returns:

$$r_t = p_t - p_{t-1} = \mu + \eta_t + \Delta\epsilon_t \tag{3.11}$$

The vector of unconditional expected returns is $E\left[r_t\right] = \mu$

3.5.2 Constant Expected Returns

We assume that prices follow a random walk. Since returns are not predictable, the first-order covariances are zero. Expected momentum profits from one-period returns can be represented as:

$$E\left[\pi_t\right] = \sigma_\mu^2 \tag{3.12}$$

Where σ_μ^2 is the cross-sectional variance of expected returns.

3.5.3 Underreaction

In order to capture the idea of stock-prices responding slowly to news, we assume that the temporary component of prices is given by:

$$\varepsilon_t = -\rho\eta_t - \rho^2\eta_{t-1} - \rho^3\eta_{t-2} - \ldots \tag{3.13}$$

Where ρ is some number between zero and 1 and η_t is news regarding dividends at time t. There will be an immediate price reaction of $(1-\rho)\eta_t$ when new information occurs. The price will reflect $\left(1-\rho^k\right)$ of the news occurred at time t after k periods has passed. Return will be given by:

$$r_t = \mu + (1-\rho)\eta_t + (\rho - 1)\varepsilon_{t-1} \tag{3.14}$$

Underreaction both decrease volatility and induce positive autocorrelation in returns. With Σ representing the dividend covariance matrix, the first-order autocovariance matrix will be given by:

$$\operatorname{cov}\left(r_t, r_{t-1}\right) = \left(\rho\frac{1-\rho}{1+\rho}\right)\Sigma \tag{3.15}$$

As we assume that underreaction is similar across stocks, Σ should be proportional to the autocovariance matrix. Since ρ is some number between 0 and 1, then the expression in the parentheses will be positive. This further means that autocorrelations and cross-serial correlations will typically be positive. By using Lo and MacKinlay's decomposition from 1990, we get the following expected momentum profit:

$$E\left[\pi_t\right] = \rho\frac{1-\rho}{1+\rho}\left[\frac{1}{N}\operatorname{tr}(\Sigma) - \frac{1}{N^2}\iota'\Sigma\iota\right] + \sigma_\mu^2 \tag{3.16}$$

The expression within the bracket will also be positive as Σ is a covariance matrix. Hence, this model of underreaction will lead to momentum.

3.5.4 Overreaction

This model of overreaction illustrates cross-serial correlation in returns as a source of momentum profits. The model assumes that investors will overreact to news regarding one firm when evaluating the prospects of others. The model contains «excess» covariance: prices covary more strongly than dividends.

We assume shocks in dividends to be completely asset-specific to emphasize the central idea of this section. We express this assumption as: $\text{cov}\,(\eta_t) = \sigma_\eta^2 I$, where I reflects an identity matrix. As investors believe that new information about one firm affects others, we can express the temporary component of price from Equation 3.9 as:

$$\varepsilon_t = B\eta_t + B\rho\eta_{t-1} + B\rho^2\eta_{t-2} + ... \tag{3.17}$$

B is a NxN-matrix with zero diagonal term as investors understand how new information regarding a firm affects its own value. B is positive off the diagonal, meaning that investors will overreact when valuing other firms. ρ is an adjustment factor for time, ranging between 0 and 1.

Fluctuations around a random walk will be persistent, although temporary. Specifically, $\varepsilon_t = \rho\varepsilon_{t-1} + B\eta_t$, while returns will be $r_t = \mu + (I + B)\eta_t + (\rho - 1)\varepsilon_{t-1}$. Returns will be more volatile and negatively autocorrelated. The return variance then becomes:

$$\text{cov}\,(r_t) = \sigma_\eta^2 \left[I + B + B' + \frac{2}{1+\rho} BB' \right] \tag{3.18}$$

which is positive off diagonal. Off-diagonal values represents the excess covariance of stocks. The first order autocovariance matrix then becomes:

$$\text{cov}\,(r_t, r_{t-1}) = \sigma_\eta^2 (\rho - 1) \left[B + \frac{1}{1+\rho} BB' \right] \tag{3.19}$$

As $\rho < 1$, and B only has positive terms, the first order autocovariance matrix is strictly negative. Thus, both autocorrelations the cross-serial correlations are negative, which shows how investors overreact to new information.

Without further restrictions on B, it's unknown whether it is negative autocovariances or negative cross-serial covariance that dominates. Lewellen (2002) stated that it is reasonable to assume that news regarding one stock will have a smaller, positive effect on other stocks:

$$B = b\left[\iota\iota' - I\right] \tag{3.20}$$

b is a scalar that ranges between zero and one. The matrix has zero on the diagonals, b elsewhere. The important aspect of this restriction on b is that it implies that a shock to one stock will have a smaller effect on other stocks. Now we can write momentum profits as:

$$E\left[\pi_t\right] = \sigma_\eta^2 \frac{b(\rho-1)(N-1)}{N}\left[\frac{b}{1+\rho} - 1\right] + \sigma_\mu^2 \tag{3.21}$$

This expression for expected momentum returns will be positive under the restrictions of b. Thus, as long as overreaction is not too large, we will expect positive momentum profits.

4 Data

4.1 Data

This thesis investigates momentum in stock returns focusing on the US stock market. The universe of assets includes all NYSE, AMEX and Nasdaq common stocks and the sample period is between January 1941 and December 2021. We rely on Ken French's research portfolios for industry, size, and double sorted size-B/M portfolios, French (2022). For tests involving individual assets, all NYSE, AMEX and Nasdaq common stocks on the Center for Research in Security Prices (CRSP) are utilized. These firms must have 12 months of past returns (no restrictions are placed on survival going forward)

For the industry portfolios, each NYSE, AMEX, and NASDAQ stock is assigned to an industry portfolio at the end of June of the year t based on its four-digit SIC code. Ken French uses Compustat SIC codes for the fiscal year ending in calendar year t-1. Whenever Compustat SIC codes are not available, CRSP SIC codes are utilized for June of year t. They then compute returns from July of t to June of t+1, French (2022).

The size portfolios include all NYSE, AMEX, and NASDAQ stocks for which there exists market equity data for June of t. The portfolios are constructed at the end of each June using the June market equity and NYSE breakpoint, French (2022).

The B/M portfolios are formed on book equity/market equity each June using NYSE breakpoints. The book equity used in June of year t is the book equity for the last fiscal year-end in t-1. Market equity is price times shares outstanding at the end of December of t-1. All NYSE, AMEX, and Nasdaq stocks for which there exists market equity data for the future of December of t-1 and June of t, and book equity t-1, French (2022).

The double sorted size-B/M portfolios, which are constructed at the end of each June, are the intersections of 2 or 5 portfolios formed on size (market equity, ME) and 3 (2x3) or 5 (5x5) portfolios created on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year-end in t-1 divided by ME for December of t-1. The BE/ME breakpoints are NYSE quintiles for 5x5 sort and 30th and 70th percentile for 2x3 sort. The portfolios for July of year t to June of t+1 include all NYSE, AMEX, and NASDAQ stocks for which we have market equity data for December of t-1 and June of t, and (positive) book equity data for t-1, French (2022).

4.2 Summary Statistics

Table 4.1 shows the summary statistics for the portfolios created for our research. As brevity is beauty, the table only displays the 10 industry portfolios, the 10 size portfolios and the 25 size-B/M portfolios. We have however also constructed 5-size portfolios, 5- and 10 B/M portfolios and 6 size-B/M portfolios, which can be seen in Appendix, Table A1.1.

10 Industry Portfolios			
Portfolio	**Avg. ret.**	**Std.dev.**	**Firms**
Non-durables	1.10%	4.18%	276
Durables	1.13%	5.35%	117
Manufacturing	1.08%	4.67%	600
Energy	1.22%	5.00%	144
Equipment	1.29%	5.63%	385
Telecom	1,04%	3.77%	48
Shops	1.18%	4.91%	325
Health	1.28%	5.06%	170
Utilities	0.95%	3.86%	132
Other	1.12%	4.92%	927
Average	**1.14%**	**4.74%**	**312**

10 Size Portfolios			
Portfolio	**Avg. ret.**	**Std. Dev.**	**Firms**
Small	1.48%	6.56%	1427
2	1.36%	5.92%	364
3	1.35%	5.56%	255
4	1.33%	5.39%	206
5	1.30%	5.14%	178
6	1.24%	4.93%	156
7	1.26%	4.86%	143
8	1.19%	4.60%	136
9	1.15%	4.34%	128
Large	1.07%	3.97%	125
Average	**1.27%**	**5.13%**	**312**

25 Size-B/M Portfolios				
Portfolio		**Avg. ret.**	**Std. Dev.**	**Firms**
Small:	Low	0.82%	7.98%	324
	2	1.21%	6.72%	219
	3	1.24%	5.97%	227
	4	1.43%	5.70%	290
	High	1.63%	6.35%	514
2:	Low	0.97%	6.65%	113
	2	1.23%	6.65%	91
	3	1.26%	5.23%	94
	4	1.34%	5.23%	93
	High	1.55%	6.20%	72
3:	Low	0.99%	6.03%	90
	2	1.19%	5.16%	75
	3	1.17%	4.84%	70
	4	1.33%	4.99%	62
	High	1.44%	5.84%	43
4:	Low	1.06%	5.40%	89
	2	1.10%	4.82%	69
	3	1.20%	4.78%	56
	4	1.26%	4.93%	45
	High	1.38%	5.84%	30
Large:	Low	0.99%	4.45%	101
	2	0.95%	4.21%	63
	3	1.08%	4.12%	46
	4	1.00%	4.63%	36
	High	1.18%	5.52%	20
Average		**1.20%**	**5.49%**	**117**

Table 4.1: Summary Statistics for portfolios formed from all NYSE, AMEX and Nasdaq stock during the period January 1941 to December 2021. The table report the average value weighted return, standard deviation, and the average number of firms for each portfolio throughout the time period.

By looking at these results, two factors stand out. First, we notice that there is a significant amount of cross-sectional variation in the portfolios. The average monthly return varies from 0.85% to 1.17%, for the industry portfolios, 0.96% to 1.36%, for the size portfolios and 0.82% to 1.63%, for the size-B/M portfolios. We also see that the standard deviations vary from 3.95% in the Utilities portfolio, to 6.38% in the Durables portfolio. Second, we see that the different portfolios are all relatively well diversified as the average number of firms per industry and in the size deciles are 339, while the portfolio constructed on size-B/M averages 117 number of firms. This fact will be important when we later assess the macroeconomic implications of the different portfolios.

4.3 Assessing replicability of Lewellen (2002)

As previously mentioned, our data differ slightly from that of Lewellen (2002). The most glaring difference is the use of different industries. Lewellen writes "Industries are based on two-digit SIC codes as reported by CRSP. They typically contain firms in consecutive two-digit codes, but some exceptions were made.". Without further context and information on said exceptions, it is unclear which major industry group is included in each portfolio. We therefore utilize the Ken French industry research portfolios. Figure A.3.1 in the appendix displays a summary of each industry group and its constituent SIC codes.

Table 4.2 below display the summary statistics for portfolios exported from the Ken French Data Library for equivalent time frames as that of Lewellen (2002).

10 Industry Portfolios			
Portfolio	**Avg. ret.**	**Std.dev.**	**Firms**
Non-durables	1.04%	4.04%	252
Durables	1.14%	6.38%	111
Manufacturing	1.03%	4.76%	566
Energy	1.10%	5.61%	145
Equipment	1.17%	5.98%	498
Telecom	0.85%	4.22%	63
Shops	1.10%	4.80%	341
Health	1.16%	4.81%	273
Utilities	0.93%	3.95%	122
Other	1.01%	5.03%	1019
Average	**1.05%**	**4.96%**	**339**

10 Size Portfolios			
Portfolio	**Avg. ret.**	**Std. Dev.**	**Firms**
Small	1.36%	6.57%	1511
2	1.26%	6.21%	409
3	1.28%	5.79%	285
4	1.22%	5.57%	230
5	1.20%	5.36%	196
6	1.16%	5.06%	171
7	1.17%	5.00%	157
8	1.14%	4.77%	150
9	1.09%	4.43%	141
Large	0.96%	4.06%	136
Average	**1.18%**	**5.28%**	**339**

25 Size-B/M Portfolios*				
Portfolio		**Avg. ret.**	**Std. Dev.**	**Firms**
Small:	Low	0.85%	7.58%	323
	2	1.29%	6.61%	204
	3	1.32%	5.98%	200
	4	1.49%	5.61%	236
	High	1.62%	5.92%	431
2:	Low	0.98%	7.11%	101
	2	1.22%	6.06%	79
	3	1.35%	5.40%	81
	4	1.45%	5.05%	79
	High	1.56%	5.71%	66
3:	Low	1.05%	6.50%	81
	2	1.25%	5.52%	65
	3	1.20%	4.90%	65
	4	1.36%	4.70%	57
	High	1.51%	5.36%	41
4:	Low	1.10%	5.77%	77
	2	1.01%	5.15%	62
	3	1.16%	4.76%	52
	4	1.37%	4.65%	43
	High	1.44%	5.29%	28
Large:	Low	1.07%	4.72%	88
	2	1.02%	4.51%	59
	3	1.01%	4.27%	44
	4	1.13%	4.23%	34
	High	1.22%	4.68%	20
Average		**1.24%**	**5.44%**	**105**

Table 4.2: Summary Statistics for portfolios formed from all NYSE, AMEX and Nasdaq stock during the period January 1941 to December 1999, (*Results for May 1963 to December 1999). The table report the average value weighted return, standard deviation and the average number of firms for each portfolio throughout the time period.

We note for the Ken French size portfolios, the returns vary from a minimum of 0.96% to a maximum of 1.36% in the 1941-1999 sample. The standard deviations vary from 4.06% to 6.57%. Lewellen notes a minimum return of 1.06% and a maximum of 1.48% with standard deviations varying from 3.97% to 6.78%. While there are some deviations in returns, despite both Lewellen and Ken French using NYSE breakpoints portfolio construction, we note that similar patterns arise. For example, we note that for both the Ken French size portfolios and Lewellen's portfolios the large firms experience the lowest return as well as the lowest standard deviations. Both samples experience increased return and standard deviations with a decrease in size.

One explanation for differences is the changes in the CRSP-data from the recently completed *"Pre62 Daily Data Series Project"*. The project added new daily data that resulted in changes to month-end prices. In addition to this, CRSP have since 2013 started to backfill shares outstanding data and including pre 1947 shares outstanding data. Lewellen did not have access to accounting data prior to 1963, thus all tests which utilizes accounting data is limited to the sample period May 1963 to December 1999. Ken French's data library have no such restriction and thus we utilize the full sample from 1941 to 2021. These month-end changes affect our autocovariance matrix and the differences can be seen in Table 4.3 below. We compare the results of the 5 size portfolios and the 5 B/M portfolios. All differences between the correlation coefficients in the size portfolios are 0.01 or less. Lewellen's results are slightly more negative for all correlations. The B/M portfolios contains somewhat larger differences, but none greater than 0.02.

	5 Size Value Weight 41-99						Lewellen (2002) 5 Size Value Weight 41-99				
	$\mathbf{R}_{\mathbf{Small},t}$	$\mathbf{R}_{\mathbf{2},t}$	$\mathbf{R}_{\mathbf{3},t}$	$\mathbf{R}_{\mathbf{4},t}$	$\mathbf{R}_{\mathbf{Large},t}$		$\mathbf{R}_{\mathbf{Small},t}$	$\mathbf{R}_{\mathbf{2},t}$	$\mathbf{R}_{\mathbf{3},t}$	$\mathbf{R}_{\mathbf{4},t}$	$\mathbf{R}_{\mathbf{Large},t}$
$\mathbf{R}_{\mathbf{Small},t-k}$	-0.02	-0.03	-0.03	**-0.04**	**-0.04**	$\mathbf{R}_{\mathbf{Small},t-k}$	-0.02	-0.03	-0.03	**-0.05**	**-0.05**
$\mathbf{R}_{\mathbf{2},t-k}$	-0.04	-0.04	-0.04	-0.05	-0.05	$\mathbf{R}_{\mathbf{2},t-k}$	-0.04	-0.04	-0.04	-0.05	-0.05
$\mathbf{R}_{\mathbf{3},t-k}$	**-0.04**	-0.05	-0.05	**-0.05**	-0.05	$\mathbf{R}_{\mathbf{3},t-k}$	**-0.05**	-0.05	-0.05	**-0.06**	-0.05
$\mathbf{R}_{\mathbf{4},t-k}$	**-0.06**	**-0.06**	-0.06	**-0.06**	-0.05	$\mathbf{R}_{\mathbf{4},t-k}$	**-0.07**	**-0.07**	-0.06	**-0.07**	-0.05
$\mathbf{R}_{\mathbf{Large},t-k}$	**-0.09**	-0.08	-0.07	-0.07	-0.04	$\mathbf{R}_{\mathbf{Large},t-k}$	**-0.10**	-0.08	-0.07	-0.07	-0.04

	5 B/M Value Weight 63-99						Lewellen (2002) 5 B/M Value Weight 63-99				
	$\mathbf{R}_{\mathbf{Low},t}$	$\mathbf{R}_{\mathbf{2},t}$	$\mathbf{R}_{\mathbf{3},t}$	$\mathbf{R}_{\mathbf{4},t}$	$\mathbf{R}_{\mathbf{High},t}$		$\mathbf{R}_{\mathbf{Low},t}$	$\mathbf{R}_{\mathbf{2},t}$	$\mathbf{R}_{\mathbf{3},t}$	$\mathbf{R}_{\mathbf{4},t}$	$\mathbf{R}_{\mathbf{High},t}$
$\mathbf{R}_{\mathbf{Low},t-k}$	**-0.05**	-0.07	**-0.06**	**-0.07**	**-0.07**	$\mathbf{R}_{\mathbf{Low},t-k}$	**-0.04**	-0.07	**-0.05**	**-0.08**	**-0.08**
$\mathbf{R}_{\mathbf{2},t-k}$	-0.03	-0.04	**-0.04**	-0.05	**-0.04**	$\mathbf{R}_{\mathbf{2},t-k}$	-0.03	-0.04	**-0.02**	-0.05	**-0.06**
$\mathbf{R}_{\mathbf{3},t-k}$	-0.04	**-0.05**	**-0.04**	-0.05	**-0.05**	$\mathbf{R}_{\mathbf{3},t-k}$	-0.04	**-0.04**	**-0.02**	-0.05	**-0.06**
$\mathbf{R}_{\mathbf{4},t-k}$	-0.05	-0.03	**-0.03**	-0.03	**-0.05**	$\mathbf{R}_{\mathbf{4},t-k}$	-0.05	-0.03	**-0.01**	-0.03	**-0.04**
$\mathbf{R}_{\mathbf{High},t-k}$	**-0.05**	**-0.03**	-0.02	-0.04	-0.04	$\mathbf{R}_{\mathbf{High},t-k}$	**-0.06**	**-0.02**	-0.02	-0.04	-0.04

Table 4.3: The table displays the average serial correlation in the 5 size and 5 B/M portfolios from our own research and those of Lewellen (2002) during the time period 1941 to 1999, and 1963 to 1999 respectively. The portfolios are formed from all NYSE, AMEX and Nasdaq stocks. Bold denotes correlation coefficients that differs with more than 0.005.

5 Results and Analysis

5.1 Momentum Profits

In this section we assess our first hypothesis by establishing the basic results of the momentum strategies. We utilize the methodology described in Section 3.2 to construct our portfolios.

			Month after formation								
Assets			1	3	5	7	9	11	13	15	17
Individual Stocks											
		Avg. ret.	**0.582**	**0.321**	**0.197**	0.108	-0.038	-0.089	**-0.281**	**-0.153**	**-0.182**
		t-statistic	5.65	3.35	2.18	1.30	-0.47	-1.13	-3.60	-2.09	-2.59
10 Industry Portfolios											
	VW	Avg. ret.	**0.540**	**0.375**	**0.228**	0.165	0.046	-0.138	**-0.252**	**-0.361**	**-0.365**
		t-statistic	4.27	3.00	1.85	1.35	0.37	-1.16	-2.16	-3.07	-3.22
	EW	Avg. ret.	**1.148**	**0.640**	**0.337**	0.159	-0.063	-0.220	**-0.356**	**-0.381**	**-0.386**
		t-statistic	7.05	4.22	2.26	1.09	-0.43	-1.54	-2.56	-2.71	-2.84
5 Size Portfolios											
	VW	Avg. ret.	**0.355**	**0.247**	**0.302**	**0.320**	**0.253**	**0.176**	0.151	**0.218**	0.132
		t-statistic	3.83	2.71	3.34	3.44	2.64	1.79	1.58	2.32	1.46
	EW	Avg. ret.	**0.449**	**0.285**	**0.323**	**0.336**	**0.252**	0.165	**0.167**	**0.169**	0.098
		t-statistic	4.44	2.96	3.40	3.45	2.52	1.59	1.66	1.76	1.05
10 Size Portfolios											
	VW	Avg. ret.	**0.340**	**0.246**	**0.270**	**0.278**	**0.227**	**0.173**	**0.145**	**0.211**	**0.116**
		t-statistic	3.87	2.79	3.22	3.28	2.55	1.90	1.65	2.46	1.41
	EW	Avg. ret.	**0.451**	**0.310**	**0.356**	**0.356**	**0.258**	**0.179**	**0.170**	**0.189**	0.112
		t-statistic	4.48	3.23	3.84	3.75	2.66	1.80	1.77	2.13	1.29
5 B/M Portfolios											
	VW	Avg. ret.	**0.391**	**0.238**	**0.163**	0.108	0.069	0.025	-0.011	-0.037	-0.024
		t-statistic	4.69	2.96	2.03	1.31	0.84	0.31	-0.13	-0.46	-0.30
	EW	Avg. ret.	**0.680**	**0.444**	**0.358**	**0.367**	**0.276**	**0.179**	0.132	0.087	**0.162**
		t-statistic	7.65	5.21	4.25	4.36	3.22	2.07	1.52	1.05	2.06
10 B/M Portfolios											
	VW	Avg. ret.	**0.422**	**0.269**	**0.203**	**0.132**	0.087	0.044	0.015	-0.036	-0.051
		t-statistic	4.98	3.38	2.53	1.64	1.07	0.56	0.18	-0.49	-0.66
	EW	Avg. ret.	**0.671**	**0.465**	**0.368**	**0.365**	**0.287**	**0.206**	**0.158**	0.103	**0.156**
		t-statistic	7.22	5.25	4.31	4.39	3.41	2.39	1.85	1.29	2.05
6 size-B/M Portfolios											
	VW	Avg. ret.	**0.552**	**0.335**	**0.292**	**0.243**	**0.210**	0.090	0.049	0.096	0.104
		t-statistic	5.43	3.37	3.06	2.55	2.15	0.94	0.51	1.00	1.12
	EW	Avg. ret.	**0.690**	**0.449**	**0.393**	**0.362**	**0.278**	**0.172**	0.154	0.137	**0.157**
		t-statistic	6.16	4.27	3.84	3.61	2.72	1.69	1.54	1.40	1.67
25 Size-B/M Portfolios											
	VW	Avg. ret.	**0.521**	**0.350**	**0.278**	**0.254**	**0.212**	0.128	0.077	0.082	0.077
		t-statistic	4.98	3.45	2.85	2.81	2.34	1.42	0.86	0.90	0.87
	EW	Avg. ret.	**0.555**	**0.388**	**0.307**	**0.296**	**0.187**	0.111	0.074	0.083	0.090
		t-statistic	5.18	3.81	3.13	3.15	1.95	1.16	0.79	0.90	1.01

Table 5.1: The table present momentum profit for strategies based on 12 month formation periods during the time period Jan. 1941 to Dec. 2021. They utilize all NYSE, AMEX and Nasdaq stocks. The strategies use individual stocks and portfolios sorted by industry, size and B/M (equal or value weighted, as seen in the table). The weights are rescaled to have \$1 long and \$1 short. Returns are measured in percent. Bold denotes estimates greater than 1.645 standard errors from zero.

We see the results of the strategy implemented on the different sets of portfolios presented in Table 5.1 above. The strategies use the average past 12 month return to calculate their portfolio weights. We invest $w_{i,t} = \frac{1}{N}(r_{i,t-1} - r_{m,t-1})$ in asset i, where $r_{i,t-i} - r_{m,t-1}$ is the lagged return of the asset in excess of the equal weighted index; we rescale the weights so that we are always \$1 long and \$1 short. There are two reasons why constructing portfolios $w_{i,t} = \frac{1}{N}(r_{i,t-1} - r_{m,t-1})$ will be more convenient for our research than constructing it by upper and lower percentiles. First, Lo and MacKinlay (1990) argued that strategies using these weights easily can be tied to autocorrelation in returns. Second, using these weights will include all assets, and not just the extremes. We get momentum profits for each lag up to 18 months after formation. For simplicity, the table only report the odd months return, even though discussions will frequently refer to the omitted months.

Both momentum in individual stock and across industry portfolios generates significant profit for the first 5 months after formation. However, these returns turn negative around 9 to 10 months after formation. Also, these negative returns become significant from month 11. Individual stocks experience a cumulative profit of 1.95% per dollar long after 6 months. In comparison, the value-weighted industries portfolios accumulate to 2.11%, while the equal-weighted industries portfolios achieve a 3.64% cumulative profit over the first 6 months.

We see that momentum is as strong, and often even stronger over longer periods in size- and size-B/M portfolios than what it is in individual stocks and industries. This is consistent with previous research done by e.g. Lewellen (2002) and Jegadeesh and Titman (2011). Throughout the first 6 months after formation, value-weighted size, B/M, and size-BM portfolios are 2.11%, 1.44%, and 2.15% respectively, with significant t-statistics of 3.17, 2.96, and 3.76. We also note that the profits for the equal-weighted portfolios are all strictly larger than those of their corresponding value-weight portfolios. The results implies that the size and B/M strategies inherit relatively large Sharpe Ratios equal to their t-statistics divided by $\sqrt{T}$.[7] For example, individual stocks 1 month return has a t-statistic of 5.65. This results in a Sharpe ratio of 0.18. In contrast to momentum profits on individual stocks, the table shows that momentum profits on size and B/M portfolios decay relatively slowly compared to individual stock and industry momentum. Especially for the size portfolios, we usually achieve significant results for all 18 months. The B/M portfolios and size-B/M portfolios are usually significant for up to about 10 months after formation.

The fact that we achieve significant results from the size and B/M portfolios can be interpreted as evidence that momentum returns is not solely being generated through firm-specific characteristics. First of all, we have relatively diversified size- and B/M portfolios, usually containing more than a hundred firms on average. Furthermore, Table 5.1: *Momentum Profits* shows that broadening the portfolios will have just a minor effect on momentum profits. The estimates in the 5- and 10-size portfolios are quite similar to each other. The same applies for both the 5- and 10-B/M portfolios, and the 6- and 25-size-B/M portfolios. Because of this diversification, we can argue that these portfolios should not inherit much idiosyncratic risk, thus making it seem likely that macroeconomic factors can explain their momentum profit.

Lewellen (2002) further explored the connection between firm, industry and size-B/M momentum by using benchmark-adjusted profits instead of raw profits. He matched each stock either to its respective industry, size decile or size-B/M quintile and then estimated profit of each strategy using returns in excess of the market. E.g., for industry momentum, he matched every stock with its belonging size decile and size-B/M quintile before forming the industry portfolios. The industry return was then the average of size and size-B/M adjusted returns for the stocks in that industry. The importance of this finding was that industry, size and size-B/M each appears to be distinct from each other. Lewellen claimed that these observations could imply one of two tings; "either firm-specific

[7] For our sample period of January 1941 to December 2021, T = 972

returns do not explain momentum at all, or there must be multiple sources of momentum in returns", (Lewellen, 2002).

5.2 Autocorrelation Patterns in Returns

The results in Section 5.1 suggests that momentum can not be fully explained by firm-specifics. In Section 3.5 we presented two models of momentum proposed by Lewellen (2002) which discussed in detail how and why momentum could occur. They illustrated how momentum consistently inherit patterns of autocorrelation and cross-serial correlation in returns. For the remainder of this thesis, we will investigate mentioned autocorrelation patterns in value-weighted industry, size and B/M portfolios with the intention to get a better understanding of what drives momentum.

In this section we will test whether the annual return of a portfolio is correlated with its own monthly return, and also how it is correlated with other portfolios' monthly return for different lags for up to 18 months. We remember from Section 3.2 that the average autocovariance is given by $\frac{\text{tr}(\Omega)}{N}$, while $\frac{\iota'\Omega\iota}{N^2}$ is the autocovariance of the market portfolio. Footnote 4 in Section 3.2 describes how we adjust this to multiple-period returns. We will investigate the resulting autocovariance matrix $\Delta_k \equiv E\left[\left(r_t^{12} - \gamma\right)\left(r_{t+k} - \mu\right)'\right]$ where γ and μ are the vectors of the expected 12- and 1 month returns, and k is the specific holding period.

5.2.1 Autocorrelations

Table 5.2 shows the autocovariance matrix for 10 industry portfolios, 5 size portfolios and 5 B/M portfolios. As a table containing all lags would be too large, Table 5.2 reports the average of the 18 lags.

In accordance with the definition of Δ_k above, the portfolio used as the predictive variable changes when we move down the columns. Meanwhile, the portfolio which has its return being predicted will change as we move across rows. As statistical significance is hard to assess analytically, we use bootstrap simulations to replicate the empirical tests. We do this using artificial time-series of returns which are created by sampling replacement from the actual return series. As we repeat this procedure 1 000 times, we create a sampling distribution under the null. We see the results presented in Table 5.2 below.

Industry Portfolios

	$\mathbf{R}_{1,t}$	$\mathbf{R}_{2,t}$	$\mathbf{R}_{3,t}$	$\mathbf{R}_{4,t}$	$\mathbf{R}_{5,t}$	$\mathbf{R}_{6,t}$	$\mathbf{R}_{7,t}$	$\mathbf{R}_{8,t}$	$\mathbf{R}_{9,t}$	$\mathbf{R}_{10,t}$
$\mathbf{R}_{1,t-k}$	-0.03	-0.05	-0.04	-0.02	-0.04	0.01	-0.03	-0.01	-0.02	-0.04
$\mathbf{R}_{2,t-k}$	-0.04	-0.05	-0.03	0.01	-0.01	0.00	-0.04	-0.01	0.00	-0,03
$\mathbf{R}_{3,t-k}$	**-0.06**	**-0.09**	**-0.06**	-0.02	-0.05	-0.03	**-0.07**	-0.02	-0.03	**-0.07**
$\mathbf{R}_{4,t-k}$	**-0.06**.	**-0.10**	**-0.07**	-0.04	**-0.08**	-0.05	**-0.07**	-0.03	-0.03	**-0.07**
$\mathbf{R}_{5,t-k}$	-0.02	-0.04	-0.03	-0.00	-0.01	-0.00	-0.03	0.01	0.02	-0.02
$\mathbf{R}_{6,t-k}$	-0.01	-0.04	-0.03	-0.04	0.00	0.03	-0.02	0.01	0.01	-0,04
$\mathbf{R}_{7,t-k}$	-0,05	-0,04	-0,04	-0.02	-0.02	0.00	-0.05	-0.02	-0.02	-0,05
$\mathbf{R}_{8,t-k}$	-0,03	-0,04	-0,04	-0.02	-0.03	0.00	-0.03	-0.01	-0.03	-0,04
$\mathbf{R}_{9,t-k}$	-0,04	-0,04	-0,04	-0.03	-0.04	-0.03	-0.04	-0.03	-0.05	-0,05
$\mathbf{R}_{10,t-k}$	-0,04	-0,06	-0,04	-0.01	-0.02	-0.01	-0.04	-0.01	-0.01	-0,04

Size Portfolios

	$\mathbf{R}_{\text{Small},t}$	$\mathbf{R}_{2,t}$	$\mathbf{R}_{3,t}$	$\mathbf{R}_{4,t}$	$\mathbf{R}_{\text{Big},t}$
$\mathbf{R}_{\text{Small},t-k}$	- 0.03	- 0.03	- 0.04	- 0.04	- 0.04
$\mathbf{R}_{2,t-k}$	**-0.05**	- 0.04	- 0.04	- 0.05	- 0.04
$\mathbf{R}_{3,t-k}$	**-0.06**	- 0.05	- 0.05	- 0.05	- 0.04
$\mathbf{R}_{4,t-k}$	**-0.07**	**-0.06**	**-0.06**	**-0.06**	- 0.04
$\mathbf{R}_{\text{Big},t-k}$	**-0.08**	**-0.06**	**-0.06**	- 0.05	- 0.02

B/M Portfolios

	$\mathbf{R}_{\text{Low},t}$	$\mathbf{R}_{2,t}$	$\mathbf{R}_{3,t}$	$\mathbf{R}_{4,t}$	$\mathbf{R}_{\text{High},t}$
$R_{\text{Low},t-k}$	-0.03	-0.05	-0.04	-0.05	-0.05
$R_{2,t-k}$	-0.05	-0.05	-0.05	**-0.06**	**-0.07**
$R_{3,t-k}$	-0.04	-0.05	-0.04	-0.06	**-0.06**
$R_{4,t-k}$	-0.05	-0.05	-0.05	-0.06	-0.06
$R_{\text{High},t-k}$	-0.04	-0.04	-0.03	-0.05	-0.06

Table 5.2: The table displays the average serial correlation in the industry, size and B/M portfolios during the time period 1941 - 2021. Bold denotes estimates that are significant at the 10% level based on bootstrap simulations.

The results of Table 5.2 shows that both autocorrelations and cross-serial correlations are always negative in the size and B/M portfolios. In the industry portfolios, we do find that Telecom (industry 6) exhibits positive autocorrelation. The industry portfolios also exhibit a few positive cross-serial correlations. However, none of these positive estimates are significant based on the bootstrap simulations. Across all portfolios, we achieve an average autocorrelation of -0.040, and an average cross-serial correlation of -0.044.

There are several interesting patterns to take notice of in the table. We see that the autocorrelation in the size portfolios is at their most negative in the third and fourth biggest quintiles, with -0.05 and -0.06 respectively. We also find that the autocorrelations are closer to zero for the very smallest and largest firms. Furthermore, the matrices are not symmetric for the size portfolios. Below the diagonal, the estimates are generally greater than the estimates above the diagonal. This indicates a lead-lag relation between these portfolios. Put differently, larger stocks seem to be "leading" smaller stocks.

Furthermore, Table 5.2 shows that reversal, not continuation, dominates the autocorrelation matrices[8]. As this observation falls true regarding all portfolios, this pattern does not seem to occur because of something specific about the certain way a portfolio is created. Moving on, the only two places where we actually find significant, average autocorrelation estimates are in the Manufacturing portfolio (industry 3) and in the size 4 quintile. With the exception of the size portfolios, we see little significance in either autocorrelations or in cross-serial correlations.

These findings are consistent with the overreaction model proposed by Lewellen (2002) in Section 3.5.4. We find little evidence of persistence in returns which the underreaction theory suggests. An alternative theory is that investors might underreact to portfolio specific news but overreact to market news.

Table 5.2 also provides intuition in how to distinguish between the different models. First, let's address the portfolio-specific underreaction story. The intuition behind this theory is that investors can react different to market-wide and idiosyncratic news. This is however something that is difficult for behavioral models to explain, (Jegadeesh and Titman, 2011). A number of previous research on the topic does not differentiate between the two types of news. They claim that their models apply to both firm-specific and general market news, (Barberis et al. (1998), Hong et al. (2007a)). Thus, even if you could argue that portfolio-specific underreaction could explain momentum returns, the results in Table 5.2 would reject that these behavioral models should be considered a general description of prices.

Another flaw to the underreaction theory is that the momentum returns for our size and B/M quintiles can't reasonably be characterized as idiosyncratic, as these portfolios are quite broad, and we consider them

[8]We will later see that changing the length of the horizons will impact these results.

macroeconomic. There is also a substantial amount of evidence that the return of such portfolios capture the common risk factors in returns, (e.g., Fama and French (2008)). This doesn't create much basis for predicting that investors might underreact to the size- and B/M-specific news, only to overreact to market-wide news (both being considered macroeconomic). The overreaction model proposed in Section 3.5.4 does however not require investors to react differently between one type of news rather than the other. It only states that momentum and negative autocorrelation could stem from the same source.

Based on the arguments of Lewellen (2002), the results from our size quintiles would provide further evidence against portfolio-specific underreaction. He assumed that negative autocorrelation could be entirely driven by market reversals. In that case, the autocorrelation of a portfolio should be a weighted average of the market and portfolio-specific return autocorrelation:

$$\operatorname{cor}(r_{it}, r_{it-1}) = \lambda_i \operatorname{cor}(r_{mt}, r_{mt-1}) + (1 - \lambda_i) \operatorname{cor}(\varepsilon_{it}, \varepsilon_{it-1}) \tag{5.1}$$

where λ_i is the squared correlation between r_i and r_m.[9] According to the model proposed by Lewellen (2002), then this should mean that most of the variation in $\operatorname{cor}(r_{it}, r_{it-1})$ should stem from differences in λ_i. To put it another way, if it's market reversals that explain negative autocorrelation, then the portfolios that have the least amount of idiosyncratic risk would be the ones who are the most negatively autocorrelated. Our results shows that this however is not true. Quintile 5 contains the least amount of idiosyncratic risk. λ_i varies from 0.68 in Quintile 1, to 0.98 in Quintile 5. However, the autocorrelation of Quintile 5 is the closest to zero.

The results of the cross-serial correlations based on a 12-month formation period are also somewhat hard to reconcile with portfolio-specific underreaction. Based on our results above, should market reversals

[9] $\operatorname{Cor}(r_{it}, r_{it-1}) = \operatorname{cov}(r_{it}, r_{it-1}) / \operatorname{var}(r_i) = \left(\beta_i^2 \rho_m + \rho_{\varepsilon i}\right) / \operatorname{var}(r_i)$ where ρ_m and $\rho_{\varepsilon i}$ are market- and portfolio-specific return autocovariances. Equation 5.1 then comes from substituting $\rho_m = \operatorname{var}(r_m) \times \operatorname{cor}(r_{mt}, r_{mt-1})$ and $\rho_{\varepsilon i} = \operatorname{var}(\varepsilon_i) \times \operatorname{cor}(\varepsilon_{it}, \varepsilon_{it-1})$ in the numerator

explain cross-serial covariances, then the covariance between $r_{i,t}$ and $r_{j,t-1}$ can be expressed as $\beta_i \beta_j \rho_M$, Lewellen (2002). Collecting assets, we get the covariance matrix $\text{cov}(r_{t-1}, r_t) = \beta\beta' \rho_M$ that has rows and columns proportional to the vector of market betas. Likewise, the cross-serial correlations matrix should have rows proportional to the vector of correlations with the market portfolio.[10] Table 5.2 shows that this however is not true. The cross-serial correlations in the bottom row of the size portfolios inherits the wrong pattern for this to be the case. The smaller stocks should be the ones with correlations closest to zero, as these should be the least similar to the stocks in the "Big" quintile. Additionally, when we move up the matrix we see a reversion in the coefficient pattern, showing that the rows are not proportional to each other.

Lewellen (2002) argued that cross-serial correlations could stem from the excess-covariance model from Section 3.5.4. However, his proposed model is not accurate enough to make decent predictions regarding autocorrelation and cross-serial correlation patterns, besides that they ought to be negative.

5.2.2 Autocorrelations and The Return Horizon

Even though Table 5.2 is an informative summary of the results, they mask how the autocorrelation changes across lags. This section seeks to further explore how autocorrelation changes as lags varies between 1 and 18 months. Table 5.3 below shows only autocorrelations, as we do not find it practical to report cross-serial correlations for each lag.

[10] Lewellen (2002) pre- and post-multiply the covariance matrix by S^{-1}, where S is a diagonal matrix with the std. deviation of the portfolios along the diagonal

Portfolio	Return Horizon (months) 1	3	5	7	9	11	13	15	17
Industry Portfolios									
Non-durables	0.009	-0.003	-0.004	-0.004	-0.010	-0.011	**-0.015**.	-0.010	-0.011
Durables	0.012	-0.003	-0.009	-0.005	**-0.015**	**-0.023**	**-0.030**	**-0.025**	**-0.027**
Manufacturing	-0.003	-0.015	**-0.016**	**-0.016**	**-0.020**	**-0.024**	**-0.023**	**-0.018**	**-0.022**
Energy	0.002	0.004	-0.002	-0.007	**-0.016**	**-0.019**	**-0.014**	**-0.020**	**-0.022**
Equipment	0.010	0.000	0.000	0.000	-0.003	-0.007	-0.007	-0.004	-0.007
Telecom	**0.024**	**0.020**	**0.014**	0.005	0.000	0.001	-0.002	0.003	0.000
Shops	0.007	-0.010	-0.011	-0.010	-0.009	**-0.016**	**-0.024**	**-0.015**	**-0.015**
Health	0.010	0.002	0.005	0.002	-0.003	-0.005	-0.008	-0.007	-0.007
Utilities	0.006	0.001	-0.010	**-0.019**	**-0.022**	**-0.018**	**-0.017**	-0.010	-0.010
Other	0.008	-0.008	-0.08	-0.009	-0.010	-0.012	**-0.018**	-0.011	**-0.015**
Average	0.009	-0.001	-0.004	-0.006	-0.011	-0.013	**-0.016**	-0.012	-0.014
Size Portfolios									
Small	0.012	-0.007	-0.005	-0.008	**-0.014**	-0.010	**-0.014**	-0.009	-0.011
2	0.002	**-0.015**	-0.008	-0.010	**-0.015**	**-0.014**	**-0.016**	-0.007	-0.013
3	-0.000	**-0.016**	-0.012	**-0.014**	**-0.015**	**-0.016**	**-0.017**	-0.009	**-0.014**
4	-0.003	**-0.017**	**-0.014**	**-0.017**	**-0.020**	**-0.021**	**-0.020**	-0.013	**-0.018**
Big	0.009	-0.001	-0.002	-0.004	-0.008	-0.012	-0.012	-0.008	-0.010
Average	0.004	-0.011	-0.008	-0.011	**-0.014**	**-0.015**	**-0.016**	-0.009	-0.013
Size-B/M Portfolios									
Small: Low	0.003	**-0.016**	-0.008	-0.008	**-0.015**	**-0.015**	**-0.017**	-0.009	-0.011
2	0.005	-0.012	-0.006	-0.009	**-0.014**	**-0.014**	**-0.017**	-0.011	**-0.018**
High	0.011	-0.006	-0.005	-0.009	-0.013	-0.012	**-0.016**	-0.009	**-0.016**
Big: Low	0.004	-0.005	-0.006	-0.005	-0.008	-0.012	-0.012	-0.009	-0.010
2	0.004	-0.006	-0.008	-0.013	**-0.017**	**-0.018**	**-0.018**	-0.009	**-0.015**
High	0.010	-0.006	-0.008	-0.012	**-0.018**	**-0.020**	**-0.021**	**-0.015**	**-0.020**
Average	0.006	-0.009	-0.007	-0.009	**-0.014**	**-0.015**	**-0.017**	-0.010	**-0.015**

Table 5.3: Autocorrelation, 1941 - 2021. The table displays autocorrelation estimates for value-weighted industry, size and size-B/M portfolios. Bold marks estimates greater 1.645 standard errors from zero. Ljung-Box Q-statistics is displayed in Table A4.1

Again, we see no strong evidence of persistence in returns when looking at autocorrelations, even at short-term horizons. For the size and size-B/M portfolios, we achieve uniformly negative estimates beyond the first month. However, for the industry portfolios, we see that several of the industries exhibits positive autocorrelation even up to 3 months after formation. These estimates are however not significant. There are two industries that stands out. The *Health* sector (industry 8) generate positive autocorrelations up until month 7, while *Telecom* (industry 6) only exhibits negative autocorrelation between month 9 and 13. However, other than for Telecom, all positive autocorrelations after the first month are insignificant. These results coincides with the research conducted by Lo and MacKinlay (1990) and Jegadeesh and Titman (1995). They argued that weekly lead-lag patterns have little effect on momentum profits.

We also observe that the estimates gradually decline for about 10 months. For size, the average autocorrelation in month 2 is -0.008, while in month 10 it drops down to -0.015. For the size portfolios, the estimates are more than 1.75 standard errors from zero in month 8 to 13. The industry portfolios follow the same pattern, averaging an autocorrelation of 0.002 in month 2 before it reaches its most negative average in month 13 at -0.016. Again, estimates are 1.75 standard deviations below zero in month 12 and 13. The way autocorrelations follows a U-shaped pattern is not reflected in momentum profits as we see them in Table 5.1.

When looking at the estimates from an economic point of view, they imply that there is significant time variation in returns. Normally, annual returns contain standard deviation that varies between 20 and 25%. E.g., a one standard deviation increase in annual returns, with a slope coefficient of -0.01, would imply a 20 to 25 basis point drop in future returns. We have many estimates of this size. E.g., the cumulative slope coefficient for the average size portfolio is -0.044 over the first 6 months, and -0.130 over the first 12 months. For industry, the corresponding estimates are -0.003 and -0.071, while for size-B/M it's -0.034 and -0.122. From this rationale, a change in expected return seems to be economically large and of significance.

5.2.3 Autocorrelations and Momentum Profits

Purely based on the results above, there is reason to argue that momentum is not something than can be explained by persistence in returns and the underreaction theory. Utilizing the Lo and MacKinlay (1990) decomposition, we investigate this claim. We recall from Equation 3.5 that expected momentum profit can be broken down into three parts:

$$E\left[\pi_{t+k}\right] = \frac{N-1}{N^2}\operatorname{tr}\left(\Delta_k\right) - \frac{1}{N^2}\left[\iota'\Delta_k\iota - \operatorname{tr}\left(\Delta_k\right)\right] + \sigma_{\mu,\gamma} \tag{5.2}$$

Here, Δ_k is the autocovariance matrix[11] defined in Section 5.2, describing the covariance between r_{t+k} and r_t^{12}. The cross-sectional covariance between 1- and 12-month expected returns is defined by $\sigma_{\mu,\gamma}$.

The first term catches autocorrelations in profits, denoted as *Auto* in Table 5.4. The second term is dependent on the cross-serial correlations, which is denoted *Cross* in the table. The final term catches the effect of cross-sectional dispersion in unconditional means, which we denote *Means* in the table.

	Industry Portfolios				5 Size Portfolios				6 Size-B/M Portfolios			
Month	Auto	Cross	Means	Total	Auto	Cross	Means	Total	Auto	Cross	Means	Total
1	2.93	-0.80	0.06	**2.19**	1.24	-0.43	0.07	**0.87**	1.96	-0.65	**0.38**	**1.71**
3	-0.28	2.02	0.06	1.80	-3.25	**4.08**	0.06	**0.90**	-2.61	**3.55**	**0.36**	**1.29**
5	-1.28	2.35	0.06	1.14	-2.35	3.26	0.07	**0.97**	-2.14	2.94	**0.37**	**1.16**
7	-2.07	2.61	0.06	0.60	-3.09	**3.94**	0.08	**0.93**	-2.93	**3.51**	**0.37**	0.96.
9	**-3.59**	**3.43**	0.06	-0.10	**-4.23**	**4.89**	0.08	**0.74**	**-4.39**	**4.58**	**0.38**	0.58
11	**-4.42**	**3.87**	0.06	-0.49	**-4.28**	**5.06**	0.07	**0.85**	**-4.71**	**4.99**	**0.38**	0.65
13	**-5.22**	**4.01**	0.06	-1.15	**-4.66**	**5.26**	0.07	**0.68**	**-5.21**	**5.40**	**0.37**	0.57
15	**-3.82**	2.18	0.06	-1.58	-2.70	**3.21**	0.06	**0.58**	-3.24	**3.34**	**0.36**	0.47
17	**-4.46**	**2.88**	0.06	-1.52	**-3.89**	**4.35**	0.06	0.51	**-4.65**	**4.78**	**0.35**	0.48
Bootstrap SE	2.10	1.75	0.05	1.14	2.32	2.14	0.09	0.39	2.46	2.03	0.10	0.61

Table 5.4: Decomposition of momentum profits, 1941 - 2021. The table displays total profits. We invest $w_{it} = (1/N)\,(r_{i,t-1} - r_{m,t-1})$ in asset i, where $(r_{i,t-1} - r_{m,t-1})$ is the lagged return of an asset in excess of the equal weighted index. Bold marks estimates greater than 1.645 standard errors from zero based on bootstrap simulations.

The results displayed in Table 5.4 substantiates the analysis from our previous results. We see that the autocorrelations are strictly negative for all portfolios after month 1 and is thus a reducing factor of momentum profits as of 3 months after formation. In month 3, the Auto-component for profits is -0.28 (t-statistic of -0.13) for the industry portfolios. It decreases to its lowest estimate in month 13 at -5.22 (t-statistic of -2.49). We can compare these estimates with their corresponding cross-serial components. The Cross-components for industry equal 2.02 (t-statistic of 1.15) and 4.01 (t-statistic of 2.30) in month 3 and 13 respectively. We see that total momentum profits decline and turns contrarian for the industry portfolios as the Cross-component does not fully offset the negative changes in the Auto-component. We see that the same pattern occurs in both the size- and size-B/M portfolios. However, here we see that total returns decrease more slowly, and does in fact never turn

[11] $\Delta_k \equiv E\left[\left(r_t^{12} - \gamma\right)\left(r_{t+k} - \mu\right)'\right]$

negative.

Looking at the cross-sectional variation in expected return, we see that it only has a minor effect on momentum profits. For industries, the Mean-component contributes to momentum by approximately 0.06% each month and are never significant. This is a small contribution relative to total profits which varies from 2.19% to -1.58%. We see the same results for size and B/M portfolios. However, the results for the double-sorted portfolios suggest that the Mean-component here has a more important role for momentum returns. We see it remains stable just below 0.40% over all months and are also all significant.

5.2.4 Market-adjusted Returns

Up until now, the analysis has presented us with two facts regarding market-adjusted returns. First, given the strategy weights in Section 3.2, momentum can be attributed to persistence in market-adjusted returns. This would imply that market-adjusted returns should exhibit positive autocorrelations. However, this will not help in distinguishing between the two models in Section 3.5. The second fact stems from what we see in the results from Section 5.2.1, where reversal in market returns does not seem fully explain the lead-lag relation among stocks. This suggests that market-adjusted returns should contain some interesting patterns of lead-lag relations.

Table 5.5 examines the predictability of market-adjusted returns. More precisely, it displays autocorrelations and cross-serial correlations for marked-adjusted returns. Market-adjusted return is simply defined as the return of the asset less the CRSP value-weighted market-index portfolio: $(r_i - r_{vw.mkt})$.

	Industry Portfolios									
	$R_{1,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{5,t}$	$R_{6,t}$	$R_{7,t}$	$R_{8,t}$	$R_{9,t}$	$R_{10,t}$
$R_{1,t-k}$	0.03	0.03	0.00	-0.03	-0.02	0.03	0.03	-0.02	-0.04	0.01
$R_{2,t-k}$	-0.05	-0.04	-0.02	0.03	0.03	0.01	-0.05	-0.02	0.00	-0.03
$R_{3,t-k}$	0.02	-0.06	0.02	0.03	-0.01	0.00	-0.03	0.01	0.01	-0.04
$R_{4,t-k}$	0.05	-0.04	0.01	0.00	-0.05	0.00	0.02	0.02	0.03	0.03
$R_{5,t-k}$	0.00	0.00	-0.02	0.01	0.02	-0.02	0.00	0.01	0.02	0.04
$R_{6,t-k}$	0.01	0.01	-0.01	-0.03	0.04	0.02	0.02	0.00	-0.02	-0.04
$R_{7,t-k}$	-0.02	0.05	0.01	-0.03	0.01	0.03	-0.01	-0.04	-0.02	-0.02
$R_{8,t-k}$	0.03	0.04	0.00	-0.03	0.01	0.01	0.03	0.00	-0.04	0.00
$R_{9,t-k}$	0.01	0.05	0.06	-0.03	0.00	-0.03	0.03	-0.04	-0.05	0.00
$R_{10,t-k}$	-0.02	-0.02	-0.01	0.00	0.02	-0.01	0.01	-0.01	-0.01	-0.01
Mkt	-0.01	-0.06	-0.04	0.03	-0.01	0.04	-0.02	0.04	0.04	-0.04

	Size Portfolios				
	$R_{Small,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{Big,t}$
$R_{Small,t-k}$	**0.07**	**0.07**	0.06	0.04	**-0.08**
$R_{2,t-k}$	0.06	0.06	0.05	0.02	**-0.07**
$R_{3,t-k}$	0.06	**0.07**	0.06	0.03	**-0.07**
$R_{4,t-k}$	0.06	0.07	0.06	0.04	-0.06
$R_{Big,t-k}$	-0.06	**-0.07**	-0.06	-0.02	**0.08**
Mkt	**-0.08**	**-0.07**	**-0.07**	**-0.07**	**0.08**

	B/M Portfolios				
	$R_{Low,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{High,t}$
$R_{Low,t-k}$	0.04	-0.03	-0.03	0.00	0.00
$R_{2,t-k}$	0.00	0.04	0.02	-0.02	-0.02
$R_{3,t-k}$	-0.03	-0.01	0.00	0.00	-0.03
$R_{4,t-k}$	-0.06	0.01	0.02	0.03	-0.02
$R_{High,t-k}$	**-0.06**	0.00	0.04	0.02	-0.03
Mkt	0.02	-0.01	0.00	0.00	-0.04

Table 5.5: Serial correlation of market-adjusted returns, 1941 - 2021. The table displays autocorrelations and cross-serial correlations for marked-adjusted returns. Market-adjusted return is the return on the asset less the CRSP value-weighted market-index portfolio ($r_i - r_{vw.mkt}$). The last row (Mkt) displays the correlation between the market-adjusted returns and the past value-weighted index returns. Bold marks estimates greater than 1.645 standard errors from zero based on bootstrap simulations.

The table show that we achieve positive autocorrelation on average for the industry, size and B/M portfolios of 0.00, 0.06 and 0.02 respectively. However, we do not achieve particularly significant results outside of the size portfolios. The size portfolios do all exhibit positive autocorrelations, although only *Small-stocks* and *Big-stocks* inherit estimates greater than 1.645 standard errors from zero based on bootstrap simulations. The estimates for the B/M portfolios are much weaker, and *High-stocks* actually exhibit negative autocorrelations. The autocorrelation seems to be the smallest and least significant for the industry portfolios. This is somewhat misleading. We remember from Table 5.1 that industry momentum only persists for about 10 months before turning into contrarian profits. Table 5.5 displays the mean over 18 months, which explains why the autocorrelations seems to be less significant here.

Moving on, cross-serial correlations also generate expected patterns of negative estimates, although not particularly significant except for between the size portfolios. However, they do reflect the contemporaneous correlation among portfolios. In their research, Boudoukh, Richardson and Whitelaw stated that lead-lag relations between portfolios depend on their contemporaneous correlations[12], (Boudoukh et al., 1994). Their conclusion holds only if $r_{i,t-1}$ doesn't inherit incremental information regarding $r_{j,t}$ beyond portfolio j's own past returns. It implies that autocorrelations in a given column should always be greater than the cross-serial correlation in the same column. Our results shows that the cross-serial correlations are usually consistent with this statement, except for in the industry portfolio. Here, we continuously see this restriction being violated.

Furthermore, in the bottom row of each panel we display the correlation between the lagged 12-month return on the CRSP value-weighted index and the portfolio-specific return. We find that market returns exhibit strong predictive power for the size portfolios. We achieve significant negative correlations for size quintiles 1 to 4, and positive significant for the Big size stocks. There are also significant estimates for several industry and High B/M stocks. Thus, in addition to being predictable by its own past return, portfolio-specific returns could also be predicted using the return of the market. This result is consistent with the theory on excess covariance in returns proposed by Lewellen (2002).

5.3 Reconciling Theories

Up until now we have utilized the same methods and return horizons as Lewellen (2002). We have found that cross-serial correlation is what drives momentum under these strategies, and we find little evidence that support the underreaction theories. Pan (2010) argued that different return horizons would however affect these results. Thus, in this section we assess the second part of our research question by examining how the role of autocorrelation and cross-serial correlation change over different horizons.

Theoretically, momentum should correspond to positive autocorrelation.

[12] $\text{cor}(r_{i,t-1}, r_{j,t}) = \text{cor}(r_{j,t-1}, r_{j,t}) \times \text{cor}(r_{i,t}, r_{j,t})$

Empirically however, momentum could also exist in the presence of negative autocorrelation since its value and the sign of serial correlation can vary with return horizons. Even though behavioral models don't specify the length of return horizons when measuring price adjustment to new information, it's a reasonable assumption to expect that the market would underreact, or belatedly overreact to news at horizons that are much shorter than 1 year. Based on this assumption Pan (2010) proposed that using shorter return horizons would assert a different role to autocorrelation, more correspondent to that of behavioral theories of underreaction. We will in this section test whether the inconsistency between behavioral models and our findings could be explained by different length of the formation period. To evaluate this issue, we repeat the different strategies, but now with shorter formation periods of 1, 3 and 6 months.

5.3.1 Autocorrelations and Momentum Profits

As mentioned, we now turn to the second part of our research question. To understand how the role of autocorrelation and cross-serial correlations change over different return horizons, we extend the tests of Section 5.2.3, now utilizing shorter time horizons. Table 5.6 shows momentum profits for strategies implemented on the industry, size and size-B/M portfolios, with horizons of 3 and 6 months. Again, the term *Auto* catches autocorrelations in profits. *Cross* is dependent on the cross-serial correlations, while *Means* catches the effect of cross-sectional dispersion in unconditional means.

3 Month Formation	Industry Portfolios				5 Size Portfolios				6 Size-B/M Portfolios			
Month	Auto	Cross	Means	Total	Auto	Cross	Means	Total	Auto	Cross	Means	Total
1	**3.03**	-1.93	0.03	**1.13**	3.70	-3.84	0.04	-0.09	**4.08**	**-3.40**	0.11	0.79
2	1.08	-0.65	0.03	0.46	-0.58	0.70	0.04	0.16	0.11	0.42	0.11	0.71
3	**4.24**	**-3.33**	0.03	0.94	0.90	-0.52	0.04	0.42	1.96	-1.35	0.11	0.71
Bootstrap SE	1.82	1.39	0.11	0.61	2.39	2.36	0.14	0.34	2.04	2.00	0.21	0.55

6 Month Formation	Industry Portfolios				5 Size Portfolios				6 Size-B/M Portfolios			
Month	Auto	Cross	Means	Total	Auto	Cross	Means	Total	Auto	Cross	Means	Total
1	3.21	-1.75	0.06	**1.52**	2.68	-2.38	0.09	0.39	3.06	-2.08	0.21	**1.20**
2	1.62	-0.71	0.06	0.97	-0.03	0.50	0.09	0.57	0.46	0.46	0.21	1.12
3	2.21	-1.06	0.06	1.20	-0.71	1.30	0.09	0.68	-0.23	0.98	0.21	0.96
4	1.06	0.20	0.06	1.32	-1.45	2.04	0.09	0.68	-1.18	1.87	0.21	0.91
5	-0.34	1.54	0.06	1.26	-2.37	2.89	0.09	0.60	-2.29	2.85	0.21	0.77
6	-1.33	2.79	0.06	**1.52**	-3.03	3.41	0.09	0.47	-3.14	**3.53**	0.21	0.61
Bootstrap SE	1.98	1.76	0.17	0.81	2.32	2.18	0.21	0.54	2.47	2.05	0.32	0.69

Table 5.6: Decomposition of momentum profits, 1941 - 2021. The table displays total profits. We invest $w_{it} = (1/N)(r_{i,t-1} - r_{m,t-1})$ in asset i, where $(r_{i,t-1} - r_{m,t-1})$ is the lagged return of an asset in excess of the equal weighted index. We use 3- and 6-month formation periods paired with 3 and 6 months of lags respectively. Bold marks estimates greater than 1.645 standard errors from zero based on bootstrap simulations.

We see that for the 3-month strategies, autocorrelations are now mostly positive, with the exception of lag 2 in the 5 size portfolios. This means that autocorrelations in these strategies with shorter formation periods actually contribute positively to momentum profits. In the industry portfolios, the Auto-component is significant at 4.24 (t-statistic of 2.34) in month 3. The cross-component for industries in the same month is significant at -3.33 (t-statistic of -2.39). This differs from our previous results using a 12-month formation period. Here, the corresponding Auto- and Cross components where -0.28 (t-statistic of -0.13) and 2.20 (t-statistic of 1.15) respectively. We see that the roles of the two components have now switched. This pattern repeats itself for the strategies on size and size-B/M portfolios.

For the 6-month strategies, we get results that more resembles our previous findings, especially in the size and size-B/M portfolios. However, we find very few of these estimates to be more than 1.645 standard errors away from zero. For the industry portfolios, the Auto-components stays positive until month 5. The Auto-component for industries is at 3.21 (t-statistic of 1.62) in month 1, and -1.33 (t-statistic of -0.67) in month 6. The average of the Auto-components in industries over all 6 months is 1.07, which is significantly higher than the average of the first 6 months in the 12-month strategy, which was -0.37. The average of the Cross-components in industries over all 6 months is 1.01, which also is significantly lower than the average of the first 6 months in the 12-month strategy, which was 1.58. For the size portfolios, the Auto-components turns negative in month 2. In month 1, the Auto-component in the size portfolios is 2.68 (statistic of 1.16) but decrease to -3.03 (t-statistic of -1.31) in month 6. For the 5 size portfolios, the average of the Auto-components over all 6 months is -0.82. Compared to the average of Auto-component in size for the first 6 months in the 12-month strategy (-1.96), we see that autocorrelation now contributes less to contrarian profits than what it did before. The average of the Cross-components in size over all 6 months is 1.29. This is much lower than the average of the first 6 months in the 12-month strategy, which was 2.81. The pattern repeat itself again for the size-B/M portfolios. The 6-month average autocorrelation is much less negative than before, while the cross-serial correlation contribution is significantly decreased.

In the 12-month formation period strategy, we saw a number of significant estimates across the different portfolios. Under the 3-month horizons we had some significant results. However, the only significant estimate in any of the 6-month strategies is the Cross-component in month 6 for the 6 size-B/M portfolios. We also note that the cross-sectional variations in expected return (Mean) still only have minor contributions to total momentum profit, and we find no sign of significance in either the 3-month strategies, nor in any of the 6-month strategies. The general lack of significance in the shorter horizon strategies are more consistent with the findings of Conrad and Kaul (1998), who argue that momentum is caused by variance of mean returns, not time-series predictability in returns.

5.3.2 Autocorrelations at 6-month Horizons

Table 5.7 shows the autocovariance matrix for the industry, 5 size, and 5 B/M portfolios. Unlike table 5.2, we now focus on the intermediate horizon of 6 months. To investigate how the return of these portfolios are correlated with themselves and other portfolios past return, we estimate the autocorrelation and cross-serial correlations in semi-annual returns.

	Industry Portfolios									
	$\mathbf{R}_{1,t}$	$\mathbf{R}_{2,t}$	$\mathbf{R}_{3,t}$	$\mathbf{R}_{4,t}$	$\mathbf{R}_{5,t}$	$\mathbf{R}_{6,t}$	$\mathbf{R}_{7,t}$	$\mathbf{R}_{8,t}$	$\mathbf{R}_{8,t}$	$\mathbf{R}_{10,t}$
$\mathbf{R}_{1,t-k}$	0.03	0.00	**-0.10**	**-0.09**	-0.02	0.01	-0.03	-0.03	**0.08**	-0.03
$\mathbf{R}_{2,t-k}$	-0.03	0.04	**-0.12**	**-0.16**	0.00	0.05	-0.02	-0.03	0.06	-0.01
$\mathbf{R}_{3,t-k}$	-0.01	0.04	-0.06	-0.06	0.02	0.04	-0.03	-0.03	0.07	-0.01
$\mathbf{R}_{4,t-k}$	0.04	**0.11**	0.05	0.02	0.05	**0.06**	0.00	-0.03	**0.08**	0.05
$\mathbf{R}_{5,t-k}$	**-0.11**	0.01	**-0.10**	**-0.10**	0.05	**0.09**	-0.05	**-0.07**	-0.03	**-0.07**
$\mathbf{R}_{6,t-k}$	0.04	**0.09**	-0.04	**-0.11**	0.05	**0.16**	0.04	-0.02	0.05	0.02
$\mathbf{R}_{7,t-k}$	0.03	0.00	**-0.10**	**-0.08**	-0.02	0.05	-0.03	-0.02	**0.12**	0.00
$\mathbf{R}_{8,t-k}$	0.02	0.01	-0.03	-0.05	0.04	**0.07**	0.02	0.04	0.05	0.01
$\mathbf{R}_{9,t-k}$	0.06	**0.06**	-0.01	-0.02	**0.08**	**0.13**	0.04	0.01	**0.10**	0.06
$\mathbf{R}_{10,t-k}$	-0.01	0.04	**-0.09**	**-0.08**	0.01	0.02	-0.04	**-0.07**	0.04	-0.02
Average	0.01	0.04	-0.06	-0.07	0.03	0.07	-0.01	-0.03	0.06	0.00

	Size Portfolios				
	$\mathbf{R}_{\mathbf{Small},t}$	$\mathbf{R}_{2,t}$	$\mathbf{R}_{3,t}$	$\mathbf{R}_{4,t}$	$\mathbf{R}_{\mathbf{Big},t}$
$\mathbf{R}_{\mathbf{Small},t-k}$	0.00	-0.03	-0.02	0.00	-0.01
$\mathbf{R}_{2,t-k}$	-0.03	**-0.06**	-0.04	-0.03	-0.01
$\mathbf{R}_{3,t-k}$	-0.04	**-0.07**	**-0.06**	-0.04	-0.01
$\mathbf{R}_{4,t-k}$	-0.05	**-0.08**	**-0.07**	-0.05	-0.01
$\mathbf{R}_{\mathbf{Big},t-k}$	-0.04	-0.05	-0.04	-0.01	0.05
Average	-0.03	-0.06	-0.05	-0.03	0.00

	B/M Portfolios				
	$\mathbf{R}_{\mathbf{Low},t}$	$\mathbf{R}_{2,t}$	$\mathbf{R}_{3,t}$	$\mathbf{R}_{4,t}$	$\mathbf{R}_{\mathbf{High},t}$
$\mathbf{R}_{\mathbf{Low},t-k}$	0.01	-0.02	-0.04	-0.05	**-0.06**
$\mathbf{R}_{,t-k}$	-0.02	-0.03	-0.03	-0.04	-0.05
$\mathbf{R}_{3,t-k}$	0.01	0.00	-0.01	-0.02	-0.02
$\mathbf{R}_{4,t-k}$	0.04	0.02	0.02	0.02	0.00
$\mathbf{R}_{\mathbf{High},t-k}$	-0.01	-0.01	-0.01	-0.01	-0.02
Average	0.01	-0.01	-0.01	-0.02	-0.03

Table 5.7: Serial correlation in industry, size and B/M portfolios, 1941 - 2021. The table displays the autocorrelations of the cumulative return over the 6-month formation period on the cumulative return of the 6 month holding period. Bold denotes estimates that are significant at the 5 % level based on bootstrap simulations.

Over the 6-month horizon, our results show that both the autocorrelations and cross-serial correlations are mostly negative in the size and B/M portfolios. The average autocorrelation and cross-serial correlation for the industry portfolio is 0.03 and 0.00. With industry portfolios exhibiting positive autocorrelation, this means that autocorrelation is now a positive contributor to momentum under this strategy. In the size portfolios, negative cross-serial correlation still dominates. The average autocorrelation for the size portfolios is -0.03, while the average cross-serial correlation is -0.04. Coherent with the results of the decomposition displayed in Table 5.6, the cross-serial covariances are mostly negative, thus it is still acting as a positive contributor to momentum. In the size-B/M portfolios, the average autocorrelation and the average cross-serial correlation is quite similar at -0.04 and -0.03 respectively. With these results, we see that autocorrelation can be a positive contributor to momentum under shorter horizons. This gives more premise for the underreaction theory than our previous results over 12-month horizons.

5.3.3 Autocorrelations and Monthly Return Horizon

Still, our results support the claim that negative cross-serial correlations between assets drives momentum for intermediate and longer horizons. This shows that behavioral models that argue for positive autocorrelation and return continuation are not able to explain momentum on intermediate horizons of 6 to 12 months. However, we see that the negative pull of autocorrelations, and the positive push from cross-serial correlation have become weaker when the horizon decreases from 12 to 6 months. Even more interestingly, the roles of autocorrelation and cross-serial correlations even reverse at the 3-month horizon. This induces the idea that shorter horizons will bring us closer to the predictions of the behavioral models.

	Forecast horizon (months)											
Portfolio	1	3	5	7	9	11	A6	A12	S6	S12	Q(6)	Q(12)
Industry Portfolios												
Non-durables	**0.112**	-0.011	**0.071**	0.021	-0.029	0.003	0.022	0.012	0.133	0.140	**16.90**	**19,00**
Durables	**0.106**	0.051	0.000	0.028	0.005	**0.056**	0.020	**0.022**	0.121	0.266	**24.23**	**27.85**
Manufacturing	**0.062**	0.006	0.015	-0.005	-0.035	-0.010	0.004	-0.003	0.022	-0.038	9.39	10.96
Energy	0.001	-0.016	0.007	**0.058**	-0.028	-0.028	0.007	-0.003	0.042	-0.039	3.08	14.58
Equipment	**0.063**	0.047	0.015	0.029	0.001	0.021	0.014	0.013	0.086	0.153	6.38	8.97
Telecom	**0.057**	**0.107**	**0.080**	0.016	-0.023	0.039	0.040	0.033	0.240	0.398	**19.02**	**25.77**
Shops	**0.131**	-0.021	0.027	-0.010	0.034	-0.003	0.006	0.010	0.037	0.116	**22.75**	**24.93**
Health	0.038	-0.026	0.048	0.031	-0.029	0.024	0.008	0.011	0.047	0.128	6.16	10.79
Utilities	**0.074**	0.029	**0.118**	0.006	-0.031	0.002	0.038	0.015	0.227	0.175	**21.62**	**23.67**
Other	**0.121**	0.011	**0.055**	0.005	-0.022	0.023	0.025	0.009	0.147	0.106	**21.09**	**24.7**
Average	0.077	0.018	0.044	0.018	-0.016	0.013	0.018	0.012	0.110	0.141		
Size Portfolios												
Small	**0.183**	-0.022	-0.002	0.039	-0.036	0.014	0.029	0.014	0.171	0.173	**35.78**	**39.96**
2	**0.135**	-0.031	-0.005	0.011	-0.021	0.001	0.009	0.001	0.052	0.017	**19.83**	**22.01**
3	**0.120**	-0.017	0.005	0.004	-0.027	-0.005	0.011	-0.001	0.064	-0.007	**14.74**	18.33
4	**0.102**	-0.006	0.028	0.004	-0.038	-0.021	0.012	-0.002	0.073	-0.026	**11.66**	15.65
Big	0.046	0.033	**0.075**	0.022	-0.024	0.001	0.017	0.012	0.102	0.143	**12.42**	13.41
Average	0.117	-0.009	0.020	0.016	-0.029	-0.002	0.015	0.005	0.092	0.060		
Size-B/M Portfolios												
Small: Low	**0.149**	-0.045	-0.011	0.034	-0.009	-0.004	0.011	0.004	0.066	0.048	**22.61**	**24.86**
2	**0.139**	-0.021	0.003	0.002	-0.028	0.001	0.015	0.006	0.087	0.066	**20.16**	**21.95**
High	**0.146**	0.002	0.005	0.011	-0.034	0.009	0.022	0.011	0.130	0.126	**24.82**	**27.02**
Big: Low	**0.071**	0.022	0.050	0.019	-0.024	-0.002	0.013	0.008	0.076	0.094	9.99	10.99
2	**0.060**	0.024	**0.092**	0.005	-0.037	-0.003	0.020	0.003	0.119	0.040	**18.22**	**20.94**
High	**0.077**	0.034	0.041	0.014	-0.022	0.007	0.025	0.010	0.148	0.116	11.85	14.2
Average	0.107	0.003	0.030	0.014	-0.026	0.001	0.017	0.007	0.104	0.082		

Table 5.8: The table reports autocorrelations for lags 1–12 of the monthly returns for value-weighted industry, size, and B/M portfolios in the time period 1941 to 2021. *A6* and *A12* are the average autocorrelation for lags of 1–6 and for lags 1–12 respectively. *S6* and *S12* report the cumulative autocorrelation for lags 1–6 and 1–12 respectively. Q(k) is the Ljung-Box Q-statistic for k order autocorrelation (Complete Ljung-Box Q-statistics is displayed in table A4.2). Bold denotes estimates that are more than 1.645 standard errors away from 0.

Short-horizon returns might be more appropriate to rely on than long horizon returns when exploring investor under- and overreaction, (Pan, 2010). We will investigate this further by calculating the autocorrelation of monthly returns for up to twelve lags. We see the results displayed in Table 5.8 above. The table shows that more often than not, the estimates of the monthly autocorrelation are positive. Besides from month 1, we do not achieve many significant estimates. Interestingly, every estimate that is significant are positive. This suggest that monthly returns actually exhibit price continuation. We also see that smaller stocks exhibit larger first-order autocorrelations than what larger stocks does, which is consistent with the literature, (Pan, 2010).

Furthermore, we choose to display the average and the sum of autocorrelations for lags 1 to 6, and 1 to 12 separately. We see that both the average and the cumulative autocorrelation are almost uniformly positive for all portfolios. For the size and size B/M portfolios, we see that autocorrelation has a negative impact over the last 6 lags. For the industry portfolios, autocorrelations actually slightly increase. The autocorrelation averages do however significantly decrease for all industry, size and size-B/M portfolios when the last 6 lags are included. The average autocorrelation in industry decreases from 0.018 to 0.012, while the averages in size and size-B/M decreases from 0.015 to 0.005 and 0.017 to 0.007 respectively.

The results of Table 5.8 indicates that there in general is positive autocorrelation across the 12 months. Thus, these findings actually support the argument of behavioral models that the momentum anomaly corresponds to positive short-term autocorrelation in returns.

6 Conclusion

This thesis has examined the two-folded research question; *What is the role of autocorrelation and cross-serial correlation for momentum in stock returns, and does this role change with different return horizons?* To answer this, our thesis conducts two sets of tests. First, we show that momentum still exists in size and B/M portfolios and is as strong as in individual stocks and industries. These findings support the idea that momentum is a pervasive feature of returns. It also confirms that momentum is not solely an attribute of firm-specific returns. We consider both the size and B/M portfolios to be relatively diversified. Thus, their returns should reflect systematic risk. Macroeconomic factors, not firm-specific returns, will then drive momentum in these portfolios.

The second set of tests focused on the autocorrelation patterns in returns and examined the results in light of behavioral theories regarding underreaction and overreaction. Furthermore, we performed the tests using different return horizons to assess whether the role of autocorrelation and cross-serial correlations can vary with formation period.

When examining longer return horizons of 6 to 12 months, we find that with a few exceptions, industry, size, and B/M portfolios are negatively autocorrelated after three months post formation. We also find that the cross-serial correlations in these portfolios are mostly negative. The results from strategies based on longer formation periods generally defy simple underreaction models. We note that the results over these horizons could be consistent with a combination of portfolio-specific underreaction alongside market reversals. However, we find this explanation a bit hard to defend based on our results in Section 5.2.4. First, we see that larger stocks are weakly negatively autocorrelated, but they significantly predict other portfolios. Second, market returns can predict portfolio-specific returns quite strongly in the size portfolios and some of the industry portfolios. This is a feature not anticipated by the underreaction story. This coincides with the findings of Lewellen (2002). Lewellen proposed models of excess covariance among stocks as an alternative to the underreaction theory. His proposed model generates autocorrelation patterns that coincide with our findings under 12-month formation periods.

When we shorten the horizons, the role of autocorrelations and cross-serial correlation changes. We argue that we achieve a better evaluation of the analogous between momentum and positive autocorrelation. This conjecture seems to be supported by the monthly autocorrelations, as autocorrelations across 12 lags in monthly return for all portfolios tend to be positive. Cross-serial correlations become less negative, thus reducing their contribution to momentum strategies. These results coincides with the results of Pan (2010) and imply that industry, size, and size-B/M portfolios exhibit return continuation, reconciling our results with common behavioral theories of underreaction.

To conclude, our results imply that cross-serial correlation drives momentum profits over longer return horizons, while negative autocorrelations act as a reducing factor. However, the roles swap when the return horizons are shortened. The autocorrelations become more positive, while cross-serial correlations become less negative. This result suggests that the conflict between Lewellen (2002) and behavioral theories exist as a consequence of different length of formation and holding periods. Theoretically, momentum should correspond to positive autocorrelation. Empirically, momentum can co-exist alongside negative autocorrelation since the value of serial-correlation varies with different return horizons. In other words, the role of autocorrelation differs when returns are measured over different horizons.

Several questions remain unanswered regarding momentum. For example, our research does not investigate momentum in individual stocks. An interesting approach would be to look at whether similar features to our results would apply to individual stock momentum. Also, a behavioral model able to differentiate between a specific type of macroeconomic news could help further validate the underreaction story, even at longer horizons.

By better understanding the relationship between momentum, autocorrelation and underreaction, cross-serial correlation and overreaction, policymakers can improve market stability and efficiency. These observations could also be interesting for investment decision making and asset pricing.

7 Appendix

A1 Summary Statistics

5 Size Portfolios			
Portfolio	**Avg. return**	**Std.dev.**	**Firms**
Small	1.29%	6.24%	1920
2	1.24%	5.64%	515
3	1.18%	5.16%	367
4	1.15%	4.83%	307
Large	0.98%	4.08%	278
Average	**1.17%**	**5.19%**	**677**

6 Size-B/M Portfolios				
Portfolio		**Avg. return**	**Std.dev.**	**Firms**
Small:	Low	1.02%	6.27%	324
	2	1.27%	5.21%	219
	High	1.47%	5.66%	227
Big:	Low	0.99%	4.38%	290
	2	1.02%	4.10%	514
	High	1.23%	4.97%	113
Average		**1.17%**	**5.1%**	**281**

10 B/M Portfolios			
Portfolio	**Avg. return**	**Std.dev.**	**Firms**
Low	0.95%	4.78%	421
2	1.04%	4.44%	296
3	1.00%	4.36%	264
4	0.98%	4.39%	253
5	1.10%	4.23%	247
6	1.13%	4.33%	247
7	1.03%	4.54%	253
8	1.24%	4.75%	273
9	1.34%	5.07%	310
High	1.40%	6.19%	369
Average	**1.12%**	**4.71%**	**293**

5 B/M Portfolios			
Portfolio	**Avg. return**	**Std.dev.**	**Firms**
Low	0.99%	4.56%	1920
2	0.98%	4.28%	515
3	1.12%	4.15%	367
4	1.13%	4.53%	307
High	1.36%	5.39%	278
Average	**1.12%**	**4.58%**	**677**

Table A1.1: Summary Statistics for portfolios formed from all NYSE, AMEX and Nasdaq stock during the period January 1941 to December 2021. The table report the average value weighted return, standard deviation and the average number of firms for each portfolio throughout the time period.

A2 Comparing autocovariance matrices with Lewellen (2002)

	5 Size Value Weight 41-99				
	$R_{Small,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{Large,t}$
$R_{Small,t-k}$	-0.02	-0.03	-0.03	**-0.04**	**-0.04**
$R_{2,t-k}$	-0.04	-0.04	-0.04	-0.05	-0.05
$R_{3,t-k}$	**-0.04**	-0.05	-0.05	**-0.05**	-0.05
$R_{4,t-k}$	**-0.06**	**-0.06**	-0.06	**-0.06**	-0.05
$R_{Large,t-k}$	**-0.09**	-0.08	-0.07	-0.07	-0.04

	Lewellen (2002) 5 Size Value Weight 41-99				
	$R_{Small,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{Large,t}$
$R_{Small,t-k}$	-0.02	-0.03	-0.03	**-0.05**	**-0.05**
$R_{2,t-k}$	-0.04	-0.04	-0.04	-0.05	-0.05
$R_{3,t-k}$	**-0.05**	-0.05	-0.05	**-0.06**	-0.05
$R_{4,t-k}$	**-0.07**	**-0.07**	-0.06	**-0.07**	-0.05
$R_{Large,t-k}$	**-0.10**	-0.08	-0.07	-0.07	-0.04

	5 B/M Value Weight 63-99				
	$R_{Low,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{High,t}$
$R_{Low,t-k}$	**-0.05**	-0.07	**-0.06**	**-0.07**	**-0.07**
$R_{2,t-k}$	-0.03	-0.04	**-0.04**	-0.05	**-0.04**
$R_{3,t-k}$	-0.04	**-0.05**	**-0.04**	-0.05	**-0.05**
$R_{4,t-k}$	-0.05	-0.03	**-0.03**	-0.03	**-0.05**
$R_{High,t-k}$	**-0.05**	**-0.03**	-0.02	-0.04	-0.04

	Lewellen (2002) 5 B/M Value Weight 63-99				
	$R_{Low,t}$	$R_{2,t}$	$R_{3,t}$	$R_{4,t}$	$R_{High,t}$
$R_{Low,t-k}$	**-0.04**	-0.07	**-0.05**	**-0.08**	**-0.08**
$R_{2,t-k}$	-0.03	-0.04	**-0.02**	-0.05	**-0.06**
$R_{3,t-k}$	-0.04	**-0.04**	**-0.02**	-0.05	**-0.06**
$R_{4,t-k}$	-0.05	-0.03	**-0.01**	-0.03	**-0.04**
$R_{High,t-k}$	**-0.06**	**-0.02**	-0.02	-0.04	-0.04

Table A2.1: The table displays the average serial correlation in the 5 size and 5 B/M portfolios from our own research and those of Lewellen (2002) during the time period 1941 to 1999, and 1963 to 1999 respectively. The portfolios are formed from all NYSE, AMEX and Nasdaq stocks. Bold denotes correlation coefficients that differs with more than 0.005.

A3 SIC Codes for Industry Groups

1. NoDur - Consumer Nondurables Food, Tobacco, Textiles, Apparel, Leather, Toys	**2. Durbl - Consumer Durables** Cars, TVs, Furniture, Household Appliances	**3. Manuf- Manufacturing** Machinery, Trucks, Planes, Chemicals, Off Furn, Paper, Com Printing	**4. Enrgy - Energy** Oil, Gas, Coal Extraction & Products	**5 HiTec - Business Equipment** Computers, Software, Electronic Equipment
0100-0999	2500-2519	2520-2589	1200-1399	3570-3579
2000-2399	2590-2599	2600-2699	2900-2999	3622-3622
2700-2749	3630-3659	2750-2769		3660-3692
2770-2799	3710-3711	2800-2829		3694-3699
3100-3199	3714-3714	2840-2899		3810-3839
3940-3989	3716-3716	3000-3099		7370-7379
	3750-3751	3200-3569		7391-7391
	3792-3792	3580-3621		8730-8734
	3900-3939	3623-3629		
	3990-3999	3700-3709		
		3712-3713		
		3715-3715		
		3717-3749		
		3752-3791		
		3793-3799		
		3860-3899		
6. Telcm - Telecom Telephone, Television Transmission	**7. Shops** Wholesale, Retail, Laundries, Repair Shops	**8. Hlth - Health** Healthcare, Drugs, Medical Equipment	**9. Utils - Utilities**	**10. Other**
4800-4899	5000-5999	2830-2839	4900-4949	Mines, Constr,
	7200-7299	3693-3693		BldMt, Trans,
	7600-7699	3840-3859		Hotels, Bus Serv,
		8000-8099		Entertainment, Finance

Table A3.1: The table displays the SIC codes for each industry group used in constructing the industry portfolios. The SIC codes are collected from Ken French's data library, French (2022).

A4 Ljung-Box test

Portfolio		Return horizon (months)								
		1	3	5	7	9	11	13	15	17
Industry Portfolios										
Non-durables		**9.62**	**11.01**	**16.00**	**17.13**	**16.92**	17.96	18.63	22.73	25.82
Durables		**6.66**	**11.11**	**16.71**	**24.75**	**24.02**	**27.54**	**26.87**	**33.13**	**32.11**
Manufacturing		3.56	3.69	4.61	9.06	10.01	11.45	11.30	18.95	18.79
Energy		0.05	1.29	4.83	9.63	10.88	11.61	14.29	15.32	22.11
Equipment		2.52	6.06	6.70	7.51	8.33	9.42	11.61	12.59	19.05
Telecom		0.47	**7.88**	**15.80**	**19.09**	**24.85**	**27.10**	**29.11**	**29.76**	**28.97**
Shops		**13.63**	**15.73**	**17.77**	**22.77**	**25.16**	**25.67**	**26.53**	**36.45**	**37.40**
Health		0.54	1.53	4.19	7.49	10.30	11.43	13.07	16.65	16.99
Utilities		2.42	6.33	**21.28**	**18.62**	**17.99**	18.44	17.44	19.97	19.64
Other		**12.5**	**14.18**	**18.28**	**21.46**	**24.25**	**26.68**	**28.04**	**36.30**	**36.12**
Average		5.19	7.88	12.62	15.75	17.27	18.73	28.04	24.19	25.70
Size portfolios										
Small		**28.30**	**33.14**	**32.03**	**35.97**	**37.15**	**39.82**	**42.76**	**41.96**	**41.26**
2		**16.00**	**16.76**	**17.55**	**19.75**	**21.23**	**23.03**	**24.72**	**29.84**	**30.14**
3		**12.37**	**12.42**	**13.16**	**14.70**	**17.73**	19.16	20.40	**27.44**	27.29
4		9.41	9.17	10.62	11.68	14.41	15.96	16.88	24.13	23.45
Big		1.02	3.19	10.49	13.38	13.34	13.69	15.26	18.83	19.80
Average		13.42	14.94	16.77	19.09	20.77	22.33	24.00	28.44	28.39
Size-B/M portfolios										
Small:	Low	**18.92**	**20.14**	**21.03**	**24.38**	**24.46**	**25.07**	**25.94**	**31.45**	**33.38**
	2	**16.10**	**17.24**	**17.65**	**19.31**	**20.91**	**22.41**	**24.58**	**30.71**	**31.40**
	High	**17.14**	**19.87**	**19.89**	**23.01**	**25.24**	**27.08**	**32.09**	**34.88**	**33.94**
Big:	Low	3.61	5.76	8.90	10.92	10.99	11.35	12.08	15.24	16.07
	2	2.60	4.54	**15.51**	**17.88**	**19.43**	**20.29**	20.12	**27.89**	**29.03**
	High	4.58	7.18	9.32	11.51	12.31	13.98	15.86	**25.42**	25.43
Average		10.49	12.46	15.38	17.84	18.89	20.03	21.78	27.60	28.21

Table A4.1: Ljung-Box test, Q-stat score for table 5.3. Bold denotes Q-statistics with p-values below 0.05.

Portfolio		Return horizon (months)					
		1	3	5	7	9	11
Industry Portfolios							
Non-durables		**10.86**	**11.15**	**15.62**	**17.50**	**18.13**	19.00
Durables		**10.07**	**13.46**	**18.45**	**25.10**	**25.23**	**27.83**
Manufacturing		3.23	3.69	4.76	9.42	10.50	10.95
Energy		0.00	0.53	3.04	7.41	12.93	14.58
Equipment		3.43	6.10	6.37	7.25	7.83	8.97
Telecom		2.82	**12.60**	**19.00**	**19.12**	**24.24**	**25.77**
Shops		**1.53**	**16.83**	**17.79**	**22.77**	**24.12**	**24.93**
Health		0.89	1.88	4.64	7.29	9.81	10.79
Utilities		2.35	6.13	**20.80**	**21.64**	**22.16**	**23.62**
Other		**13.56**	**13.76**	**17.83**	**21.10**	**23.73**	**24.70**
Average		6.25	8.61	12.83	15.86	17.87	19.11
Size Portfolios							
Small		**34.89**	**35.62**	**35.66**	**37.23**	**39.03**	**39.96**
2		**18.10**	**19.17**	**19.22**	**19.93**	**21.93**	**22.00**
3		**13.29**	**13.98**	**14.04**	**14.74**	**18.26**	18.33
4		**9.03**	**9.48**	10.34	11.67	15.05	15.65
Big		1.53	3.38	9.86	12.86	13.37	13.40
Average		15.37	16.33	17.82	19.29	21.53	21.87
Size-B/M Portfolios							
Small:	Low	**20.29**	**22.36**	**22.59**	**23.54**	**24.84**	**24.86**
	2	**19.19**	**19.54**	**19.67**	**20.16**	**21.91**	**21.95**
	High	**22.82**	**22.97**	**23.26**	**24.99**	**26.65**	**27.01**
Big:	Low	3.84	5.57	8.10	10.38	10.90	10.98
	2	3.04	4.58	**14.36**	**18.24**	**20.66**	**20.94**
	High	**6.53**	**7.92**	**10.18**	**12.08**	**13.32**	**14.19**
Average		12.62	13.82	16.36	18.23	19.71	19.99

Table A4.2: Ljung-Box test, Q-stat score for table 5.8. Bold denotes Q-statistics with p-values below 0.05.

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