A Study of Momentum Effects on the Swedish Stock Market using Time Series Regression

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Abstract

This study investigates if momentum effects can be found on the Swedish stock market by testing a cross-sectional momentum strategy on historical data. To explain the results mathematically, a second approach, involving time series regression for predicting future returns is introduced and thereby extends the cross-sectional theory. The result of the study shows that momentum effects through the cross-sectional strategy exist on the Swedish stock market. Although positive return is found, the time series regression do not give any significance for predicting future returns. Hence, there is a contradiction between the two approaches.

Keywords: momentum, time series regression, ex ante volatility, stationary process
En Studie av Momentumeffekter på den Svenska Aktiemarknaden med hjälp av Tidsserieregession

Sammanfattning

Denna studie undersöker om momentumeffekter föreligger på den svenska aktiemarknaden med hjälp av två olika tillvägagångssätt. Först testas momentumstrategin på historisk data och därefter genomförs tidsserieregession för att undersöka om resultaten har statistisk signifikans för att prediktera framtida avkastning. Resultatet visar att momentumeffekter existerar på den svenska aktiemarknaden. Trots att positiv avkastning erhålls ger tidsserieregessionen ingen indikation på att prediktering av framtida avkastning är möjlig. Följaktigen finns det en motsägelse mellan de två tillvägagångssätten.
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1 Introduction

In this section the reader is introduced to the momentum strategy and its previous literature. The problem formulation, purpose and contribution followed by the limitations of the study are then presented.

1.1 Background

The desire to outperform the financial market is the target for most investors. Therefore, many investors want to develop trading strategies to achieve this. One example is the momentum strategy which was introduced by Jegadeesh and Titman in 1993. The momentum strategy is based on the assumption that stock prices tend to overreact to information and that assets tend to continue in the same direction as their historical performance. To exploit momentum, Jegadeesh and Titman constructed a portfolio of assets with long positions in past winners and short positions in past losers (Jegadeesh and Titman, 1993). This strategy (which is referred to as cross-sectional momentum) gave an abnormal return for holding periods of 3-12 months on the US market. Hence, momentum was showed.

When Jegadeesh and Titman’s first paper was published it was given a lot of attention since it challenged the efficiency of the market. Their study also argued with previous research which focused on reverse patterns on the stock market known as mean reversion or contrarian effects, i.e. on long term (3-5 years), past losing stocks should outperform past winners. Reverse patterns were shown by DeBondt and Thaler (1985). With inspiration from the research of Jegadeesh and Titman in 1993, several other studies were made in different settings with similar results. Hence, their result was not just a coincidence.

The findings of momentum profitability means that future return could be predicted from past return. If such a dependency exists, momentum effects can be exploited. Moskowitz et al. (2011) extended the research by Jegadeesh and
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Titman by adding the term “time series momentum” which they found to be remarkably consistent over different asset classes and markets. By applying time series regression they found strong predictability from a security's own past return for a large set of different assets, not only stocks. The results strengthened Jagedeesh and Titman's findings since they showed, through time series analysis, that the past 12 months excess return was a positive predictor for future return. The "trend" held for about a year for all the different securities and then disappeared for longer time horizons, which Jagedeesh and Titman assumed, but never showed.

Since investment strategies like momentum is based on market inefficiency, the subject is highly debated. Many economists, who favors the efficient market hypothesis, mean that performing such strategies is only a waste of time and money. They argue that the findings of momentum can be reduced to data mining or misspecified tests (Jegadeesh and Titman, 2001).

1.2 Problem Definition

The aim of this report is to examine if momentum effects exist on the Swedish stock market. Momentum strategies will be executed according to suggestions by Jegadeesh and Titman (1993), extended with the time series research by Moskowitz et al. (2012). The two different strategies will be evaluated against the mathematical theory behind time series regression.

1.3 Purpose and Contribution

The purpose of this study is to identify any return that arises in the market due to momentum effects. If the market meets the effective market hypothesis, it should not be possible to exploit returns with strategies such as momentum. The study contributes to the already existing studies of momentum strategies but is now tested on the Swedish stock market. It can be considered relevant as a check of and to what degree the market comply with the effective market
hypothsis.

1.4 Limitations

The work is limited to the Swedish stock market for Large Capital stocks. As a theoretical basis, the effective market hypothesis and time series regression are used. To keep the report general, no consideration will be taken to taxes, transaction costs nor the risk free rate when calculating the return. Hence the excess return will be left out and only the simple return will be dealt with. The time period which is investigated is the years 2007-2016. The period covers a full business cycle and should therefore not bias the analysis.

2 Theory

This section is devoted to the theory used in this study. To understand momentum effects both economical and mathematical aspects need to be considered.

2.1 Economical Theory

For this section, two fundamental theories in economy are presented. The first is known as The Efficient Market Hypothesis, which states that asset prices fully reflect all available information. The second theory is The Random Walk Hypothesis, which explain that stock prices evolve according to a random walk. Hence, stock price changes are random and not predictable.

2.1.1 The Efficient Market Hypothesis

The efficient market hypothesis was developed by Eugene Fama and presented in his article ”Efficient Capital Markets: A Review of Theory and Empirical Work” (1970). It has become a fundamental theory in financial economics and a debated topic among economists.

The theory states that stocks are always traded at their fair value. This means
that share prices fully reflect all relevant information about the stocks and thereby, it should be impossible to outperform the market in the long run according to the investment theory of the efficient market hypothesis. A consequence of this is that investors’ only way to obtain higher returns is to purchase investments with higher risk. Analogously, a strategy such as momentum should not yield excess return if the market works efficiently.

Saying that share prices “fully reflect” all relevant information about stocks is a rather vague terminology, but also a very strong assumption. One of many critics is Schleifner (2000), who argues that the assumption of the efficient market hypothesis highly depends on the idea of rational investors.

Even though Fama claims that the efficient market hypothesis holds, he introduces three different levels of efficiency (Fama, 1970). The levels are presented briefly below.

- **Weak form efficiency** – prices today reflect all historical information available and arbitrage profits will not be achieved. Investors may find trends on the market but these will soon be adjusted and cancelled out. This is explained by the random walk, which means that stock prices move independently and random.

- **Semi-strong efficiency** – this level also contains the weak form. It says that all public information that is available is included in stock prices. Public available information could be information from financial statements and annual reports. This level means that stock prices immediately adjust when news are published and obtaining excess return based on fundamental analysis or equity research would not be possible.

- **Strong efficiency** – this form of market efficiency states that all of the information (including information that is not public) is included in stock prices. No investor, even with insider information, can make excess return using any information.
Fama has concluded that the two weaker forms of efficiency holds for the criticism while the strong form can be considered too strong. It can instead be seen as a benchmark level of market efficiency.

A direct implication of the efficient market hypothesis is that any investment strategy which is based on available information, will not yield any profit and hence not be able to outperform the market. If the efficient market hypothesis holds, making such strategies will only be a waste of time and money since the market truly knows how to value stock prices.

2.1.2 The Random Walk Hypothesis

The behaviour of stocks is captured in the theory known as the random walk hypothesis which was introduced by Karl Pearson in a letter to Nature in 1905. The concept of random walks are naturally connected to the efficient market hypothesis in its weak form. The idea of the theory is that stock prices are independent of each other and changes (walks) behave in a random manner and stock prices cannot be predicted (Fama, 1970). However, one should be careful to assume that the random walk and the efficient market hypothesis are the same since a random walk of stock prices does not imply rational investors.

There has been many studies done to investigate the possibility to predict stock prices. For example Lo and MacKinley (1999) suggested that short-run serial correlation is not necessarily zero. They concluded that evidence of momentum found which they proposed as an effect of investors “jumping on the bandwagon” as they identify trends in particular stock prices; i.e. they act irrational and follow the move of other investors.

The irrational behaviour among investors can be captured through concepts from behavioural finance. One of the key concepts is known as herding, which explains how individuals in a group can act collectively. The identification of
2.2 Mathematical Theory

herding in investor behaviour was done by Schiller (2000) in his academic study of behavioural finance.

In the long run, the same evidence has not been found. It has actually been showed that there is negative autocorrelation when looking at stock behaviour for longer periods. This is called mean reversion. The assumption of mean reversion states that stock prices tend to move towards the average price over time which has been highly debated among economists since it was presented. One of the early evidence of mean reversion was made by DeBondt and Thaler (1985) who found that stock-losers after 3 to 5 years started outperforming the former winners on the US market. Even though their study focused on investigating market efficiency, the tendency of mean reverting pattern was found.

Later, Fama and French (1988) more deeply examined evidence of mean reversion on the US market and found first-lag autocorrelation on stock to be negative for 36-, 48- and 60-months return on stock portfolios. They found that the autocorrelation was weak for short holding periods and larger for longer periods, reaching maximum of 3-5 year return.

As for the momentum strategy, many empirical studies for examine profitability based on strategies on mean reversion have been done on stock markets to exploit patterns in prices. Based on research findings, it seems that both strategies work simultaneously but on different time horizons.

2.2 Mathematical Theory

The mathematical theory behind this study mainly constitutes from time series regression analysis and the general assumptions and properties for time series regression are thereby stated. Further, the volatility estimation which is used to scale the return is presented, followed by the regression model for stock return along with suitable significance testing. Lastly, stationary processes are defined.
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2.2.1 Time Series Regression

To forecast future share prices by analyzing their past values, time series data is considered. Time series are made by any metric that is measured over regular time intervals. The main difference between time series regression and the ordinary least-squares regression is that the assumption of uncorrelated or independent errors is usually not appropriate. For time series data there is often an auto-correlation structure for the errors; this means that errors are correlated with themselves at different time periods. The effect of auto-correlation on the ordinary least-squares procedure can be captured as follows (Montgomery, Peck, Vining, 2012)

1. The ordinary least squares (OLS) regression coefficients are still unbiased, but they are no longer minimum variance estimates.

2. When the errors are auto-correlated, the residual mean square may underestimate the error variance $\sigma^2$. This affects the standard errors of the coefficients which may be too small, making confidence and prediction intervals shorter than they actually should be. Underestimating the error variance gives false impression of precision and forecast accuracy.

3. Confidence and prediction intervals and tests of hypothesis based on $t$ and $F$ distributions are no longer exact procedures.

If auto-correlation exists, the residuals of identical sign will occur in clusters. One way to deal with the problem of auto-correlation is to use the method of General Least Squares\(^1\). A commonly used test for auto-correlation is the one developed by Durbin and Watson (1950, 1951, 1971). Their test is based on the assumption that the errors in the regression model are generated by a first-order auto-regressive process for equally long time periods,

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\(^1\)General least squares is a method in regression analysis to estimate unknown parameters in a linear regression model. It is especially used when there is correlation between the residuals.
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\[ \varepsilon_t = \phi \varepsilon_{t-1} + a_t, \]  

(1)

where \( \varepsilon_t \) is the error term at period \( t \), \( a_t \) is a normally distributed random variable with mean 0 and variance \( \sigma_a^2 \). \( \phi \) is the parameter which defines the relationship between the errors \( \varepsilon_t \) and \( \varepsilon_{t-1} \). \( \phi \) is often referred to as the autocorrelation parameter (Montgomery et al. 2012).

Unlike cross-sectional data, time series data is characterized by data sets that come with a temporal ordering. Cross-sectional data is viewed as random outcomes and hence the ordinary least squares estimators are considered to be random variables. The randomness for time series though is not obvious. Share price series satisfy the intuitive requirements for being outcomes of random variables, if some historical conditions had been different, the obtained realization for the process had been different as well. Therefore it is a stochastic process.

To use time series regression, some of the basic properties of Ordinary Least Squares (OLS), must be altered from the cross-sectional analysis (Wooldridge, 2000):

1. The times series process follows a model which is linear in its parameters,

\[ Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t, \]

where \( t = 1, 2, ..., n \), \( n \) is the number of time periods and \( \varepsilon_t : t = 1, 2, ..., n \) is the sequence of errors.

2. Zero conditional mean: The expected value of the disturbances \( \varepsilon_t \), given the regressor for all observations (time periods), is zero for each \( t \),

\[ E(\varepsilon_t | Z) = 0, \quad t = 1, 2, ..., n, \]

where \( Z = (X_1, X_2, ..., X_n)^T \), denotes all regressor variables for all \( n \) time periods.
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3. No perfect collinearity: In the underlying time series process no independent variable is a perfect linear combination of the others (or a constant).

4. Homoskedasticity:

\[ \text{Var}[\varepsilon_t|X] = \text{Var}[\varepsilon_t] = \sigma^2, \quad t = 1, 2, \ldots, n, \]

that is, conditional on \( X \) the variance of \( \varepsilon_t \) is the same for all \( t \).

5. No serial correlation; Conditional on \( X \), the errors in two different time periods are uncorrelated,

\[ \text{Corr}[\varepsilon_t, \varepsilon_s|X] = 0 \quad \forall t \neq s, \text{ and } t, s \in \{1, 2, \ldots, n\}. \]

6. Normality; The errors \( \varepsilon_t \) are independently and identically distributed as \( N(0, \sigma^2) \) and independent of \( X \).

In this report, the first order auto-regressive time series model (Montgomery, Peck, Vining, 2012) will be considered;

\[ Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_t, \]

that is, the regressor is the one lag response variable.

2.2.2 Ex Ante Volatility Estimate

The simple return, \( r_t \), of the stock is scaled by its volatility since the volatility among stocks varies. An effect of the scaling is that fair comparisons between stocks can be done. For estimation of volatility the ex ante volatility \(^2\sigma_t\), is computed for each stock and time in accordance with Moskowitz et al (2012).

The ex ante volatility is calculated as;

\[ \sigma_t^2 = 261(1 - \delta) \sum_{i=0}^{\infty} \delta^i (r_{t-1-i} - \bar{r}_t)^2, \quad (2) \]

\(^2\)“Ex ante” refers to any prediction that is made prior to either before all of the variables are known, or before the event has occurred. In this case, ex ante volatility refers to the prediction of future volatility based on weighted historical data where the latest values have the highest weights.
where \( r_t \) is exactly specified in section 3.1 and the scalar 261 scales the variance as annual. The weights \((1 - \delta)\delta^i\) sums up to one and \(\delta\) is chosen so that the centre of the mass weights \(\sum_{i=0}^{\infty}(1-\delta)\delta^i = 60\) days. The exponentially weighted average return, \(\bar{r}_t\), is computed according to:

\[
\bar{r}_t^2 = \lambda \bar{r}_{t-1}^2 + (1 - \lambda) r_{t-1}^2,
\]

(3)

where \(\lambda = 0.95\). The value is normally set between 0.95 and 0.99 (Holton, 2003).

Exponentially weighted average adds weighted factors which decrease exponentially. Hence, the weighting for older values decreases but never reaches zero. Also, the most recent values have higher weights and thereby larger impact on the volatility which is desirable.

Ex ante volatility is used because it is a fairly simple model with lack of look-ahead bias in the volatility estimate. To ensure exclusion of look-ahead bias we use the volatility estimates at time \(t-1\) for returns at time \(t\).

### 2.2.3 Scaling the Autoregressive Time Series Model

Due to the scaling of the simple return, the autoregressive time series model presented in section 3.2.2, will be modified according to Moskowitz et al. (2012):

\[
r_t^s / \sigma_{t-1}^s = \beta_0 + \beta_h r_{t-h}^s / \sigma_{t-h-1}^s + \varepsilon_t^s.
\]

(4)

The simple return \(r_t^s\) for stock \(s\) at time \(t\) is regressed on its return with lag \(h\). Note that, the above model does only calculate the estimates for a single stock \(s\) and for one lag \(h\). Both returns are scaled by their ex ante volatilities \(\sigma_{t-1}^s\), the scaling is similar to using Generalized Least Squares instead of Ordinary Least Squares.
2.2.4 Test of Significance

In statistics, test on regression coefficients are commonly used to determine which regressors are important. Adding or removing variables to a model will affect the sum of squares for regression and thus also the quality and usefulness of the model. In this report, t-statistics are used to test the predictability of the time series regression model, which test the hypothesis of nonzero coefficients with a significance level of 5%. To measure the significance of coefficients, p-values are considered. A certain lag is a good predictor for future returns if the null hypothesis, \( H_0 \), can be rejected for that specific lag. The following hypotheses for testing the significance is used and go in line with the study made by Moskowitz et al. (2012),

\[
H_0 : \beta_h = 0, \quad H_1 : \beta_h \neq 0,
\]

where \( \beta_h \) is the regressor for lag \( h \) being tested. If \( H_0 \) is not rejected, this indicates that the regressor \( h \) can be deleted from the model and is thereby not a good predictor for future returns. The test statistic for the hypothesis is,

\[
t_0 = \frac{\hat{\beta}_h}{se(\hat{\beta}_h)},
\]

where \( \hat{\beta}_h \) is the unbiased estimate of \( \beta_h \) and \( se(\hat{\beta}_h) \) is the standard error of \( \hat{\beta}_h \).

As mentioned in section 3.2.2, the main difference between time series regression and the Ordinary Least Squares regression is that the assumption of uncorrelated or independent errors is usually not appropriate. A consequence of this is that tests on hypotheses based on t distribution, such as the t-statistics, is no longer an exact procedure. In order to test the time series regressions by t-statistics, all returns are divided by their volatility to put them on the same scale. This is similar to using General Least Squares instead of Ordinary Least Squares.
2.2.5 Stationary Processes

A stationary process is a stochastic process. An important property of a stationary process is that the unconditional joint probability distribution of the process does not change over time. Hence, parameters such as variance and mean also do not change over time. In time series analysis, stationary processes are one of the main underlying assumptions, and data which is not stationary will often be transformed to become stationary. Formal definition of a stationary process:

Let \( \{Y_t\} \) be a stochastic process and let \( F_Y(y_{t_1+\tau}, \ldots, y_{t_k+\tau}) \) be the cumulative distribution function of the unconditional joint distribution of \( \{Y_t\} \) at times \( t_1 + \tau, ..., t_k + \tau \). Then, \( \{Y_t\} \) is said to be strictly stationary if, for all \( k, \tau \) and \( t_1, ..., t_k \)

\[
F_Y(y_{t_1+\tau}, \ldots, y_{t_k+\tau}) = F_Y(y_{t_1}, \ldots, y_{t_k}).
\]

Since, \( \tau \) does not affect \( F_Y(\cdot) \), \( F_Y \) is not a function of time (Borkar, 1995).
3 Explorative Data Analysis

In this section, the sample construction and other data processing steps needed for the analysis are presented.

3.1 Return Definition

The adjusted stock price is generally used to calculate the simple stock return. The adjusted stock price excludes the effects of eventual changes in the price due to dividends and splits. The simple return, which is used in previous studies of momentum, is defined with the formula (Campbell et al. 1997),

\[ r_t = \frac{p_t}{p_{t-1}} - 1, \]  

(7)

where \( r_t \) is the net return at date \( t \), \( p_t \) the adjusted stock price at date \( t \) and \( p_{t-1} \) adjusted stock price at date \( t-1 \). Note that the return \( r_t \) can take negative values while the price \( p_t \) is always positive.

Formula (7) is used to calculate the monthly stock return at the end of each month.

When calculating the return, no consideration is taken to taxes or transaction costs. This is because it would be impossible to keep the report general if adjustments were made for taxes and transaction costs. Different investors may have different transaction costs depending on their economic position. As an example, it would be reasonable to assume that large investors pay less in commission than small investors.

3.2 Sample Construction

The data is sourced from OMX Stockholm Large Cap which is owned and operated by Nasdaq Stockholm AB. The data sample which is studied consists of ten years (2007-2016) of daily stock prices for companies listed as Large Cap during the whole time period, i.e. stocks which have not been listed on the
Large Cap during the whole period or have gaps in data are excluded. A-stocks are also excluded from the sample. The stock price data is obtained from prices published on Yahoo Finance. The period covers a full business cycle containing both economic recession and boom. Stocks listed on OMX Stockholm Small Cap and Mid Cap are overall more volatile than Large Cap listed stocks (Carlson, 2017). Thus, they would be over represented in the top portfolios and hence excluded from the report.
4 Methodology of the Momentum Strategy

The strategy which is used in this work is in accordance with the original study by Jagadeesh and Titman, but is extended according to the approach by Moskowitz et al. (2012) with time series regression. Hence, two different approaches to investigate eventual momentum effects are done.

4.1 Adjusting Sample to Market Imperfections

To get a fair sample of stocks, those which have not been included on the Large Cap during the full period (2007-2016) are excluded. These restrictions give a sample of 55 stocks for which the daily return are calculated by equation (7). Here, $p_t$ is the adjusted closing price, that is, the closing price adjusted for corporate actions such as dividend payments and splits. A full list of the 55 stocks is to be found in the Appendix.

4.2 Time Series Regression for Momentum Strategy

As a first step, before any time series regression is performed, stocks are investigated based on their price and daily return and the time series data are plotted. An indication whether the data is stationary or not, can be provided by looking at the different plots. To investigate the existence of auto-correlation, the built in function `ACF()` in R is used, which computes an estimate of the auto-correlation of the errors for the time series data. Auto-correlation estimations are done for time series data of both stock price and daily return.

Secondly, the stocks individual monthly return is scaled by the stocks ex ante standard deviation to make them comparable. The time series regression is then computed according to equation (4). For all stocks and months, regression are performed for lags of $h = 1, 2, ..., 24$ months. The full regression model for all the different stocks and lags then becomes:
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\[ \sum_{s=1}^{N} \frac{r_{t}^s}{\sigma_{t-1}^s} = \beta_0 + \beta_1 \sum_{s=1}^{N} \frac{r_{t-1}^s}{\sigma_{t-1}^s-1} + \beta_2 \sum_{s=1}^{N} \frac{r_{t-2}^s}{\sigma_{t-2}^s-1} + \ldots + \beta_{24} \sum_{s=1}^{N} \frac{r_{t-24}^s}{\sigma_{t-24}^s-1} + \varepsilon_t \]

(8)

where \(N\) is the number of stocks and \(\varepsilon_t = \sum_{s=1}^{N} \varepsilon_t^s\). The error term, \(\varepsilon_t^s\), represents the error for stock number \(s\) at time \(t\). Since \(N\) is large, the normality assumption can be made by the Central Limit Theorem, thus \(\varepsilon_t\) is normally distributed.

The time series predictability of future returns is used to predict price continuations and reversals for the stocks. The purpose of the regression is to identify if past return is a predictor for future return. If that is the case, it can explain the existence of momentum effects and profitability. The t-statistics will reveal if the different coefficients, i.e. the different lags, are good predictors for future returns. If the null hypothesis can be rejected for a certain lag, the lagged return is a good predictor for future return. If that is the case it could work as a mathematical explanation why a cross-sectional momentum strategy is profitable.

4.3 Cross-Sectional Momentum Strategy

The second approach is to implement the cross-sectional strategy. As described in the introduction, the momentum theory is based on the assumption that stocks will continue to perform as they have done historically. Hence, the constructed equally weighted portfolios by Jegadeesh and Titman (1993) consists of short positions on previous losers and long positions on previous winners, making the portfolios self financing. The portfolios performance period contains of one evaluation period \(k\), and one holding period \(h\), which yields strategy \((k, h)\).

The strategy in this study is similar to the one Jegadeesh and Titman suggested in 1993 but not to the full extent. Instead of both going long and short, this study is limited to only long positions for the four best performed stocks.
4.4 Implementing Momentum Strategy in R

The combinations of evaluation and holding periods are also constrained to evaluation periods of 3, 6, 9 and 12 months with a fix holding period of 1 month. Further, a month will be skipped between the evaluation and holding period which, according to Jegadeesh and Titman (1993, p. 68), ”avoids some of the bid-ask spread, price pressure, and lagged reaction effects that underlie the evidence documented in Jegadeesh (1990) and Lehmann (1990)”. New equally weighted portfolios are then made every month during the whole period (2007-2016). Hence, the study presents profitability of four different strategies.

4.4 Implementing Momentum Strategy in R

By using the packages ”Financial Instruments”, ”TTR” and ”PerformanceAnalytics” the cross-sectional momentum strategy is tested and evaluated in R. The built in function ROC() is applied to calculate the rate of change of the stocks. For evaluation periods of 3, 6, 9 and 12 months the stocks are ranked based on their returns during a holding period of 1 month. With the R function CAGR() the compounded average annual return\(^3\) of the portfolios are obtained. These returns justify if there is a possibility to gain from the momentum strategy on the market or not.

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\(^3\)Compounded annual growth rate (CAGR) is a term for the geometric progression of constant return for a time period. CAGR is defined as: 
\[
CAGR(t_0, t_n) = \left( \frac{R(t_n)}{R(t_0)} \right)^{\frac{t_n-t_0}{12}} - 1
\]
where \(R(t)\) is the monthly return for month \(t\).
5 Results

This section presents the results. To begin with, stationary testing for stock price data and return is conducted to conclude if the time series data represents stationary processes. Secondly, the time series regression model for the scaled return is presented followed by the results from the cross-sectional momentum strategy.

5.1 Stationary Testing

To illustrate time series and stationary processes, the data for ABB is presented (further examples of stock data are to be found in Appendix). First, the adjusted closing price for ABB is presented followed by the monthly return. Since lack of auto-correlation is necessary for time series analysis, an auto-correlation plot is made for both the data of price and return.

![Adjusted closing price of ABB](image)

Figure 1: The graph shows the adjusted closing price for ABB

The above graph for the adjusted closing price for ABB does not behave as
a stationary process since the data is inconsistent and do not vary around a constant mean.

Figure 2: The auto-correlation for the adjusted closed stock price of ABB.

The ACF-function reveals that there exists auto-correlation for stock price data. Since a perfectly stationary process should have no evidence of auto-correlation, low values are desirable. For the stock price data of ABB, the values of auto-correlation are especially high for short lags and drops for higher. Due to the existence of auto-correlation, stock price data can not be considered as a stationary process and time series regression analysis can not be applied.
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Figure 3: The graph shows the monthly return for ABB.

Figure 1 and 3 shows the difference between a non stationary and what could be a stationary process. In figure 3 the mean is fixed around 0 and does not change dramatically over time. The data continue to vary around the mean which indicates that it may be a stationary process.
5.1 Stationary Testing

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As the graph in Figure 4 presents, the return data has less auto-correlation than the price data. In difference from auto-correlation for price data (Figure 1), there is no trend for the values of auto-correlation for the different lags. For the return of ABB, most values of auto-correlation representing the different lags are low. As seen in the graph, the absolute values of auto-correlation for lags of 4, 8 and 14 are higher than desired.

Figure 4: Auto-correlation for the return of ABB.
When looking at the full set of stocks, stationarity is obtained for the scaled return. This shows that a sum of independent stationary processes is also a stationary process. Figure 5 shows the time series for the return of all stocks, divided by the total number of stocks in order to receive the expected return. The fluctuations are larger in the beginning of the time period which is probably a result of the economic recession in 2008.

Figure 5: Scaled return of all stocks. The summed return for all stocks is divided by the total number of stocks in order to get the expected return.
Figure 6: Auto-correlation of scaled return, all assets

The ACF-plot for the return obtained from all stocks shows that the auto-correlation is sufficiently low for most lags. The absolute value of auto-correlation for the lag representing 14 months is higher than desired. Although the auto-correlation is not perfectly low for all lags, the time series regression model will be computed.

5.2 Time Series Regression Model

Since the return data has low auto-correlation it is, according to the assumption for time series, qualified to be used for time series regression. By summing the return for all stocks scaled by their individual ex ante volatility the stationarity is kept since the stationary processes for stock return are independent of each other. The scaling may even affect the process to be more stationary since the variance stabilizes. The regression model can, according to the above results of stationarity, be performed on the scaled return data according to equation 28.
(8). The following parameters, t-statistics and p-values are given from the time series regression model and are presented in Table 1.

Table 1: The coefficients, t-values and p-values for the time series regression

<table>
<thead>
<tr>
<th>Monthly lag</th>
<th>Estimate</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.019734</td>
<td>0.818</td>
<td>0.41697</td>
</tr>
<tr>
<td>1</td>
<td>-0.441908</td>
<td>-3.306</td>
<td>0.00168</td>
</tr>
<tr>
<td>2</td>
<td>-0.150690</td>
<td>-1.031</td>
<td>0.30726</td>
</tr>
<tr>
<td>3</td>
<td>0.112237</td>
<td>0.757</td>
<td>0.45229</td>
</tr>
<tr>
<td>4</td>
<td>0.090944</td>
<td>0.617</td>
<td>0.53950</td>
</tr>
<tr>
<td>5</td>
<td>0.005307</td>
<td>0.037</td>
<td>0.97028</td>
</tr>
<tr>
<td>6</td>
<td>-0.152251</td>
<td>-1.102</td>
<td>0.27548</td>
</tr>
<tr>
<td>7</td>
<td>-0.033378</td>
<td>-0.293</td>
<td>0.77064</td>
</tr>
<tr>
<td>8</td>
<td>-0.056899</td>
<td>0.505</td>
<td>0.61537</td>
</tr>
<tr>
<td>9</td>
<td>0.015865</td>
<td>0.143</td>
<td>0.88700</td>
</tr>
<tr>
<td>10</td>
<td>0.051197</td>
<td>0.459</td>
<td>0.64780</td>
</tr>
<tr>
<td>11</td>
<td>0.114585</td>
<td>1.088</td>
<td>0.28126</td>
</tr>
<tr>
<td>12</td>
<td>0.166832</td>
<td>1.562</td>
<td>0.12412</td>
</tr>
<tr>
<td>13</td>
<td>0.097938</td>
<td>0.911</td>
<td>0.36618</td>
</tr>
<tr>
<td>14</td>
<td>0.049946</td>
<td>0.479</td>
<td>0.63380</td>
</tr>
<tr>
<td>15</td>
<td>0.032456</td>
<td>0.381</td>
<td>0.70445</td>
</tr>
<tr>
<td>16</td>
<td>0.055141</td>
<td>0.732</td>
<td>0.46717</td>
</tr>
<tr>
<td>17</td>
<td>0.074000</td>
<td>1.046</td>
<td>0.30017</td>
</tr>
<tr>
<td>18</td>
<td>-0.019942</td>
<td>-0.283</td>
<td>0.77826</td>
</tr>
<tr>
<td>19</td>
<td>-0.034857</td>
<td>-0.510</td>
<td>0.61234</td>
</tr>
<tr>
<td>20</td>
<td>-0.112312</td>
<td>-1.801</td>
<td>0.07733</td>
</tr>
<tr>
<td>21</td>
<td>-0.037192</td>
<td>-0.583</td>
<td>0.56224</td>
</tr>
<tr>
<td>22</td>
<td>-0.027504</td>
<td>-0.436</td>
<td>0.66470</td>
</tr>
<tr>
<td>23</td>
<td>-0.076200</td>
<td>-1.215</td>
<td>0.22956</td>
</tr>
<tr>
<td>24</td>
<td>-0.117537</td>
<td>-2.105</td>
<td>0.03996</td>
</tr>
</tbody>
</table>
The table shows that most coefficients are not significant since their p-values are too large, which means that the null hypothesis of coefficients being nonzero can not be rejected. Hence, the model does not imply that lagged return can predict future return. The only coefficients which are significant at the chosen significance level of 5%, are the coefficients representing one and 24 months lag. Since 24 months lag have not been studied in either Jegadeesh and Titmans (1993) research nor Moskowitz et al. (2012), the one month lag estimator will be the only coefficient for further investigation.

Figure 7: The t-statistics reveal which lags are good predictors of future returns. A high absolute value is desirable. Lags of one month and 24 months are the only coefficients significant at the chosen significant level of 5%.

The key assumption for the existence of momentum profitability is that a stocks historical performance is a predictor for its future performance. The above graph shows that the t-statistics for coefficients representing the different lags give spread indications of significance without pattern. Hence, the results from the time series regression model do not show that past return can predict fu-
ture return nor explain eventual momentum effects for lags up to 12 months. It can be seen that, no lag except one month and 24 months has sufficiently high t-statistic or low p-value to be considered significant. The result is unexpected and different compared to the result received by Moskowitz et al. (2012). They found that t-statistics for up to 12 months lag were all significant, meaning that past return of up to 12 months lag could predict future return.

To see how well the time series regression model fits actual data, a plot of the model with the significant estimator $\beta_1$ is presented in Figure 8 together with the actual data.

![Real values vs. time series regression model, with one month lag](image)

Figure 8: The graph shows the time series regression model for the significant estimator of one month lag ($\beta_1$) in red and the actual data in black.

5.3 Cross-Sectional Momentum Strategy

Implementing the cross-sectional momentum strategy in R gives the following cumulative return for portfolios based on 3, 6, 9 and 12 months evaluation peri-
5.3 Cross-Sectional Momentum Strategy  Carolina Ljung, Maria Svedberg

ods and a holding period of 1 month. The portfolios contains equally weights of the top four stocks and are rebalanced every month. Note that no consideration has been taken to costs such as transaction costs and taxes.

**Momentum Cumulative Return: Top 4 Assets**

![Cumulative Return Graph](image)

Figure 9: The top graph shows the cumulative return of the different evaluation periods. It reveals that the 12-month period is the most profitable for a portfolio containing the top 4 stocks.

<table>
<thead>
<tr>
<th>Evaluation period (months)</th>
<th>CAGR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>21.28</td>
</tr>
<tr>
<td>6</td>
<td>20.26</td>
</tr>
<tr>
<td>9</td>
<td>20.03</td>
</tr>
<tr>
<td>12</td>
<td>22.38</td>
</tr>
</tbody>
</table>

The returns from the cross-sectional momentum strategies are presented in Ta-
5.3 Cross-Sectional Momentum Strategy Carolina Ljung, Maria Svedberg

As shown in the above results, all four different strategies give positive return. The strategy with highest return is the one with an evaluation period of 12 months which gave a compounded annual growth rate (CAGR) of 22.38%.
6 Discussion

The result from the cross-sectional momentum strategies indicates that there is evidence of inefficiency on the Swedish stock market during the period 2007 to 2016. Even though the strategies used in this study are not as extensive as the ones Jegadeesh and Titman (1993) first suggested, the results are in line with the results they received with positive return for cross-sectional momentum strategies. According to the efficient market hypothesis and the theory of the random walk, these kinds of results would be impossible to achieve since the theory of efficient markets states that historical performance should not affect future performance. Thus, there is a contradiction between Jegadeesh and Titman’s result from 1993 and the economical theory. Jegadeesh and Titman themselves explain their results as an effect of consistency in delayed price reaction to firm specific information and that it was not due to any systematic risk or lead-lag price effects. Hence, they suggest that a more sophisticated explanation to their findings could be to further investigate investor behaviour.

Ever since Jegadeesh and Titman published their first study in 1993, many economists have tried to analyze their findings by applying the same strategy on different markets to see if the results are consistent. Moskowitz et al. (2012) strategy is an extension to the cross-sectional strategy since they introduced the time series aspect to their momentum strategy and also looked at more assets than just stocks. Through the time series term they could mathematically explain momentum profitability and thereby strengthen the momentum theory by Jegadeesh and Titman but also investigated the diversification of momentum effects across many different assets. The investigation whether lagged return could predict future return is the key concept behind momentum profitability, which makes it a natural extension to the cross-sectional momentum analysis. The results received in this study is partly made according to Moskowitz et al. (2012) with the same assumptions for the time series regression analysis. The t-statistics and p-values from the time series regression model are though
not similar to the t-statistic received by Moskowitz et al. (2012) since they found that lags up to 12 months were significant.

When decomposing the time series regression and cross-sectional momentum results an inconsistency is found. As Figure 9 reveals, momentum effects do exist on the Swedish stock market according to the cross-sectional approach. However, following the mathematical theory behind time series data, such as stock prices, and evaluating their capability as a predictor for future returns, no evidence for momentum effects are found. Analyzing the t-statistics in Figure 7, no clear pattern is shown and thus no conclusion can be drawn about good predictability. What causes the cross-sectional outcome and are any of the two results trustworthy?

Time series momentum is related to the concept known as “momentum” in finance literature, which primarily refers to cross-sectional momentum. Cross-sectional momentum focuses on assets relative performance in the cross section where securities which outperform their peers recently (past 3 to 12 months) will on average continue to do so in the near future. The main difference between time series momentum and cross-sectional, according to Moskowitz et al. (2012), is that time series regression focuses only on securities own past performance rather than its relative. He argues that time series momentum well matches the predictions of many known behavioural and rational asset pricing model since they focus on a single risky asset. Time series momentum is thereby preferred over cross-sectional since it captures individual security momentum. For this reason, the mathematical approach in this report is reviewed as the most accurate.

To further discuss the result yielded by the cross-sectional momentum strategy, the reader should notice that no consideration is taken to transaction costs or taxes. If these would have been taken into account, the annual compounded return would probably have been lower, since the portfolio is re-weighted every
month and would therefore involve transactions. Likewise, this report handles the simple and not the excess return. If the study was to be followed out with the excess return instead, the cross-sectional momentum strategy would not yield as high return as it currently does. This is because a stock investment is expected to grow with the risk free rate and is therefore not considered to outperform or "beat" the market due to that increase. From this perspective, the outcome of the momentum strategy in this report can be rather misleading. The true expected profit is therefore lower than the average annual return presented in the results. Thus the outcome from the two approaches perhaps are more alike than first admitted, if the transaction costs and excess return were to be taken into account.
7 Conclusion

The conclusion of this report is that, by performing cross-sectional momentum strategies, the existence of momentum effects are found on the Swedish stock market. Since no consideration has been taken to transaction costs, taxes and the risk free rate, the profit from the cross-sectional momentum strategies may be slightly lower than presented. However, the result from the cross-sectional strategy can not be justified by the time series regression model since the model gave no evidence that past return could predict future return for up to 12 months lag.
8 Further research

Since existence of time series momentum is one of the most direct test of the efficient market hypothesis and the random walk hypothesis, a natural continuation of this study is to examine the time series momentum strategy further. Likewise, clustering can be investigated to study if specific businesses are characterized by momentum. This would be of great interest to deepen the extent of examining the existence of momentum effects. Further, analyzing a younger market can contribute to more understanding within the field. A market less developed than the Swedish stock market is likely to have a higher proportion of incorrectly priced stocks and is therefore interesting to explore from a momentum effects perspective.
References


## Appendix

Table 3: Stocks listed on Stockholm OMX Large Cap and used in this study.

<table>
<thead>
<tr>
<th>Stock Name</th>
<th>Stock Name</th>
<th>Stock Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAK</td>
<td>Hexpol B</td>
<td>Sandvik</td>
</tr>
<tr>
<td>ABB</td>
<td>Holmen B</td>
<td>SCA B</td>
</tr>
<tr>
<td>Alfa Laval</td>
<td>Husqvarna B</td>
<td>SEB C</td>
</tr>
<tr>
<td>AstraZeneca</td>
<td>ICA Gruppen</td>
<td>Securitas B</td>
</tr>
<tr>
<td>Atlas Copco B</td>
<td>Investor B</td>
<td>Skanska B</td>
</tr>
<tr>
<td>Avanza Bank Holding</td>
<td>Kinnevik B</td>
<td>SKF B</td>
</tr>
<tr>
<td>Axfod</td>
<td>JM</td>
<td>SSAB B</td>
</tr>
<tr>
<td>Axis</td>
<td>Kungsleden</td>
<td>Stora Enso R</td>
</tr>
<tr>
<td>BillerudKorsnäs</td>
<td>Latour B</td>
<td>Sweco B</td>
</tr>
<tr>
<td>Boliden</td>
<td>Lundberg B</td>
<td>Swedish Match</td>
</tr>
<tr>
<td>Electrolux B</td>
<td>Lundin Petroleum</td>
<td>Swedish Orphan Biovitrum</td>
</tr>
<tr>
<td>Elekta B</td>
<td>Millicom International Cellular SDB</td>
<td>Tele2 B</td>
</tr>
<tr>
<td>Ericsson B</td>
<td>MTG B</td>
<td>Tieto</td>
</tr>
<tr>
<td>Fabege</td>
<td>NCC B</td>
<td>Trelleborg B</td>
</tr>
<tr>
<td>Fingerprint Cards B</td>
<td>Nibe Industrier B</td>
<td>Wallenstam B</td>
</tr>
<tr>
<td>Getinge B</td>
<td>Nokia</td>
<td>Wihlborgs Fastigheter</td>
</tr>
<tr>
<td>H&amp;M B</td>
<td>Nordea Bank</td>
<td>AF B</td>
</tr>
<tr>
<td>Handelsbanken B</td>
<td>Peab B</td>
<td></td>
</tr>
<tr>
<td>Hexagon B</td>
<td>SAAB B</td>
<td></td>
</tr>
</tbody>
</table>
The below graphs show adjusted closing price data and return with respectively auto-correlation graphs for Atlas Copco B and Fabege. They all show how return time series data has lower auto-correlation than stock price data, meaning that return data are more stationary.