UNIVERSITY OF GOTHENBURG

SCHOOL OF BUSINESS, ECONOMICS AND LAW

# Performance of Small- and Large-cap stock portfolios

*The importance of market anomalies across business cycles*

*Master´s Thesis – 30 credits*
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*By*

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## Abstract

This Master´s thesis investigated the importance of the market anomalies size (market capitalization), value (Book-to-Market ratio) and momentum (lagged short-term momentum) for equity returns of small- and large-cap composite stock portfolios. The study focused on two contrasting stock markets (NASDAQ OMX and NYSE) across domestic business cycles over the time-period 2006 to 2021.

Several studies focused on asset pricing have during the last decades demonstrated that the original *Capital Asset Pricing Model (CAPM)* has limited capacity to explain and predict cross-sectional and temporal variations in expected equity returns. Equity returns have been suggested to be influenced by market anomalies such as size, value, and momentum. In this thesis, the econometric approach included single- (*CAPM*) and multi-factor modelling (*Fama-French Three-factor model* and *Carhart Four-Factor model*) of composite stock portfolios based on market capitalization. Overall, there was a size-effect where the small-cap portfolios outperformed the large-cap portfolios, as well as the *OMXSGI* and *NYSE Composite* market benchmarks over the aggregate sample period. However, the relative stock performance and general patterns in equity returns of the two composite stock portfolios and market benchmarks varied within and between years. The financial indicators *Sharpe Ratio* and *Jensen´s alpha* suggested a higher risk-adjusted equity return for the small- compared to the large-cap stock portfolios, as well as for the market benchmark in a temporal isolation determined by the domestic business cycles in Sweden and the USA. Alpha-values for the small-cap portfolios seemed enhanced during boom- (more positive) or bust- (more negative) periods. In contrast, alpha-values for the large-cap portfolios were generally more at par with the market performance, especially during bust-periods. Over the aggregate sample period, however, alpha-values for both stock portfolios and stock markets seemed to converge towards zero. The multi-factor model regressions supported a positive size premium (SMB) for the small-cap portfolios and a negative size-premium for the large-cap portfolios. During boom-periods, the modelling approach indicated an enhanced size premium for the small (positive) and large (negative)-cap stock portfolios. Although no clear patterns were observed for value (HML) and momentum (UMD), the multi-factor modelling revealed positive value-effects on equity returns particularly during bust-periods and negative effects during boom-periods, irrespective of market capitalization. The UMD-coefficients seemed more pronounced (larger/smaller) from modelling of shorter time periods related to the domestic business cycles, compared to the aggregate sample period (2006-2021).

Despite the observations of a size effect, particular for the small-cap portfolio on NASDAQ OMX, the financial mechanisms that controlled equity returns appeared complex. The significant temporal variations between the equity returns of the two portfolios and the market benchmarks, along with multi-factor econometric modelling, directly implied that additional financial factors other than size, value and momentum may be important for the observed equity returns. In fact, market capitalization may serve as a proxy for one or several undisclosed financial factors correlated with size.



**Keywords:** Stock performance, Market anomalies, Asset pricing, Portfolio sorting techniques, Factor-portfolio sorting techniques, Value effect, Size effect, Momentum effect, Temporal influences, Business cycles, GDP-gap, Single-and Multi-Factor models, CAPM, Fama-French Three-Factor model, Carhart Four-Factor model, Risk-adjusted equity returns, Sharpe Ratio, Jensen´s alpha, NASDAQ OMX and NYSE

## Abbreviations

B/M = Book-to-Market ratio
BE = Book value of equity
BEA = Bureau of Economic Analysis
BG = Big-Growth (factor-portfolio)
BL = Big-Losers (factor-portfolio)
BN = Big-Neutral (factor-portfolio)
BV = Big-Value (factor-portfolio)
BW = Big-Winners (factor-portfolio)
CAPM = Capital Asset Pricing Model
CH4 = Carhart Four-Factor model
EMH = Efficient Market Hypothesis
FF3 = Fama-French Three-Factor model
GDP = Gross Domestic Product
GICS = Global Industry Classification Standard
HML = High-Minus-Low (model factor)
KI = Konjunkturinstitutet (National Institute of Economic Research in Sweden)
Market cap = Market capitalization
ME = Market value of equity
NASDAQ = National Association of Securities Dealer Automated Quotation system
NYSE = New York Stock Exchange
OECD = Organization for Economic Co-operation and Development
OLS = Ordinary Least Squares
SG = Small-Growth (factor-portfolio)
SL = Small-Losers (factor-portfolio)
SMB = Small-Minus-Big (model factor)
SN = Small-Neutral (factor-portfolio)
SR = Sharpe Ratio
STDV = Standard Deviation
SV = Small-Value (factor-portfolio)
SW = Small-Winners (factor-portfolio)
UMD = Up-Minus-Down (model factor)

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## 1. Introduction

Theories in asset pricing aim to explain factors controlling the price of an asset by linking the expected rate of return to the risks associated with the investment (Bodie et al., 2014). Factors are often described as quantitative characteristics shared across a set of securities that govern the price of an asset (Chen, 2020). In the early 1960s it became apparent that stocks with certain firm characteristics predominately explained the differences in the rate of returns observed between diversified stock portfolios. However, studies focused on asset pricing have indicated contrasting details in the detailed composition and number of factors required to explain the rate of return of an investment (Hull, 2012).

The concept *factor investing* refers to the investment practice of targeting specific firm characteristics (i.e. factors) that describe differences in equity returns. A factor-based investment strategy relies on quantitative data and financial information to weigh stock portfolios towards-/away from specific factors in the attempt to generate sustainable excess returns (Chen, 2020). A broad spectrum of potential financial factors has been assessed by several single- and multi-factor asset pricing models to explain and predict the relationship between risk and rate of return of stock portfolios (Bodie et al., 2014).

### 1.1. Capital Asset Pricing Model

The *Capital Asset Pricing Model (CAPM)* originally developed by Sharpe (1964), Lintner (1965) and Mossin (1966) constitutes a single-factor asset pricing model widely recognized and often used to capture the risk and return trade-off for securities, in particular stocks. The basic principles of *CAPM* and subsequent theoretical extensions are based on the theoretical framework originally developed by Markowitz (1952). A fundament in the theoretical framework of finance is the link and trade-off between risk exposure and expected return of a specific investment. This trade-off infers that high (or low) levels of risk are associated with high (or low) expected returns (Markowitz, 1952). Consequently, by increasing the risk exposure the expected return is assumed to increase for a specific investment. Such feedback relies on the assumption of risk aversion and the selection of investments based on the highest expected return in relation to individual risk preferences (Hull, 2012).

Financial compensation for risky investments and time value of money entails a risk premium, often defined from the expected rate of return exceeding the risk-free return (Anderson and Brooks, 2006). Investment opportunities are commonly evaluated based on the trade-off between risk- and return of the investment.

Market and firm-specific risks are two forms of risk that may affect the assets/securities of a firm. Whereas market risk is normally considered to be systematic and to affect in principle all asset classes, the firm-specific risk is unsystematic and only affects the specific firm. The firm-specific risk can be diversified to arbitrarily low levels by investing in an assortment of diverse assets. Thus, the firm-specific risk should not be priced by the market. In contrast, market risk can normally not be mitigated through diversification of stock portfolios as macroeconomic effects are often economy wide (Hull, 2012). According to Sharpe (1964), Lintner (1965) and Mossin (1966) such risks should thereby be priced by the market.

The exposure to market risk and level of compensation (expected rate of return) required to bear additional risks can be estimated using the framework of *CAPM*. In the original asset pricing equation of *CAPM* (Eq. 1), the sensitivity to market risk is represented by the model coefficient beta. Beta is a measure of the contribution of the security/portfolio to the variance of the market portfolio, normalized to the total variance of the market portfolio (Hull, 2012).

The relation between beta and expected rate of return can be expressed (Bodie et al., 2014):

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] \tag{1}$$

$E(r_i)$ = expected rate of return of portfolio/security i
$r_f$ = risk-free rate of return
$\beta_i$ = contribution of the individual portfolio/security to the variance of the market portfolio, normalized to the total variance of the market portfolio (i.e. sensitivity of the individual portfolio/security to market volatility)
$E(r_m)$ = expected rate of return of the market portfolio/index
$E(r_m) - r_f$ = market risk premium

where:

$$\beta_i = \frac{Cov(r_i, r_m)}{var(r_m)} \tag{2}$$

According to the original *CAPM* and the asset pricing equation (Eq. 1), market risk is the main factor controlling expected returns from securities/portfolios. Thus, sensitivity to market risk is presumably the main factor that governs the price of a security/portfolio.

## 1.2. Fama-French Three-Factor model

Since the construction of *CAPM* (Sharpe, 1964; Lintner, 1965; Mossin, 1966) several studies in asset pricing have suggested that additional factors may affect the risk and return trade-off for equities, both over time and in the cross-section (e.g. Banz, 1981; Fama and French, 1992; Bodie et al., 2014). Investigations have indicated that cross-sectional variations in average stock returns are associated with e.g. market capitalization (size) and Book-to-Market ratio (B/M; value) (Banz, 1981; Fama and French, 1992). Small-cap stocks were often observed to outperform large-cap stocks, and value stocks (high B/M) to outperform growth stocks (low B/M) in terms of average- and risk-adjusted equity returns. Similar observations have since been made in other international studies (Malin and Veeraraghavan, 2004; Crain, 2011; Hou et al., 2015) which further support that market anomalies, e.g. size and value effects, are not efficiently priced by the original *CAPM*. Consequently, the *Fama-French Three-Factor model* (Fama and French, 1992; 1996) was developed to describe and predict the expected rate of returns for securities more accurately. In addition to the market factor, the *Fama-French Three-Factor model* accounts for market capitalization/size (Small-Minus-Big; SMB) and Book-to-Market ratio/value (High-Minus-Low; HML). This theoretical model for asset pricing is widely used to empirically describe and estimate the trade-off between risk and rate of return for securities/portfolios (Fama and French, 1992; 1996; Hull, 2012).

The *Fama-French Three-Factor model* is formulated (Fama and French, 1996):

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] + \beta_{iSMB}E(SMB) + \beta_{iHML}E(HML) \tag{3}$$

$E(r_i)$ = expected rate of return of portfolio/security i
$r_f$ = risk-free rate of return
$\beta_i$ = contribution of the individual portfolio/security to the variance of the market portfolio, normalized to the total variance of the market portfolio (i.e., sensitivity of the individual portfolio/security to market volatility)
$E(r_m)$ = expected rate of return of the market portfolio/index
$E(r_m) - r_f$ = market risk premium
$\beta_{iSMB}$ and $\beta_{iHML}$ = sensitivity of the individual portfolio/security to SMB and HML respectively
$E(SMB)$ = size-/SMB premium
$E(HML)$ = value-/HML premium

## 1.3. Carhart Four-Factor model

The *Carhart Four-Factor model* (Carhart, 1997) extended the theoretical principles of *CAPM* and the *Fama-French Three-Factor model* by, in addition to size (Small-Minus-Big; SMB) and value (High-Minus-Low; HML), also including a factor for momentum (Up-Minus-Down; UMD) in the asset pricing equation. According to Jegadeesh and Titman (1993) and

Carhart (1997) stock prices often exhibit momentum, i.e. a tendency for the stock price to continue rising (or declining) following a period of increase (or decrease). Low and Tan (2016) argued that such multi-factor extension further explained model projections of equity returns, particularly in the cross-section.

The *Carhart Four-Factor model* is often formulated (Carhart, 1997):

$$E(r_i) = r_f + \beta_i\left[E(r_m) - r_f\right] + \beta_{iSMB}E(SMB) + \beta_{iHML}E(HML) + \beta_{iUMD}E(UMD) \tag{4}$$

$E(r_i)$ = expected rate of return of portfolio/security i
$r_f$ = risk-free rate of return
$\beta_i$ = contribution of the individual portfolio/security to the variance of the market portfolio, normalized to the total variance of the market portfolio (i.e., sensitivity of the portfolio/security to market volatility)
$E(r_m)$ = expected rate of return of the market portfolio/index
$E(r_m) - r_f$ = market risk premium
$\beta_{iSMB}$, $\beta_{iHML}$ and $\beta_{iUMD}$ = sensivity of the individual portfolio/security to SMB, HML and UMD respectively
$E(SMB)$ = size-/SMB premium
$E(HML)$ = value-/HML premium
$E(UMD)$ = momentum-/UMD premium

### 1.4. Efficient Market Hypothesis

The underlying assumptions that describe the behavior of stock markets have been theorized, for example by the *Efficient Market Hypothesis (EMH).* According to *EMH,* stock performance is assumed to change randomly over time and asset prices are considered to fully reflect all available information (Fama, 1969). These assumptions imply that, in principle, it would not be possible to outperform the market on a risk-adjusted basis since market prices typically follow arbitrary patterns and only react to new information. In contrast to the principles of *EMH*, small-cap firms have often been observed to outperform large-cap firms in terms of average- and risk-adjusted equity returns (Banz, 1981; Fama and French, 1992; 1996). Furthermore, firms with a high Book-to-Market ratio (value stocks) and a positive lagged short-term momentum were observed to outperform firms with a low Book-to-Market ratio (growth stocks) and a negative lagged short-term momentum (Jegadeesh and Titman, 1993; Carhart, 1997). The market phenomena of general size- (Small-Minus-Big; SMB), value- (High-Minus-Low; HML) and momentum (Up-Minus-Down; UMD) effects on equity returns are considered market anomalies in the sense that they constitute predictabilities inconsistent with generally recognized theories of asset pricing. Market anomalies such as these therefore challenge basic principles of the *EMH*, including the assumption that excess returns are only earned by chance or by increasing the risk of assets. Such empirical observations also challenge the principles of active investment strategies and that a consistent outperformance relative to the general market would enable individual investors to structure an investment portfolio without relying on stock picking or market timing (Bodie et al., 2014).

## 2. Literature review

Since the introduction of the *CAPM* (Sharpe, 1964; Lintner, 1965; Mossin, 1966), several studies focused on asset pricing have suggested additional factors (market anomalies) that may affect the risk and return trade-off for stocks, both over time and in the cross-section. In addition to size (market capitalization; Banz, 1981; Fama and French, 1992; 1996), value (Book-to-Market ratio, B/M; Fama and French, 1992; 1996; Cakici and Topyan, 2014) and momentum (Jegadeesh and Titman, 1993; Carhart, 1997; Low and Tan, 2016), market anomalies suggested to affect rates of equity return also include e.g. price-to-earning ratio (P/E; Anderson and Brooks, 2006; Fama and French, 1992), liquidity (Amihud and Mendelson, 1986; Amihud, 2002; Hou et al., 2015), sin (e.g. Hong and Kacperczyk, 2009), and financial leverage (e.g. George and Hwang, 2007; Gomes and Schmid, 2010). Furthermore, temporal effects within and between years (e.g. the *January*-, *Turn-of-the-month*- or *Weekend effects*) have also been acknowledged as potentially important for equity returns (Keim, 1983; Crain, 2011, Canady, 2019). Thus, the single-factor model, *CAPM*, seemingly needs to be revised to describe and predict the relation between risk exposure and equity returns more accurately.

Observations on asset pricing and the importance of market anomalies are, however, often inconsistent with significant differences in the controls and quantitative importance for equity returns (e.g. Malin and Veeraraghavan, 2004; Bodie et al, 2014). Also, although a wide recognition and apparent consensus of some market anomalies (e.g. size, value, liquidity and momentum) their relative importance and controlling mechanisms frequently reveal temporal and regional tendencies related to the characteristics of the stock market investigated (Lustig and Leinbach, 1983; Fama and French, 1998; Hou et al., 2017). These characteristics encompass e.g. the relative importance of different industry sectors (e.g. Bauer et al., 2005) as well as domestic business cycles of the respective country (e.g. Keim, 1983; Crain, 2011; Canady, 2019). In this thesis, the market anomalies size (market capitalization), value (Book-to-Market ratio; B/M) and momentum (lagged short-term momentum) were the primary focus of investigations.

## 2.1. Market anomalies size, value and momentum

### 2.1.1. Size effects

Banz (1981) suggested market capitalization (firm size) as an important financial factor for the control of equity returns. From 1940 to 1981 a negative correlation was observed between market capitalization and equity return on the New York Stock Exchange (NYSE). On average, smaller firms were associated with higher risk-adjusted returns than those of larger firms. This *size effect* implied that the single-factor instrument for financial evaluations (*CAPM*) did not accurately account for size as an explanatory variable during evaluations of equity returns. However, although a significant size-related effect was observed on risk-adjusted equity returns, it was not known if market capitalization (firm size) per se was responsible for this effect. Observations may rather have been caused by undisclosed factors correlated with market capitalization (Banz, 1981).

The *CAPM* comprised an appropriate analytical tool to evaluate the performance of large-cap firms in stock portfolios sorted by market capitalization (firm size; Lustig and Leinbach, 1983). However, in conjunction with Banz (1981), the single-factor model was inconsistent in the ability to describe the performance of small-cap firms. Consequently, observations of excess returns by small-cap stocks were suggested to be caused by a market compensation for efforts to obtain adequate and sufficient information (Lustig and Leinbach, 1983). Overall and in contrast to large firms, small firms seemed neglected by large trading institutions whereby timely and accurate financial information about smaller firms was less available. Such information defiance made neglected firms (e.g. small-cap firms) riskier investments that commanded higher returns. Additional and supporting evidence of such *neglected-firm effect* embedded in the general *size effect* was further provided by Arbel and Strebel (1983).

Complementary studies have indicated a time-dependent size effect with most pronounced effects during January (e.g. Keim, 1983; Crain, 2011; Canady, 2019). For example, over the period 1963-1979 approximately 50 % of the average size effect observed on the New York Stock Exchange (NYSE) were due to abnormal equity returns in January (Keim, 1983). Additionally, more than 50 % of the January premium were suggested attributed to the large returns from trading during the first week of the year. Thus, the correlation between firm size (market capitalization) and excess returns appeared most pronounced in January than any other month.

Although a general size effect has been indicated in several stock markets world-wide (e.g. Chan et al, 1991, Fama and French, 1998; Hou et al., 2015), contrasting observations have also been reported. Malin and Veeraraghavan (2004), for example, investigated the robustness of the *Fama-French Three-Factor model* for stocks listed in Germany, France, and the U.K. According to their study, there seemed to be a small size effect associated with the French- and German stock markets. In contrast, the inverse relationship was discovered on the stock market in the U.K. where the importance of size for equity returns was closely associated with meta-structures and the financial composition of the specific stock market. Furthermore, Scheurle and Spremann (2010) inferred that size mainly represents the risk associated with the initial phase of an upward economic trend.

#### 2.1.2. Value effects

Basu (1977; 1983) was among the first studies to acknowledge value (Book-to-Market ratio; B/M) as an important financial factor for equity returns. Observations supported a positive correlation between B/M and equity returns when evaluating common stocks on NYSE. It was further suggested that value effects were not independent of market capitalization (size) and that the combined effects from both financial factors on expected equity returns were more complex than previously assumed. Observations by Banz (1981) of negative correlations between firm size (market capitalization) and equity returns were further confirmed and strengthened by Fama and French (1992; 1996). In addition to size (market capitalization) there was a tendency for value stocks (low P/E ratio, high B/M) to provide higher average equity returns than growth stocks (high P/E, low B/M) (Fama and French, 1996; Cakici and Topyan, 2014). Consequently, Fama and French (1992; 1996) introduced an extension of the original *CAPM* in which size (Small-Minus-Big; SMB) and value (High-Minus-Low; HML) were included as additional model factors, i.e. the *Fama-French Three-Factor model*. The three-factor extension was suggested to improve the model predictability and describe equity returns formed by size (market capitalization) and value (Book-to-Market ratio; B/M) more accurately than previously used asset pricing models (Chan et al., 1991; Fama and French, 1992; 1996; Cakici and Topyan, 2014).

Complementary studies have confirmed and further strengthened positive correlations between value (Book-to-Market ratio; B/M) and equity returns. For example, a significant positive relationship between B/M and equity returns of firms listed in Japan was reported in the study by Chan et al. (1991). Further, from 1992 to 2012, B/M was identified as a significant control of future returns in eight emerging markets in Asia (Cakici and Topyan, 2014).

Although a general value effect has been observed on several stock markets, e.g. in Japan (Chan et al., 1991), USA (Fama and French, 1992; 1996) and Germany (Fama and French, 1998; Hull, 2012), contrasting observations have also been demonstrated. Malin and Veeraraghavan (2004), for example, investigated the robustness of the *Fama-French Three-factor model* and could not identify value effects for equities listed in Germany, France and the U.K. Inversely, these authors reported a *growth effect* in which the investigated growth stocks provided relatively higher equity returns than the value stocks. Furthermore, Hull (2012) observed a temporal dependency between value effects and the performance of growth- and value stocks. Also, growth- (or value) stocks, irrespective of market capitalization, tended to outperform the market during boom-(or bust) periods (Fama and French, 1998; Petkova and Zhang, 2005; Scheurle and Spremann, 2010).

### 2.1.3. Momentum effects

Jegadeesh and Titman (1993) was the first study to suggest momentum (lagged short-term momentum) as an important financial factor to explain expected equity returns. A positive correlation was reported between equity returns and firm stocks that performed well in the one-year past. The momentum effect was described as the tendency for stock prices to remain increasing (or decreasing) following a period of increase (or decrease). A strategy was therefore inferred to buy (or sell) firm stocks which have performed well (or poorly) during the previous year. Such strategy would, on average, generate a compounded excess equity return of 12 % per annum between 1965 to 1989 in the USA (Jegadeesh and Titman, 1993). Observations of a momentum effect were further confirmed and strengthened in the studies by Asness et al. (2013) and Fama and French (2012), in which momentum effects were demonstrated on stock markets in North America, Europe, and Pacific regions in Asia. However, no conclusive evidence of momentum-related returns was found in Japan (Fama and French, 2012).

The observations of positive correlations between momentum (lagged short-term) and equity returns were further refined and constituted the base for the introduction of the *Carhart Four-Factor model* (Carhart, 1997). The model formed a theoretical extension of the *Fama-French Three-Factor model* (Fama and French, 1992; 1996), including momentum (Up-Minus-

Down; UMD) as an additional model factor. Such model extension further improved the capacity to predict equity returns in econometric models (Carhart, 1997; Scheurle and Spremann, 2010; Low and Tan, 2016).

However, although a general momentum effect has been observed in several national stock markets, there are also contrasting observations. Lo and MacKinlay (1988) reported a positive momentum particularly over short- to intermediate time horizons in the aggregate market (NYSE). In contrast, negative effects of momentum were observed over longer time horizons. Such tendencies were suggested mainly attributed to a short-term market overreaction, causing momentum in prices and subsequent long-term reversals when the market recognized past errors. Similar observations of a momentum effect over shorter time-intervals, while contrasting and inconsistent effects over longer periods, were made by Low and Tan (2016). Momentum effects also seemed to be cyclic, with patterns related to domestic business cycles and the evolution of boom-/bust-periods (Low and Tan, 2016). In contrast, there was no evidence of a momentum effect across business cycles on NYSE between 1926 and 2007 (Scheurle and Spremann; 2010).

## 3. Objectives and rationale

Econometric studies on potential correlations between market anomalies such as size (market capitalization), value (Book-to-Market ratio) and momentum (lagged short-term momentum), and their eventual effects on the risk- and return trade-off for equities often appear inconclusive and divergent (e.g. Crain, 2011; Bodie et al., 2014). Additionally, there are contrasting results from studies focused on the importance of various market anomalies for the equity return of different stock markets (e.g. Chan et al., 1991; Bodie et al., 2014; Hou et al., 2015), time periods (Horowitz et al., 2000; Crain, 2011) as well as across domestic business cycles of the respective countries (Crain, 2011; Canady, 2019).

*The overall aims* of this Master´s Thesis were to:

- Quantitatively evaluate the importance of a suite of market anomalies for equity returns of small- and large-cap stocks in contrasting stock markets
- Quantitatively evaluate equity returns across domestic business cycles

*Specific objectives* were to:

- Quantitatively evaluate the importance of the market anomalies size, value and momentum for equity returns of small- and large-cap stocks on NASDAQ OMX and NYSE over the time-period 2006-2021
- Quantitatively evaluate equity returns across domestic business cycles over the time-period 2006-2021

In accordance with contrasting observations on the importance of market anomalies over time and across different stock markets, it was motivated to perform detailed investigations focused on these aspects in a temporal- and international context. In this thesis, the performance of the American- (New York Stock Exchange; NYSE), and Swedish (NASDAQ OMX) equity markets was evaluated across the respective domestic business cycle.

Quantitative analyses related to market anomalies and equity returns have predominately considered stock markets in larger OECD countries, e.g. USA (Banz, 1981; Fama and French, 1992; 1996; Low and Tan, 2016), Japan (Chan et al., 1991; Fama and French, 1998), France and Germany (Malin and Veeraraghavan, 2004; Crain, 2011). As a consequence, there are fewer studies that focus on the importance of market anomalies for equity returns in smaller markets, e.g. the Swedish equity market (NASDAQ OMX). It was therefore considered interesting to in detail compare and investigate the importance of market anomalies for equity returns on the Swedish equity market.

Furthermore, quantitative analyses on the NYSE have largely focused on the pre- and subprime mortgage crisis (2007 to 2010). Important objectives of the present study therefore encompassed detailed investigations focused on the significance of these market anomalies/factors for equity returns over time, by also including the less exhaustively covered post-subprime crisis period as well as economic effects associated with the most recent/current COVID-19 recession.

To isolate specific effects from a particular market capitalization, two composite portfolios based on market capitalization were constructed on the respective stock market (Bauer et al., 2005). The portfolios contained stocks from large- and small-cap firms listed on NASDAQ OMX and NYSE, respectively. The stock portfolios were quantitatively evaluated based on average- and risk-adjusted equity returns. Statistical evaluations were made using single- (*CAPM*; Sharpe, 1964, Lintner, 1965; Mossin, 1966) and multi-factor asset pricing models (*Fama-French Three-Factor model*; Fama and French, 1992; and *Carhart Four-Factor model*; Carhart, 1997). These multi-factor models facilitated detailed investigations on the relative importance of market capitalization, Book-to-Market ratio (B/M), and momentum as additional factors in the pricing equation.

## 4. Data handling and methodology

The analytical protocols encompassed general collection of pricing data for equities and market indices, as well as associated delimitations necessary for the comparative- and econometric analyses. A detailed description of the composite portfolio- and factor-portfolio sorting techniques underlying the econometric data analyses is presented in the following sections. Sections also include a description of techniques used for temporal classifications of business cycles, quantitative calculations and computational analyses, as well as methods for statistical assessments.

### 4.1. Data collection, general delimitations and market indices

The pricing data for equities traded on the Swedish- (NASDAQ OMX) and American (NYSE) equity markets over the sample period January 2006 to January 2021 was collected on a daily and monthly basis from Refinitiv Eikon and Bloomberg (Thomson Reuters, 2021; Bloomberg L.P., 2021). Data on a daily frequency was used for comparative econometric analyses and to improve the inferential properties of the samples. Monthly frequency data was primarily used for comparison and to illustrate the development of equity returns over time.

Within each composite portfolio, firms with continuous data of stock prices for the entire sample period (2006-2021) were prioritized and selected for the model analyses. Firms were excluded from model evaluations if stock prices were missing for three months or longer (Bodie et al., 2014).

To compute the model factors Small-Minus-Big (SMB), High-Minus-Low (HML) and Up-Minus-Down (UMD), fundamental information of firms listed on NASDAQ OMX and NYSE was collected from Refinitiv Eikon (Thomson Reuters, 2021) and Bloomberg (Bloomberg L.P., 2021). The information included firm-specific balance sheets with total assets, total liabilities and total equity, as well as income statements (net income), annual reports (book value of equity; BE) and interim reports (book value of equity; BE).

The Swedish (*statsobligationsräntan*) and the American (*Treasury bill*) risk-free rates were collected monthly from the Swedish Riksbank (2021) and U.S Department of the Treasury (2021), respectively. To conform to the general format of model analyses, the monthly risk-free rates were converted to daily frequencies by dividing the monthly risk-free rate by the number of days of the respective month.

The market index, *OMXSGI* (GI – gross index), was used as benchmark for the Swedish equity market during econometric model comparisons and development of equity returns over time for small-, mid-, and large-cap stocks. *OMXSGI* was used as market reference for the development of stocks on the Swedish equity market since total returns included share price development and share dividends. Similarly, the market index *New York Stock Exchange (NYSE) Composite*, was used as benchmark during econometric model comparisons and development of equity returns over time for small-, mid-, and large-cap stocks on the American equity market. The *NYSE Composite* was used as market reference since total returns included share price development and share dividends. In contrast to many other NYSE market benchmarks (e.g., *S&P 500, Russel 300, Dow Jones Industrial Average*) this benchmark covers all listed common stocks on NYSE, irrespective of market capitalization. Such analytical approach was considered beneficial because main analyses included evaluations of the equity returns for composite portfolios of small- and large market capitalizations.

The delimitation and sorting of firms into industry sectors was made according to the Global Industry Classification Standard (GICS; MSCI, 1999). GICS separates between ten different industry sectors: Real estate, Technology, Financials, Utilities, Telecommunications, Health care, Consumer goods and services, Industrials, Basic materials and Energy.

### 4.2. Composite portfolio sorting techniques and market capitalization

Model evaluations of potential size effects on the equity returns of stock markets commonly categorize and differentiate between composite portfolios based on market capitalization. In this thesis, the categorization between firms of different market capitalizations (small-, mid-, and large-cap stocks) on NASDAQ OMX and NYSE was made according to the definitions of market capitalization provided by the respective stock market (Table 1).

**Table 1.** Principles for general categorization of large-, mid- and small-cap stocks on NASDAQ OMX (NASDAQ Inc, 2021) and New York Stock Exchange (NYSE Inc., 2021) based on information of market capitalization provided by the respective stock market.

| | NASDAQ OMX | New York Stock Exchange |
|---|---|---|
| **Large-cap** | Market value over one billion EUR | Market value of at least 10 billion USD |
| **Mid-cap** | Market value between 150 million EUR and one billion EUR | Market value between 2 billion USD and 10 billion USD |
| **Small-cap** | Market value below 150 million EUR | Market value between 300 million USD and 2 billion USD |

Market capitalization was in this study defined from the total market value of all outstanding shares for the individual firm, calculated by multiplying the number of outstanding shares by the current share price. The delimitation for small- and large-cap firms (Table 1) was used to sort stocks into two composite portfolios on each of the NASDAQ OMX and NYSE stock markets, representing small-cap and large-cap stocks, respectively (Fig. 1).

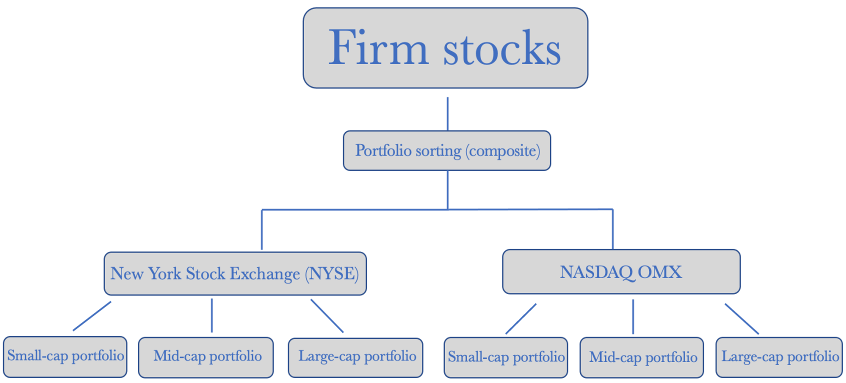


**Figure 1.** General analytical principles used to sort composite stock portfolios based on market capitalization on NASDAQ OMX and NYSE.

The separation of portfolios based on market capitalization was made to isolate potential effects from the market anomalies/model factors Small-Minus-Big (SMB), High-Minus-Low (HML) and Up-Minus-Down (UMD) on firms associated with a particular market capitalization (Bauer et al., 2005; Crain, 2011). The small- and large-cap stock portfolios were used for econometric model evaluations, whereas portfolios representing mid-cap stocks were included in the general comparative analysis of equity returns over time (Hull, 2012).

### 4.3. Temporal classifications of business cycles

While the state of the domestic economy is often characterized by the level of economic activity in relation to a specific trend or level of economic equilibrium, a domestic business cycle can be described as the recurring variations in economic activity around a specific level of economic equilibrium (Gottfries, 2013). Activities of the entire economy are normally quantified by the Gross Domestic Product (GDP; Eq. 5), and the time dependent trends of business cycles are often used for comparisons of potential GDP (Eq. 6; Field, 2014).

$$GDP = C + I + G + (X - M) \tag{5}$$

$C$ = Private consumption expenditures (households, non-profit organizations)
$I$ = Investments or business expenditures (businesses, real-estate purchases by households)
$G$ = Government expenditures (governmental goods and service purchases)
$X$ = Export expenditures (sale of domestic goods and services to foreign entities)
$M$ = Import expenditures (purchase of foreign goods and services)

$$GDP_{potential} = PEE + PEP \tag{6}$$

$PEE$ = Potential economic employment. Refers to the level of economic employment compatible with a stable wage development normalized to the inflation rate. "Potential" indicates the highest level of employment compatible with a stable inflation.
$PEP$ = Potential economic productivity. Describes the difference between actual and most efficient/optimal level of economic productivity. "Potential" refers to the potential of economic productivity with respect to an ideal level of productivity given the current available factors of production in the country.

Although there are several empirical measures to define business cycles, the difference between real- and potential GDP (i.e. the GDP-gap) was in this thesis used for temporal classifications of the domestic business cycles in Sweden and in the USA. The real GDP was calculated from the non-inflation adjusted GDP (nominal GDP) normalized to the GDP deflator (R) (Gottfries, 2013):

$$Real\ GDP = \frac{Nominal\ GDP}{R} \tag{7}$$

$R$ = GDP deflator. A price index that describes the annual impact of inflation on the general GDP.

The GDP-gap, expressed in relation to the real GDP, was calculated according to:

$$GDP\ gap = \frac{real\ GDP - potential\ GDP}{real\ GDP} \tag{8}$$

The economy was considered to be in a boom (or bust)-period if real GDP was larger (or smaller) than potential GDP. A positive (or negative) GDP-gap thus corresponded to a boom (or bust)-period, while a GDP-gap close to zero was considered to reflect a balanced economic state. During the sample period January 2006 to January 2021, economic data associated with GDP, real GDP, nominal GDP and potential GDP from Sweden and the USA was collected on an annual frequency from the National Institute of Economic Research in Sweden (KI; Konjunkturinstitutet; 2021) and U.S Bureau of Economic Analysis (BEA; 2021), respectively. The country-specific data on potential GDP and real GDP was used to compute the annual GDP-gap.

### 4.4. Quantitative calculations and computations

#### 4.4.1. Rate of returns

The rate of return is defined from the net yield of an investment over a specified time-period, t. Typically, return is expressed and visualized relative to the initial cost of the investment (Hull, 2012). Rates of return at time t ($r_t$) for the respective stock portfolio were in the present study calculated according to:

$$r_t = \frac{P_t}{P_{t-1}} - 1 \quad (9)$$

$P_t$ = security price (at time t)
$P_{t-1}$ = security price (at time t-1)

The total daily rate of return was estimated from the closing price of stocks each day, while total monthly rate of return was computed from the closing price of each month (Bloomberg L.P., 2021; Thomson Reuters, 2021). In accordance with the use of *OMXSGI* and *NYSE Composite* as return indices for the development of stocks on the Swedish- and American equity markets, respectively, the price of stocks included share price developments and share dividends.

### 4.4.2. Book-to-Market ratio

The Book-to-Market ratio (B/M) is often used as an indicator of firm value. In this thesis, B/M was defined as the book value of equity (BE) divided by the market value of equity (ME) (Hull, 2012):

$$Book\ to\ Market\ ratio = \frac{Book\ value\ of\ equity_i}{Market\ value\ of\ equity_i} \tag{10}$$

Book value of equity = original cost of the asset reduced by any depreciation, amortization or impairment costs made against the asset.
Market value of equity = market capitalization (number of outstanding shares multiplied by the current share price)
$i$ = the i:th data observation

The book value of equity refers to the common equity of the firm, i.e. the amount available for the shareholders following the payment of all firm liabilities. The BE of individual firms was primarily collected from annual- and interim reports. For firms with undocumented values, BE was calculated from (Bodie et al., 2014):

$$Book\ value\ of\ equity_i = (1 - t) \cdot UR_i + TR_i + E_i \tag{11}$$

$t$ = tax-rate
$UR_i$ = untaxed reserves of the firm
$TR_i$ = taxed reserves of the firm (e.g., amounts payable, accrued liabilities or other amounts owing in respect of taxes attributable to the operations of the individual firm)
$E_i$= equity of the firm

The market value of equity, or market capitalization, relates to the total currency value of equity for the firm. The market capitalization is a conservative measure of firm value and is calculated by multiplying the current stock price by the total number of outstanding shares.

A high B/M indicates that the general market value and the equity of the firm is lower than its book value. Stocks with a high B/M are often referred to as value stocks. Similarly, a low B/M indicates that the equity of the firms is valued lower than the book value. Stocks with a low B/M are considered growth stocks as they are typically associated with a potential for future growth (Fama and French, 1992). Eventual effects from B/M on the performance of stock portfolios are often referred to as *value effects*. Fundamental information used to calculate ME, BE and B/M for individual firms listed on NASDAQ OMX and NYSE was collected from Refinitiv Eikon and Bloomberg (Thomson Reuters, 2021; Bloomberg L.P., 2021).

### 4.4.3. One-year past rate of returns

In the present study, the one-year past rate of return (lagged short-term momentum) refers to the rate of return provided by a particular firm over the last 12 months, excluding the most recent month (Asness et al., 2013). One-year past returns are often used to indicate firm-specific lagged short-term momentum. Here, one-year past returns were defined as the difference between the last non-zero price of the previous month and the last non-zero price 12 months ago, normalized to the last non-zero price 12 months ago (Asness et al., 2013; 2018; Eq.12).

$$r_t = \frac{P_{t-1}}{P_{t-12}} - 1 \qquad (12)$$

$P_{t-1}$ = security price (at time t-1, i.e., previous month)
$P_{t-12}$= security price (at time t-12, i.e., 12 months ago)

Data used to calculate one-year past rate of returns for individual firms listed on NASDAQ OMX and NYSE was collected from Refinitiv Eikon and Bloomberg (Thomson Reuters, 2021; Bloomberg L.P., 2021).

### 4.4.4. Risk- and risk-adjusted performance metrics

The risk, or volatility, is generally defined as the probability of unexpected outcomes (Field, 2014). The risk of individual stock portfolios was in this study inferred from the standard deviation of the rate of returns (Bodie et al, 2014):

$$\hat{\sigma}_p = \sqrt{\frac{1}{n-1}\sum_{s=1}^{n}[r(s) - \bar{r}]^2} \qquad (13)$$

$\hat{\sigma}_p$ = estimated standard deviation of the portfolio´s rate of returns (i.e., portfolio risk)
$r(s)$ = realized rate of return in each scenario
$\bar{r}$ = deviations from the sample arithmetic average

In principle, however, the standard deviation can only be used as an appropriate measure of portfolio risk if the distribution of data approximately follows a normal probability distribution ($r_p - r_f \sim N(\mu, \sigma^2)$) (Field, 2014). The underlying probability distributions of the rates of return for the small-, mid, large-cap portfolios on NASDAQ OMX and NYSE were therefore evaluated by histograms and quantile-quantile (q-q) plots (Field, 2014; Appendix A).

The *Sharpe Ratio* (SR; Sharpe, 1994) and *Jensen´s alpha* (Jensen, 1967) are metrics frequently used to evaluate the risk-adjusted performance of stock portfolios. The *Sharpe Ratio*, or reward-to-volatility ratio, constitutes one of the most common methods for calculating risk-adjusted returns and represents the additional level of return investors receive per unit change of total risk-exposure (Bodie et al, 2014). The *Sharpe Ratio (SR)* is defined as the average return earned in excess of the risk-free rate, normalized to the volatility (total risk) of the stock portfolio. (Hull, 2012; Sharpe, 1994):

$$SR = \frac{r_p - r_f}{\sigma_p} \tag{14}$$

$r_p$ = portfolio rate of return
$r_f$ = risk-free rate of return
$\sigma_p$= total volatility of the portfolio´s rate of returns

*Jensen´s alpha* is a measure of risk-adjusted performance frequently used to evaluate the marginal return associated with unit exposure to a given strategy. It represents the average return from an investment, above or below that predicted by *CAPM* (Eq.15), *Fama-French Three-Factor model* (Eq.16), or *Carhart Four-Factor model* (Eq.17), respectively.

$$\alpha_p = r_p - \left[r_f + \beta_{mkt}\left(r_m - r_f\right)\right] \tag{15}$$

$$\alpha_p = r_p - \left[r_f + \beta_{mkt}\left(r_m - r_f\right) + \beta_{SMB}(SMB) + \beta_{HML}(HML)\right] \tag{16}$$

$$\alpha_p = r_p - \left[r_f + \beta_{mkt}\left(r_m - r_f\right) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{UMD}(UMD)\right] \tag{17}$$

$r_p$ = portfolio rate of return
$r_f$ = risk-free rate of return
$\beta_{mkt}$ = portfolio beta (i.e. sensitivity of the portfolio/security to market volatility)
$r_m$ = rate of return of the market portfolio/index
$\beta_{SMB}$ = factor loading on the SMB portfolio
$\beta_{HML}$ = factor loading on the HML portfolio
$\beta_{UMD}$ = factor loading on the UMD portfolio

The underlying probability distributions of data related to equity returns need to be considered to evaluate the statistical significance of the risk-adjusted performance (Stock and Watson, 2015). In the event of non-normality, corrections of data were made to compensate for violations of normality (Opdyke, 2007):

$$\widehat{SE(\widehat{SR})} = \sqrt{\frac{1-\widehat{\gamma_3}\widehat{SR}\frac{\widehat{\gamma_4}-1}{4}\widehat{SR^2}}{n-1}} \tag{18}$$

where:

$\gamma_3 = \frac{\mu_3}{\sigma^3}$ and $\gamma_4 = \frac{\mu_4}{\sigma^4}$

$\hat{\gamma}_3$ = estimated skewness of the distribution (third central moment)
$\widehat{\gamma_4}$ = estimated kurtosis of the distribution (fourth central moment)
$n$ = number of observations

The Student´s two-sided t-test was used to evaluate statistical difference between the respective risk-adjusted performance metrics of two stock portfolios (StataCorp. V16, 2019):

$$t_{df} = \frac{(\bar{x}_1-\bar{x}_2)-d_0}{\sqrt{\left(\frac{s_1^2}{n_1}+\frac{s_2^2}{n_2}\right)}} \tag{19}$$

$\bar{x}_i$ = point estimate of the individual portfolio
$d_0$ = hypothesized difference between the portfolios (i.e., zero; no superior ability)
$s_i^2$ = estimated variance of the individual portfolio (squared STDV)
$n_i$ = number of observations of the individual portfolio

## 4.5. Factor-portfolio sorting techniques

Methodologies used to construct and sort factor-portfolios based on size-(Small-Minus-Big; SMB), value-(High-Minus-Low; HML) and momentum-(Up-Minus-Down; UMD) were based on Asness et al. (2013; 2018) and Daniel and Moskowitz (2016). The breakpoints for size (market cap), Book-to-Market ratio (B/M) and momentum (one-year past returns) were refreshed monthly. The factor portfolio was consistently rebalanced at the same frequency. In this study, the factor portfolios were value-weighted (Asness et al., 2013; 2018; Daniel and Moskowitz, 2016).

### 4.5.1. Small-Minus-Big factor

The Small-Minus-Big (SMB)-portfolios were constructed by sorting stocks based on market capitalization. The sample of firms was assigned into two factor-portfolios sorted on market capitalization on NASDAQ OMX and NYSE, respectively. The breakpoint for separation between categories was set at the 80th percentile (Asness et al., 2013). Firms with an ME above the 80th percentile was categorized as "big", while firms with an ME below the 80th percentile were referred to as "small". Similar to the studies by Asness et al. (2013; 2018) and Daniel and Moskowitz (2016), six HML-portfolios (Small-Growth, SG; Small-Neutral, SN; Small-Value, SV; Big-Growth, BG; Big-Neutral, BN; Big-Value, BV) and four UMD-portfolios (Small-Winners, SW; Small-Losers, SL; Big-Winners, BW; Big-Losers, BL) were sorted within the "small" and "big" portfolios on each of the NASDAQ OMX and NYSE, respectively (Fig. 2).

The value assigned by the SMB-factor can be formulated as the average rate of return of the three small-portfolios minus the average rate of return of the three big-portfolios (Asness et al., 2013; Fama and French, 1993):

$$SMB = \frac{r_{SG}+r_{SN}+r_{SV}}{3} - \frac{r_{BG}+r_{BN}+r_{BV}}{3} \qquad (20)$$

$r_{SG}$ = rate of return Small-Growth (factor-portfolio)
$r_{SN}$ = rate of return Small-Neutral (factor-portfolio)
$r_{SV}$= rate of return Small-Value (factor-portfolio)
$r_{BG}$ = rate of return Big-Growth (factor-portfolio)
$r_{BN}$ = rate of return Big-Neutral (factor-portfolio)
$r_{BV}$ = rate of return Big-Value (factor-portfolio)

### 4.5.2. High-Minus-Low factor

The High-Minus-Low (HML)-portfolios were constructed by sorting stocks based on Book-to-Market ratio (B/M; Eq. 10). Firms were separated based on B/M for the breakpoints < 30th percentile (growth stocks), 30th-70th percentile (neutral stocks) and > 70th percentile (value stocks) on NASDAQ OMX and NYSE, respectively (Asness et al., 2013; 2018; Daniel and Moskowitz, 2016). The HML-portfolios assigned firms from the size-sorted factor portfolios to three portfolios sorted by B/M on NASDAQ OMX and NYSE, respectively (Fig. 2). The value assigned by the HML-factor was formulated from the average rate of return of the two value-portfolios, minus the average of the two growth-portfolios (Asness et al., 2013)

$$HML = \frac{r_{SV}+r_{BV}}{2} - \frac{r_{SG}+r_{BG}}{2} \qquad (21)$$

$r_{SV}$ = rate of return Small-Value (factor-portfolio)
$r_{BV}$ = rate of return Big-Value (factor-portfolio)
$r_{SG}$ = rate of return Small-Growth (factor-portfolio)
$r_{BG}$ = rate of return Big-Growth (factor-portfolio)

#### 4.5.3. Up-Minus-Down factor

The Up-Minus-Down (UMD)-portfolios were constructed from stocks based on the one-year past returns, i.e. the difference between the last non-zero price of the previous month and the last non-zero price 12 months ago, normalized to the last non-zero price 12 months ago (Eq. 12).

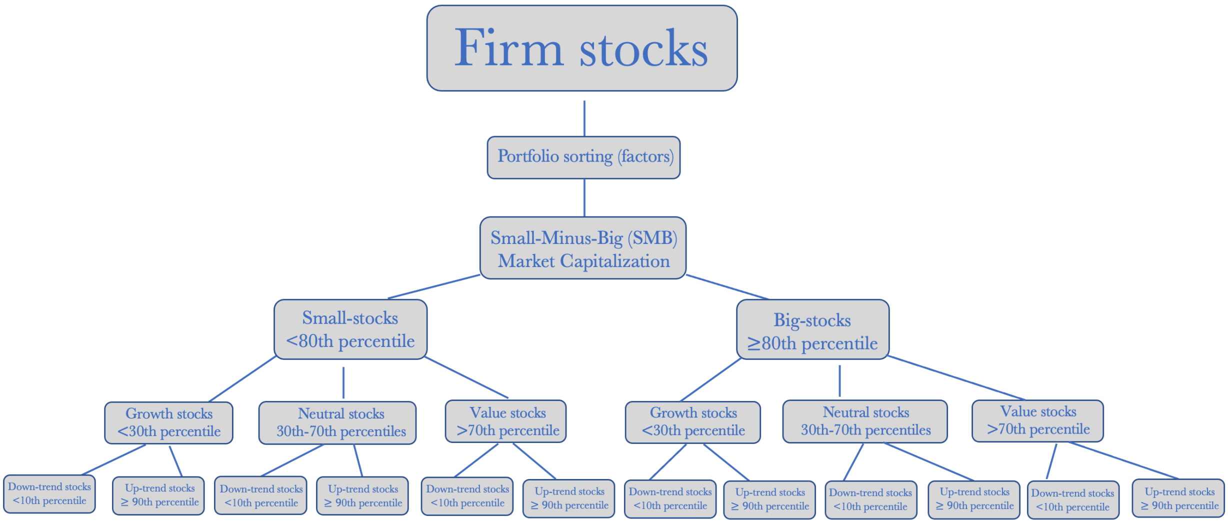


**Figure 2.** General overview of principles for factor-portfolio sorting based on market capitalization (SMB), Book-to-Market ratio (HML) and one-year rate of returns (UMD) on NASDAQ OMX and NYSE.

Firms with the highest (or lowest) one-year past rate of returns within the specific interval were denoted “winners” (or “losers”), categorized by its upward-trend (or downward trend; Asness et al., 2018). The UMD-portfolios were constructed by separating firms based on the one-year past rate of return for the breakpoints < $10^{th}$ percentile (“Losers”; downward trend stock) and > $90^{th}$ percentile (“Winners”; upward trend stock) on NASDAQ OMX and NYSE, respectively (Fig. 2). The UMD-portfolios assigned firms into either of the two size-sorted portfolios on NASDAQ OMX and NYSE, respectively (Fig. 2; Asness et al., 2013; 2018). The value assigned by the UMD-factor was calculated from the average rate of return of the two portfolios with the highest return, minus the average return of the two portfolios with the lowest return:

$$UMD = \frac{r_{SW}+r_{BW}}{2} - \frac{r_{SL}+r_{BL}}{2} \tag{22}$$

$r_{SW}$ = rate of return Small-Winners (factor-portfolio)
$r_{BW}$ = rate of return Big-Winners (factor-portfolio)
$r_{SL}$ = rate of return Small-Losers (factor-portfolio)
$r_{BL}$ = rate of return Big-Losers (factor-portfolio)

Overall, the combination of factor-portfolio sorting techniques resulted in ten different factor-portfolios on each of the NASDAQ OMX and NYSE stock markets, respectively. There were six HML-portfolios based on size and B/M, and four UMD-portfolios based on size and one-year past returns. The factor-portfolio sorting was executed in Python (Python SF, 2021).

### 4.6. Econometric approach

The single-factor asset pricing model, *CAPM* (Sharpe, 1964; Lintner, 1965; Mossin, 1966), and the multi-factor asset pricing models, *Fama-French Three-Factor model* (Fama and French, 1992) and *Carhart Four-Factor model* (Carhart, 1997) were used to quantitatively evaluate the importance of market anomalies for equity returns. OLS model-regressions (Eq. 1, 3, 4) were statistically assessed in Stata (StataCorp V16, 2019). The regression for *CAPM* was formulated:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{mkt,i}(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \tag{23}$$

$r_{i,t}$ = rate of return on the individual portfolio/security i at time t
$r_{f,t}$ = risk-free rate of return at time t
$\alpha_i$ = CAPM alpha (i.e. the risk-adjusted return for portfolio i)
$r_{m,t} - r_{f,t}$ = excess return of the market at time t (market premium)
$\varepsilon_{i,t}$ = error term for portfolio/security i at time t

The regression for the *Fama-French Three-Factor model*:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{mkt,i}(r_{m,t} - r_{f,t}) + \beta_{size,i}(SMB_t) + \beta_{value,i}(HML_t) + \varepsilon_{i,t} \tag{24}$$

$r_{i,t}$ = rate of return on the individual portfolio/security i at time t
$r_{f,t}$ = risk-free rate of return at time t
$\alpha_i$ = Three-Factor alpha (i.e. the risk-adjusted return for portfolio i)
$r_{m,t} - r_{f,t}$ = excess return of the market at time t (market premium)
$\beta_{size,i}$ = risk premium capturing size-/Small-Minus-Big effects at time t
$\beta_{value,i}$ = risk premium capturing value-/High-Minus-Low effects at time t
$\varepsilon_{i,t}$ = error term for portfolio/security i at time t

The regression for the *Carhart Four-Factor model*:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{mkt,i}(r_{m,t} - r_{f,t}) + \beta_{size,i}(SMB_t) + \beta_{value,i}(HML_t) + \beta_{mom,i}(UMD_t) + \varepsilon_{i,t} \tag{25}$$

$r_{i,t}$ = rate of return on the individual portfolio/security i at time t
$r_{f,t}$ = risk-free rate of return at time t
$\alpha_i$ = Four-Factor alpha (i.e. the risk-adjusted return for portfolio i)
$r_{m,t} - r_{f,t}$ = excess return of the market at time t (market premium)
$\beta_{size,i}$ = risk premium capturing size-/Small-Minus-Big effects at time t
$\beta_{value,i}$ = risk premium capturing value-/High-Minus-Low effects at time t.
$\beta_{mom,i}$ = risk premium capturing momentum-/Up-Minus-Down effects at time t
$\varepsilon_{i,t}$ = error term for portfolio/security i at time t

The intercept of the respective asset pricing model relates to different forms of *Jensen´s alpha* (Eq.15, 16, 17) and captures the risk-adjusted return of the portfolio. A positive (or negative) value of the intercept suggests an outperformance (or underperformance) of the specific portfolio relative to the market. The coefficient for the excess market returns (beta) represents the sensitivity to market risk. A beta value higher (or lower) than one implies higher (or lower) sensitivity to market risk compared to the market portfolio. A suite of econometric model specifications (*CAPM*, *Fama-French Three-Factor model* and *Carhart Four-Factor model*) was used to test the robustness of model observations and to evaluate the importance of individual model specification for the predictive capacity of the statistical model.

### 4.6.1. Statistical assessment

The use of OLS regressions to assess stock portfolios and derive accurate OLS estimates relies on several underlying assumptions. For example, homogeneity of variance, serial correlation and multicollinearity were used to statistically validate the OLS regressions. Homogeneity of variance, or homoscedasticity, entails a constant conditional variance of the error term (Stock and Watson, 2015):

$$E[\varepsilon^2|X_1, \dots, X_k] = \sigma^2 \tag{26}$$

$E$ = expectation operator
$X$ = independent variable/-s
$\sigma^2$ = variance
$\varepsilon^2$ = variability of the error term
$\varepsilon$ = error term/residual term

Homoscedasticity was evaluated using the White and Breusch-Pagan tests (Appendix B). Further, serial, or auto-correlations, indicate potential correlations between an error term from one time-period, and an error term for a subsequent time-period. Error terms should be uncorrelated over time to ensure statistical efficiency of the OLS estimator (Field, 2014):

$$Cov(\varepsilon_i, \varepsilon_j) = 0 \tag{27}$$

(for all $i \neq j$)
$Cov$ = covariance (i.e., the joint variability of two random variables)
$\varepsilon$ = error term

First-order serial correlations are typically the strongest order of serial correlations in time-series analysis. The Breusch-Godfrey test was used to evaluate serial correlations (Appendix B; Stock and Watson, 2015).

Multicollinearity describes the linear inter-correlation among independent variables in multi-factor regression models. Although multicollinearity, in principle, does not violate the Gauss-Markov theorem or affect the statistical unbiasedness of the estimator, it may induce inflation of the variances and thereby cause a decreased precision of the OLS estimates (Field, 2014). The degree of multicollinearity was evaluated by correlation matrices for the independent variables (Appendix B; Field, 2014).

Furthermore, to test for seasonality in the equity data, dummy variables representing individual months were created. A joint significance-/F-test was used to evaluate potential seasonality in the respective dataset (Appendix C).

## 5. Results

### 5.1. Probability distributions and data statistics

The distribution of pricing data for the small-, mid- and large-cap composite portfolios on the NASDAQ OMX and NYSE stock markets approximately followed normal distributions as evidenced by the third- (skewness) and forth-(kurtosis) central moments of the distributions (Table 2). Additional support of data normality was provided by histograms and corresponding quantile-quantile (q-q) plots (Appendix A). The histograms confirmed a symmetrical shape of the data distributions, and the pricing data was distributed along the diagonal line in the q-q-plots, further symbolizing normality of the data set (Appendix A). Although a few potential outliers were identified, particularly for the large- and small-cap portfolios, modelling based on standard deviation of measurements was considered a robust quantity of portfolio risk. No basic corrections were therefore made in the dataset.

Statistical assessment of the OLS assumptions included tests of heteroskedasticity (White and Breusch-Pagan tests), tests of serial correlations (Breusch-Godfrey test) and tests of multicollinearity (correlation matrices) (Appendix B). Obtained p-values from the White and Breusch-Pagan tests indicated that the null hypothesis (constant variance of the error term) could be rejected on a 10 % level of significance (p-value $< 0.1$) for the stock portfolios on NASDAQ OMX and NYSE (Appendix B). Similarly, p-values from the Breusch-Godfrey test suggested that the null hypothesis (no serial correlations) could be rejected on a 5 % level of significance (p-values $< 0.05$). Additional tests with higher levels of lag in the residuals confirmed serial correlations in the dataset. Newey-West standard errors were therefore used in the statistical analyses of the stock portfolios to account for heteroscedasticity and serial-correlations. Moreover, the correlation matrices suggested that the null hypothesis (no multicollinearity) was not violated (|correlation values| < 0.9). No adjustment for multicollinearity was therefore made (Appendix B).

Furthermore, p-values from the seasonality test indicated that the null hypothesis (no seasonality) could be rejected on a 10 % level of significance (p-value < 0.1) for the large-cap portfolios, while data was not statistically significant for the small-cap portfolios (p-value > 0.1) (Appendix C). Dummy variables controlling for individual months were accounted for and used in the subsequent regressions.

### 5.2. Temporal evolution of domestic business cycles

Temporal evolution of the domestic business cycles in Sweden and the USA was graphically evaluated from 2006 to 2021 (Fig. 3). Overall, between 2006 and 2021 the annual GDP-gaps in Sweden and in the USA could be separated into four main subperiods (Fig. 3). Following an initial positive economic development 2006 and 2007, the GDP-gap drastically decreased and reached local minima in 2009 (-6 % in Sweden and -5.1 % in the USA). After 2009, the economic situation progressively improved and resulted in positive GDP-gaps 2015-2019 (Sweden) and 2018-2019 (USA). In 2020, the global COVID-19 pandemic caused a downturn in the world economy which significantly affected the GDP-gap both in Sweden (-4.3 %) and in the USA (-7.2 %). Since late 2020, however, there has been a steady positive trend towards a recovery in the economic development for both countries (Fig. 3). Although similar basic patterns were observed between the two countries, the duration and detailed temporal resolution were different.

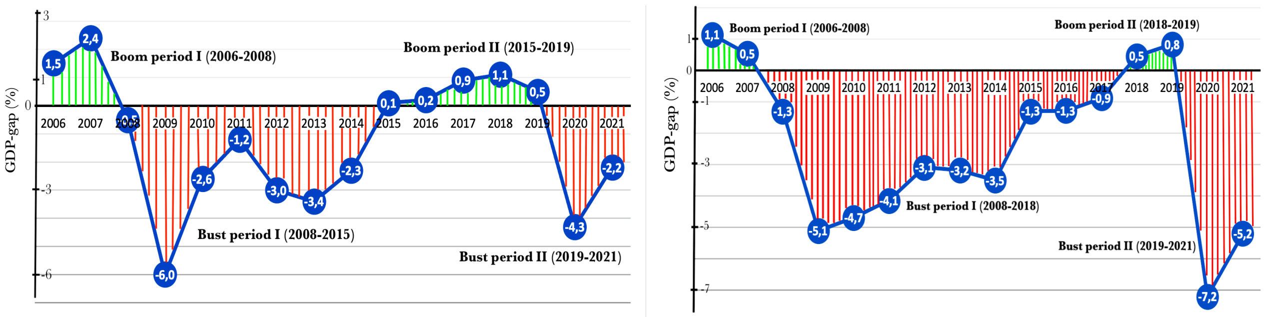


**Figure 3.** Schematic illustration of the business cycles in Sweden (left) and the USA (right) between 2006 and 2021. The business cycles were calculated from the difference between real- and potential GDP normalized to real GDP (the GDP-gap). For 2021, the GDP-gap was estimated based on data from Q1 2021. A positive GDP-gap corresponds to a boom-period (dashed green), a negative GDP-gap corresponds to a bust-period (dashed red) and a GDP-gap close to zero correspond to a balanced economic period/state.

In Sweden, for example, the years immediately prior to 2008 were characterized by relatively high economic growth (e.g. GDP increased by 4.7 % between 2005 and 2006, and 3.4 % between 2006 and 2007). The trend was reversed in 2007/2008 with the start of the *subprime crisis* and in 2008 the GDP decreased by -0.5 % compared to 2007. According to the GDP-gap, the *subprime crisis* in Sweden lasted until 2015 (Bust-period I). However, the economic decline was not continuously uniform during the entire bust-period, but also included years of relative economic recovery (e.g. 2009-2011 and 2013-2015). The *post-subprime crisis* was characterized by economic growth and there was a relatively strong recovery of the Swedish economy between 2015 and 2019 (Boom-period II). The boom-period II abruptly ended 2019/2020 by the *2020 stock market crash* with significant economic implications on the Swedish and American economies (Bust-period II; the COVID-19 recession).

Similar to the situation in Sweden, although perhaps not as pronounced, the years prior to 2008 were characterized by relatively high economic growth also in the USA. For example, GDP increased by 2.9 % between 2005 and 2006, and 1.9 % between 2006 and 2007 (Boom period I). The U.S economy thereafter declined rapidly as a result of the *subprime crisis*. Although a positive economic development for individual years, economic implications from the *subprime crisis* seemed more severe for the American- compared to the Swedish domestic economy (Bust period I, 2008-2018; Fig. 3). For example, there was a slower but more continuous recovery of the American economy during the period 2009 to 2017/2018. Similar to patterns in the development of the Swedish economy, the boom-period II (2018/2019) was abruptly ended by the *2020 stock market crash* (Bust-period II, 2019-2021). However, implications from the COVID-19 crisis seemed larger for the American- (GDP-gap = -7.2 %) compared to the Swedish economy (GDP-gap = -4.3 %).

### 5.3. Equity returns of stock portfolios

#### 5.3.1. General patterns of equity returns

Average monthly equity returns and the performance of the small-, mid-, and large-cap composite stock portfolios over time are illustrated in Figure 4. Data on the general importance of size (Small-Minus-Big; SMB), value (High-Minus-Low; HML) and momentum (Up-Minus-Down; UMD) as market anomalies for the equity returns is summarized in Table 2.

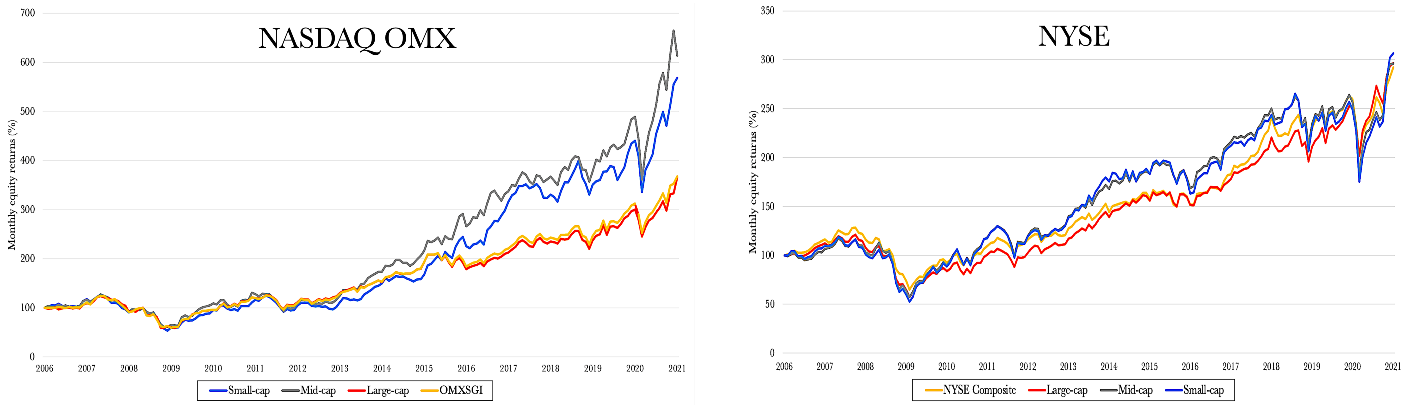


**Figure 4.** Average monthly equity returns over time for the small-(solid blue), mid-(solid grey) and large-cap (solid orange) stock portfolios from January 2006 to January 2021 on NASDAQ OMX (left) and NYSE (right). The development of the market index *OMXSGI* (NASDAQ OMX, left) and *NYSE Composite* (NYSE, right) were included for comparison (solid yellow). The equity returns were normalized and compared to the respective starting value (100 % at t=0). Data was collected monthly from Refinitiv Eikon (Thomson Reuters, 2021).

Overall, the average monthly equity returns for the small-cap portfolios (NASDAQ OMX: 1.16 %; NYSE: 1.01 %) were similar to or higher than average returns for the large-cap portfolios (NASDAQ OMX: 0.84 %; NYSE: 0.69 %), as well as for the respective market benchmarks (*OMXSGI*: 0.86 %; *NYSE Composite*: 0.72 %) during the investigated sample period (2006-2021; Fig. 4; Table 2). The average monthly equity returns for the large-cap portfolios was similar to or lower than the respective market benchmark on both stock markets. The differences between the small- and large-cap portfolios, and those between the portfolios and the market benchmarks, were especially pronounced on the Swedish stock market NASDAQ OMX from 2015/2016 to 2021 (Fig. 4). Similarly, the small-cap portfolio seemed to outperform the large-cap portfolio also on NYSE from 2010 to 2019 (Fig. 4). In contrast to these observations, the returns of the large-cap portfolio were significantly higher than returns of the small-cap portfolio on NYSE during the period associated with the COVID-19 crisis 2020/2021 (Fig. 4). The average monthly equity returns for the small-cap portfolio were higher than equity returns for the mid-cap portfolio on NYSE (1.01 % compared to 0.85 %). In contrast, equity returns for the small-cap portfolio were on average slightly lower than for the mid-cap portfolio on NASDAQ OMX (1.16 % compared to 1.28 %).

**Table 2.** Average monthly equity return (%) for the composite stock portfolios sorted by market capitalization during the sample period January 2006 to January 2021 on NASDAQ OMX (left) and NYSE (right). Positive values indicate an increased return and negative values indicate a decreased return at the end compared to the value of the portfolio at the beginning of each month. Statistic evaluation includes mean, median, standard deviation (STDV) as well as minimum and maximum values of equity return for the composite small-, mid- and large-cap portfolios. The market indices *OMXSGI* (Market; NASDAQ OMX) and *NYSE Composite* (Market; NYSE) are shown for comparison. General effects from the Small-Minus-Big (SMB), High-Minus-Low (HML) and Up-Minus-Down (UMD) factor-portfolios were included as coefficients in the multi-factor model evaluations. Skewness was used to quantify the extent to which a probability distribution differed from a normal distribution. Kurtosis is a measure of the "tailedness" of the probability distribution.

| | NASDAQ OMX | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variables** | **Small** | **Mid** | **Large** | **Market** | **SMB** | **HML** | **UMD** |
| Mean | 1.16 | 1.28 | 0.84 | 0.86 | 0.73 | -0.08 | 0.47 |
| Median | 1.05 | 1.46 | 1.24 | 1.43 | -0.35 | -0.35 | 0.08 |
| Variance | 30.2 | 33.1 | 25.4 | 24.7 | 0.13 | 0.06 | 0.11 |
| STDV | 5.48 | 5.73 | 5.02 | 4.96 | 3.53 | 2.54 | 3.16 |
| Min | -18.6 | -18.8 | -25.9 | -17.8 | -7.56 | -5.61 | -9.18 |
| Max | 15.6 | 26.1 | 18.2 | 21.6 | 10.6 | 6.02 | 9.88 |
| Skewness | -0.41 | 0.05 | -1.02 | -1.03 | 0.72 | 0.46 | 0.17 |
| Kurtosis | 1.14 | 2.29 | 5.1 | 2.79 | 3.71 | 2.93 | 3.59 |
| No.observations | 181 | 181 | 181 | 181 | 181 | 181 | 181 |

| | NYSE | | | | | | |
|---|---|---|---|---|---|---|---|
| **Variables** | **Small** | **Mid** | **Large** | **Market** | **SMB** | **HML** | **UMD** |
| Mean | 1.01 | 0.85 | 0.69 | 0.72 | 0.15 | -0.13 | 0.34 |
| Median | 1.16 | 1.21 | 1.19 | 0.83 | -0.21 | -0.32 | 0.08 |
| Variance | 34.5 | 27.8 | 19.1 | 17.8 | 0.12 | 0.06 | 0.1 |
| STDV | 5.87 | 5.27 | 4.37 | 4.22 | 3.23 | 2.54 | 3.06 |
| Min | -23.1 | -21.8 | -16.9 | -14.1 | -7.88 | -5.55 | -9.19 |
| Max | 19.7 | 14.8 | 12.7 | 11.8 | 10.9 | 6.25 | 9.76 |
| Skewness | -0.52 | -0.75 | -0.66 | -0.63 | 0.75 | 0.42 | 0.16 |
| Kurtosis | 2.62 | 2.9 | 1.71 | 1.54 | 3.79 | 2.87 | 3.56 |
| No.observations | 181 | 181 | 181 | 181 | 181 | 181 | 181 |

Furthermore, from 2006 to 2014/2015 the average monthly returns of the large-cap portfolio were similar to or slightly higher compared to the small-cap portfolio on NASDAQ OMX. Similarly, although the difference was not as pronounced, the average monthly equity returns from 2006 to 2009 were slightly higher for the large-cap portfolio compared to the small-cap portfolio on NYSE (Fig. 4).

Overall, the variation in average monthly equity returns seemed higher for the small-cap compared to the large-cap portfolios and the market benchmark on the respective stock market (Fig. 4, 5; Table 2). The higher average monthly equity returns for small-cap stocks were motivated by higher portfolio risks ($\sigma_{small,OMX}$ = 5.48 %; $\sigma_{small,NYSE}$ = 5.87 %; Table 2) compared to those of the large-cap portfolios ($\sigma_{large,OMX}$ = 5.02 %; $\sigma_{large,NYSE}$ = 4.37 %; Table 2). Additionally, the relatively higher average monthly equity returns of the mid-cap portfolio on NASDAQ OMX was motivated by a higher portfolio risk ($\sigma_{mid,OMX}$ = 5.73 %) compared to those of the small-cap portfolio ($\sigma_{small,OMX}$ = 5.48 %). Similarly, the relatively lower average monthly equity returns of the mid-cap portfolio on NYSE (0.85 %) were associated with a lower portfolio risk ($\sigma_{mid,NYSE}$ = 5.27 %) compared to those of the small-cap portfolio ($\sigma_{small,NYSE}$ = 5.87 %).

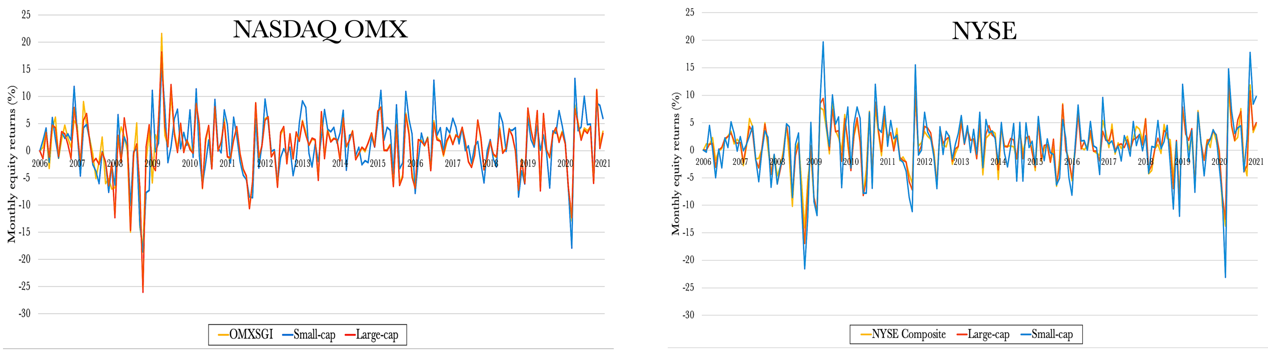


**Figure 5.** Monthly equity returns (%) over time for the small- (solid blue) and large-cap (solid orange) portfolios on NASDAQ OMX (left) and NYSE (right). The performance of the market benchmarks *OMXSGI* (left) and *NYSE Composite* (right) is illustrated for comparison (solid yellow).

Although somewhat different patterns between the two stock markets, the variability in monthly equity returns seemed correlated with and was particularly significant during periods of financial- and economic instability (e.g. *Subprime crisis 2008*, *European debt crisis 2009*, *Black Monday 2011* and *COVID-19-crisis*; Fig. 4, 5). The variability in average equity returns over the entire period 2006-2021 was in general most pronounced for the small-cap portfolios on both stock markets. However, during the *subprime crisis* 2008 the variability on NASDAQ OMX was particularly evident for the large-cap portfolio. In contrast and in line with the more general trend, the variability was during the *subprime crisis* more pronounced for the small- compared to the large-cap portfolio on NYSE (Fig. 4, 5).

### 5.3.2. Equity returns and market anomalies

The *Fama-French Three-Factor model* (Fama and French, 1992) is designed also to account for size (Small-Minus-Big; SMB) and value (High-Minus-Low; HML) during evaluations of equity returns. Value stocks (i.e. high B/M) are often considered to outperform growth stocks (i.e. low B/M) over time (e.g. Cakici and Topyan, 2014). In the present study, there were only small- or negligible effects on the average monthly equity returns using the HML-approach on the NASDAQ OMX ($HML_{OMX}$ = -0.08%) and NYSE ($HML_{NYSE}$ = -0.13%) stock portfolios (Table 2). In contrast and in line with higher equity returns observed for the small- relative to the large-cap portfolios (Table 2; Fig. 4), positive SMB-factors as a consequence from the *Fama-French Three-Factor* modelling suggested a small size premium (Table 2). The SMB-factor was higher on NASDAQ OMX ($SMB_{OMX}$ = 0.73 %) relative to that modelled from stocks on NYSE ($SMB_{NYSE}$= 0.15 %). Including momentum (Up-Minus-Down; UMD) as a factor in the *Carhart Four-Factor model* indicated that momentum positively affected equity returns on both NASDAQ OMX ($UMD_{OMX}$= 0.47 %) and NYSE ($UMD_{NYSE}$ = 0.34 %).

## 5.4. Risk-adjusted performance of stock portfolios

Risk-adjusted return characterizes the return from an investment normalized to the risk associated with the return (Bodie et al., 2014). As such, risk-adjusted performance metrics constitute a viable tool to assess the long-term viability of specific investment strategies. Common metrics for risk-adjusted performance include *Sharpe ratio* (Sharpe, 1994) and *Jensen´s alpha* (Jensen, 1967). A summary of the risk-adjusted performance for the small- and large-cap stock portfolios evaluated by *Sharpe Ratio* and *Jensen´s alpha* over the sample period 2006-2021 is presented in Table 3.

**Table 3.** Risk-adjusted performance of the small- and large-cap composite stock portfolios evaluated by *Sharpe Ratio* and *Jensen´s alpha* over the entire period 2006-2021 on NASDAQ OMX (left) and NYSE (right). P-values were based on two-sided Student´s t-test included to statistically evaluate differences of performance metrics between the small- and large-cap stock portfolios on the respective stock market. The null hypothesis implies no difference between the large- and small-cap portfolio on the respective stock market. *** = statistical significance at 0.01 level, ** = statistical significance at 0.05 level and * = statistical significance at 0.10 level.

| | NASDAQ OMX | | NYSE | |
|---|---|---|---|---|
| | Risk-adjusted performance metrics | | Risk-adjusted performance metrics | |
| **Tests** | **Large-cap portfolio** | **Small-cap portfolio** | **Large-cap portfolio** | **Small-cap portfolio** |
| *Sharpe Ratio (SR)* | 0.167* | 0.212* | 0.135 | 0.171 |
| *p-value (SR)* | 0.098 | - | 0.363 | - |
| *Jensen´s alpha (CAPM)* | -0.003 | 0.006 | -0.001 | 0.005 |
| *p-value (CAPM)* | 0.257 | - | 0.187 | - |
| *Jensen's alpha (FF3)* | -0.005 | 0.008 | -0.008* | 0.009* |
| *p-value (FF3)* | 0.102 | - | 0.067 | - |
| *Jensen´s alpha (CH4)* | -0.006* | 0.009* | -0.009* | 0.011* |
| *p-value (CH4)* | 0.067 | - | 0.094 | - |

The higher *Sharpe ratio (SR)* for the small- compared to the large-cap portfolios suggested that the small-cap portfolios were more profitable investments than the large-cap portfolios in terms of risk-adjusted equity returns on both stock markets (Table 3). The p-values of the documented two-sided t-test indicated a significant (p-value < 0.1) difference between the risk-adjusted performance *(SR)* of the large- and small-cap portfolios on NASDAQ OMX. In contrast, the risk-adjusted performance *(SR)* was not significantly different between the two stock portfolios on NYSE (p-value > 0.1; Table 3). Although not statistically significant, the economic compensation for the risk exposure seemed more pronounced for the small-cap compared to the large-cap portfolios over the aggregate sample period 2006-2021.

The intercept of model regressions (alpha coefficient; *Jensen´s alpha*) statistically captures the risk-adjusted return of stock portfolios (Table 3, 4, 5). A positive (or negative) value for

*Jensen´s alpha* indicates a risk-adjusted return higher (or lower) than the fair value predicted by *CAPM* (Eq.15), *Fama-French Three-Factor model* (*FF3;* Eq.16) or *Carhart-Four-Factor model* (*CH4;* Eq.17*)*, respectively (Stock and Watson, 2015). In the present study, *Jensen´s alpha* for the large-cap portfolios ($\alpha_{large,CAPM,OMX}$= -0.003; $\alpha_{large,FF3,OMX}$=-0.005; $\alpha_{large,CH4,OMX}$=-0.006; $\alpha_{large,CAPM,NYSE}$=-0.001; $\alpha_{large,FF3,NYSE}$=-0.008; $\alpha_{large,CH4,NYSE}$= -0.009) suggested a stock performance similar to or slightly lower, than that of the market (Table 3, 4). The alpha-values for the small-cap portfolios ($\alpha_{small,CAPM,OMX}$= 0.006; $\alpha_{small,FF3,OMX}$= 0.008; $\alpha_{small,CH4,OMX}$= 0.009; $\alpha_{small,CAPM,NYSE}$= 0.005; $\alpha_{small,FF3,NYSE}$= 0.009; $\alpha_{small,CH4,NYSE}$= 0.011), however, indicated a slightly higher stock performance than that of the market. Overall, these observations suggested that the risk-adjusted returns were slightly higher than the fair values predicted by *CAPM*, *Fama-French Three-Factor model (FF3)* and *Carhart-Four-Factor model (CH4)* for the small-cap portfolios, but slightly lower than those predicted for the large-cap portfolios. However, the difference in *Jensen´s alpha* was statistically significant (p-value < 0.1) only for the two stock portfolios evaluated by the *Carhart-Four-Factor model (CH4)* on NASDAQ OMX and by the *Fama-French Three-Factor model (FF3)* and *Carhart-Four-Factor model (CH4)* on NYSE (p-value < 0.1; Table 3).

**5.5. Model evaluations and market anomalies**

The composite stock portfolios were evaluated using single- (*CAPM*; Sharpe, 1964; Lintner, 1965; Mossin, 1966) and multi-factor asset pricing models (*Fama-French Three-Factor model*; Fama and French, 1992 and *Carhart Four-Factor model*; Carhart, 1997). These asset pricing models enabled detailed studies of size (market capitalization), value (Book-to-Market ratio; B/M) and momentum (Up-Minus-Down; UMD) as market anomalies for equity returns. To quantify the importance of these market anomalies, the small- and large-cap composite portfolios were evaluated using three separate OLS regressions related to the single- and multi-factor asset pricing models (Table 4).

According to *CAPM*, the market coefficient (beta) illustrates the sensitivity to market volatility (Eq. 1, 23). In the present study, the market coefficients of the large-cap portfolios ($Market_{large,CAPM,OMX}$= 0.966; $Market_{large,FF3,OMX}$=0.979; $Market_{large,CH4,OMX}$= 0.981; $Market_{large,CAPM,NYSE}$= 0.989; $Market_{large,FF3,NYSE}$= 0.990; $Market_{large,CH4,NYSE}$= 0.995) suggested a sensitivity to market volatility similar to or slightly lower than, that of the market. Thus, the large-cap portfolios resembled overall patterns of the respective market relatively well throughout the aggregate time-period (2006-2021). In contrast, the market coefficients for the small-cap portfolios indicated a sensitivity slightly above unity ($Market_{small,CAPM,OMX}$= 1.001; $Market_{small,FF3,OMX}$= 1.023; $Market_{small,CH4,OMX}$= 1.023; $Market_{small,CAPM,NYSE}$= 1.014; $Market_{small,FF3,NYSE}$=1.019; $Market_{small,CH4,NYSE}$= 1.020). These observations also supported results from the initial analysis of more volatile small-cap portfolios compared to large-cap portfolios and market benchmarks (*OMXSGI* and *NYSE Composite*; Table 2; Fig. 4). The market coefficients were statistically significant (p-value < 0.01) for stock portfolios in both the single- and multi-factor model specifications (Table 4).

The SMB-coefficients, or size premiums, sustained by the specific portfolios were positive for the small-cap portfolios ($SMB_{small,FF3,OMX}$=0.131; $SMB_{small,FF3,NYSE}$=0.064) and slightly negative for the large-cap portfolios ($SMB_{large,FF3,OMX}$=-0.022; $SMB_{large,FF3,NYSE}$=-0.005) (Table 4). Although not all SMB-coefficients were statistically significant (p-value > 0.1; Table 4) on NASDAQ OMX and NYSE, the single- and three-factor regression analyses suggested a positive size premium for the small-cap portfolios and a negative size-dependent premium for the large-cap portfolios on both stock markets.

Similar patterns with a positive size premium for the small-cap and a negative size premium for the large-cap portfolios were observed using the *Carhart-Four-Factor model* ($SMB_{large,CH4,OMX}$=-0.020; $SMB_{small,CH4,OMX}$=0.099; $SMB_{large,CH4,NYSE}$=-0.003; $SMB_{small,CH4,NYSE}$=0.065; Table 4). The SMB-coefficients for the large-cap portfolios were statistically significant (p-value < 0.1). Overall, model predictions (adjusted $R^2$) appeared higher for the large-cap compared the small-cap portfolios on both stock markets (Table 4). Including momentum (Up-Minus-Down; UMD) as an additional pricing factor in the *Carhart Four-Factor* regression did not seem to significantly improve the adjusted $R^2$. This suggested that momentum did not significantly improve the predictive capacity of the small- and large-cap stock portfolios across the aggregate sample period.

The HML-coefficients, or value effects/premiums, were positive for the small-cap portfolios ($HML_{small,FF3,OMX}$=0.091; $HML_{small,FF3,NYSE}$=0.064) and slightly negative for the large-cap portfolios ($HML_{large,FF3,OMX}$=-0.005; $HML_{large,FF3,NYSE}$=-0.008) (Table 4). The *Fama-French Three-Factor* modelling therefore indicated a positive value-premium for small-cap stocks and a negative value premium for the large-cap stocks. Overall, similar patterns were observed estimating HML-value effects by the *Carhart-Four-Factor model* ($HML_{small,CH4,OMX}$=0.089; $HML_{small,CH4,NYSE}$=0.071; $HML_{large,CH4,OMX}$=-0.012; $HML_{large,CH4,NYSE}$=-0.009). The HML-coefficients were statistically significant for both stock portfolios ($p$-value < 0.1) on NYSE. On NASDAQ OMX, however, HML-coefficients were statistically significant ($p$-value < 0.1) only for the large-cap portfolio.

The UMD-coefficient captures the momentum effects sustained by the specific portfolio (Eq 4, 25). Somewhat contrasting patterns were observed for the UMD-coefficients between the NASDAQ OMX and NYSE stock markets (Table 4). The UMD-coefficient for the large-cap portfolio were close to zero on both stock markets ($UMD_{large,CH4,OMX}$=0.002; $UMD_{large,CH4,NYSE}$ =-0.004). In contrast, UMD-coefficients for momentum were larger and positive for the small-cap portfolios on both NASDAQ OMX ($UMD_{small,CH4,OMX}$=0.117) and NYSE ($UMD_{small,CH4,NYSE}$=0.032). Although not statistically significant ($p$-value > 0.1) the *Carhart-Four-Factor* modelling therefore indicated a positive momentum for the small-cap portfolios on NASDAQ OMX and NYSE over the aggregate period 2006-2021. The momentum effect appeared most pronounced for the small-cap portfolio on NASDAQ OMX.

| | NASDAQ OMX | | | | | |
|---|---|---|---|---|---|---|
| | **Capital Asset Pricing Model** | | **Fama-French Three-Factor Model** | | **Carhart-Four-Factor Model** | |
| **Variables** | **Large-cap Portfolio** | **Small-cap Portfolio** | **Large-cap Portfolio** | **Small-cap Portfolio** | **Large-cap Portfolio** | **Small-cap Portfolio** |
| *Alpha* | -0.003<br>(0.002) | 0.006**<br>(0.005) | -0.005*<br>(0.003) | 0.008*<br>(0.004) | -0.006*<br>(0.003) | 0.009<br>(0.004) |
| *Market* | 0.966***<br>(0.022) | 1.001***<br>(0.042) | 0.979***<br>(0.024) | 1.023***<br>(0.038) | 0.981***<br>(0.024) | 1.023***<br>(0.064) |
| *SMB* | - | - | -0.022*<br>(0.035) | 0.131**<br>(0.056) | -0.020**<br>(0.042) | 0.099<br>(0.065) |
| *HML* | - | - | -0.005*<br>(0.054) | 0.091<br>(0.087) | -0.012*<br>(0.061) | 0.089<br>(0.107) |
| *UMD* | - | - | - | - | 0.002<br>(0.028) | 0.117<br>(0.043) |
| *Adjusted R-squared* | 0.521 | 0.443 | 0.535 | 0.446 | 0.536 | 0.447 |

| | NYSE | | | | | |
|---|---|---|---|---|---|---|
| | **Capital Asset Pricing Model** | | **Fama-French Three-Factor Model** | | **Carhart-Four-Factor Model** | |
| **Variables** | **Large-cap Portfolio** | **Small-cap Portfolio** | **Large-cap Portfolio** | **Small-cap Portfolio** | **Large-cap Portfolio** | **Small-cap Portfolio** |
| *Alpha* | -0.001<br>(0.002) | 0.005<br>(0.003) | -0.008*<br>(0.006) | 0.009*<br>(0.004) | -0.009**<br>(0.006) | 0.011*<br>(0.09) |
| *Market* | 0.989***<br>(0.007) | 1.014***<br>(0.056) | 0.990***<br>(0.007) | 1.019**<br>(0.059) | 0.995**<br>(0.021) | 1.020***<br>(0.059) |
| *SMB* | - | - | -0.005<br>(0.007) | 0.064*<br>(0.011) | -0.003*<br>(0.023) | 0.065<br>(0.072) |
| *HML* | - | - | -0.008*<br>(0.123) | 0.064<br>(0.097) | -0.009*<br>(0.124) | 0.071*<br>(0.083) |
| *UMD* | - | - | - | - | -0.004<br>(0.070) | 0.032<br>(0.006) |
| *Adjusted R-squared* | 0.426 | 0.403 | 0.501 | 0.496 | 0.503 | 0.496 |

**Table 4.** Statistical evaluation of equity returns for the small- and large-cap composite stock portfolios on NASDAQ OMX (top) and NYSE (bottom) using the *Capital Asset Pricing Model (CAPM*), the *Fama French Three-Factor (FF3)* and the *Carhart Four-Factor models (CH4*) over the entire sample period January 2006 to January 2021. The variables alpha (model constants), market benchmarks *OMXSGI* (NASDAQ OMX, top) and *NYSE Composite* (NYSE, bottom), Small-Minus-Big (SMB), High-Minus-Low (HML) and Up-Minus-Down (UMD) are presented together with the adjusted coefficient of determination (Adjusted $R^2$) for each of the regressions. Newey-West standard errors are provided within the parentheses. The expected return-beta relation in *CAPM* was calculated from $r_{i,t} - r_{f,t = alpha +}\ \beta_i^{mkt}(r_{m,t} - r_{f,t})$., the *Fama-French Three-Factor regression*: $r_{i,t} - r_{f,t = alpha +}\ \beta_i^{mkt}(r_{m,t} - r_{f,t}) + \beta_i^{size}(SMB_t) + \beta_i^{value}(HML_t)$, and the *Carhart Four-Factor regression*: $r_{i,t} - r_{f,t = alpha +}\ \beta_i^{mkt}(r_{m,t} - r_{f,t}) + \beta_i^{size}(SMB_t) + \beta_i^{value}(HML_t) + \beta_i^{mom}(UMD_t)$.

*** = statistical significance at 0.01 level.

** = statistical significance at 0.05 level.

* = statistical significance at 0.10 level.

### 5.5.1. Temporal effects and model evaluations

To isolate potential temporal trends, the performance of the small- and large-cap composite portfolios was evaluated using single- (*CAPM*) and multi-factor asset pricing models (*Fama-French Three-Factor model* and *Carhart Four-Factor model*) in a temporal context (Table 5). The temporal isolation of the respective stock market was made in comparison to the evolution of the domestic business cycles in Sweden and the USA, and in relation to the economic subperiods defined from the respective business cycle (Fig. 3; Table 5).

In general, model predictions and the adjusted coefficient of determination (adjusted $R^2$) appeared higher for the large-cap compared to the small-cap portfolios on both stock markets during a majority of subperiods, irrespective of prevailing economic conditions (i.e. business cycles; Table 5). The adjusted $R^2$ for the large- and small-cap portfolios varied from 0.325 to 0.502 (large-cap) and from 0.287 to 0.48 (small-cap) on NASDAQ OMX. Similarly, adjusted $R^2$ varied from 0.267 to 0.411 (large-cap) and from 0.263 to 0.405 (small-cap) on NYSE.

The market coefficients of the large-cap portfolios indicated a sensitivity to market volatility similar to or slightly lower than that of the market during all economic subperiods (Market = 0.944 - 0.999; Table 5), Thus, the large-cap portfolios seemed to mimic the overall patterns of the respective market relatively well across the domestic business cycles. In contrast, the market coefficients for the small-cap portfolios indicated a sensitivity similar to or above unity that of the market during all subperiods, irrespective of prevailing economic conditions (Market = 1.002-1.120; Table 5). Thus, the small-cap portfolios seemed more volatile compared to the market benchmarks *OMXSGI* (NASDAQ OMX) and *NYSE Composite* (NYSE) during all economic subperiods.

Although variations were observed over time, the alpha-values for the small-cap portfolios indicated a performance similar to or slightly higher ($\alpha_{\text{small,OMX}}$= 0.003-0.231; $\alpha_{\text{small,NYSE}}$ = 0.001-0.112) than that of the market in all subperiods (Table 5). Alpha-values for the small-cap portfolios seemed larger during boom-periods and smaller during bust-periods (Table 5). In contrast, the alpha-values for the large-cap portfolios indicated a performance similar to or slightly lower than that of the market ($\alpha_{\text{large,OMX}}$= -0.098 to -0.001; $\alpha_{\text{large,NYSE}}$= -0.120 to -0.004). Alpha-values for the large-cap portfolios were generally more at par with the market performance during bust-periods and slightly lower than the market during boom-periods (Table 5).

The SMB-coefficient captures the size premium sustained by the specific portfolio. The SMB-coefficients of the large-cap portfolios were mainly negative across all economic subperiods ($SMB_{large,OMX}$= -0.123 to -0.001; $SMB_{large,NYSE}$= -0.065 to -0.002). In contrast, the SMB-coefficients of the small-cap portfolios were positive ($SMB_{small,OMX}$= 0.001 to 0.141; $SMB_{small,NYSE}$= 0.008 to 0.121; Table 5). Thus, in a temporal context across the economic subperiods the single-and multi-factor regression analyses suggested a positive size premium for the small-cap portfolios and a negative premium for the large-cap portfolios on both stock markets. Patterns indicated a positive size premium for the small-cap portfolios particularly during boom-periods. Similarly, a negative size premium for the large-cap portfolios was observed mainly during boom-periods (Table 5).

The HML-coefficients reveal potential value effects of specific stock portfolios. In the present study, there were no obvious patterns in value effects for the large- and small-cap portfolios across economic subperiods of both stock markets ($HML_{large,OMX}$= -0.111 to 0.076; $HML_{large,NYSE}$= -0.023 to 0.012; $HML_{small,OMX}$= -0.113 to 0.02; $HML_{small,NYSE}$= -0.102 to 0.021; Table 5). Although no clear patterns were observed comparing the development of the stock portfolios over time and across business cycles, the modelling approach indicated a positive value effect during bust-periods and a negative value effect during boom periods, independent of market capitalization (Table 5).

The UMD-coefficients indicate potential effects from momentum on stock portfolios. Similar to observations made for value, there were no obvious patterns of momentum for the large- and small-cap portfolios across economic subperiods on both stock markets ($UMD_{large,OMX}$ = -0.011 to 0.067; $UMD_{large,NYSE}$= -0.091 to 0.054; $UMD_{small,OMX}$= -0.010 to 0.081; $UMD_{small,NYSE}$ = -0.082 to 0.042; Table 5). Although no clear patterns could be asserted across the economic subperiods, the UMD-coefficients seemed more pronounced (larger/smaller) in comparison to the momentum effects modelled from the aggregate time-period (Table 4; Table 5).

## NASDAQ OMX

**Capital Asset Pricing Model**

| Variables | Large-cap portfolio 2006-2008 | Large-cap portfolio 2008-2015 | Large-cap portfolio 2015-2019 | Large-cap portfolio 2019-2021 | Small-cap portfolio 2006-2008 | Small-cap portfolio 2008-2015 | Small-cap portfolio 2015-2019 | Small-cap portfolio 2019-2021 |
|---|---|---|---|---|---|---|---|---|
| *Alpha* | -0.025 (0.009) | -0.001** (0.003) | -0.062* (0.006) | -0.004 (0.006) | 0.004 (0.014) | 0.003* (0.007) | 0.115* (0.014) | 0.007 (0.019) |
| *Market* | 0.944** (0.057) | 0.993*** (0.022) | 0.965*** (0.058) | 0.990*** (0.058) | 1.09*** (0.088) | 1.004*** (0.055) | 1.120*** (0.059) | 1.033*** (0.059) |
| *SMB* | - | - | - | - | - | - | - | - |
| *HML* | - | - | - | - | - | - | - | - |
| *UMD* | - | - | - | - | - | - | - | - |
| *Adjusted R-squared* | 0.325 | 0.411 | 0.489 | 0.405 | 0.287 | 0.423 | 0.478 | 0.341 |

**Fama-French Three-Factor Model**

| Variables | Large-cap portfolio 2006-2008 | Large-cap portfolio 2008-2015 | Large-cap portfolio 2015-2019 | Large-cap portfolio 2019-2021 | Small-cap portfolio 2006-2008 | Small-cap portfolio 2008-2015 | Small-cap portfolio 2015-2019 | Small-cap portfolio 2019-2021 |
|---|---|---|---|---|---|---|---|---|
| *Alpha* | -0.098 (0.011) | -0.005 (0.003) | -0.097* (0.005) | -0.011 (0.065) | 0.076 (0.013) | 0.008** (0.006) | 0.115* (0.006) | 0.006* (0.006) |
| *Market* | 0.976*** (0.066) | 0.982*** (0.025) | 0.957*** (0.047) | 0.983*** (0.047) | 1.081*** (0.082) | 1.078*** (0.048) | 1.099*** (0.062) | 1.052*** (0.062) |
| *SMB* | -0.008* (0.066) | -0.001 (0.067) | -0.123 (0.011) | -0.072* (0.071) | 0.091* (0.021) | 0.007 (0.121) | 0.141 (0.087) | 0.122* (0.066) |
| *HML* | -0.008 (0.060) | 0,015* (0.043) | -0.111* (0.054) | 0.076 (0.120) | -0.012 (0.099) | 0.002* (0.004) | -0.111 (0.069) | 0.001 (0.166) |
| *UMD* | - | - | - | - | - | - | - | - |
| *Adjusted R-squared* | 0.368 | 0.412 | 0.499 | 0.399 | 0.289 | 0.423 | 0.478 | 0.347 |

**Carhart Four-Factor Model**

| Variables | Large-cap portfolio 2006-2008 | Large-cap portfolio 2008-2015 | Large-cap portfolio 2015-2019 | Large-cap portfolio 2019-2021 | Small-cap portfolio 2006-2008 | Small-cap portfolio 2008-2015 | Small-cap portfolio 2015-2019 | Small-cap portfolio 2019-2021 |
|---|---|---|---|---|---|---|---|---|
| *Alpha* | -0.078 (0.023) | 0.001* (0.010) | -0.098* (0.005) | -0.001 (0.021) | 0.087 (0.023) | 0.015** (0.044) | 0.231* (0.006) | 0.007 (0.006) |
| *Market* | 0.981*** (0.066) | 0.988*** (0.027) | 0.999*** (0.047) | 0.976 (0.023) | 1.054*** (0.083) | 1.006*** (0.049) | 1.077** (0.061) | 1.052* (0.061) |
| *SMB* | -0.009 (0.231) | -0.001* (0.005) | -0.088* (0.021) | -0.01* (0.066) | 0.091 (0.111) | 0.001* (0.095) | 0.140* (0.060) | 0.008* (0.046) |
| *HML* | -0.008* (0.066) | 0.044* (0.021) | -0.105 (0.122) | 0,018* (0.068) | -0.015 (0.076) | 0.002* (0.044) | -0.113* (0.044) | 0.010 (0.089) |
| *UMD* | 0.002 (0.188) | -0.011** (0.096) | 0.067 (0.155) | 0.008* (0.066) | -0.009* (0.106) | -0.010* (0.091) | 0.081 (0.028) | -0.005 (0.186) |
| *Adjusted R-squared* | 0.369 | 0.423 | 0.502 | 0.401 | 0.302 | 0.432 | 0.480 | 0.348 |

## NYSE

**Capital Asset Pricing Model**

| Variables | Large-cap portfolio 2006-2008 | Large-cap portfolio 2008-2018 | Large-cap portfolio 2018-2019 | Large-cap portfolio 2019-2021 | Small-cap portfolio 2006-2008 | Small-cap portfolio 2008-2018 | Small-cap portfolio 2018-2019 | Small-cap portfolio 2019-2021 |
|---|---|---|---|---|---|---|---|---|
| *Alpha* | -0.081* (0.043) | -0.005* (0.087) | -0.120 (0.121) | -0.012* (0.121) | 0.099* (0.091) | 0.001* (0.018) | 0.009 (0.091) | 0.012 (0.155) |
| *Market* | 0.951** (0.052) | 0.992*** (0.022) | 0.987 (0.222) | 0.989*** (0.043) | 1.091*** (0.054) | 1.110*** (0.008) | 1.002 (0.245) | 1.098* (0.189) |
| *SMB* | - | - | - | - | - | - | - | - |
| *HML* | - | - | - | - | - | - | - | - |
| *UMD* | - | - | - | - | - | - | - | - |
| *Adjusted R-squared* | 0.267 | 0.389 | 0.302 | 0.392 | 0.263 | 0.304 | 0.401 | 0.345 |

**Fama-French Three-Factor Model**

| Variables | Large-cap portfolio 2006-2008 | Large-cap portfolio 2008-2018 | Large-cap portfolio 2018-2019 | Large-cap portfolio 2019-2021 | Small-cap portfolio 2006-2008 | Small-cap portfolio 2008-2018 | Small-cap portfolio 2018-2019 | Small-cap portfolio 2019-2021 |
|---|---|---|---|---|---|---|---|---|
| *Alpha* | -0.008* (0.082) | -0.005* (0.006) | -0.102 (0.129) | -0.006* (0.077) | 0.082* (0.054) | 0.002* (0.102) | 0.092 (0.091) | 0.013 (0.101) |
| *Market* | 0.985*** (0.034) | 0.999** (0.088) | 0.966 (0.138) | 0.987** (0.091) | 1.055*** (0.023) | 1.111** (0.062) | 1.009** (0.097) | 1.088* (0.090) |
| *SMB* | -0.008** (0.032) | -0.012* (0.084) | -0.052 (0.134) | -0.006 (0.115) | 0.063 (0.034) | 0.090* (0.076) | 0.121 (0.098) | 0.008 (0.072) |
| *HML* | -0.023 (0.099) | 0.002* (0.034) | -0.019 (0.034) | 0.001* (0.061) | -0.014 (0.012) | 0.002 (0.231) | -0.007 (0.114) | 0.021 (0.098) |
| *UMD* | - | - | - | - | - | - | - | - |
| *Adjusted R-squared* | 0.268 | 0.392 | 0.404 | 0.393 | 0.278 | 0.344 | 0.403 | 0.345 |

**Carhart Four-Factor Model**

| Variables | Large-cap portfolio 2006-2008 | Large-cap portfolio 2008-2018 | Large-cap portfolio 2018-2019 | Large-cap portfolio 2019-2021 | Small-cap portfolio 2006-2008 | Small-cap portfolio 2008-2018 | Small-cap portfolio 2018-2019 | Small-cap portfolio 2019-2021 |
|---|---|---|---|---|---|---|---|---|
| *Alpha* | -0.008** (0.065) | -0.004* (0.021 | -0.098 (0.112) | -0.09* (0.025) | 0.112* (0.005) | 0.006* (0.044) | 0.013* (0.231) | 0.008 (0.112) |
| *Market* | 0.988*** (0.042) | 0.997*** (0.034) | 0.999 (0.109) | 0.998 (0.112) | 1.043*** (0.031) | 1.097*** (0.008) | 1.005** (0.098) | 1.088* (0.100) |
| *SMB* | -0.021 (0.030) | -0.023** (0.023) | -0.065 (0.099) | -0.002 (0.155) | 0.062* (0.032) | 0.008* (0.012) | 0.119 (0.102) | 0.011 (0.045) |
| *HML* | -0.018 (0.074) | 0.012* (0.067) | -0.009 (0.084) | 0.003* (0.022) | -0.022 (0.034) | -0.005* (0.043) | -0.102 (0.122) | 0.02* (0.014) |
| *UMD* | -0.091 (0.084) | -0.011* (0.134) | 0.054 (0.249) | -0.01* (0.031) | 0.001 (0.091) | -0.001** (0.030 | 0.042 (0.034) | -0.082 (0.166) |
| *Adjusted R-squared* | 0.269 | 0.411 | 0.406 | 0.399 | 0.288 | 0.346 | 0.405 | 0.398 |

**Table 5.** Statistical evaluation of equity returns for the small- and large-cap composite stock portfolios on NASDAQ OMX (top) and NYSE (bottom) using the *Capital Asset Pricing Model (CAPM),* the *Fama French Three-Factor (FF3)* and the *Carhart Four-Factor (CH4)* models across the respective domestic business cycle (Boom-period; green and Bust-period; red). The variables alpha (model constants), market benchmarks *OMXSGI* (NASDAQ OMX, top) and *NYSE Composite* (NYSE, bottom), Small-Minus-Big (SMB), High-Minus-Low (HML) and Up-Minus-Down (UMD) are presented together with the adjusted coefficients of determination (Adjusted $R^2$) for each of the regressions. Newey-West standard errors are provided within the parentheses. The expected return-beta relation in *CAPM* was calculated from $r_{i,t} - r_{f,t} = \text{alpha} + \beta_i^{mkt}(r_{m,t} - r_{f,t})$., the *Fama-French Three-factor regression*: $r_{i,t} - r_{f,t} = \text{alpha} + \beta_i^{mkt}(r_{m,t} - r_{f,t}) + \beta_i^{size}(SMB_t) + \beta_i^{value}(HML_t)$, and the *Carhart Four-factor regression*: $r_{i,t} - r_{f,t} = \text{alpha} + \beta_i^{mkt}(r_{m,t} - r_{f,t}) + \beta_i^{size}(SMB_t) + \beta_i^{value}(HML_t) + \beta_i^{mom}(UMD_t)$.

*** = statistical significance at 0.01 level.
** = statistical significance at 0.05 level.
* = statistical significance at 0.10 level.

## 6. Analysis and discussion

Single- (*CAPM*) and multi-factor asset pricing models (*Fama and French Three-Factor model* and *Carhart Four-Factor model*) were in the present study used to quantitatively evaluate the importance of the market anomalies size (Small-Minus-Big; SMB), value (High-Minus-Low; HML) and momentum (Up-Minus-Down; UMD) for equity returns of two composite stock portfolios based on market capitalization on NASDAQ OMX and NYSE. Quantitative model evaluations were performed in aggregate- and temporal contexts related to domestic business cycles over the sample period 2006-2021.

### 6.1. General patterns and controls of equity returns

Pricing data from the investigated period suggested that the average monthly equity returns were higher for the small- compared to the large-cap portfolios, as well as relative to *OMXSGI* and *NYSE Composite* market indices (Fig. 4; Table 2). In addition, the volatility, expressed as the standard deviation of equity returns from stock portfolios, seemed higher for the small- relative to the large-cap portfolio and the market indices (Fig. 4, 5; Table 2). These findings agree with basic financial theories that small-cap stock portfolios are generally associated with enhanced risk exposure (e.g. Markowitz, 1952; Hull, 2012) and that high (or low) levels of risk are associated with high (or low) levels of expected returns (Hull, 2012). However, although higher average equity returns were modelled for the small- compared to the large-cap portfolios and the market indices, there were periods where the small-cap portfolios seemed to underperform compared to the equity returns of the large-cap portfolio and the respective market benchmark (Fig. 4). To further illustrate the performance of the stock markets and to compare the small- and large-cap composite portfolios, the difference in equity returns between the two stock portfolios was calculated with time (Fig. 6).

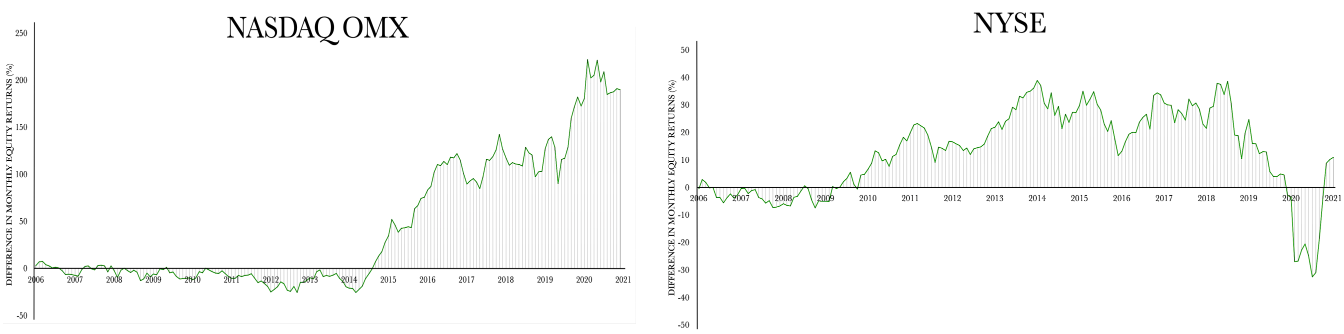


**Figure 6.** Difference in monthly equity returns (%) between the small- and large-cap stock portfolio on NASDAQ OMX (left) and NYSE (right).

The generally higher average monthly equity returns of the small-cap portfolios were mainly associated with periods of high economic growth and relatively low market volatility (i.e. boom-periods; Fig. 4, 6). The temporal development of the large-cap portfolio seemed inverse, where high average monthly equity returns relative to the small-cap portfolios were typically observed for periods of relatively low (or negative) economic growth and high market volatility (i.e. bust-periods; Fig. 4, 6). Shiller (2015) suggested that contrasting patterns in the performance of stock portfolios sorted by market capitalization across financial business cycles were partly caused by irrational exuberance (excessive optimism) and extrapolation of potential stability into the future. In periods characterized by economic growth and stability (boom-periods), there is a tendency for investors to increase their risk exposure with a preference towards small-cap stocks (e.g. Shiller, 2015). The inverse behavior of investors and a preference towards safety and large-cap stocks is often observed during economic instability and bust-periods (Gottfries, 2013). In the present study, examples of such inverse market behavior were observed e.g. on NYSE during the *COVID-19 downfall* (Fig. 4, 6, 7).

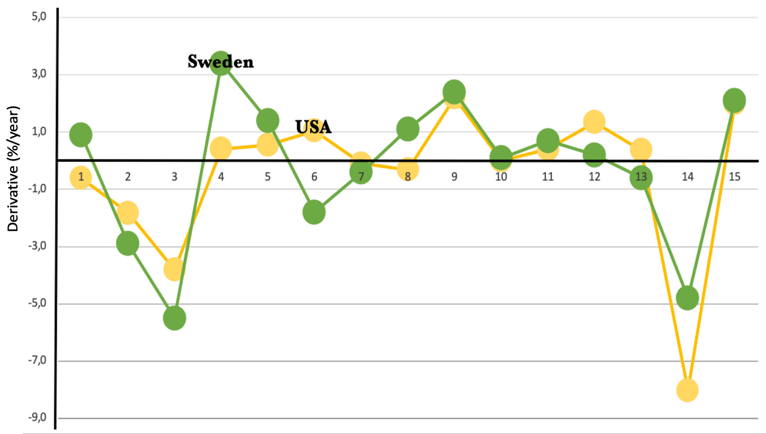


**Figure 7.** Calculated annual change (derivative; dy/dx) in the GDP-gap for the Swedish-(green) and American (yellow) domestic economies over the sample period (2006-2021; i.e. 15 years of study). A positive derivative illustrates a positive development and increased GDP-gap between adjacent years. Similarly, a negative derivative denotes a negative trend between years.

The *COVID-19 crisis* 2019/2020 (year 14) caused the largest drop in the American domestic economy (GDP-gap) over the investigated period (Fig. 3, 7). Another large negative change in the economies was observed in 2008/2009 (*subprime crisis,* year 3). The largest positive change in the Swedish and American domestic economies were observed in 2009/2010 (Sweden, year 4), 2014/2015 (year 9) and 2020/2021 (Sweden and USA, year 15) (Fig. 3, 7).

Furthermore, there were higher average monthly equity returns of the composite stock portfolios on NASDAQ OMX compared to NYSE during the sample period (Fig. 4; Table 2). Although the higher average monthly equity returns seemed related to a higher risk exposure for the large- and mid-cap portfolios, the average monthly equity return was higher and the volatility was lower for the small-cap portfolio on NASDAQ OMX compared to NYSE (Fig. 4; Table 2). From a historical- (1900-2021) and international perspective, the real- and nominal equity returns have been comparably high in both Sweden and the USA (Fig. 8). Observations of relatively higher average equity returns on NASDAQ OMX (Sweden) compared to e.g. NYSE (USA) are in accordance with previous studies investigating equity returns across stock markets (e.g. Dimson, 2002; Bodie et al., 2014; Fig. 8).

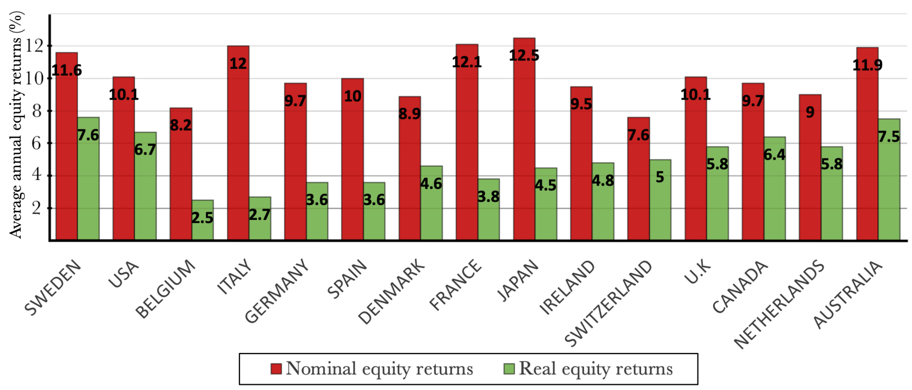


**Figure 8.** Average annual nominal-(red) and real (green) equity returns in Sweden, USA and 13 additional stock markets during 1900-2021. Modified from Dimson et al. (2002) complemented with data from Thomson Reuters (2021).

### 6.2. Risk-adjusted performances

The risk-adjusted performance of the stock portfolios was assessed by the econometric coefficient *Jensen´s alpha* (model regression alphas; Jensen, 1967), and the financial indicator *Sharpe ratio* (Sharpe, 1994). Overall, model indicators across the aggregated period of investigations suggested a higher risk-adjusted equity return for the small-cap portfolios compared to the respective large-cap portfolio (Fig. 4; Table 3, 4). Higher risk-adjusted returns for the small- compared to the large-cap portfolios inferred that small-cap stocks were more profitable investments than large-cap stocks in terms of the risk-and return trade-off during the aggregate sample period (Field, 2014; Table 3, 4). Although variations in magnitude with time, the alpha-values for the small-cap portfolios indicated a performance similar to or slightly higher than that of the market (Table 5). In contrast, the alpha-values for the large-cap portfolios inferred a performance similar to or slightly lower than that of the market. Alpha-values for the small-cap portfolios seemed larger during boom-periods and smaller during bust-periods. Further, alpha-values of the large-cap portfolios were generally more at par with the market performance during bust-periods and slightly lower than the market during boom-periods (Table 5). Although non-zero alpha values have previously been reported, particularly over shorter time intervals (Bollen and Busse, 2004; Berk and Green, 2004), composite portfolios do normally not consistently outperform the market benchmark on average (Fama and French, 1996; Hull, 2012). Similar assertions of non-zero alphas during shorter time intervals/subperiods were made in the present study (Table 5). Although variations with time, multi-factor modelling across the entire sample period (2006-2021) confirmed a risk-adjusted performance of the small- and large-cap stock portfolios close to that of the respective stock market (Table 4). Overall, this study therefore supported the overarching idea that composite portfolios do not consistently outperform the market benchmark (Fama, 1969). However, although stock portfolios on average and over longer periods were correctly priced in accordance with the *EMH* (Fama, 1969), temporal deviations from the general concepts and theoretical framework were observed when isolating and modelling shorter subperiods (e.g. Fama and French 1992; Bodie et al., 2014; Table 5).

### 6.3. Size-, value- and momentum effects

In agreement with Banz (1981) and Fama and French (1992; 1996), the multi-factor models over the aggregate sample period (2006-2021) suggested a positive risk premium for the small-cap stock portfolios and a negative risk premium for the large-cap stock portfolios on both stock markets (Table 4). In the present study and in accordance to e.g. Malin and Veeraraghavan (2004), such size premiums seemed more pronounced on NASDAQ OMX (i.e. European stock markets), compared to observations made on NYSE (Table 4).

The temporal isolation of equity returns in subperiods determined by the domestic business cycles (Fig. 3) suggested slightly different temporal patterns between the stock portfolios on NASDAQ OMX and NYSE, respectively (Fig. 4; Table 5). As was also suggested by e.g. Banz (1981), the size premiums were not constant with time but varied significantly across the subperiods of investigation (Fig. 3; Table 5). According to Liew and Vassalou (2000) and Scheurle and Spremann (2010), different risk-adjusted performance observed for stocks sorted on capitalization were attributed to a more significant spread between small- and large-cap stocks in affluent (boom-periods) than during bust-periods. In the present study, the single-and multi-factor regression analyses confirmed such observations also across the domestic business cycles (Table 5). There was a tendency for small- (or large)-cap portfolios to reveal a more positive (or negative) size premium during boom-periods (Crain, 2011; Table 5). Despite the observations of a size effect, particular for the small-cap portfolio on NASDAQ OMX, financial mechanisms that control size effects seem complex and not fully elucidated. The significant temporal variations between the equity returns of the two portfolios and the market benchmark on the respective stock market, directly implied that additional financial factors other than size may also be important for the equity returns observed (Cakici and Topyan, 2016; Fig. 4, 5). In fact, market capitalization may serve as a proxy for one or several undisclosed financial factors correlated with size (Banz, 1981; Bodie et al., 2014).

Furthermore, the multi-factor models over the aggregate sample period (2006-2021) indicated a positive value premium (High-Minus-Low; HML) for small-cap stocks and a negative value premium for the large-cap stocks on both stock markets (Table 4). A combination of potential growth and value effects over time was also observed in the study by Malin and Veeraghavan (2004). In the temporal isolation and in direct comparison to the domestic business cycles (Fig. 3), multi-factor modelling revealed positive HML-coefficients supporting value effects particularly during bust-periods. In contrast, negative HML-coefficients supporting growth effects were observed particularly during boom-periods. Patterns seemed largely unrelated to market capitalization and stock market preferences (Table 5). Petkova and Zhang (2005) reported a tendency for the HML-coefficients to be negative in boom-periods (growth stocks > value stocks) and positive in bust-periods (value stocks > growth stocks). On average, value firms (high B/M) have financial capital that is more tangible. Potential investments may thereby expose firms with such firm characteristics to enhanced risks for economic downturns because excess capacity from assets is already in place in the event of a severe recession. In contrast, growth firms are likely more capable to adapt to an economic downturn by deferring investment plans (Petkova and Zhang, 2005). Thus, there is a propensity for growth stocks to perform well during boom-periods, and for value stocks to perform well during bust-periods (Fama and French, 1998; Cakici and Topyan, 2016).

The multi-factor modelling approach integrated over the aggregate sample period (2006-2021) further suggested a positive momentum effect for small-cap portfolios on both stock markets (Table 4). In contrast, the UMD-coefficients were slightly negative for the large-cap portfolio on NYSE. Overall, however, the UMD-coefficients were small and close to zero across the aggregate sample period for both portfolios on both stock markets which suggested limited effects from momentum on risk-adjusted equity returns (Chan et al., 1991; Table 4). In the temporal isolation and over shorter economic subperiods, potential effects from momentum seemed enhanced in both directions (positive and negative; Table 5). A potential momentum effect over shorter subperiods (e.g. business cycles) and inconsistent results over longer time-intervals (e.g. aggregate economic periods) are in accordance with e.g. Low and Tan (2016). However, in contrast to Low and Tan (2016) there were no re-occurring patterns in momentum (Up-Minus-Down; UMD) for the stock portfolios in the present study (Table 5). A potential negative/positive momentum effect seemed equally likely across the economic subperiods defined from the domestic business cycles (Scheurle and Spremann, 2010).

As the multi-factor asset pricing models included size (Small-Minus-Big; SMB), value (High-Minus-Low; HML) and momentum (Up-Minus-Down; UMD) the predictive capacity was expected to improve compared to the capacity inherent to *CAPM* (Fama and French, 1992). In the present study, the ability to predict equity returns (adjusted $R^2$) was, however, not dramatically different between the asset pricing models (Table 4, 5). Similarities between model predictions of equity returns were especially evident over the aggregate sample period (2006-2021) (Table 4). In addition, only minor improvements were made in the predictive capacity of the multi-factor models compared to predictions by *CAPM* for specific stock portfolios across different subperiods of the domestic business cycles (Fig. 3; Table 5). These observations supported that additional factors potentially partly correlated with the factors included in the multi-factor models (SMB, HML and UMD), were important for the observed risk-adjusted equity returns and general stock performance (Fig. 3; Table 5; George and Huang, 2007).

### 6.4. Additional factors for econometric multi-factor modelling

As supported by data from the present study, the performance of stock portfolios sorted by market capitalization may be linked to cyclical factors associated with the status and general characteristics of the domestic economy (Crain, 2011; Table 5). Additionally, patterns of equity return for stock portfolios may be related to industry-unique firm characteristics and potential calendar effects (Crain, 2011; Bodie et al., 2014; Canady, 2019).

#### 6.4.1. Industry sectors and affiliations

There are direct and indirect financial correlations between domestic business cycles and the character and composition of the local, regional, national, and global economy (Hull, 2012). Overall, the state of the economy depends on a large variety of factors, including e.g. the development of several interdependent industry sectors and affiliations that do not necessarily follow the patterns observed for the aggregate domestic economy (Gottfries, 2013). The absolute and relative contribution of industry sectors in the domestic economy are important controls for domestic business cycles and may therefore also constitute potential factors that indirectly affect the performance of stock markets (Long and Plosser, 1987; Shea, 2002). For example, firms from cyclical sectors (e.g. consumer goods and services) are typically more sensitive to macroeconomic shocks than non-cyclical firms (e.g. health care; Bodie et al., 2014).

The observed inability of multi-factor asset pricing models to accurately describe and compensate for the risk- and return trade-off may therefore be industry-dependent. Potential drawbacks of the econometric models may also rely on the contemporary market status, in which individual industry sectors perform differently in different business cycles (Canady, 2019). In the present study, for example, there were significant discrepancies in the average monthly equity returns for stocks of individual GICS industry classifications (Fig. 9).

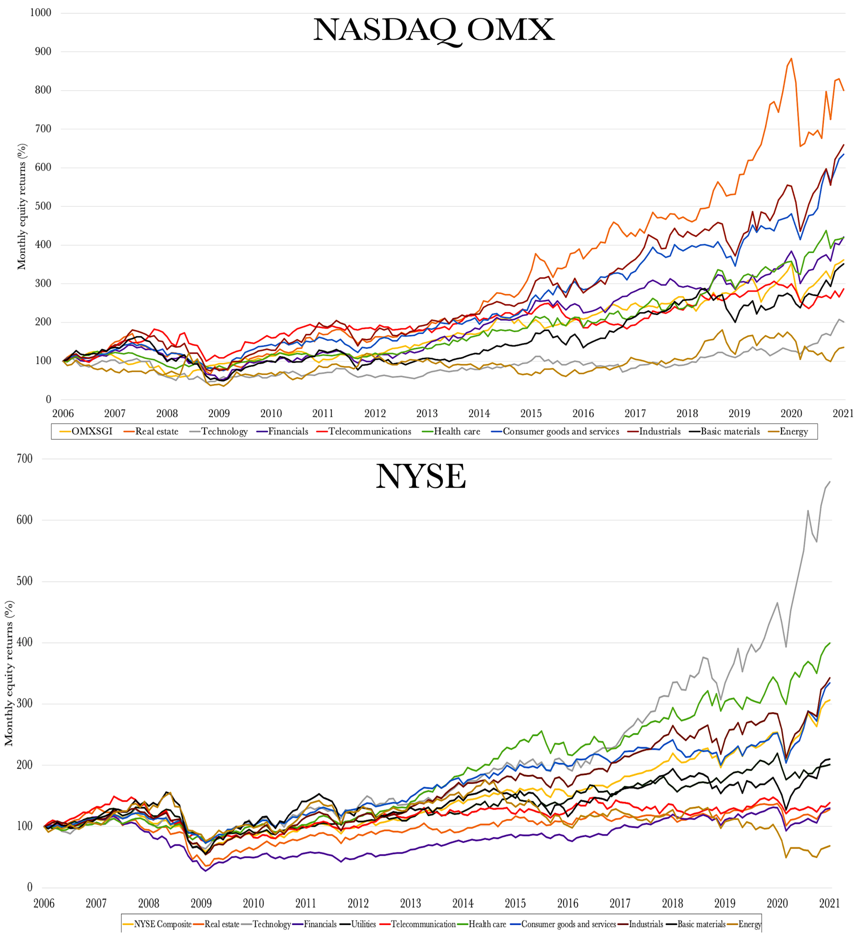


**Figure 9.** Industry dependent average monthly equity returns (%) over time for firms from individual GICS industries on NASDAQ OMX (top) and NYSE (bottom). The development of the market indices (solid yellow) *OMXSGI* (NASDAQ OMX, top) and *NYSE Composite* (NYSE, bottom) were included for comparison. The equity returns were normalized and compared to the respective starting value (100 % at t=0). Data was collected monthly from Refinitiv Eikon (Thomson Reuters, 2021).

As the small- and large-cap portfolios contained stocks from a wide spectrum of GICS industries (Appendix D) the performance of specific stock portfolios was potentially influenced by the absolute and relative composition of industries in the portfolios. Although the portfolios were well-diversified through a random firm-selection and composite factor-portfolio sorting methodology (Asness et al., 2013; 2018), there may still be biases in the absolute and relative composition of industry affiliations. For example, the small-cap composite portfolios contained a large fraction of firm stocks from high-performing GICS industry sectors on NASDAQ OMX (e.g. industrials = 24 %) and NYSE (e.g. industrials = 18 %) (Appendix D). In contrast, the composite large-cap portfolios contained several firm stocks from relatively low-performing GICS industry sectors on NASDAQ OMX (e.g. basic materials = 10 %) and NYSE (e.g. financials = 14 %) (Appendix D). A different composite- and factor-portfolio sorting methodology may therefore have provided different patterns in equity returns for the small- and large-cap portfolios on NASDAQ OMX and NYSE.

### 6.4.2. Intra-annual variations of equity returns

Several studies have suggested a time-dependent attribution to the abnormal returns earned by the small-cap portfolios, particularly in January (e.g. Keim, 1983; Crain, 2011). In the present study, evaluations of potential temporal effects on equity returns (Fig. 3; Table 5; Appendix C) indicated calendar effects and patterns associated to within-year phenomena. In response to these indications, seasonality was accounted for in the regression modelling by including dummy variables controlling for individual months. However, joint-significance-/F-tests for dummy variables representing individual months are limited to joint effects, whereby abnormal returns for specific months (e.g. January) cannot be distinguished and statistically evaluated by this approach.

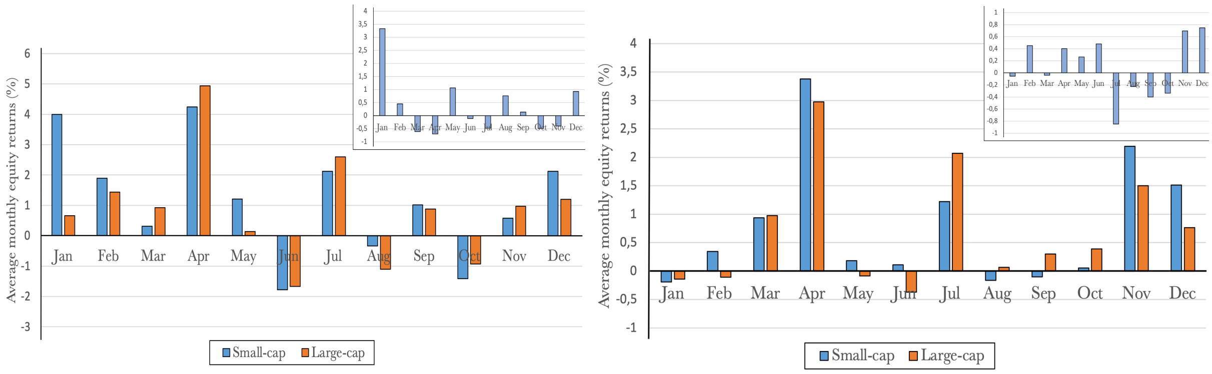


**Figure 10.** Intra-annual average monthly performance and equity returns (%) for the small- (solid blue) and large-cap (solid orange) composite portfolios on NASDAQ OMX (left) and NYSE (right) during the sample period January 2006 to January 2021. The monthly net difference between the two portfolios on the respective stock market was illustrated seperately for comparison (inset top right).

The present study confirmed intra-annual variations in equity returns, with different patterns between the small- and large-cap portfolios as well as between the two stock markets (Fig. 10). Although significant variations in equity returns between months there was no obvious correlation for the intra-annual variation in equity returns across stock portfolios between years (not shown). Overall, the average monthly equity returns for the small-cap portfolio were on average larger in January (3.99 %) and April (4.23 %) compared to the other months on NASDAQ OMX. Additionally, the difference in equity returns between the small- and large-cap portfolios was the largest in January (3.33 %), which supported a *January effect* on NASDAQ OMX (Crain, 2011; Fig. 10). However, contrasting patterns were found on NYSE, where the small-cap portfolio performed particularly well in April (3.37 %) and November (2.19 %; Fig. 10). The difference in equity returns between the small- and large-cap portfolios was on average most pronounced in December (0.75 %). In January equity returns were even higher for the large-cap compared to the small-cap portfolio (-0.005 %) on NYSE (Fig. 10).

Although several studies have indicated a general time-dependent size effect, the aggregate and general January effect observed for equity returns across stock markets and portfolios could only partly be verified in the present investigation.

## 7. Conclusions

An important aim of this Master´s thesis was to quantitatively evaluate the importance of market anomalies for equity returns in an international context over domestic business cycles. Specific objectives were to quantitatively evaluate the equity performance of small- and large-cap stocks on NASDAQ OMX and NYSE during the sample period 2006-2021. The underlying econometric approach included single- (*CAPM*) and multi-factor asset pricing models (*Fama-French Three-factor model* and *Carhart Four-Factor model*) in two composite stock portfolios based on market capitalization on the respective stock market. From the present study, the following main conclusions were made:

- On average, the small-cap composite stock portfolios outperformed the *OMXSGI* and *NYSE Composite* market benchmarks over the sample period. However, the absolute and relative stock performance, as well as general patterns in equity returns of the small- and large cap stock portfolios and market benchmarks, varied within and between years. Observed patterns were at least partly related to the domestic business cycles.

- Financial indicators (*Sharpe Ratio* and *Jensen´s alpha*) suggested a higher risk-adjusted equity return for the small- compared to the large-cap stock portfolios. In a temporal isolation determined by the domestic business cycles in Sweden and the USA, alpha-values were positive for the small-cap portfolios and negative for the large-cap portfolios across all economic subperiods. Alpha-values for the small-cap portfolios seemed enhanced during boom- (more positive) or bust- (more negative) periods. In contrast, alpha-values for the large-cap portfolios were generally more at par with the market performance during bust-periods and slightly lower than the market during boom-periods. Over the aggregate sample period (2006-2021), however, alpha-values for both stock portfolios converged towards zero.

- The three (FF3)- and four (CH4)- factor model regressions supported a positive size premium (SMB) for the small-cap portfolios and a negative size premium for the large-cap portfolios on both stock markets. In a temporal isolation, small- (or large)-cap portfolios suggested a more positive (or negative) size premium during boom-periods.

- There were no clear pattern in effects from value (HML) or momentum (UMD) on equity returns. However, the modelling approach indicated positive value-effects during bust-periods and negative-value effects during boom periods, irrespective of market capitalization of the composite stock portfolios. Similarly, the UMD-coefficients seemed more pronounced (larger/smaller) from detailed modelling during shorter time periods related to the domestic business cycles, compared to observations from the aggregate sample period (2006-2021).

- The small- and large-cap portfolios contained stocks from a wide spectrum of GICS industries and the performance of specific stock portfolios was potentially influenced by the absolute and relative composition of industries in the portfolios. The quantitative importance of specific industry sectors and affiliations for equity returns was, however, not specifically evaluated within the framework of the present study.

- On average, the intra-annual patterns in monthly equity returns and the difference in equity returns between the small- and large-cap portfolios supported higher equity returns for the small-cap portfolio in January compared to the other months on NASDAQ OMX. A more general January effect across market capitalization and stock markets was, however, not observed.

## 8. Acknowledgements

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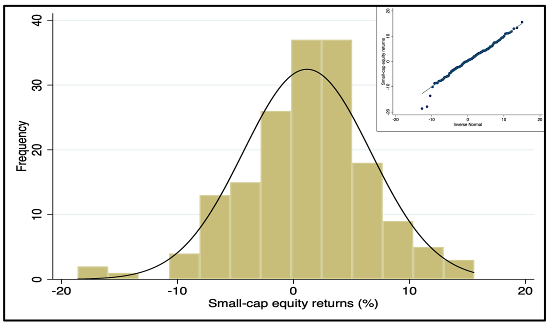
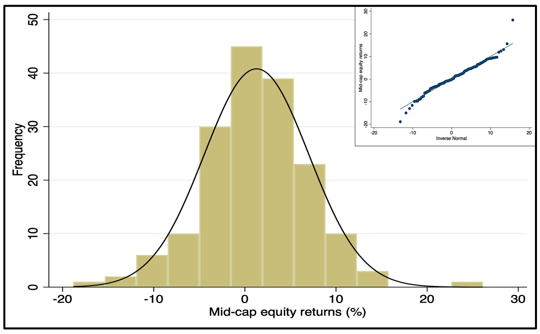
# 10. Appendices

## 10.1. Appendix A

### Statistical normality tests



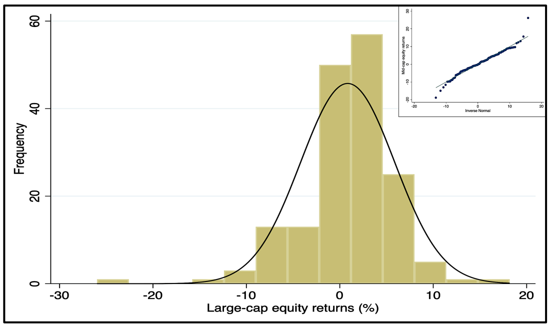
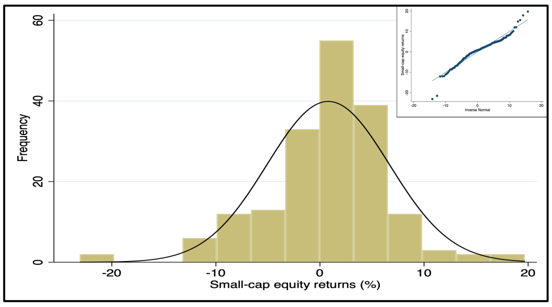
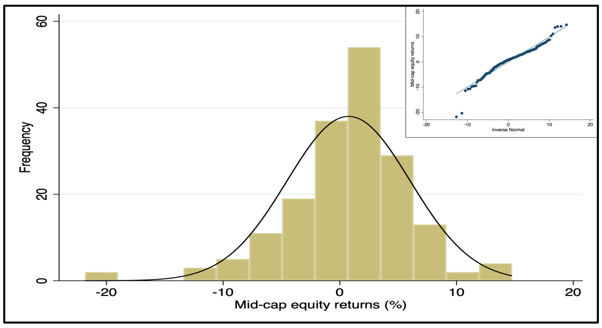




**Figure A1.** Distribution of data representing equity returns of the small-cap (upper left panel), mid-cap (upper right panel) and large-cap (lower panel) stock portfolios on NASDAQ OMX. Data was fitted against a normal distribution of data for comparison with respect to normality. A corresponding quantile-quantile (q-q) plot for each stock portfolio is illustrated separately for comparison (inset top right). In the q-q plot the quantiles of equity returns were plotted against the quantiles of the normal distribution.



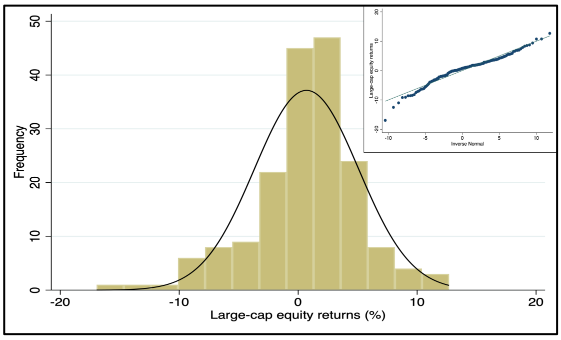




**Figure A2.** Distribution of data for equity return of the small-cap (upper left panel), mid-cap (upper right panel) and large-cap portfolio (lower panel) stock portfolios on NYSE. Data was fitted against a normal distribution of data for comparison with respect to normality. A corresponding quantile-quantile (q-q) plot for each stock portfolio is illustrated separately for comparison (inset top right). In the q-q plot the quantiles of equity returns were plotted against the quantiles of the normal distribution.

## 10.2. Appendix B

### Statistical assessments of the Ordinary Least Squares (OLS) assumptions

**Table B1.** Statistical evaluation of heteroscedasticity for the large- and small-cap composite stock portfolios on NASDAQ OMX and NYSE using the Breusch-Pagan and White test (Stock and Watson, 2015). According to the null hypothesis, the variance of the error term is constant. The values denote p-values.

| | **Tests of heteroskedasticity** | | | |
|---|---|---|---|---|
| | **Large-cap portfolio** | | **Small-cap portfolio** | |
| **Tests** | **NASDAQ OMX** | **NYSE** | **NASDAQ OMX** | **NYSE** |
| *White test* | 0.072 | 0.078 | 0.066 | 0.073 |
| | | | | |
| *Breusch-Pagan test* | 0.097 | 0.098 | 0.052 | 0.054 |

**Table B2.** Statistical evaluation of serial correlation for the large- and small-cap composite stock portfolios on NASDAQ OMX and NYSE using the Breusch-Godfrey test (Stock and Watson, 2015). According to the null hypothesis, there are no serial correlations in the dataset. The values represent p-values. The described Breusch-Godfrey test has a lag of 1 in the residuals (prediction errors).

| | **Test of serial correlation** | | | |
|---|---|---|---|---|
| | **Large-cap portfolio** | | **Small-cap portfolio** | |
| **Test** | **NASDAQ OMX** | **NYSE** | **NASDAQ OMX** | **NYSE** |
| *Breusch-Godfrey test* | 0.035 | 0.023 | 0.032 | 0.048 |

**Table B3.** Statistical evaluation of multicollinearity for the large- and small-cap composite stock portfolios on NASDAQ OMX using a correlation matrix that describes the correlation between the variables SMB (Small-Minus-Big), HML (High-Minus-Low) and UMD (Up-Minus-Down). The underlying assumption of no-multicollinearity is often considered to be violated if the correlation between two independent variables is larger than 0.9 (or smaller than -0.9) (Field, 2014).

| Variables | Market | SMB | HML | UMD |
|---|---|---|---|---|
| Market | 1 | | | |
| SMB | -0.394 | 1 | | |
| HML | 0.102 | -0.341 | 1 | |
| UMD | -0.006 | -0.088 | -0.1732 | 1 |

**Table B4:** Statistical evaluation of multicollinearity for the large- and small-cap composite stock portfolios on NYSE using a correlation matrix that describes the correlation between the variables SMB (Small-Minus-Big), HML (High-Minus-Low) and UMD (Up-Minus-Down). The underlying assumption of no-multicollinearity is often considered to be violated if the correlation between two independent variables is larger than 0.9 (or smaller than -0.9) (Field, 2014).

| Variables | Market | SMB | HML | UMD |
|---|---|---|---|---|
| Market | 1 | | | |
| SMB | -0.421 | 1 | | |
| HML | 0.121 | -0.302 | 1 | |
| UMD | -0.011 | -0.109 | -0.175 | 1 |

## 10.3 Appendix C

### Statistical validity tests

**Table C1:** Statistical evaluation of seasonality for the small- and large-cap portfolios on NASDAQ OMX and NYSE using joint significance-/F-test of dummy variables of individual months (Field, 2014). According to the null hypothesis, there are no seasonality in the dataset. The values represent p-values.

| | Test of seasonality | | | |
|---|---|---|---|---|
| | Large-cap portfolio | | Small-cap portfolio | |
| **Test** | **NASDAQ OMX** | **NYSE** | **NASDAQ OMX** | **NYSE** |
| *Seasonality* | 0.076 | 0.099 | 0.229 | 0.107 |

## 10.4. Appendix D

**Figure D1.** The relative proportion of individual GICS industry sectors contained in the small-cap (left), mid-cap (mid) and large-cap portfolio (right) on NASDAQ OMX.

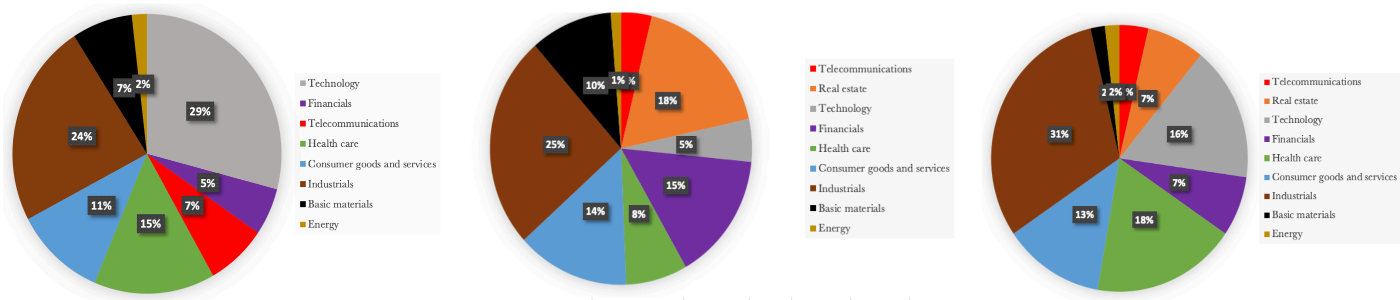



**Figure D2.** The relative proportion of individual GICS industry sectors contained in the small-cap (left), mid-cap (mid) and large-cap portfolio (right) on NYSE.