Asset growth and the cross-section of stock returns: Evidence from Nordic equity markets

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Abstract

We investigate the relationship between firm year-on-year percentage change in total assets and subsequent stock returns in Nordic equity markets. Asset growth rates are strong predictors of future stock returns and hold for firm capitalization. Of particular interest, the asset growth effect is present among large capitalization Nordic stocks. In a sample of big Nordic stocks spanning from 1991 to 2019, the average spread between value–weighted low and high growth portfolios is 8.73% per annum. In Sweden alone, the average spread is 11.75%. The long-short asset growth portfolio for big Nordic stocks has significant nonzero intercepts when measured against three-, four- and six-factor models. On an individual stock level, the asset growth effect remains even when controlling for standard determinants of stock returns. When decomposing total asset growth, we find that certain balance sheet items act as predictors of future stock returns. Finally, a time series analysis reveals that the long-short asset growth portfolio appears to be inversely related to downturns in the overall market.

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Contents

1 Introduction

The relationship between firm characteristics and cross-sectional stock returns have been closely studied over the past decades. The underlying economic premise of this research, whether it is sought to be proven or disproven, is that well-functioning capital markets price assets efficiently. One of the most influential ideas of this research is the Capital Asset Pricing Model (CAPM) (Treynor, 1961; Sharpe, 1964; Lintner, 1965). The CAPM states that the expected risk premium of an asset is determined by the asset's exposure to a comprehensive market portfolio, its systematic risk (Black, Jensen and Scholes, 1972). However, the CAPM has proven inadequate in explaining certain systematic variations in stock returns. This has given reason for researchers to focus on whether certain stock characteristics lead to predictability in returns.

Cooper, Gulen, and Schill (2008) were first to document total asset growth as a strong predictor of stock returns. They find that firms with high year-on-year percentage change in total assets, that grow by external financing, capital investments and acquisitions, subsequently report poor stock returns. In contrast, firms that experience asset contraction, share repurchases, and debt retirement show the opposite results. Cooper et al. (2008) focus on the U.S. market over the period 1968 to 2003 and document an annual 20% value-weighted return spread between low and high asset growth firms. Moreover, they do not find any basis for a risk-based explanation and favor a mispricing argument for the effect. Since the original discovery by Cooper et al. (2008), the asset growth effect has been researched across other markets and geographies. Watanabe et al. (2013) and Titman, Wei and Xie (2013) find evidence of an asset growth effect across a large international sample. Gray and Johnson (2011) further show that an asset growth effect exists in the Australian equity market, both on portfolio and individual stock level. Yao et al. (2011) study nine markets in Asia and find a pervasive negative relation between asset growth and future stock returns.

The purpose of this paper is to extend this research and study the asset growth effect in Nordic equity markets, comprising of Sweden, Norway, Denmark and Finland, over the period from 1991 to 2019. Such efforts are meaningful for many reasons. First, Nordic equity markets remain unexplored as a region for the asset growth effect. These markets represent well-developed market-based economies and have delivered strong returns over the past several decades (Evli, 2020). This is of high interest, as Watanabe et al. (2013) argue that the asset growth effect is stronger in developed markets. Second, recent studies show that an investment factor formed by sorting on total asset growth adds much predictive power for the cross-section of stock returns (Fama and French, 2015). It is therefore of increased importance to study the effect's robustness across equity markets also outside of the U.S. Finally, we are able to study more than a decade of additional data since the original publication by Cooper et al. (2008).

The empirical methodology applied in this paper is consistent with previous research. First, stocks are allocated into quintiles at the end of June of each year *t* based on annual asset growth rates. Next, portfolios are formed from July of year *t* to June of year *t*+1. We hold the portfolios for one year and then rebalance. Consistent with the findings of Cooper et al. (2008), we find that the low growth quintile exhibits statistically higher returns than the high growth quintile. We find that low growth firms produce equal-weighted (EW) monthly returns of 0.95%, whilst high growth firms generate a far inferior 0.43%. The results are replicated for value-weighted (VW) portfolios, where the low growth quintile produces average monthly returns of 1.39%, whilst the high growth quintile generates only 0.86%. The spread between the low and high growth quintiles are significant for both EW and VW portfolios. Fama and French (2008) argue that the asset growth effect is primarily driven by small capitalization stocks and stress the importance of examining the effect across size groupings. Following the methodology of Cooper et al. (2008), we rank firms into one of three groups (small, medium and big) based on the 30th and 70th market capitalization percentiles in June of year *t*. Interestingly, in contrast to Fama and French (2008), we find that big stocks exhibit the strongest asset growth effect, both in terms of magnitude and statistical significance.

The negative relation between asset growth and subsequent stock returns remain when we control for the standard risk factors of Fama and French (1993). When testing the spread of a zero-cost portfolio (long low growth stocks and short high growth stocks) against the Fama and French (1993) three–factor model, we find consistent and significant nonzero intercepts. Of particular interest, the negative relation between asset growth and subsequent risk-adjusted returns remains significant for big Nordic stocks, further suggesting that the effect is not primarily driven by small-capitalization stocks. In terms of economic significance, the VW three-factor spread between big low growth firms and big high growth firms amounts to 7.44% annually. Sweden is the largest market in the Nordics both in terms of market capitalization and number of stocks. To examine the consistency of the Nordic results, we study Sweden as an example of an individual country. The results remain largely unchanged.

After we find evidence of an asset growth effect on a portfolio level, we investigate the marginal effect on an individual stock level by performing Fama–MacBeth (1973) two-step regressions. We control for other previously documented determinants of cross-sectional returns, such as the book-to-market ratio, market capitalization, momentum variables (DeBondt and Thaler, 1985; Fama and French, 1992; Jegadeesh and Titman, 1993) and the growth measures net operating assets (Hirshleifer et al, 2004) and accruals (Sloan, 1996). Total asset growth retains its forecasting ability on an individual stock level.

To better understand the underlying drivers of the asset growth effect, we follow Cooper et al. (2008) and Cooper et al. (2017) and decompose total asset growth into major components of both the investment and financing side of the balance sheet. The results suggest that several different subcomponents have explanatory power for future returns, but that these vary widely across size groupings.

After decomposing total asset growth, we examine how portfolios sorted on asset growth perform in a time series analysis. We focus on big stocks since they are the strongest drivers of the asset growth effect on a portfolio level. The asset growth effect appears to be stable over time for both EW and VW portfolios. Moreover, the spread portfolio appears to be inversely related to downturns in the overall market.

To further test the robustness of the asset growth effect in Nordic equity markets, we control for three additional risk factors: momentum (*UMD*), betting against beta (*BAB*) and quality minus junk (*QMJ*) (Carhart, 1997; Frazzini and Pedersen, 2014; Assnes et al, 2019). The negative relation between asset growth and subsequent abnormal returns remains even after we control for exposure to these factors as well. Of particular interest, asset growth retains its predicative power for big stocks. In terms of economic significance, the VW six-factor spread for big stocks amounts to 10.30% annually.

The remainder of this paper is organized as follows. Section 2 presents a summary of previous literature and theory surrounding both stock market anomalies in general and the asset growth effect specifically. Section 3 describes our data collection method, as well as sample construction and empirical methodology. Section 4 presents our results and analyzes our findings. Section 5 provides robustness tests, to provide further evidence of our main findings. Section 6 concludes.

2 Related Literature

In this section, we review existing literature. We begin by explaining the theoretical framework underlying asset pricing research. Next, we describe the record of previous research made on the asset growth effect. We conclude by presenting two of the main explanations for the asset growth effect.

2.1 Background on Asset Pricing Research

2.1.1 Efficient Market Hypothesis and CAPM

The Efficient Market Hypothesis (EMH) was introduced by Eugene Fama in 1965 and has since served as a pillar of modern portfolio theory (Fama, 1965). The concept of market efficiency is used to describe a market where stock prices reflect all relevant and available information. According to the EMH, assets always trade at their fair value, making it impossible to earn consistent abnormal returns from investment strategies. Therefore, in an efficient market, the return an investor can earn corresponds to his exposure to risk; the only way an investor can obtain higher returns is by taking on more risk.

The fundamental model explaining this relationship is the CAPM (Treynor, 1961; Sharpe, 1964; Lintner, 1965). The CAPM states that the expected risk premium of an asset is determined by the asset's exposure to a comprehensive market portfolio, its' systematic risk (Black, Jensen and Scholes, 1972). Although the model remains a pillar in financial theory and application, it performs poorly empirically when large market indices are used as proxy for the market portfolio (Fama and French, 2004). Essentially, the CAPM is unable to explain certain systematic variations in stock returns and thus proves inadequate.

2.1.2 Stock Market Anomalies

Since the introduction of the EMH and the CAPM, numerous studies have been published documenting patterns in cross-sectional stock returns that deviate from these models. These patterns have subsequently been referred to as stock market anomalies. Banz (1981) has found a size premium where stocks with low market capitalization produce higher returns than those with high market capitalization. Moreover Rosenberg, Reid and Lanstein (1984) find that firms with high book-to-market ratios generate abnormal stock returns (the value premium). Fama and French (1993) show that the size and value premiums complement the CAPM. They form a three-factor model, which explains a far greater portion of variation in stock returns than the original CAPM. Although the three-factor model improves the predictive power of cross-sectional stock returns, several other documented anomalies remain unexplained (Fama and French, 2008). Among these, firms with higher profitability generate higher stock returns (Fairfield, Whisenant and Yohn, 2003), firms with higher accruals report lower stock returns (Sloan, 1996) and firms experience lower stock returns after equity issuances (Loughran and Ritter, 1995). Jegadeesh and Titman (1993) document a momentum premium where stocks with low (high) returns over the past year tend to have low (high) future returns. Carhart (1997) forms a four-factor model by adding the momentum premium to the Fama and French (1993) three-factor model. Since the publication of the three- and four-factor models, several new factors have been proposed. Among these, Frazzini and Pedersen (2014) show that Betting Against Beta (*BAB*), a portfolio long low beta stocks and short high beta stocks, produces superior risk-adjusted returns. Assnes et al. (2019) also show that high quality stocks outperform low quality stocks and form the Quality Minus Junk Factor (*QMJ*). More factors and pricing anomalies are continuously being found.

2.2 Empirical Evidence

2.2.1 U.S. Market

A number of studies on the U.S. stock market document the relationship between firm-level investment and subsequent stock returns. For instance, Titman, Wei and Xie (2004) find that firms that substantially increase capital investments subsequently experience negative risk-adjusted returns. Baker et al. (2003) and Anderson and Garcia-Feijoo (2006) find a negative relation between current capital expenditure and future stock returns. Richardson and Sloan (2003) study the relation between external financing and subsequent stock returns. These studies provide evidence of a negative relation between several subcomponents of firm-level investment and financing activity and future stock returns.

Cooper et al. (2008) are the first to capture a firm's overall investment by creating a simple measure of total asset growth. They show that total asset growth provides greater predictive power for future stock returns than growth in any individual investment or financing activity. Total asset growth also turns out to be more powerful than previously documented determinants in predicting the cross-section of stock returns. Lipson, Mortal and Schill (2011) examine the asset growth effect among different size groups and find that the effect remains across groupings. Lam and Wei (2011) document that total asset growth is empirically stronger than subcomponents of firm expansion.

2.2.2 International Markets

Watanabe et al. (2013) examine whether the negative relationship between asset growth and subsequent stock returns is present internationally. They study 40 countries from the time period 1982 to 2006 and investigate to which extent country characteristics influence the magnitude of the asset growth effect. They find that, in aggregate, the asset growth effect exists across international equity markets. In addition to this, they find that the asset growth effect is stronger in more developed countries with more efficient stock markets. Titman et al. (2013) also study the asset growth effect on a large international sample. They find that most equity markets exhibit a negative relation between asset growth and future stock returns but find substantial cross-country differences. Similar to Watanabe et al. (2013) they conclude that the asset growth effect is stronger in developed markets.

Li, Becker and Rosenfeld (2012) provide further evidence on the asset growth effect in international markets. They study the MSCI World Universe, which incorporates all developed markets. They find a strong negative relationship between asset growth and future stock returns. The predictive power is particularly strong for two-year total asset growth rates and survives adjustments of both size and book-to-market factors. Moreover, the asset growth effect is prevalent among both small and large capitalization stocks.

Yao et al. (2011) study nine markets in Asia during the period from 1981 to 2007. They find a pervasive negative relation between asset growth and future stock returns. However, the relation is weaker than in the U.S. market.

Gray and Johnson (2011) provide evidence of an asset growth effect in the Australian equity market. Interestingly, the asset growth rate holds its predictive power for both small and large capitalization stocks. On the other hand, Bettman, Kosev and Sault (2011) find that value-weighted returns fail to confirm an asset growth effect, concluding that the evidence is misleading due to overstated influence of small capitalization stocks.

As of yet, no study on the asset growth effect has focused on the Nordic region. There are a few studies that include individual Nordic markets as part of their international sample (Li et al, 2012; Titman et al, 2013; Watanabe et al, 2013). However, they study Nordic equity markets from the viewpoint of cross-country comparisons and conclude that an asset growth effect can be seen internationally.

2.3 Explanations of the Asset Growth Effect

2.3.1 Risk-Based Explanations

Since Cooper et al. (2008) originally discovered the asset growth effect, it has become regarded as a risk factor (Fama and French, 2015). More specifically, it has become known as the investment factor and has been formed by taking the difference between returns on diversified portfolios of low and high asset growth stocks. Fama and French (2015) derive the investment factor from rearranging the dividend discount model, where lower expected returns are implied from a higher expected growth in book value.

Cooper et al. (2008) do not favor a risk-based explanation for the asset growth effect. Their study provides evidence suggesting that both the three-factor model (Fama and French, 1993) and the four-factor model (Carhart, 1997) fail to explain variations in returns from the asset growth effect. Cooper et al. (2008) do however point to studies which describe how risk possibly decreases as a result of increased investment. Berk, Green and Naik (1999) measure expected returns with regards to growth options relative to firm assets. They suggest that increased investment broadens the asset base, which leads to lower dependence on growth options from each individual asset. Thus, a lower return is to be expected from the decreased risk following increased asset base diversification. However, Cooper et al. (2008) dismiss this theoretical explanation due to a multitude of reasons. First, the model of Berk et al. (1999) exhibits a relation to size and BM factors (Anderson and Garcia-Feijoo, 2006), and thus should be captured by the three-factor model. This deviation would cause the cost of capital, implied by the asset growth effect, to reach unprecedented levels and thus seems implausible. Instead, they find evidence suggesting market inefficiency and propose that aggressive growth strategies by corporate managers, in combination with investors' over-extrapolation, are possible causes behind the strong dispersion. Fama and French (2008) claim that the asset growth effect is essentially only prevalent in micro- and small-cap stocks, whilst not identifying a reliable relation for big stocks.

2.3.2 Mispricing Explanations

The second major explanation of the asset growth effect is attributable to theories of mispricing. Mispricing explanations tend to relate to behavioral finance literature. In this setting, mispricing of assets occurs due to systematic psychological biases and/or limitations of efficient arbitrage (De Bondt and Thaler, 1985; Shleifer and Vishny, 1997). The hallmark of behavioral finance theories is the overreaction hypothesis, which states that investors overreact to past firm performance (De Bondt and Thaler, 1985; Lakonishok, Shleifer and Vishny, 1994). Cooper et al. (2008) test this hypothesis by examining operating profitability for each asset growth decile and find that high growth firms tend to have negative profitability shocks and vice versa. Moreover, they find evidence of lower (higher) mean returns on earnings announcement days for high (low) asset growth stocks, indicating that abnormal returns are a result of systematically unanticipated bad (good) news, confirming the hypothesis put forth by La Porta et al. (1997).

This view has been further supported in academic literature. Gray and Johnson (2011) study the Australian equity market and find that the asset growth effect cannot be explained in full by risk. Moreover, they find a substantial negative relationship between asset growth and future stock returns for large capitalization stocks. This result contradicts the explanation that the asset growth effect is only prevalent among small capitalization stocks, as proposed by Fama and French (2008).

Finally, Lam and Wei (2011) examine both the limits-to-arbitrage hypothesis of Shleifer and Vishny (1997) and the q-theory with investment frictions of Li and Zhang (2010) with regards to the asset growth effect. They find evidence that proxies for both hypotheses are often highly correlated and supported by similar amounts of evidence, thus providing cause for further scrutiny.

3 Data and Empirical Methodology

In this section, we describe the source of our data. We further explain the empirical methodology and the construction process of portfolios and factors. Finally, we report summary statistics.

3.1 Sample construction

Monthly return data and annual accounting items are obtained from Thomson Reuters Datastream and Worldscope Database. Monthly factor returns are found in AQR's public data library. We use all common stocks listed on NASDAQ OMX in Sweden, Denmark and Finland, and on Oslo Stock Exchange in Norway between 1990 and 2019. We thus exclude closed-end-funds, depositary receipts, exchange-traded funds, preference shares and warrants. The stocks are allocated to their respective market based both on the country of exchange and country of domicile. We only include major securities and we use primary quotes for equities traded on several exchanges, as defined by Datastream. Following Fama and French (1993) and Cooper et al. (2008), we include both active and defunct firms to avoid overestimating historical performance and survivorship bias. Defunct firms are those who have merged, defaulted or were delisted during the sample period. Furthermore, we follow Fama and French (1992) and Cooper et al. (2008) in excluding financial firms. This is because high leverage is common in financial firms, whilst it is a sign of distress in nonfinancial firms.

The full Nordic sample consists of monthly observations of 2654 firms with 991 active and 1663 dead, stretching over a time period of 336 months. Table I reports a summary of the total number of stocks included in the sample.

Table I
Summary of the Number of Stocks

The sample is created over the period from 1990 to 2019. Dead stocks have merged, defaulted or delisted during the sample period. Nordics is created by adding Sweden, Norway, Denmark and Finland together.

	Total	Active	Dead
Nordics	2654	991	1663
Sweden	1340	578	762
Norway	591	173	418
Denmark	452	108	344
Finland	271	132	139

Sweden is the largest market and accounts for roughly 50% of the Nordic sample. Finland is the smallest market with only 10% of total stocks. We denote all returns and fundamental data in SEK since Sweden is the largest market both in terms of market capitalization and number of stocks. Following Fama and French (2012) we ignore exchange rate risk and implicitly assume complete purchasing power parity or that assets cannot be used to hedge exchange rate risk.

Datastream has reported issues with data quality, such as decimal jumps in return data (Porter and Ince, 2006). Consistent with previous research, we winsorize all variables at the 1st and 99th percentiles of their respective distributions, to filter out suspiciously large stock returns in any direction (Watanabe et al, 2013). Our return data has been calculated by importing the Total Return Index for each firm (Datastream item RI), which is a price measure adjusted for both corporate actions and dividends. The Total Return Index is defined as:

$$RI_t = RI_{t-1} \times \frac{P_t + D_t}{P_{t-1}}, \tag{1}$$

where *RI* is the Total Return Index at time *t* and *t*–1, *P* is the share price at time *t* and *t*–1 and *D* is the dividend paid at time *t*. For delisted firms, Datastream continues to report the last closing price after delisting, and we therefore remove all price data after delisting has occurred. When constructing yearly asset growth rates, we obtain Total Assets (Worldscope item WC02999) for each year between 1990 to 2017. We follow Cooper et al. (2008) and define total asset growth as the year-on-year percentage change in Total Assets:

$$ASSETG_t = \frac{TA_{t-1} - TA_{t-2}}{TA_{t-2}}, \tag{2}$$

where *ASSETG* denotes the asset growth rate and *TA* are Total Assets in year *t*–1 and *t*–2. To compute this measure, a firm must have nonzero total assets in both year *t*–1 and *t*–2. Figure 1 reports time series summary statistics for annual asset growth rates for the Nordic sample.

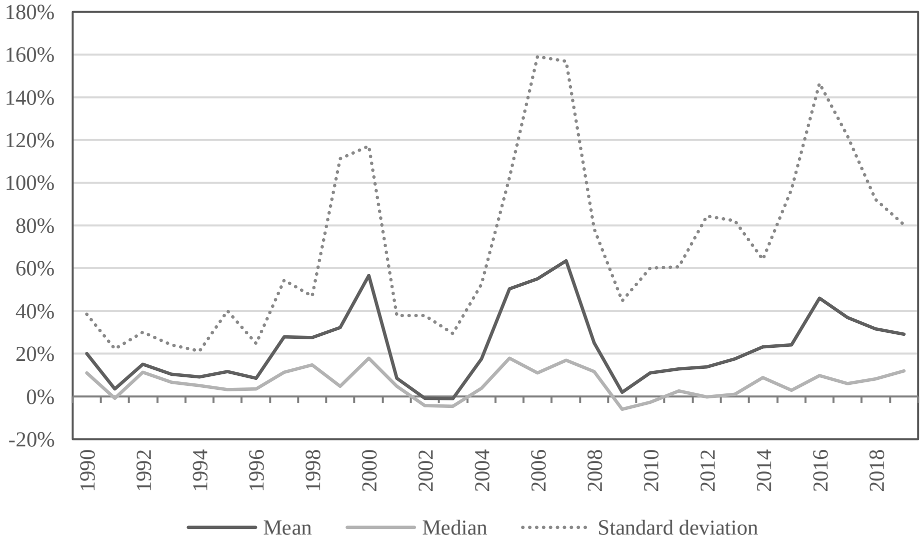

Figure I. Times series summary statistics for annual asset growth rates. The figure reports cross-sectional summary statistics for annual asset growth rates for Nordic nonfinancial firms from 1990 to 2019.

3.2 Empirical Methodology

3.2.1 Portfolio Sorting

Following the sorting methodology of Fama and French (1992, 1993, 2015) and Cooper et al. (2008), stocks are allocated into quintiles at the end of June of each year *t* based on annual asset growth rates. Cooper et al. (2008) allocate stocks into deciles, but to ensure a sufficient number of stocks in each portfolio we sort into quintiles. The reason for allocating stocks in June is to mitigate the lag between firms' annual reports and the availability of this data to investors. The firms in quintile 1 are those with the lowest asset growth rates, whilst firms in quintile 5 are those with the highest. Once firms have been assigned to quintiles, we calculate monthly returns for EW and VW portfolios for the next 12 months between July of year *t* and June of year *t*+1. The portfolios are rebalanced yearly.[1]

We further form portfolios controlling for firm capitalization to understand if the asset growth effect is persistent across size groupings. Following the methodology of Cooper et al. (2008), firms are ranked into one of three groups based on the 30th and 70th market capitalization percentiles at the end of June of year *t*. After size groups have been formed, stocks within each group are assigned to quintiles, again based on annual asset growth rates, and subsequently used to form EW and VW portfolios for the next 12 months.

[1] Portfolios are rebalanced yearly based on asset growth rates and weighting within portfolios is done monthly.

Next, we construct a zero-cost portfolio consisting of a long position in low growth firms (quintile 1) and a short position in high growth firms (quintile 5). Spreads from zero-cost portfolios are likely to be partially explained by risk factors such as size and the book-to-market ratio. Thus, to examine the risk-adjusted predictive power of the asset growth effect, we control for the Fama and French (1993) three-factor model. The model is defined as follows:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it}, \tag{3}$$

where *ri* is the monthly portfolio return, *rf* is the monthly risk-free rate, *rm* is the monthly market return, *SMB* is the average return difference between small and large capitalization stocks and *HML* is the average return difference between low and high book-to-market stocks. We explain the factor construction in greater detail in Section 3.3.

3.2.2 Fama–MacBeth Regressions

Following Cooper et al. (2008), we further examine the asset growth effect from a Fama–MacBeth framework (Fama and MacBeth, 1973). Instead of aggregating stocks into portfolios, the Fama–MacBeth cross-sectional regression is conducted on an individual stock level. The procedure of the Fama–MacBeth regression can be divided into two steps. In the first step, we perform a time-series estimation of asset betas, by regressing stock returns against a selection of variables. Then, in a second step, we perform cross-sectional regressions, where stock returns are regressed against the estimated betas of the previous step to determine the risk premium for each variable. The variables used in the Fama–Macbeth regressions will now be described.

The base set of variables used in every model are the natural logarithm of market capitalization and the book-to-market ratio, and two momentum variables defined as lagged past 6- and 36-month returns (Banz, 1981; Rosenberg et al, 1984; DeBondt and Thaler, 1985; Jegadeesh and Titman, 1993). We add three additional models to test whether the asset growth effect holds in combination with other growth-related variables. First, we add a lagged asset growth measure between *t*–3 and *t*–2 (*L2ASSETG*). Next, we examine the original model with the addition of scaled net operating assets (*NOA/A)* by Hirschleifer et al. (2004). Finally, we add the accruals (*ACCRUALS*) measure by Sloan (1996) to the original model.[2] We further divide stocks into three size groupings (small, medium and big) by dividing stocks at the 30th

[2] We provide detailed explanations of variable construction in Appendix.

and 70th market capitalization percentiles and test whether the asset growth effect holds across size groups. Furthermore, the Fama–MacBeth methodology only provides standard errors corrected for cross-sectional correlation. It is however prone to autocorrelated standard errors, and we therefore apply the Newey–West (1987) procedure to decrease correlation between error terms.

In Section 5, we apply the Fama-Macbeth methodology again to provide a decomposition of the asset growth effect. Following Cooper et al. (2008), we divide the asset investment side of the balance sheet into year-on-year change in cash, non-cash current assets, other assets and property, plant and equipment. We divide the asset financing side into year-on-year change in debt, retained earnings, operating liabilities and stock financing. We regress annual stock returns against lagged values of each subcomponent.

3.3 Description of Risk Factors

We download data on factor returns from the AQR Data Library (AQR, 2020). We filter and merge monthly factor returns with the monthly returns of our asset growth portfolios. The data is available from 1990-07-02, but because sufficient accounting data is not available before 1990, our first portfolios are formed 1991-06-30. Therefore, we use monthly factor returns from 1991-06-30 to 2019-06-30. The Quality Minus Junk Factor (*QMJ*) is not available before 1995-06-30. We download factor returns for each Nordic country individually and construct the aggregated Nordic factors by weighting each country's portfolio by the country's total lagged (t–1) market capitalization.

A description of how the factors are constructed will now follow. The Market Factor (*MKT*), contains VW returns on all available stocks minus the one-month Treasury bill rate. The other factors are constructed by using 2x3 conditional sorts, by first assigning stocks into two size-sorted portfolios based on their market capitalization, with the size breakpoint as the 80th percentile of market capitalization, and then sorting stocks on the second variable. The second variable is divided into three portfolios within each size group, at the 30th and 70th percentiles of that variables' relevant value-measurement. This method of sorting leads to six portfolios, divided into two size groups with the second variable determining the other dimension of how portfolios are sorted. Factors are rebalanced monthly to maintain value weights. The following factors are used in our study:

- Value Factor (*HML*) is long the average return of two portfolios of small and big stocks above the 70th book-to-market percentile and short the average return of two portfolios of small and big stocks below the 30th book-to-market percentile.
- Size Factor (*SMB*) is long the average return of three book-to-market sorted portfolios below the 80th market capitalization percentile and short the average return of three book-to-market sorted portfolios above the 80th market capitalization percentile.
- Momentum Factor (*UMD*) is long the average return of two portfolios of small and big stocks above the 70th percentile of prior cumulative returns and short the average return of two portfolios of small and big stocks below the 30th percentile of prior cumulative returns.[3]
- Betting Against Beta Factor (*BAB*) is long low-beta stocks and short high-beta stocks (Frazzini and Pedersen, 2014). To construct the *BAB* factor all stocks are ranked in ascending order based on their estimated beta and assigned to one of two portfolios: low-beta and high-beta. Stocks are weighted by the ranked betas where lower-beta stocks have larger weights in the low-beta portfolio and higher-beta stocks have larger weights in the high-beta portfolio. Both the low and high beta portfolios are scaled to have a beta of one at portfolio formation.
- Quality Minus Junk Factor (*QMJ*) is long the average return of two portfolios of small and big stocks above the 70th quality percentile and short the average return of two portfolios of small and big stocks below the 30th quality percentile (Assnes et al, 2019). The quality score is the average of four aspects: *profitability, growth, safety* and *payout*.

3.4 Descriptive Statistics

Table II reports summary statistics for the main variables used in our study. We have divided the table into Panel A, which reports statistics for the full Nordic sample and Panel B, which reports statistics from our largest subsample, Sweden. Cell values are calculated as time-series averages of annual cross-sectional medians.

Asset growth (*ASSETG*) increases monotonically by design and is substantially higher for high growth than low growth firms in both samples. In the Nordic sample, high growth firms have an average asset growth rate of 65.93%, whilst low growth firms report an average asset growth rate of –17.10%. Medium-rate growth firms (Quintile 3) report an average growth

[3] Cumulative prior returns from months t–12 to t–2 where t is the portfolio formation date.

rate of 6.05%. In line with Cooper et al. (2008) and Gray and Johnson (2011) there is also some evidence of persistence in asset growth rates across time. Lagged Asset Growth (*L2ASSETG*) increases monotonically from low to high growth firms, thus mirroring *ASSETG* albeit with much less variation between quintiles. For our Nordic sample, low growth firms have an average lagged growth rate of 1.71%, whilst high growth firms report an average lagged growth of 14.76%.

In both samples, medium-rate growth firms are the largest both in terms of book value of assets (*ASSETS*) and market value (*MV*). In the full Nordic sample, the average market value for medium-rate growth firms is SEKm 1106. The market value for both high and low growth firms is substantially lower, with high growth firms reporting an average market value of SEKm 637 and low growth firms an even lower average of SEKm 303. High growth firms are thus not the largest firms in either of our samples, and even have the lowest book value of assets of all quintiles in the full Nordic sample.

The average book-to-market ratio (*BM*) decreases monotonically from low to high growth firms, thus characterizing firms with high asset growth rates as also being growth firms according to the Fama and French (1993) definition. For our full Nordic sample, low growth firms report an average book-to-market ratio of 0.88 whilst high growth firms report an average of 0.52. These results are consistent with growth in capital expenditure conditioning subsequent *BM* portfolio classification (Anderson and Garcia-Feijoo, 2006; Cooper et al, 2008).

With regards to stock performance, high growth firms have substantially higher average past 36-month returns (*BHRET36*) than low growth firms. In our full Nordic sample, *BHRET36* increases monotonically from low to high growth firms, with low growth firms reporting returns of –21.13%, whilst high growth firms report 58.31%. With regards to average past 6-month returns (*BHRET06*), high and low growth firms report the lowest returns of all quintiles. In our full Nordic sample, low growth firms have slightly higher past 6-month returns than high growth firms, of 4.5% and 4.3% respectively.

The year-on-year change in scaled net operating assets (*NOA/A*) is higher for low growth firms than for high growth firms in both samples but does not show a consistent pattern across quintiles. In both samples, the average year-on-year change in accruals (*ACCRUALS*) increases monotonically from low to high growth firms and remains negative across all quintiles.

Table II

Characteristics of Asset Growth Quintiles

This table reports the characteristics of Nordic and Swedish stocks in each asset growth quintile in the year prior to the portfolio formation date. At the end of June of each year *t* from 1991 to 2018, stocks are allocated into quintiles according to their asset growth rate (*ASSETG*) defined as the year-on-year percentage change in total assets from the fiscal year ending in calendar year *t*–2 to fiscal year ending in calendar year *t*–1. *L2ASSETG* is the lagged asset growth rate defined as the percentage change in total assets from year *t*–3 to *t*–2. *ASSETS* is total assets in millions of SEK from the fiscal year ending in calendar year *t*–1. *MV* is market value of equity in millions of SEK at the end of June of year *t*. Accounting variables book-to-market ratio (*BM*), scaled net operating assets (*NOA/A*) and accruals (*ACCRUALS*) are calculated in year *t*–1. *BHRET06* is the buy-and-hold return from January to June in year *t*. *BHRET36* is the 36-month buy-and-hold return from July in year *t*–3 to June of year *t*. The numbers in each cell are the time-series average of yearly cross-sectional medians. All numbers except for *ASSETS* and *MV* are in decimal form. Panel A reports the characteristics of Nordic stocks and Panel B reports the characteristics of Swedish stocks.

Panel A: Nordics

Quintile	ASSETG	L2ASSETG	ASSETS	MV	BM	BHRET06	BHRET36	NOA/A	ACCRUALS
1 (Low)	–0.1710	0.0171	627.92	303.43	0.8848	0.0454	–0.2113	0.5584	–0.0473
2	–0.0199	0.0378	1471.60	758.15	0.8617	0.0855	0.1402	0.6088	–0.0332
3	0.0605	0.0598	1663.43	1106.99	0.7805	0.0792	0.3713	0.5975	–0.0227
4	0.1764	0.1016	1311.15	996.05	0.6411	0.0770	0.5617	0.5672	–0.0141
5 (high)	0.6593	0.1476	620.75	636.82	0.5221	0.0428	0.5831	0.5253	–0.0047

Panel B: Sweden

Quintile	ASSETG	L2ASSETG	ASSETS	MV	BM	BHRET06	BHRET36	NOA/A	ACCRUALS
1 (Low)	–0.1866	0.0321	1000.50	246.94	1.0055	0.0032	–0.2396	0.5098	–0.0412
2	–0.0169	0.0420	1774.47	760.24	0.9953	0.1018	0.1065	0.5754	–0.0259
3	0.0709	0.0740	1853.23	1125.82	0.8375	0.0731	0.4231	0.5583	–0.0140
4	0.2089	0.1175	1405.27	714.21	0.7234	0.0684	0.6400	0.5299	–0.0061
5 (High)	0.7857	0.1664	767.73	558.22	0.6611	0.0338	0.5881	0.4769	–0.0011

4 Empirical Results

4.1 Cross-sectional Portfolio Regressions

4.1.1 Full Nordic Sample

Table III reports the average monthly raw returns for each asset growth quintile over the period July 1991 through June 2019 for both EW and VW portfolios. The spread is the difference in returns of low (quintile 1) and high (quintile 5) growth firms. In Panel A, we report EW portfolio returns separately for all firms, small firms, medium firms and big firms. When all stocks are pooled (in row "All"), low growth firms have an average monthly return of 0.98%, high growth firms have an average monthly return of 0.43%, and the monthly spread equals 0.54% (*p* value = 0.0046). Economically, the EW spread portfolio exhibits annual returns of 6.70%.

When value-weighting portfolio returns for all firms, the asset growth effect remains significant (*p* value = 0.0525) with a monthly spread of 0.52% (Panel B). Interestingly, the average VW monthly returns fall in a perfectly monotonic fashion across the five quintiles, with low growth firms earning 1.39% per month, decreasing to 0.86% for high growth firms. Thus, when all stocks are pooled, there appears to be a significant asset growth effect for both EW and VW portfolios.

We further examine portfolio returns across size groupings. For EW portfolios, there is a clear and significant asset growth effect across all groups (small, medium and big). In Panel A, small low growth firms earn average monthly portfolio returns of 1.07% and small high growth firms earn average returns of 0.35%, a monthly spread of 0.72% (*p* value = 0.0141). The monthly EW portfolio spread for medium sized firms is marginally significant and lower at 0.42% (*p* value = 0.0718), increasing to a highly significant 0.72% for big firms (*p* value = 0.0024).

When turning to VW returns in Panel B, the observed asset growth effect is dampened. The average VW spreads in small and medium firms are insignificant. However, this is not the case for big firms, where low growth firms earn average monthly returns of 1.44% and high growth firms earn average monthly returns of 0.74%, a spread of 0.70% (*p* value = 0.0068).

Table III

Nordic Asset Growth Quintile Portfolio Returns

In June of each year *t* from 1991 to 2018, all Nordic stocks are sorted into quintile portfolios based on their total asset growth rate defined as the year-on-year percentage change in total assets from the fiscal year end of *t*–2 to the fiscal year end of *t*–1. The portfolios are held for one year and then rebalanced i.e. from July of year *t* to June of year *t*+1. Panel A reports average monthly equal-weighted raw portfolio returns, and Panel B reports average monthly value-weighted raw portfolio returns. The spread portfolio is the difference between low growth stocks (quintile 1) and high growth stocks (quintile 5). We report portfolio returns for all firms, small-sized firms, medium-sized firms and big-sized firms separately. Firms are ranked into one of three size groups in June of year *t* based on the 30th and 70th market capitalization percentiles.

Nordics	Asset Growth Quintiles					Spread	t (spread)	*p* value
	1 (low)	2	3	4	5 (high)			
Panel A: Equal-weighted portfolio returns								
All	0.0098	0.0119	0.0118	0.0105	0.0043	0.0054	2.8507	0.0046
Small	0.0107	0.0108	0.0120	0.0099	0.0035	0.0072	2.4677	0.0141
Medium	0.0086	0.0103	0.0105	0.0113	0.0044	0.0042	1.8063	0.0718
Big	0.0130	0.0133	0.0116	0.0100	0.0058	0.0072	3.0636	0.0024
Panel B: Value-weighted portfolio returns								
All	0.0139	0.0133	0.0124	0.0093	0.0086	0.0052	1.9462	0.0525
Small	0.0056	0.0074	0.0094	0.0114	0.0045	0.0011	0.3099	0.7569
Medium	0.0088	0.0107	0.0112	0.0131	0.0069	0.0019	0.7301	0.4659
Big	0.0144	0.0137	0.0096	0.0107	0.0074	0.0070	2.7244	0.0068

Interestingly, for big firms, the decrease in VW average returns across asset growth quintiles is near monotonic. To put our results into perspective, the evidence found by Cooper et al. (2008) has been criticized by Fama and French (2008), who argue that the asset growth effect is primarily driven by small stocks, and that the effect is nonexistent among big stocks. In contrast to this, Table III suggests that there is a negative relation between asset growth and subsequent stock returns for big stocks in Nordic equity markets. This holds true for both EW and VW portfolios. These findings are in line with Gray and Johnson (2011) who find evidence of an asset growth effect in the largest Australian stocks. Economically, the VW spread portfolio for big stocks exhibits an average annual return of 8.73%.

Returns for spread portfolios are likely to be partially explained by other known risk factors. To examine the predictive power of the asset growth effect, we therefore control for the Fama and French (1993) three-factor model. We report monthly three-factor alphas for asset growth quintiles for the full sample and across the three size groupings. In Table IV, we report risk-adjusted EW and VW portfolio returns from July 1991 through June 2019. Panel A presents the EW portfolio three-factor alphas for all firms, small firms, medium firms and big firms separately. In Panel A, when all stocks are pooled, low growth firms have a monthly alpha of 0.33%, high growth firms have a monthly alpha of –0.21%, and the spread equals 0.54% (*p* value = 0.0037).

When value-weighting the portfolio three-factor alphas for all firms, the asset growth effect remains marginally significant. In Table IV Panel B, low growth firms have a monthly alpha of 0.54% and high growth firms have a monthly alpha of 0.10%. The VW spread for all firms is 0.45% (*p* value = 0.0721). Similar to the VW portfolio returns, the VW risk-adjusted portfolio returns decrease in a perfectly monotonic fashion as we move from low growth firms to high growth firms.

Next, we report three–factor alphas across the three size groupings. Using EW portfolios, the risk-adjusted asset growth effect remains significant for both small and big firms. As can be seen in Table IV Panel A, small low growth firms have a monthly alpha of 0.57%, small high growth firms have a monthly alpha of –0.16%, and the spread equals 0.74% (*p* value = 0.0130). Big low growth firms have a monthly alpha of 0.52% and big high growth firms have a monthly alpha of –0.20%, with a spread of 0.72% (*p* value = 0.0005). The monthly EW risk-adjusted spread for medium-sized firms is insignificant (*p* value = 0.1150).

Table IV Panel B reports VW risk-adjusted returns across the three size groupings. Consistent with raw VW portfolio returns, the negative relation between growth and abnormal

Table IV
Nordic Fama and French (1993) Three-factor Risk-adjusted Portfolio Returns

In June of each year *t* from 1991 to 2018, all Nordic stocks are sorted into quintile portfolios based on their total asset growth rate defined as the year-on-year percentage change in total assets from the fiscal year end of *t*–2 to the fiscal year end of *t*–1. The portfolios are held for one year and then rebalanced i.e. from July of year *t* to June of year *t*+1. Panel A reports average monthly equal-weighted Fama and French (1993) three-factor alphas, and Panel B reports average monthly value-weighted Fama and French (1993) three-factor alphas. The spread portfolio is the difference between low asset growth stocks (quintile 1) and high asset growth stocks (quintile 5). We report portfolio returns for all firms, small-sized firms, medium-sized firms and big sized-firms separately. Firms are ranked into one of three size groups in June of year *t* based on the 30th and 70th market capitalization percentiles.

Nordics	Asset Growth Quintiles					Spread	t (spread)	*p* value
	1 (low)	2	3	4	5 (high)			
Panel A: Risk-adjusted equal-weighted portfolio returns								
All	0.0033	0.0054	0.0055	0.0040	–0.0021	0.0054	2.9200	0.0037
Small	0.0057	0.0050	0.0073	0.0048	–0.0016	0.0074	2.4960	0.0130
Medium	0.0018	0.0041	0.0045	0.0052	–0.0018	0.0036	1.5810	0.1150
Big	0.0052	0.0056	0.0042	0.0026	–0.0020	0.0072	3.5340	0.0005
Panel B: Risk-adjusted value-weighted portfolio returns								
All	0.0054	0.0050	0.0047	0.0017	0.0010	0.0045	1.8040	0.0721
Small	0.0001	0.0016	0.0049	0.0062	–0.0008	0.0009	0.2630	0.7927
Medium	0.0017	0.0044	0.0051	0.0069	0.0004	0.0013	0.4870	0.6260
Big	0.0057	0.0058	0.0018	0.0029	–0.0003	0.0060	2.4630	0.0143

returns is only found for big firms. Big low growth firms have a monthly alpha of 0.57% and big high growth firms exhibit a monthly alpha of –0.03%. The VW risk-adjusted spread for big firms generates a monthly alpha of 0.60% (*p* value = 0.0143).

To summarize, when all stocks are pooled there is strong evidence supporting an asset growth effect in the Nordics over the period from July 1991 through June 2019. This holds true for both EW and VW portfolios adjusted for risk factors proposed by Fama and French (1993). Of particular interest, Table IV suggests that the negative relation between asset growth and subsequent risk-adjusted returns remains significant for big Nordic stocks. In contrast to the findings of both Fama and French (2008) and Cooper et al. (2008), the asset growth effect in the Nordics is mainly driven by large capitalization stocks.

4.1.2 Subsample: Sweden

Sweden is the largest market in the Nordics both in terms of market capitalization and number of stocks. To examine the consistency of our Nordic findings, we study Sweden as an example of an individual country. We follow the same portfolio sort methodology as for the Nordic sample. In the following, we report EW and VW raw and risk-adjusted returns over the period July 1991 through June 2019 for Swedish stocks.

In Table V Panel A, we report EW portfolio returns. When all stocks are pooled, low growth firms have an average monthly return of 1.16%, high growth firms have an average monthly return of 0.53%, and the spread equals 0.63% (*p* value = 0.0213). However, this finding disappears when we use VW to form portfolios (in Panel B). Thus, when Swedish stocks are pooled, there appears to be a significant asset growth effect only for EW portfolios. Interestingly, when the three size groupings (small, medium and big) are considered, there is no evidence of an asset growth effect for small-sized firms. This applies to both EW and VW portfolios. The medium-sized firms exhibit a marginally significant negative relationship between asset growth and future stock returns when using EW to form portfolios (Panel A). The most striking finding in Table V is that there is a strong significant asset growth effect in big Swedish stocks. Using EW to form portfolios, big low growth firms earn average monthly returns of 1.38% and big high growth firms earn average monthly returns of 0.66%, a monthly spread of 0.72% (*p* value = 0.0212). When considering VW portfolio returns for big firms, the monthly spread is even higher at 0.93% (*p* value = 0.0297). Economically, the VW spread for big Swedish firms generates significant average annual returns of 11.75%. In Table VI, we

Table V
Swedish Asset Growth Quintile Portfolio Returns

In June of each year *t* from 1991 to 2018, all Swedish stocks are sorted into quintile portfolios based on their total asset growth rate defined as the year-on-year percentage change in total assets from the fiscal year end of *t*–2 to the fiscal year end of *t*–1. The portfolios are held for one year and then rebalanced i.e. from July of year *t* to June of year *t*+1. Panel A reports average monthly equal-weighted raw portfolio returns, and Panel B reports average monthly value-weighted raw portfolio returns. The spread portfolio is the difference between low asset growth stocks (quintile 1) and high asset growth stocks (quintile 5). We report portfolio returns for all firms, small-sized firms, medium sized-firms and big-sized firms separately. Firms are ranked into one of three size groups in June of year *t* based on the 30th and 70th market capitalization percentiles.

Sweden	Asset Growth Quintiles					Spread	t (spread)	*p* value
	1 (low)	2	3	4	5 (high)			
Panel A: Equal-weighted portfolio returns								
All	0.0116	0.0127	0.0117	0.0119	0.0053	0.0063	2.3139	0.0213
Small	0.0155	0.0095	0.0119	0.0109	0.0075	0.0080	1.3052	0.1927
Medium	0.0113	0.0115	0.0125	0.0114	0.0056	0.0056	1.7090	0.0884
Big	0.0138	0.0128	0.0116	0.0120	0.0066	0.0072	2.3152	0.0212
Panel B: Value-weighted portfolio returns								
All	0.0141	0.0152	0.0093	0.0121	0.0089	0.0052	1.4185	0.1570
Small	0.0065	0.0044	0.0103	0.0079	0.0015	0.0050	0.7570	0.4496
Medium	0.0096	0.0107	0.0132	0.0134	0.0078	0.0018	0.4834	0.6291
Big	0.0168	0.0122	0.0094	0.0107	0.0074	0.0093	2.1828	0.0297

Table VI

Swedish Fama and French (1993) Three-factor Risk-adjusted Portfolio Returns

In June of each year *t* from 1991 to 2018, all Swedish stocks are sorted into quintile portfolios based on their total asset growth rate defined as the year-on-year percentage change in total assets from the fiscal year end of *t*–2 to the fiscal year end of *t*–1. The portfolios are held for one year and then rebalanced i.e. from July of year *t* to June of year *t*+1. Panel A reports average monthly equal-weighted Fama and French (1993) three-factor alphas, and Panel B reports average monthly value-weighted Fama and French (1993) three-factor alphas. The spread portfolio is the difference between low asset growth stocks (quintile 1) and high asset growth stocks (quintile 5). We report portfolio returns for all firms, small-sized firms, medium-sized firms and big sized-firms separately. Firms are ranked into one of three size groups in June of year *t* based on the 30th and 70th market capitalization percentiles.

Sweden	Asset Growth Quintiles					Spread	t (spread)	*p* value
	1 (low)	2	3	4	5 (high)			
Panel A: Risk-adjusted equal-weighted portfolio returns								
All	0.0050	0.0054	0.0047	0.0046	–0.0010	0.0060	2.2160	0.0274
Small	0.0108	0.0033	0.0071	0.0051	0.0028	0.0079	1.2860	0.1990
Medium	0.0044	0.0050	0.0055	0.0046	–0.0007	0.0051	1.5670	0.1180
Big	0.0047	0.0042	0.0037	0.0042	–0.0013	0.0060	2.1680	0.0309
Panel B: Risk-adjusted value-weighted portfolio returns								
All	0.0055	0.0054	0.0018	0.0041	0.0013	0.0042	1.1970	0.2320
Small	0.0013	–0.0014	0.0054	0.0018	–0.0030	0.0043	0.6470	0.5178
Medium	0.0026	0.0039	0.0060	0.0066	0.0011	0.0015	0.3980	0.6910
Big	0.0075	0.0029	0.0018	0.0026	–0.0002	0.0077	1.8520	0.0650

report three-factor alphas. When all stocks are pooled, only EW portfolios exhibit a significant risk-adjusted asset growth effect. As can be seen in Panel A, the EW spread generates a significant monthly alpha of 0.60% (*p* value = 0.0274). Turning to the size groupings, there is no evidence of a risk-adjusted asset growth effect in neither small nor medium-sized firms. This holds true for both EW and VW portfolios. Of particular interest, the asset growth effect for big Swedish firms remains significant also after controlling for Fama and French (1993) risk factors. Using EW to form portfolios for big firms, low growth firms have a monthly alpha of 0.47% and high growth firms have a monthly alpha of –0.13%, resulting in a monthly three-factor spread of 0.60% (*p* value = 0.0309). Using VW to form portfolios, the spread generates an even higher monthly alpha of 0.77% (*p* value = 0.0650). These results are highly interesting, as they suggest that, in Sweden, only big stocks exhibit a significant asset growth effect.

4.2 Cross-Sectional Fama–MacBeth Regressions

In this section, we continue to investigate the asset growth effect on the Nordic sample. To better understand the marginal effect of asset growth on stock returns we conduct Fama–MacBeth (1973) two-step regressions over the period July 1991 through June 2019. Instead of aggregating stocks into portfolios, the Fama–MacBeth framework analyzes returns on an individual stock level.

Table VII reports results from the stock-level analysis. In Panel A, we report results for the full sample. Model 1 in Panel A suggests that the asset growth effect is not subsumed when controlling for other covariates commonly related to stock returns. Interestingly, together with the momentum variable *BHRET06*, asset growth turns out to be the strongest predictor of future returns in terms of *p* value. In line with our previous results, asset growth is inversely related to returns with a coefficient of –0.0557 (*p* value = 0.0219). Thus, the Fama–MacBeth regression confirms the significant negative relation between asset growth and returns from the portfolio sort regressions of Section 4.1.

In Model 2, we augment the initial variables with the lagged asset growth variable *L2ASSETG*. In this model, both asset growth variables (*ASSETG* and *L2ASSETG*) exhibit significant results. Consistent with intuition, *L2ASSETG* is inversely related to returns with a coefficient of –0.0432 (*p* value = 0.0399). *ASSETG* is largely unchanged from the first model with a coefficient of –0.0560 (*p* value = 0.0220). The asset growth effect remains strong and significant even when we control for the growth rate variables *NOA/A* and *ACCRUALS* in

Table VII

Fama–MacBeth Regressions of Annual Returns on Asset Growth and Other Key Characteristics

This table reports estimates from cross-sectional Fama–MacBeth regressions at an individual stock level for the Nordic sample. Annual stock returns from July 1991 to June 2019 are regressed on lagged accounting and return-based variables. The two-step regression is repeated each year. The beta estimates are time-series averages of the annual cross-sectional regression estimates. *ASSETG* is defined as the year-on-year percentage change in total assets from the fiscal year ending in calendar year *t*–2 to fiscal year ending in calendar year *t*–1. *BM* is the book-to-market ratio calculated in fiscal year ending in year *t*–1. *MV* is market value at the end of June of year *t*. *BHRET06* is the buy-and-hold return from January to June in year *t*. *BHRET36* is the 36-month buy-and-hold return from July in year *t*–3 to June of year *t*. *L2ASSETG* is the lagged asset growth rate defined as the percentage change in total assets from year *t*–3 to *t*–2. Net operating assets divided by total assets (*NOA/A*) and accruals (*ACCRUALS*) are calculated in year *t*–1. We report beta estimates for all firms (Panel A), small-sized firms (Panel B), medium-sized firms (Panel C) and big-sized firms (Panel D) separately. Firms are ranked into one of three size groups in June of year *t* based on the 30th and 70th market capitalization percentiles. The *p* values reported in parenthesis are adjusted for first-order autocorrelation.

Panel A: All Firms										
Model		Intercept	ASSETG	BM	MV	BHRET06	BHRET36	L2ASSETG	NOA/A	ACCRUALS
1	Beta	0.1605	–0.0557	0.0180	–0.0031	0.1802	0.0139			
	p value	(0.1396)	(0.0219)	(0.2067)	(0.6105)	(<0.0001)	(0.1441)			
2	Beta	0.1612	–0.0560	0.0184	–0.0028	0.1731	0.0172	–0.0432		
	p value	(0.1291)	(0.0220)	(0.2006)	(0.6368)	(<0.0001)	(0.0693)	(0.0399)		
3	Beta	0.2034	–0.0575	0.0220	–0.0024	0.1760	0.0107		–0.0942	
	p value	(0.0915)	(0.0204)	(0.0943)	(0.6956)	(<0.0001)	(0.2769)		(0.0693)	
4	Beta	0.1527	–0.0509	0.0179	–0.0029	0.1810	0.0157			–0.0847
	p value	(0.1497)	(0.0338)	(0.2126)	(0.6319)	(<0.0001)	(0.0935)			(0.2414)

Table VII – *Continued*

Panel B: Small Firms

Model		Intercept	ASSETG	BM	MV	BHRET06	BHRET36	L2ASSETG	NOA/A	ACCRUALS
1	Beta	0.0637	–0.0674	0.0257	0.0077	0.2061	0.0256			
	p value	(0.8105)	(0.4521)	(0.3298)	(0.7501)	(0.0002)	(0.3522)			
2	Beta	0.2094	–0.1732	0.0128	–0.0059	0.1546	0.0535	–0.0415		
	p value	(0.3620)	(0.0648)	(0.6767)	(0.7588)	(0.0058)	(0.0474)	(0.5544)		
3	Beta	0.0138	–0.0442	0.0330	0.0187	0.2059	0.0209		–0.1228	
	p value	(0.9686)	(0.6476)	(0.2584)	(0.5683)	(0.0002)	(0.4619)		(0.0217)	
4	Beta	0.0889	–0.0142	0.0251	0.0043	0.2153	0.0375			–0.2801
	p value	(0.7234)	(0.8379)	(0.3320)	(0.8490)	(0.0002)	(0.1486)			(0.1000)

Table VII – *Continued*

Panel C: Medium Firms

Model		Intercept	ASSETG	BM	MV	BHRET06	BHRET36	L2ASSETG	NOA/A	ACCRUALS
1	Beta	–0.0933	–0.0467	–0.0002	0.0157	0.1997	0.0106			
	p value	(0.6026)	(0.2155)	(0.9936)	(0.2391)	(<0.0001)	(0.4390)			
2	Beta	–0.0854	–0.0444	–0.0005	0.0153	0.1929	0.0146	–0.0354		
	p value	(0.6324)	(0.2377)	(0.9793)	(0.2532)	(<0.0001)	(0.2602)	(0.2497)		
3	Beta	–0.1031	–0.0481	0.0067	0.0215	0.1939	0.0081		–0.1136	
	p value	(0.5623)	(0.1845)	(0.6798)	(0.0973)	(<0.0001)	(0.5659)		(0.0157)	
4	Beta	–0.0670	–0.0456	–0.0017	0.0133	0.1996	0.0120			0.0205
	p value	(0.7152)	(0.2124)	(0.9332)	(0.3265)	(<0.0001)	(0.3909)			(0.8246)

Panel D: Big Firms

Model		Intercept	ASSETG	BM	MV	BHRET06	BHRET36	L2ASSETG	NOA/A	ACCRUALS
1	Beta	0.0856	–0.0500	0.0255	0.0031	0.1092	0.0074			
	p value	(0.5394)	(0.0643)	(0.1238)	(0.6671)	(0.0243)	(0.5835)			
2	Beta	0.0869	–0.0512	0.0248	0.0034	0.1039	0.0084	–0.0174		
	p value	(0.5324)	(0.0638)	(0.1355)	(0.6352)	(0.0244)	(0.5292)	(0.6512)		
3	Beta	0.1569	–0.0519	0.0286	0.0022	0.1041	0.0031		–0.1069	
	p value	(0.2903)	(0.0607)	(0.0780)	(0.7677)	(0.0335)	(0.8182)		(0.1541)	
4	Beta	0.0716	–0.0391	0.0266	0.0037	0.1140	0.0071			–0.0940
	p value	(0.6056)	(0.1385)	(0.1116)	(0.6108)	(0.0201)	(0.5982)			(0.4646)

Model 3 and 4. Hirshleifer et al. (2004) report a negative relationship between the cumulative accruals measure net operating assets (*NOA/A*) and returns. In Model 3 *NOA/A* is marginally significant with a coefficient of –0.0942 (*p* value = 0.0693). Sloan (1996) find a negative relation between accruals and future returns. In Model 4, *ACCRUALS* exhibits the expected sign but is insignificant. In all models, we find evidence of a strong 6-month momentum effect with coefficients ranging from 0.1731 to 0.1810 (*p* value < 0.0001). Neither of the growth rate variables subsume the asset growth effect; *ASSETG* remains negative and significant in Model 3 and 4 with coefficients of –0.0575 (*p* value = 0.0204) and –0.0509 (*p* value = 0.0338) respectively. To put these results into perspective, running the same models, Cooper et al. (2008) report similar but slightly higher coefficients on *ASSETG* of –0.0918 and –0.0704 respectively. Economically, the coefficient on *ASSETG* in Model 4 suggests that a 100% increase in asset growth would reduce the future 12 month return by an average of 5.09%. To summarize, the Fama–MacBeth regressions provide evidence supporting an asset growth effect on an individual stock level over the period July 1991 through June 2019. *ASSETG* remains negative and statistically significant in all four models, thus confirming the results in the cross-sectional portfolio regressions of Table IV.

Next, we examine the results from the Fama–MacBeth (1973) regressions across size groupings. For small firms in Panel B, Model 1 documents a negative coefficient on asset growth, but the results are not significant (*p* value = 0.4521). The only significant variable in Model 1 is the prior 6-month momentum variable *BHRET06* with a strong coefficient of 0.2061 (*p* value = 0.0002). Interestingly, when including lagged asset growth (*L2ASSETG*) in Model 2, *ASSETG* becomes marginally significant with a coefficient of –0.1732 (*p* value = 0.0648). There is no asset growth effect in Model 3 (*NOA/A)* or Model 4 (*ACCRUALS)*. All together, we find little evidence of an asset growth effect on an individual stock level for small firms.

In Panel C, we report Fama–MacBeth coefficients for medium-sized firms. Recall that we did not find significant evidence of an asset growth effect for medium-sized firms in the risk–adjusted portfolio sort of Table IV. This also hold true in the Fama–MacBeth (1973) regressions where *ASSETG* is insignificant in all models.

In Panel D, we report the Fama–MacBeth regression results for big firms. In Model 1, the slope of *ASSETG* is negative and marginally significant at –0.0500 (*p* value = 0.0643). When including the additional control variables *L2ASSETG* in Model 2 and *NOA/A* in Model 3, the results remain largely unchanged. When we control for *ACCRUALS* in regression Model 4, all variables are insignificant except for *BHRET06*.

Taken as a whole, the results in this section suggest that when all stocks are pooled in Panel A, the Fama–MacBeth two-step regressions support a negative relation between asset growth and subsequent returns as documented at the portfolio level. When dividing the sample into size groups, the results are somewhat inconsistent. For small firms, the regression slopes of *ASSETG* are insignificant in a majority of the models. Consistent with our risk-adjusted portfolio sort regressions of Table IV, there is no asset growth effect firms medium-sized firms on an individual stock level. Curiously, small and medium-sized firms exhibit stronger relation to the 6-month momentum variable and *NOA/A*. Of particular interest, the asset growth effect for big Nordic stocks remains marginally significant on an individual stock level after controlling for other determinants of future returns

4.3 Decomposing Asset Growth

Total asset growth is affected by several different balance sheet items. To better understand the underlying drivers of the total asset growth effect, we follow Cooper et al. (2008) and Cooper et al. (2017) by decomposing total asset growth into major subcomponents. Total asset growth is divided into 1) asset investment components and 2) asset financing components. For comparability reasons, we follow Cooper et al. (2008) and define the asset investment composition as follows:

Total asset growth (*ASSETG*)
= Cash growth (*ΔCASH*)
+ Noncash current assets growth (*ΔCA*)
+ Property plant and equipment growth (*ΔPPE*)
+ Other assets growth (*ΔOA*)

Whereas the asset financing composition is defined as:

Total asset growth (*ASSETG*)
= Operating liabilities growth (*ΔOpL*)
+ Debt financing growth (*ΔDEBT*)
+ Stock financing growth (*ΔSTOCK*)
+ Retained earnings growth (*ΔRE*)

For detailed definitions of the subcomponents, refer to Appendix I. All subcomponents are scaled by lagged total assets so that each side of the balance sheet equals the percentage growth in total assets. To understand the explanatory power of the subcomponents, we employ Fama–MacBeth (1973) two-step regressions over the period July 1991 through June 2019. We run the regressions for all firms and for the three size groups separately. As described in section 3.2.2, to ensure robustness of our results, the standard errors from the Fama–MacBeth regressions are adjusted for first-order autocorrelation.

In Table VIII Panel A, we report the regression results for all firms. Looking at the asset investment side, we only find a significant negative coefficient for change in property, plant and equipment (*ΔPPE*) of -0.1444 (*p* value = 0.0266). Of particular interest, the change in cash (*ΔCASH*) is significant but with a positive coefficient of 0.0966 (*p* value = 0.0333). When we perform the regression on all investment variables, only the coefficient on cash remains significant (marginally). Turning to the asset financing side for all firms, we find significant negative regression slopes for change in operating liabilities (*ΔOpL*) and change in debt (*ΔDEBT*) with coefficients of -0.0594 (*p* value = 0.0512) and -0.1538 (*p* value = 0.0428) respectively. When all financing variables are regressed, only *ΔOpL* remains significant.

In Panel B, we report Fama–MacBeth coefficients for small capitalization firms. None of the investment components exhibit significant relationships in any of the regressions. On the financing side, only change in stock financing (*ΔSTOCK)* is marginally significant with a negative coefficient of -0.1952 (*p* value = 0.0747). This could be a result of firms experiencing lower returns after equity issuances (Loughran and Ritter, 1995).

We report the results for medium-sized firms in Panel C. The only significant subcomponents in medium sized firms are *ΔCASH* and change in retained earnings (*ΔRE)* and they both exhibit a positive relation with future returns. Both effects are large in magnitude with coefficients of 0.1956 (*p* value = 0.0173) and 0.1845 (*p* value = 0.0661) respectively. The positive *ΔCASH* effect remains also when we perform the regression on all investment components. One potential explanation of this is the documented positive relationship between firms building excess cash reserves, in anticipation of future investment opportunities, and future stock returns (Simutin, 2010).

Lastly, we report the results for big firms in Panel D. With regards to investment components, big firms report a marginally significant coefficient for changes in noncash current assets (*ΔCA)* of -0.1459 (*p* value = 0.0982). *ΔPPE* exhibits the strongest negative relationship with future returns, with a coefficient of -0.3151 (*p* value = 0.0089). In terms of

Table VIII
Fama–MacBeth Regressions of Annual Returns on Asset Growth: Decompositions

This table reports estimates from cross-sectional Fama–MacBeth regressions of annual stock returns from July 1991 to June 2019 on subcomponents of asset growth. The two-step regression is repeated each year. The beta estimates are time-series averages of the annual cross-sectional regression estimates. On the left side, we report the asset investment decomposition defined as cash growth (*ΔCASH*), noncash current assets growth (*ΔCA*), property, plant and equipment growth (*ΔPPE*) and other assets growth (*ΔOA*). On the right side, we report the asset financing decomposition defined as operating liabilities growth (*ΔOpL*), debt financing growth (*ΔDEBT*), stock financing growth (*ΔSTOCK*) and retained earnings growth (*ΔRE*). All variables are scaled by lagged total assets. We report beta estimates for all firms (Panel A), small-sized firms (Panel B), medium-sized firms (Panel C) and big-sized firms (Panel D) separately. Firms are ranked into one of three size groups in June of year *t* based on the 30_{th} and 70_{th} market capitalization percentiles. The *p* values reported in parenthesis are adjusted for first-order autocorrelation using the Newey–West (1987) procedure.

Panel A: All Firms								
Intercept	ΔCASH	ΔCA	ΔPPE	ΔOA	ΔOpL	ΔDEBT	ΔSTOCK	ΔRE
0.1517	0.0966							
(0.0028)	(0.0333)							
0.1397		–0.0550						
(0.0078)		(0.2454)						
0.1462			–0.1444					
(0.0052)			(0.0266)					
0.1443				–0.0829				
(0.0058)				(0.1226)				
0.1592	0.1111	–0.0767	–0.1275	–0.0750				
(0.0016)	(0.0980)	(0.2463)	(0.1999)	(0.3046)				
0.1445					–0.0594			
(0.0055)					(0.0512)			
0.1439						–0.1538		
(0.0061)						(0.0428)		
0.1436							–0.0692	
(0.0058)							(0.1114)	
0.1409								0.1031
(0.0068)								(0.1670)
0.1429					–0.1995	–0.0541	0.1154	0.0361
(0.0054)					(0.0288)	(0.5830)	(0.1956)	(0.5304)

Table VIII – *Continued*

Panel B: Small firms								
Intercept	ΔCASH	ΔCA	ΔPPE	ΔOA	ΔOpL	ΔDEBT	ΔSTOCK	ΔRE
0.1630	0.0529							
(0.0057)	(0.7770)							
0.1367		–0.1531						
(0.0189)		(0.1550)						
0.1438			–0.2143					
(0.0168)			(0.1986)					
0.1414				–0.0203				
(0.0190)				(0.8622)				
0.1673	–0.2515	–0.2088	0.0319	0.1477				
(0.0049)	(0.2408)	(0.1981)	(0.8912)	(0.4175)				
0.1375					–0.1548			
(0.0181)					(0.1094)			
0.1305						–0.1923		
(0.0324)						(0.1672)		
0.1399							–0.1952	
(0.0171)							(0.0747)	
0.1362								0.0839
(0.0203)								(0.4822)
0.1287					–0.1013	–0.1217	–0.0960	0.1510
(0.0230)					(0.4971)	(0.3749)	(0.5955)	(0.4257)

Table VIII – *Continued*

Panel C: Medium firms								
Intercept	ΔCASH	ΔCA	ΔPPE	ΔOA	ΔOpL	ΔDEBT	ΔSTOCK	ΔRE
0.1440	0.1956							
(0.0044)	(0.0173)							
0.1348		–0.0056						
(0.0114)		(0.9373)						
0.1452			–0.1013					
(0.0076)			(0.2567)					
0.1453				–0.1022				
(0.0070)				(0.3319)				
0.1504	0.2403	0.0552	–0.0867	–0.1420				
(0.0018)	(0.0318)	(0.5697)	(0.4712)	(0.3332)				
0.1428					–0.0208			
(0.0066)					(0.6025)			
0.1419						–0.0745		
(0.0094)						(0.3056)		
0.1403							–0.0119	
(0.0092)							(0.8637)	
0.1376								0.1845
(0.0114)								(0.0661)
0.1339					0.0654	-0.1208	0.0306	0.2009
(0.0094)					(0.5406)	(0.2337)	(0.8897)	(0.3553)

Table VIII – *Continued*

Panel D: Big firms								
Intercept	ΔCASH	ΔCA	ΔPPE	ΔOA	ΔOpL	ΔDEBT	ΔSTOCK	ΔRE
0.1504	–0.0217							
(0.0011)	(0.8498)							
0.1522		–0.1459						
(0.0008)		(0.0982)						
0.1557			–0.3151					
(0.0006)			(0.0089)					
0.1479				0.0093				
(0.0012)				(0.9252)				
0.1608	–0.0968	–0.1189	–0.3653	0.0018				
(0.0004)	(0.4187)	(0.2526)	(0.0023)	(0.9859)				
0.1586					–0.1094			
(0.0004)					(0.0407)			
0.1553						–0.3151		
(0.0007)						(0.0001)		
0.1532							–0.0440	
(0.0009)							(0.5970)	
0.1503								0.0765
(0.0011)								(0.4524)
0.1622					–0.1644	–0.1717	0.1856	0.2665
(0.0003)					(0.1997)	(0.3626)	(0.2684)	(0.1374)

economic significance, a 100% increase in property plant and equipment would on average reduce future 12 month returns with 31.51%. This is consistent with findings of Titman, Wei and Xie (2004) who document a negative relation between abnormal capital investments and subsequent stock returns. The relation between PPE and stock returns remains negative and significant when the subcomponents are regressed together. Next, we examine the asset financing variables. We find that increases in *ΔOpL* and *ΔDEBT* are associated with significant negative coefficients. *ΔDEBT* exhibits the strongest negative relation with future returns, with a coefficient of -0.3151 (*p* value = 0.0001). However, when introduced together, none of the financing components are statistically significant.

To summarize, the results suggest that different subcomponents of total asset growth have explanatory power for future stock returns. These, however, vary largely across size groups. Of particular interest, big firms exhibit a strong negative relationship between both *ΔPPE* and *ΔDEBT* and future stock returns. Richardson and Sloan (2003) find an especially strong negative relation when proceeds from external financing are invested in net operating assets as opposed to being stored as cash or charged against income. This might explain why we see such strong coefficients on both *ΔPPE* and *ΔDEBT*.

4.4 Time Series Analysis of the Asset Growth Effect

In previous sections, we have identified an asset growth effect both on a portfolio and an individual stock level. In this section, we study how the asset growth effect performs over time for big stocks. Big stocks exhibit the strongest asset growth effect on a portfolio level, both in terms of magnitude and statistical significance. Moreover, big stocks tend to be the most liquid and are thus more likely to be used in investment strategies (Gray and Johnson, 2011).

In Figure II and III, we plot cumulative log returns for EW and VW low growth (P1), high growth (P5) and spread portfolios from July 1991 to June 2019. We utilize log returns to reduce the variation of the time series. This is done to improve comparability of variables. Across the sample period, we observe that both spread portfolios appear to increase steadily over time. This is similar to findings of Cooper et al. (2008) who document that low growth firms consistently outperform high growth firms for both EW and VW portfolios. The most striking finding is that the spread portfolio appears to appreciate when P1 and/or P5 experience(s) large drawdowns. However, the plots suggest that during rapid runups shortly before downturns for P1 and/or P5, the spread portfolio drifts sideways or even decreases. This observation warrants further scrutiny, and we thus proceed by plotting spread portfolios against the Market Factor (*MKT*).

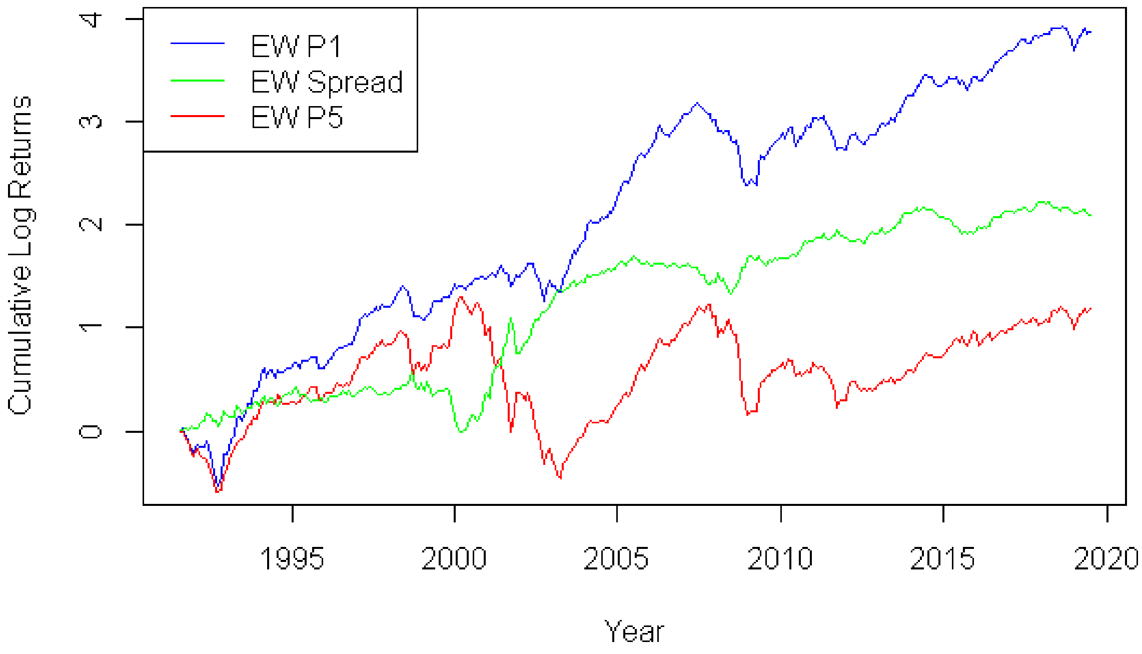

Figure II. EW Cumulative Log Returns for Big Stocks. The figure plots EW cumulative log returns for big low growth (P1), big high growth (P5) and spread portfolios from July 1991 to June 2019. We consider the full Nordic sample.

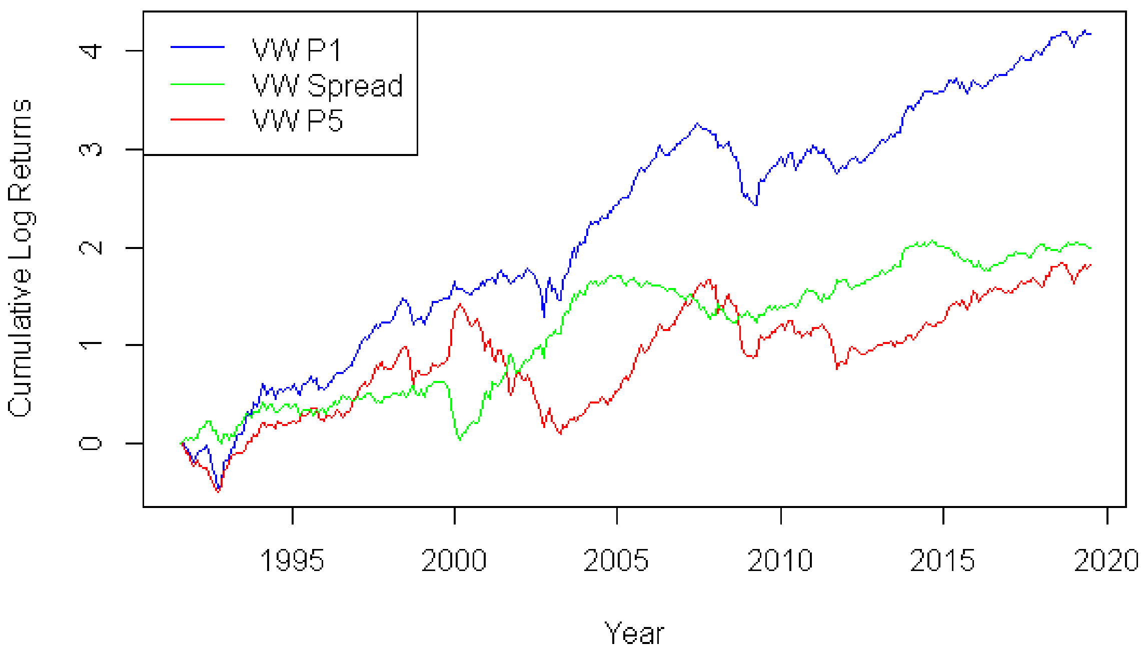

Figure III. VW Cumulative Log Returns for Big Stocks. The figure plots VW cumulative log returns for big low growth (P1), big high growth (P5) and spread portfolios from July 1991 to June 2019. We consider the full Nordic sample.

Figure IV and V strengthen the analysis from previous observations. The spread portfolios perform well during times of large market downturns. Moving chronologically along Figure V, the first and only major drawdown for the VW spread portfolio occurs around the millennium shift. During this period, *MKT* ascends, and the two portfolios diverge. As *MKT* subsequently plunges the spread portfolio rises rapidly. A similar pattern follows during the next late upturn period (2005-2007). *MKT* appreciates strongly whilst the spread portfolio decreases. Once *MKT* plunges, the spread portfolio again appreciates. We do not provide further analysis but suggest that there appears to be a negative correlation between *MKT* and the spread portfolios during times of major drawdowns for *MKT*. To conclude, the asset growth effect seems to be insensitive to large market downturns but appears to be vulnerable to rapid market appreciations. More plots are available in Appendix IV-IX.

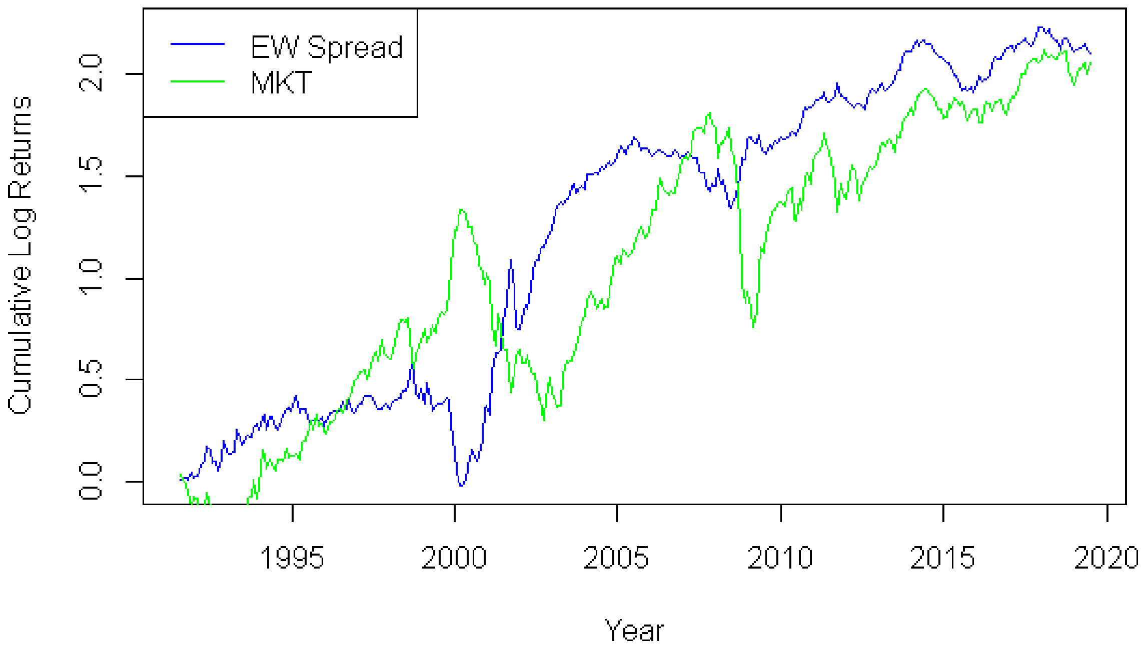

Figure IV. EW Cumulative Log Returns for Big Stocks and MKT. The figure plots cumulative log returns for the market factor (*MKT*) and for the EW spread portfolio for big stocks from July 1991 to June 2019. We consider the full Nordic sample.

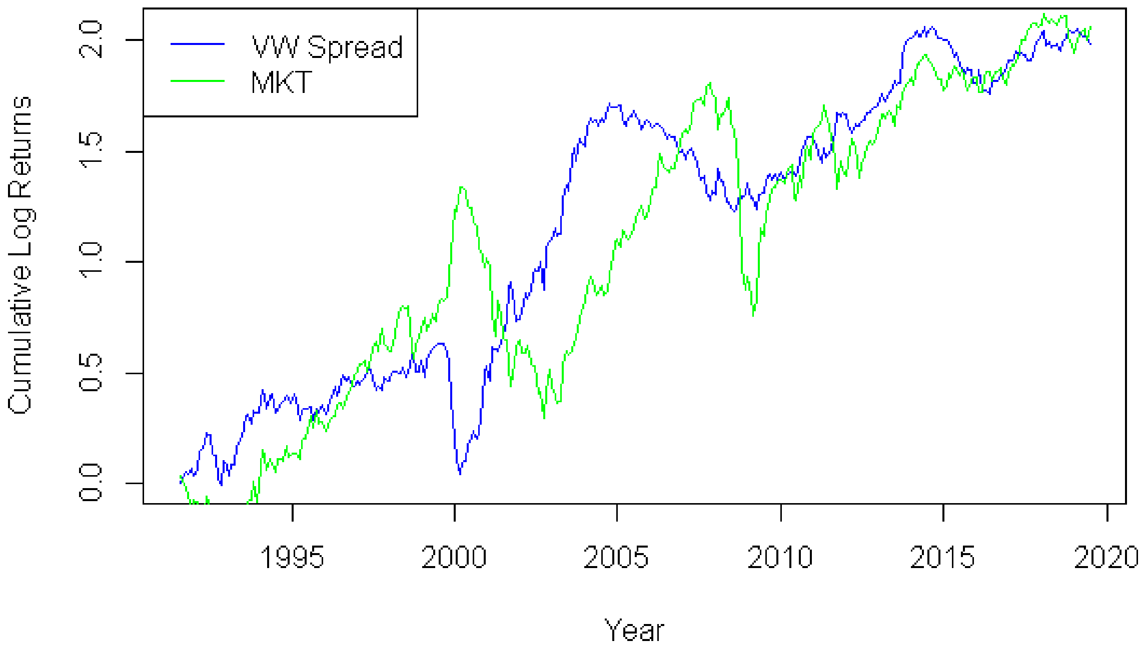

Figure V. VW Cumulative Log Returns for Big Stocks and MKT. The figure plots cumulative log returns for the market factor (*MKT*) and for the VW spread portfolio for big stocks from July 1991 to June 2019. We consider the full Nordic sample.

5 Robustness Tests

5.1 Four-factor model

To further test the robustness of the asset growth effect in Nordic equity markets, we regress our portfolios sorted on asset growth against Carhart's four-factor model (1997). The model is defined as:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + d_i UMD_t + \varepsilon_{it}, \qquad (4)$$

where the momentum factor *UMD* is introduced in addition to the previously used Fama and French (1993) three-factor model. We follow the same procedure as for the portfolio sorts of Table IV and report EW and VW risk-adjusted monthly returns for the full Nordic sample (Appendix II). We also test across size groupings.

The results are similar to when we control for the Fama and French (1993) three-factor model. When all stocks are pooled, the EW spread generates an average monthly alpha of 0.60% (p value = 0.0021), whilst the VW spread generates an average monthly alpha of 0.48% (p value = 0.0640). Furthermore, the four-factor results remain robust across the three size groups. For EW portfolios, the average monthly alpha spread is 0.69% (p value = 0.0250) for small firms, 0.44% (p value = 0.0641) for medium-sized firms and 0.62% (p value = 0.0034) for big firms. Taken together, we find significant EW alphas across all size groups when controlling for the four-factor model. Recall that for medium-sized firms, the three-factor alpha is insignificant, and has thus improved when controlling for the four-factor model.

Turning to VW portfolios, the results are largely unchanged compared to the three-factor model. The average monthly four-factor alphas for small and medium-sized firms remain insignificant and the strong monthly four-factor alpha for big firms persists at 0.77% (p value = 0.0024). Economically, this corresponds to an average annual alpha of 9.64%. In conclusion, the documented asset growth effect survives Carhart's four-factor model.

5.2 Six-factor model

To further test the robustness of the asset growth effect, we regress our portfolios sorted on asset growth against an extended six-factor model. The model is defined as:

$$r_{it} - r_{ft} = \alpha_i + \beta_i(r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + d_i UMD_t + g_i BAB_t + q_i QMJ_t + \varepsilon_{it}, \tag{5}$$

where the Betting Against Beta Factor (*BAB)* and the Quality Minus Junk Factor (*QMJ)* are introduced in addition to the previously used Carhart (1997) four-factor model. These factors have proven to predict cross-sectional stock returns unexplained by traditional risk factors (Frazzini and Pedersen, 2014; Asness et al, 2019) and are thus interesting to include in our analysis. Factor returns for *QMJ* are available from 1995-07-01 and we therefore perform regressions over the period from July 1995 to June 2019.

The results are similar to when we control for Carhart's (1997) four-factor model. In Appendix III, Panel A, we report EW risk-adjusted portfolio returns. When all stocks are pooled, the spread portfolio generates an average monthly alpha of 0.53% (p = 0.0132). In Panel B, when using VW to form portfolios for all firms, the asset growth effect remains significant with an average monthly alpha of 0.82% (p = 0.0030) for the spread portfolio.

Next, we turn to EW monthly alphas across the three size groupings. When returns are adjusted for *BAB* and *QMJ*, abnormal returns to the small and medium spread portfolios are statistically insignificant. Of particular interest, big low growth firms remain significant with a monthly alpha of 0.98%, big high growth firms have a monthly alpha of 0.44%, and the spread equals 0.55% (p = 0.0170). Using VW to form portfolios, the big firm spread is even stronger at 0.82% (p = 0.0030). To conclude, the asset growth effect in Nordic equity markets remains significant for the full sample and for big firms when we control for exposure to *BAB* and *QMJ* factors in addition to Carhart's (1997) four-factor model. In terms of economic significance, the VW spread portfolio earns an average annual six-factor alpha of 10.30% for big firms.

6 Conclusion

In this paper, we study the asset growth effect in Nordic equity markets. Consistent with the findings of Cooper et al. (2008), there is a negative relationship between total asset growth and future stock returns. This holds true even when controlling for the Fama and French (1993) three-factor model. Of particular interest, the negative relation remains significant for large capitalization stocks. In a sample spanning from 1991 to 2019, a VW portfolio of low asset growth big stocks outperforms a portfolio of high asset growth big stocks with an average monthly three-factor alpha of 0.60%, amounting to 7.44% annually. To examine the consistency of the Nordic results, we study Sweden as a subsample within the Nordics. The findings suggest that within size groups, only big Swedish stocks exhibit a significant risk-adjusted asset growth effect.

To examine the predictive power of asset growth on an individual stock level, we perform Fama–MacBeth two-step regressions. The asset growth effect remains a strong determinant of future stock returns when controlling for other covariates commonly related to cross-sectional stock returns. The results are statistically significant when considering the full sample. Big stocks exhibit an asset growth effect with marginally significant results.

To better understand the drivers of the observed asset growth effect, we decompose total asset growth into major subcomponents. Certain subcomponents hold strong predictive power but vary both in terms of their coefficients and significance across size groups. Considering investment activity in big stocks, growth in *PPE* is highly significant and substantial in magnitude. In terms of economic significance, a 100% increase in *PPE* would on average reduce the future 12 month buy-and-hold return with 31.51%. This is consistent with findings of Titman, Wei and Xie (2004) who document a negative relation between abnormal capital investment and subsequent stock returns. On the financing side, the same holds true for growth in *DEBT*. This is consistent with Richardson and Sloan (2003) who find a strong negative relationship between investment in net operating assets, financed with externally raised capital, and subsequent stock returns. Curiously, medium-sized firms exhibit a positive relationship between both growth in *CASH* and *RE* and future stock returns. One potential explanation of this is the documented positive relationship between firms building excess cash reserves, in anticipation of future investment opportunities, and future stock returns (Simutin, 2010).

From our time series analysis, we observe that the long-short (spread) asset growth portfolio displays stable performance over time. This is in line with Cooper et al. (2008) who document that low growth firms consistently outperform high growth firms. Moreover, the EW and VW spread portfolios appear to be negatively correlated with large market downturns but tend to decrease with strong market upturns.

The asset growth effect remains significant when we control for exposure to the four-factor model of Carhart (1997) and an extended six-factor model augmented with *BAB* and *QMJ* factors. Interestingly, the big stock VW spread portfolio generates a highly significant annual six-factor alpha of 10.30%.

The findings in our paper raise several inquiries for future research. First, it would be interesting to examine how the asset growth effect performs during different time periods. In particular, examining the asset growth effect during times of crises. From the results in our time series analysis, there appears to be a strong negative relation between both the EW and VW spread portfolios and the Market Factor (*MKT*). The cause behind this could be further examined. Second, we suggest that one could investigate whether other variables correlate with asset growth. One such variable appears to be the long horizon momentum variable (*BHRET36),* which is substantially higher for high growth firms than for low growth firms. This could be the result of aggressive growth strategies by corporate managers coupled with overextrapolation by investors as proposed by Cooper et al. (2008). As a final thought, it would be valuable to examine the reasons underlying the asset growth effect in Nordic equity markets. Cooper et al. (2008) and Gray and Johnson (2011) both dismiss a risk-based explanation in U.S. and Australian equity markets, respectively. They instead favor a mispricing explanation. Given the strength of the asset growth effect in Nordic equity markets, it seems likely that a risk-based explanation will face great challenges.

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Appendix

Appendix I. Variable definitions.

For comparability reasons, we define the variables used in this study following Cooper et al. (2008).

ASSETG is the year-on-year percentage change in total assets from the fiscal year ending in calendar year *t*–2 to the fiscal year ending in calendar year *t*–1.

Book equity is defined as common equity plus deferred taxes in the fiscal year ending in calendar year *t*–1.[4]

BM is the book-to-market ratio calculated by dividing book equity for the fiscal year ending in year *t*–1 by the market value of equity in the fiscal year ending in year *t*–1.

MV is the market value of equity at the end of June (*t*).

BHRET06 is the 6-month buy-and-hold return from January to June in year *t*.

BHRET36 is the 36-month buy-and-hold return from July in year *t*–3 to June of year *t*

L2ASSETG is the lagged asset growth rate defined as the percentage change in total assets from year *t*–3 to *t*–2.

NOA/A is derived by dividing NOA (net operating assets) from Hirschleifer et al. (2004) by lagged total assets.

ACCRUALS, from Sloan (1996) is defined as: [(Change in Current Assets – Change in Cash) – (Change in Current Liabilities – Change in Short-term Debt – Change in Taxes Payable) – Depreciation Expense] / Average Total Assets)]

ΔCASH is the year-on-year percentage change in cash and short-term investments (Cash) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1.

ΔCA is the year-on-year percentage change in noncash cash current assets (defined as: Current Assets – Cash and Short-term Investments) between the fiscal year ending in calendar year *t*–2 and fiscal year ending in calendar year *t*–1.

ΔPPE is the year-on-year percentage change in property, plant and equipment (PPE) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1.

[4] In Cooper et al. (2008) book equity is calculated as stockholders' equity plus deferred taxes and investment credit minus book value of preferred stock. However, Worldscope organizes accounting data differently than Compustat (the database Cooper et al. (2008) use) and thus we instead use common equity.

ΔOA is the year-on-year percentage change in other assets (defined as: Total Assets – Cash – Current Assets – PPE) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1.

ΔDEBT is the year-on-year percentage change in debt (defined as: Short-term Debt + Long-term Debt) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1.

ΔRE is the year-on-year percentage change in retained earnings (RE) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1.

ΔSTOCK is the year-on-year percentage change in stock financing (defined as: Common Equity + Preferred Stock + Minority Interest – Retained Earnings) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1

ΔOpL is the year-on-year percentage change in operating liabilities (defined as: Total Assets – RE – Stock Financing – Debt) between the fiscal year ending in calendar year *t*–2 and the fiscal year ending in calendar year *t*–1.

Appendix II
Nordic Carhart (1997) Four-factor Risk-adjusted Portfolio Returns

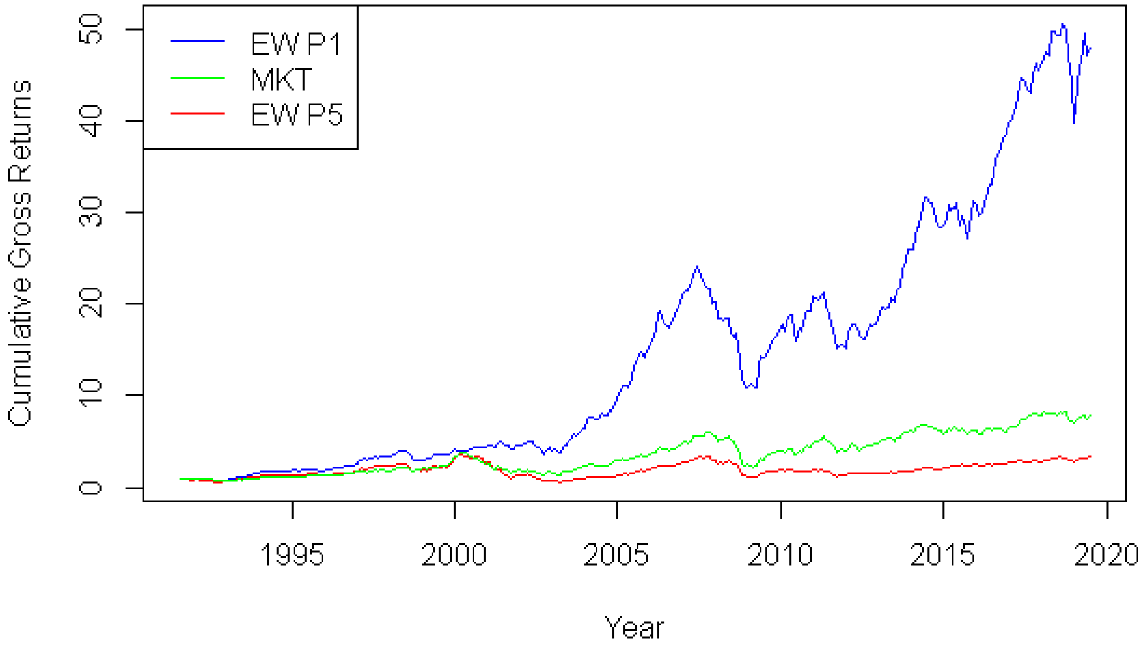
In June of each year *t* from 1991 to 2018, all Nordic stocks are sorted into quintile portfolios based on their total asset growth rate defined as the year-on-year percentage change in total assets from the fiscal year end of *t*–2 to the fiscal year end of *t*–1. The portfolios are held for one year and then rebalanced i.e. from July of year *t* to June of year *t*+1. Panel A reports average monthly equal-weighted Carhart (1997) four-factor alphas, and Panel B reports average monthly value-weighted Carhart (1997) four-factor alphas. The spread portfolio is the difference between low asset growth stocks (quintile 1) and high asset growth stocks (quintile 5). We report portfolio returns for all firms, small-sized firms, medium-sized firms and big-sized firms separately. Firms are ranked into one of three size groups in June of year *t* based on the 30_{th} and 70_{th} market capitalization percentiles.

Nordics	Asset Growth Quintiles					Spread	t (spread)	*p* value
	1 (low)	2	3	4	5 (high)			
Panel A: Risk-adjusted equal-weighted portfolio returns								
All	0.0070	0.0074	0.0074	0.0066	0.0010	0.0060	3.1030	0.0021
Small	0.0088	0.0081	0.0094	0.0073	0.0018	0.0069	2.2510	0.0250
Medium	0.0057	0.0060	0.0066	0.0074	0.0012	0.0044	1.8570	0.0641
Big	0.0079	0.0081	0.0061	0.0047	0.0017	0.0062	2.9520	0.0034
Panel B: Risk-adjusted value-weighted portfolio returns								
All	0.0073	0.0079	0.0061	0.0031	0.0025	0.0048	1.8590	0.0640
Small	0.0014	0.0023	0.0060	0.0065	0.0015	–0.0001	–0.0170	0.9863
Medium	0.0051	0.0057	0.0065	0.0078	0.0014	0.0037	1.3880	0.1660
Big	0.0088	0.0074	0.0036	0.0044	0.0011	0.0077	3.0640	0.0024

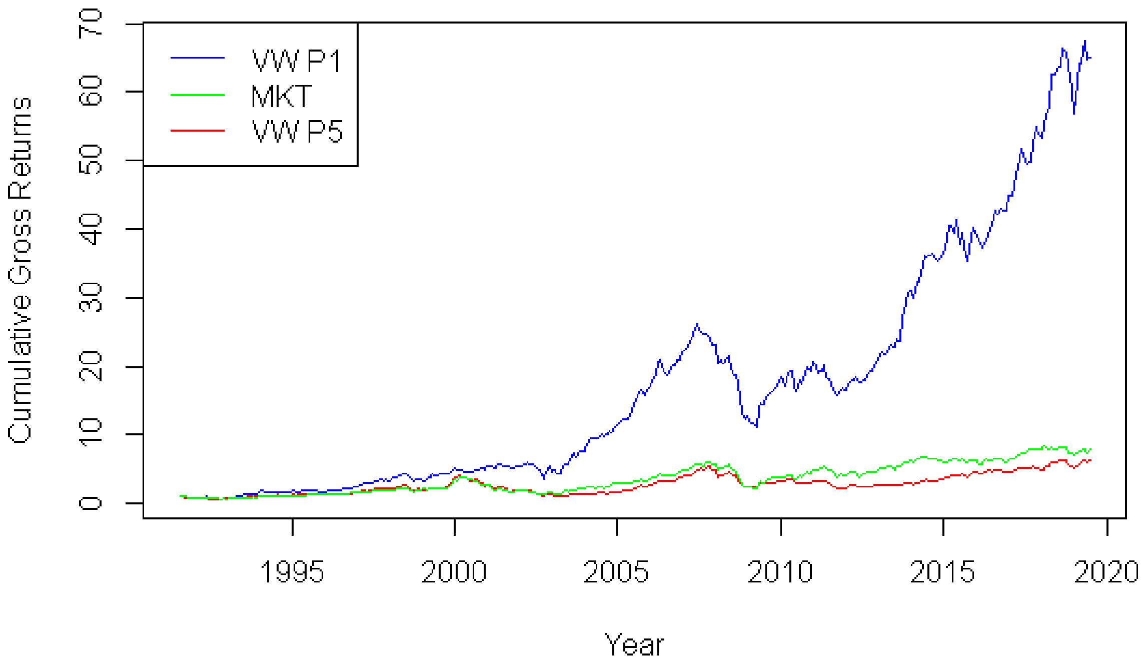
Appendix III
Nordic Six-factor Risk-adjusted Portfolio Returns

In June of each year *t* from 1995 to 2018, all Nordic stocks are sorted into quintile portfolios based on their total asset growth rate defined as the year-on-year percentage change in total assets from the fiscal year end of *t*–2 to the fiscal year end of *t*–1. The portfolios are held for one year and then rebalanced i.e. from July of year *t* to June of year *t*+1. Panel A reports average monthly equal-weighted six-factor alphas, and Panel B reports average monthly value-weighted six-factor alphas. The spread portfolio is the difference between low asset growth stocks (quintile 1) and high asset growth stocks (quintile 5). We report portfolio returns for all firms, small-sized firms, medium-sized firms and big-sized firms separately. Firms are ranked into one of three size groups in June of year *t* based on the 30th and 70th market capitalization percentiles.

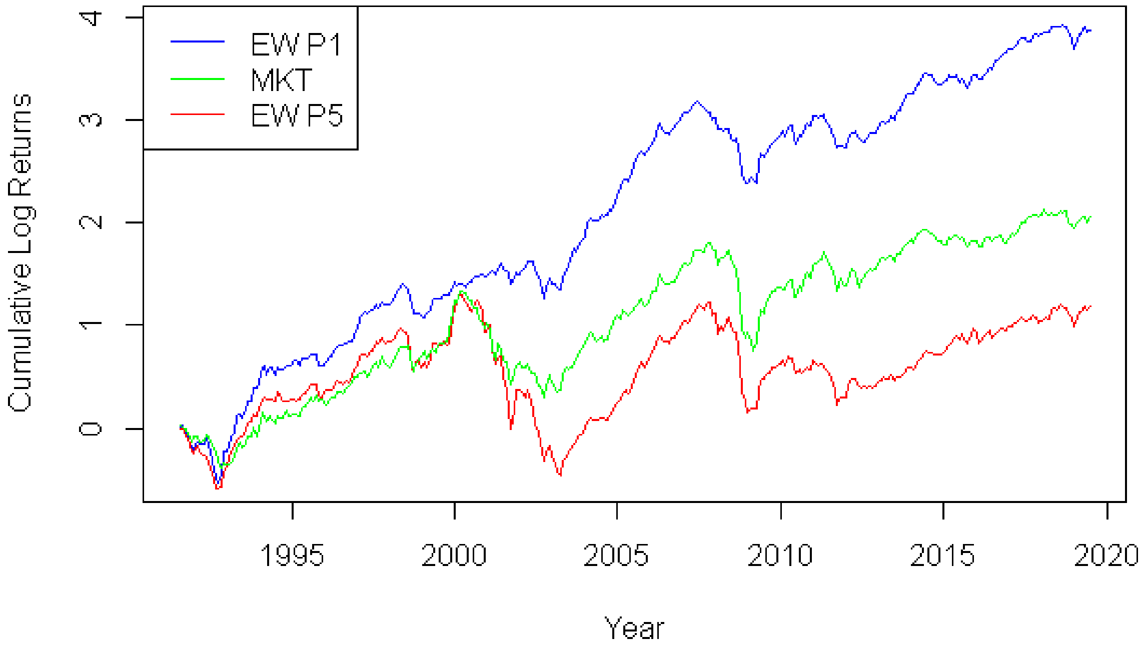
Nordics	Asset Growth Quintiles					Spread	t (spread)	*p* value
	1 (low)	2	3	4	5 (high)			
Panel A: Risk-adjusted equal-weighted portfolio returns								
All	0.0080	0.0085	0.0079	0.0068	0.0027	0.0053	2.4930	0.0132
Small	0.0088	0.0084	0.0088	0.0064	0.0034	0.0054	1.5730	0.1170
Medium	0.0070	0.0065	0.0065	0.0070	0.0033	0.0037	1.4510	0.1478
Big	0.0098	0.0095	0.0083	0.0062	0.0044	0.0055	2.4010	0.0170
Panel B: Risk-adjusted value-weighted portfolio returns								
All	0.0103	0.0108	0.0086	0.0030	0.0048	0.0055	1.8880	0.0600
Small	0.0024	0.0020	0.0079	0.0060	0.0026	–0.0002	–0.0410	0.9673
Medium	0.0070	0.0069	0.0067	0.0083	0.0042	0.0028	1.0210	0.3080
Big	0.0119	0.0101	0.0055	0.0049	0.0037	0.0082	2.9910	0.0030



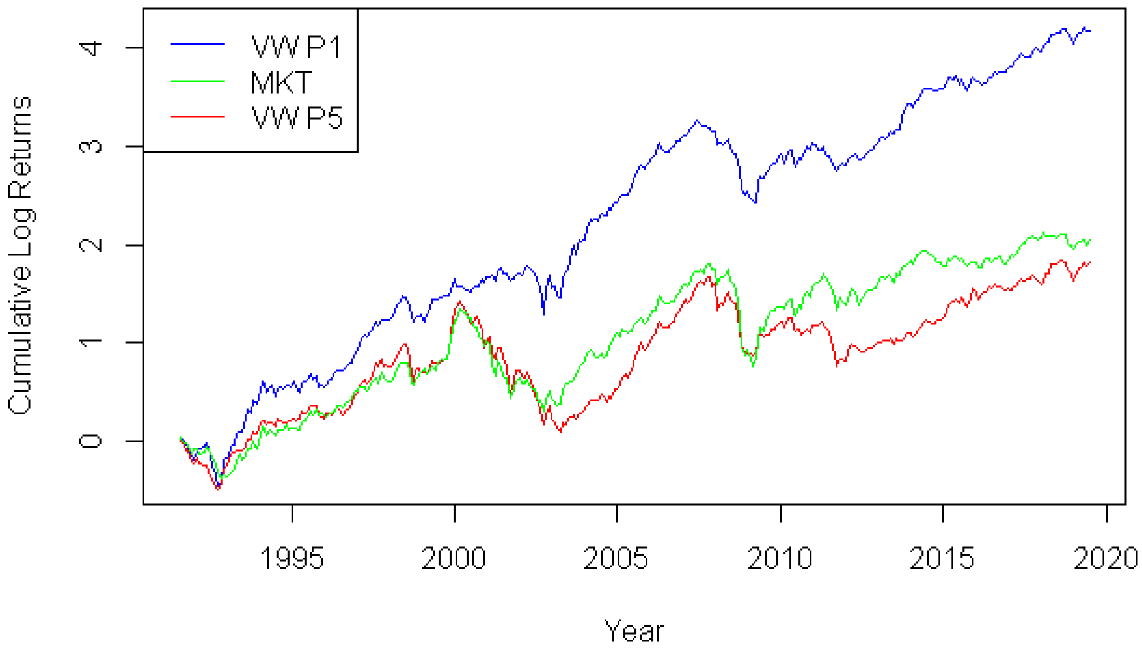
Appendix IV. EW portfolios and MKT Cumulative Gross Returns Over Time. The figure plots cumulative gross returns for the market factor (*MKT*) and EW cumulative gross returns for big low growth (P1) and big high growth (P5) portfolios from July 1991 to June 2019. We consider the full Nordic sample.



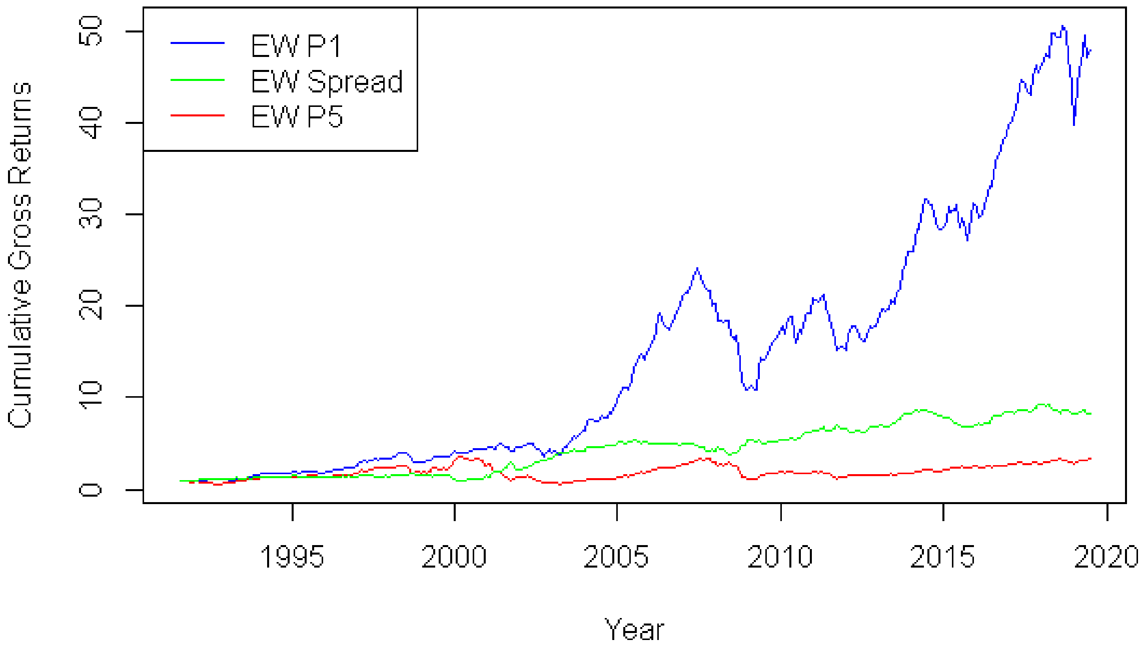
Appendix V. VW portfolios and MKT Cumulative Gross Returns Over Time. The figure plots cumulative gross returns for the market factor (*MKT*) and VW cumulative gross returns for big low growth (P1) and big high growth (P5) portfolios from July 1991 to June 2019. We consider the full Nordic sample.



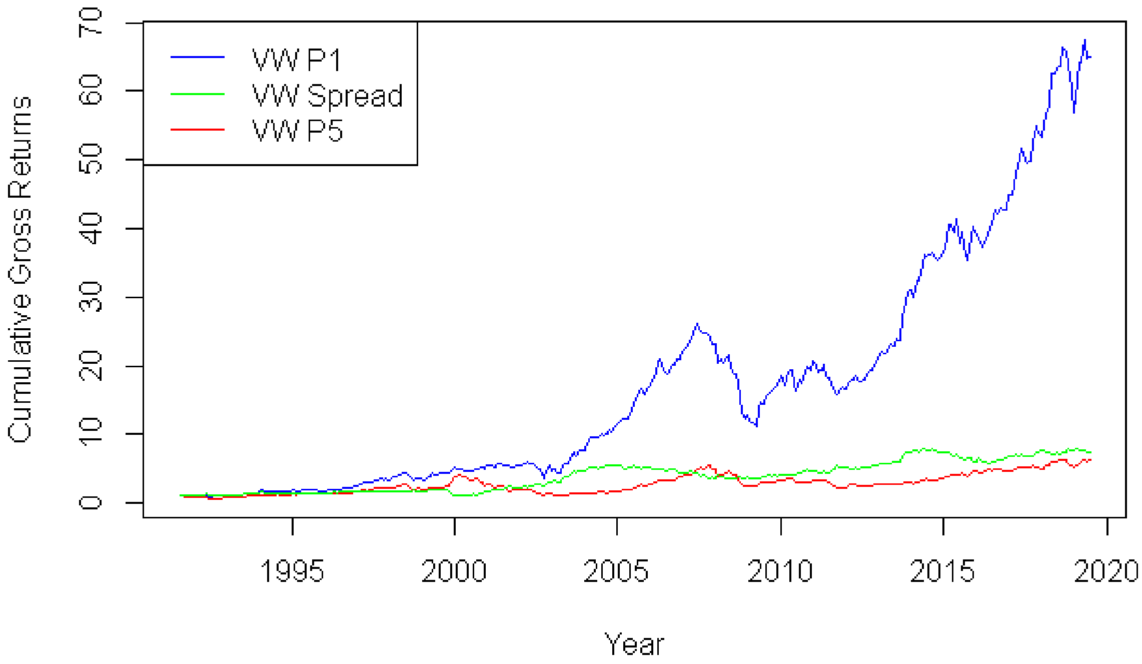
Appendix VI. EW portfolios and MKT Cumulative Log Returns Over Time. The figure plots cumulative log returns for the market factor (*MKT*) and EW cumulative log returns for big low growth (P1) and big high growth (P5) portfolios from July 1991 to June 2019. We consider the full Nordic sample.



Appendix VII. VW portfolios and MKT Cumulative Log Returns Over Time. The figure plots cumulative log returns for the market factor (*MKT*) and VW cumulative log returns for big low growth (P1) and big high growth (P5) portfolios from July 1991 to June 2019. We consider the full Nordic sample.



Appendix VIII. EW Cumulative Gross Returns Over Time. The figure plots EW cumulative gross returns for big low growth (P1), big high growth (P5) and spread portfolios from July 1991 to June 2019. We consider the full Nordic sample.



Appendix IX. VW Cumulative Gross Returns Over Time. The figure plots VW cumulative gross returns for big low growth (P1), big high growth (P5) and spread portfolios from July 1991 to June 2019. We consider the full Nordic sample.